Attention and Valuation for Sequences of Rewards

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Abstract

(to be added)

1 Introduction

Attention is pivotal for people to make decisions in information-rich environments. In everyday life, people often face economic decisions that involve receiving rewards at different points in time. For instance, to decide whether to invest in a pension plan, they have to take into account the potential benefits they could receive at various future times. Such decisions usually require people to calculate the total value of multiple rewards, each with multiple attributes (time and amount). Because of the variety of information involved, it is highly likely that attention plays a key role in their decision processes. However, there is a significant gap in research on how attention may affect the valuation of reward sequences. In this paper, we explore this topic with three pre-registered experiments.

To valuate a sequence of rewards, people may have to process the information about each amount they could receive, and then bind it with certain time information, and finally, aggregate them to obtain a representation of total value. We borrow from the previous research about attention and propose that attention plays a role in each stage of this process. First, when they process an individual amount, they need to extract certain information from their mind and use it as an evidence to support their valuatation. Paying more attention to the amount may facilitate the extraction of information and amplify its value. Relevant literature includes drift-diffusion models {(DDMs, see Ratcliff et al., 2016)) and query theory (Weber et al., 2007; Johnson et al., 2007). In addition, Krajbich et al. (2010) import an attention parameter into DDMs to capture this effect. Second, when people combine the amount and time attributes, they may tend to focus on one attribute and ignore the other. A relevant evidence is that consumers sometimes use the "take-the-best" heuristic (Gigerenzer and Gaissmaier, 2011) in multi-attribute choices: taking into account only one attribute each time and and making choices entirely based on that attribute. Third, when they integrate the different information to construct an aggregate value representation, they may tend to overweight the rewards with large values and underweight (but still assign some weight to) the rewards with small values, given the former attract more of their attention. The relevant evidence include value-driven attentional capture(Hickey et al., 2010; Anderson et al., 2011; Chelazzi et al., 2013) and the hidden-zero effect (Magen et al., 2008; Radu et al., 2011; Read et al., 2017). The same notion has been widely adopted by theories involving risky choices, such as the salience theory (Bordalo et al., 2012, 2013) and utility-weighted sampling (Lieder et al., 2018).

In three separate experiments, we investigated each of the three channels through which attention operates. In each experiment, we set up a simple choice context in which decision makers are asked to choose between two options. Under one option, they can receive an amount M immediately (e.g. "receive £120 today"). Under the other option, they can receive an amount X_1 immediately and another amount X_T in delay T (e.g. "receive £80 today and £70 in 12 months"). The latter option is called a "sequence option" and we investigate how decision makers' preference for this option is affected by attention and elements in that option.

In Experiment 1, we exogenously direct the decision makers' attention to the delayed reward in the sequence option. We force the decision makers to view the options before they are allowed to make a choice, and then block out a part of each option. After they have made a choice, an additional question appears on the same screen asking them the content of the sequence option. The part being blocked contains the delayed reward of the sequence option, so they have to answer the question in the situation of having access to this relevant information. To correctly answer the additional question, decision makers have to pay special attention to the delayed reward during the forced viewing period (when considering their choices). We find that this manipulation method significantly increase their preference for the sequence option, which indicates the value of the delayed reward might be amiplified by attention. Moreover, we apply the same manipulation method to a perceptual choice task (irrelevant to valuation) and find it has no effect on choices. This experiment also provides a direct evidence on how attention can affect intertemporal choices.

Experiment 2-3 investigate the role of attention by manipulating the elements in the sequence option. In Experiment 2, we leave a blank for the amount M, and ask participants to identify which level of this amount can make them indifferent between the two options. Suppose decision makers are indifferent between the two options when $M = Y$. We find a substantial proportion of participants totally ignore the time attribute in this task: their answers are simply the sum of two amounts in the sequennce option, i.e. $Y = X_1 + X_T$ (they do not consider any delay discounting). These specific responses may be related to a heuristic as they take less time than other responses.

For the remaining participants in Experiment 2, we find $Y - X_1$ is decreasing in X_1, keeping the others equal. This behavioral pattern significantly deviates from some widely-used discounted utility theories. The discounted utility theories typically assume $u(Y) = u(X_1) + w_T \cdot u(X_T)$, where $u(.)$ is a concave utility function and w_T is a discount factor. Under certain T and X_T, $u(Y) - u(X_1)$ should be constant. Because $u(.)$ is concave, each increase in X_1 should incur a larger increase in Y. So, this implies that $Y - X_1$ is increasing in X_1 (note Y could be decomposed to $Y - X_1$ and X_1), which is opposite to our finding.

The behavioral pattern that $Y - X_1$ decreases with X_1, as well as the results of Experiment 3, can provide an implication for modifying the discounted utility theories. Note X_1 is a common amount in both options. Thus, $Y - X_1$ reflects the present value of the delayed reward. Our finding suggests increasing the immediate reward X_1 in the sequence option could make the value of delayed reward more discounted. In Experiment 3, we investigate the interactions between the values of different rewards in the sequence option with another approach: participants are asked to make a series of choices under different M, X_1, X_T and T (elements in those options). We infer the indifference points bewteen options through these choices. We find that, keeping the others equal, under a larger X_1, their indifference points characterized by X_T exhibit a greater randomity. Meanwhile, under a larger X_T, their indifference points characterized by X_1 also exhibit a greater randomity. We estimate the implication of these results for the discounted utility theories by estimating a probabilistic choice model. The model estimation results suggest that increasing the amount of one reward (either X_1 or X_T) could make the value of the other reward more discounted. In other words, people tend to underweight a small reward when there is a large reward in the sequence.

Moreover, in Experiment 3, we also find that under a larger sequence length T, the participants' indifference points characterized by X_1 exhibit a greater randomity. Within the discounted utility framework, this could indicate that the value of the immediate reward is more discounted when the immediate reward and the delayed reward in the same sequence are far away from each other (there are more zero values between them). This result is consistent with the hidden zero effect. To our knowledge, the result is not captured by most of the existing discounted utility theories. We propose that one method to incorporate this in discounted utility is to assume that the total capacity of weights (discount factors) that a decision maker can allocate across different time points is fixed at some certain level.

The remainder of this paper is organized as follows. Section 2 discusses the possible channels through with attention can affect the valuation of reward sequences. Section 3 presents the implications of overweighting (underweighting) certain values within the discounted utility framework. Section 4-6 presents the each experiments. Section 6 discusses the relationship between our experimental results and the existing theories about time discounting.

2 How Attention May Shape the Value of A Reward Sequence

2.1 Elemental Properties of Attention

There is currently no consensus among scholars on what attention is. However, many scholars have acknowledged that attention is constituted by multiple cognitive mechanisms, and identified some of its elemental properties. Here we present four properties of attention on which our research is grounded.

First, attention is selective. Back in 1890, William James described the underlying principle of attention as "withdrawal from some things in order to deal effectively with others". Since then, various studies have suggested attention has the function of filtering certain information into consciousness (or inhibiting the processing of other information) when people are overloaded with information. A more modern view, proposed by Gottlieb and Balan (2010), Gottlieb (2012) and Sharot and Sunstein (2020), describes attention as an active sampler, making selections based on the utility of information. These scholars summarize a range of neuroscientific evidence and state that people tend to pay attention to information with higher instrumental utility (reducing uncertainty), hedonic utility (associated with a significant reward), or cognitive utility (satisfying curiosity).

Second, attention is the allocation of limited capacity. This capacity view of attention was firstly proposed by Kahneman (1973). According to Kahneman's view, processing information consumes cognitive resources in the brain, therefore people need attention to allocate their limited cognitive resources to different information sources.

Third, attention could be driven by both exogenous factors and endogenous factors. These factors drive attention through various ways. A salient stimuli which is exogenous, can naturally capture attention, whereas a goal which is endogenous, can alter attention through consuming cognitive resources. Notably, recent research suggests an endogenous factor can also capture attention (Awh et al., 2012; Failing and Theeuwes, 2018). A typical example is "*value-driven attentional capture*"(Hickey et al., 2010; Anderson et al., 2011; Chelazzi et al., 2013). In relevant studies, researchers ask people to do a series of visual search tasks, and in each task, people can get a reward for detecting a target object from distractors. The value-driven attentional capture effect implies that an object associated with large rewards in preceding tasks can capture participants' attention. Therefore, when it is being a distractor, it can naturally slow down the target detection.

Fourth, attention is decisive for people to resolve objects, and to scrutinize and recognize their features and actions (He et al., 1996; Intriligator and Cavanagh, 2001). Figure 1 demonstrates the role of attention in this respect with a simple example. Many scholars use "spotlight" as a metaphor for attention. For areas illuminated by the spotlight, people can easily discern any changes occurring within. But for areas outside of the spotlight, they may not be sensitive to changes happening there.

Figure 1: The role of attention in resolving objects

Note: Keep your eyes around 30cm away from the page, and fixate the cross. The letters to the right are easily seen. However, it may be difficult to identify what the fifth letter is ("**N**") because few attention is paid to it.

2.2 Attention Enhances Values for Individual Rewards

There is a growing body of literature suggesting, when people face a choice between multiple rewards, directing their attention to one reward (or the positive aspects of it) can increase its value.[1] A theoretical explanation involves viewing the valuation of a certain reward as

[1] Orquin and Loose (2013) reviewed some relevant evidence. For more recent studies, see Smith and Krajbich (2019), Gwinn et al. (2019) and Pleskac et al. (2023). For studies in the field of intertemporal choices, see Franco-Watkins et al. (2016) and Fisher (2021). Also, note all rewards in this paper refer to positive rewards (gains rather than losses).

an evidence-accumulation process. When decision makers selectively spend more cognitive resources processing a positive reward, they may be able to accumulate a greater amount of evidence to support their preference for it, thereby increasing its value. Or, if they selectively prioritize the processing of positive evidence toward a reward, it may inhibit the processing of the negative evidence that emerges subsequently, which also increases its value.

Examining the causal effect of attention on reward valuation involves exogeneously manipulating the drivers of attention in experimental settings. In existing studies, there are two typical attention manipulation methods. The first is through controlling the gaze duration, such as presenting rewards in order and each with certain duration (Shimojo et al., 2003; Armel et al., 2008; Fisher, 2021; Bhatnagar and Orquin, 2022). The second is to prioritize the processing of certain information. For example, one can increase visual saliency of an option (Milosavljevic et al., 2012), or ask participants to fixate a certain area around the option when making choices (Lim et al., 2011), to let them prioritize the perceptual processing of that option. Besides, in a choice task, Weber et al. (2007) ask people to think about the positive aspects of an option first and then the negative aspects, and list their thoughts. This manipulation prioritizes the processing of certain semantic information. In a review, Mormann and Russo (2021) argue that gaze duration is not identical to attention. Thus, we design our study with the second method.

Most studies on causal relationship between attention and value are set up with two options, and each option contains only one reward. So far, the only study investigating this topic in the intertemporal choice field is Fisher (2021). In that study, participants are presented with a small-sooner reward (SS) and a large-later reward (LL), and the researcher finds directing their attention to one reward can increase the preference for it. In our Experiment 1, we investigate whether we can apply a similar result to the case where an option is a sequence of multiple rewards. To illustrate, imagine that you face a choice between:

A. receive £200 today

B. receive £100 today and £130 in 6 months

Taking receiving £100 today as the benchmark. By choosing option A, you can get an additional amount of £100 today; by choosing option B, you can get an additional amount of £130 in 6 months later. So, the choice is similar with a choice between SS and LL. Suppose before you make the decision, we direct your attention to the second reward in option B, i.e. receiving £130 in 6 months. Then, your preference for option B may increase, because it is the same as directing your attention to a LL. To test this hypothesis, in Experiment 1, we design a novel attention manipulation method which let participants to prioritize the semantic processing of that reward. We find this method can effectively alter participants' preferences in our experimental context.

2.3 Inattention to Time Attribute

When people face a choice between SS and LL, some may make comparisons between attributes (time and amount) while others may make comparisons between rewards. For instance, in one study, Reeck et al. (2017) cluster participants into two groups using their mouse trajectories during the decision process. About half of the participants tend to switch mouse between attributes and the other half tend to switch mouse between options. The former may indicate attribute-wise comparison while the latter may indicate option-wise comparison.

One study of Fisher (2021) investigates how allocating attention across attributes may affect the choice between SS and LL. The researcher finds that directing participants' attention to the time attribute can increase their preference for SS while to the amount attribute can increase their preference for LL. However, in a choice involving sequences, focusing on one attribute and ignoring the other could have a different implication for decision making. As an illustration, imagine that you have two options:

C. receive £100 today and £70 in 6 months

D. receive ________ today

and you can fill in the blank in option C with any amount. Then, with what amount, you would become indifferent between the two options? The answer will depend on how you value each option. Suppose you think about each attribute separately. In terms of the amount attribute, option C contains two amounts, £100 and £70. In terms of the time attribute, option C contains two dates when you can receive a positive reward, “today” and “6 months later”. Since the question asks you to fill in an amount, focusing on amounts and ignoring the times may be more nature than the opposite. In an extreme case, if you totally ignore the time attribute, then the times should have no impact on your valuation, so the amount you fill should be exactly the sum of two amounts in option C. In Experiment 2, we find a supportive evidence for this. Notably, this causes their behavior to deviate from any prediction made through time discounting theories.

2.4 (In-)attention to Small Values

Now suppose a decision maker valuates a reward sequence by valuing each reward (rather than each attribute) separately and then binding the values together. In Section 2.2, we discuss how attention may affect the value of each individual reward. Here we discuss how attention may affect the process of binding values together.

Our discussion is primarily driven by the evidence of *value-driven attention capture* and the *hidden-zero effect*. The value-driven attentional capture implies objects with large values can capture people’s attention, particularly in visual search. We propose the same remark could apply to the valuation of reward sequences. Once a reward is associated with a large value, it also captures attention and thus, given attention is limited, people become inattentive to other (small) rewards in the sequence. As a result, they may take more into account the large rewards and less into account the small rewards during their valuation of the sequence.

Consider the choice between option C and option D again. Suppose the earlier amount in option C is increased from £100 to £1,000, so that the option becomes “receive £1,000 today and £70 in 6 months”. Then, when a decision maker is valuing this option, the earlier amount £1,000 can capture more of her attention and the later amount £70 could be relatively ignored. In the original case, she may value option C equally as much as “receive £160 today”, which implies the present value of the later amount is equal to £60. But in the case that the earlier amount is increased to £1,000, whether she can get an additional amount of £70 in 6 months later is less important, so the present value of the later amount could decrease to some smaller number (say, equal to £20). Under this circumstance, she may value option C equally as much as "receive £1,020 today". Moreover, since she ignores the later amount, she would be insensitive to the changes in that while valuating the sequence. In other words, any change in the later amount should lead to a smaller change in the total value of sequence.

The hidden-zero effect (Magen et al., 2008; Radu et al., 2011) implies when decision makers valuate a reward sequence, they also take into account the value of zero rewards. Read et al. (2017) find the hidden-zero effect is asymmetric. To illustrate, suppose people are indifferent between "receive £100 now" (SS), and "receive £120 in 1 year" (LL). The (asymmetric) hidden-zero effect indicates, keeping the others equal, changing SS to "receive £100 now and £0 in 1 year" would make people more likely to choose LL, whereas changing LL to "receive £0 now and £120 in 1 year" has no effect on their preferences. An explanation is that people perceive the original SS as a single immediate reward (or a very short sequence) and the original LL as a sequence delivering zero reward at any time within a year. Specifying the zero amount for SS triggers people to notice there are zero rewards delivered in the far future, which they originally did not consider. Given their attention is limited, this may reduce their attention to the immediate reward £100. As a result, they take less into account the amount £100 and more into account zeros which they will receive in the future, thereby devaluing the SS. By contrast, when valuing the LL, they have already taken those zeros into account, so specifying the zero amount has no effect on their preferences for LL.

In the case that a decision maker can "receive £100 today and £70 in 6 months", the hidden-zero effect has another implication. If we increase the delay "6 months" to "12 months", there will be more zeros being considered in this sequence and thus the attention assigned to both the earlier and later amounts should decrease. On the one hand, this should decreases the total value of sequence. On the other hand, the total value should be less sensitive to not only the changes in the later amount, but also the changes in the earlier amount.

3 Implications of Attention to Small Values for Time Discounting

3.1 Theoretical Background

We restate the arguments about (in-)attention to small values in Section 2.4 with a more formal framework. Consider a decision maker facing a choice between two options. Under one option, she could receive X_1 now and X_T in delay T; under the other option, she could receive M now and no reward at any other times (X_1, X_T, T, and $M > 0$). According to the additive discounted utility theories, the value of the former option can be represented by $w_1 \cdot u(X_1) + w_2 \cdot u(X_T)$ and that of the latter option can be represented by $k \cdot u(M)$, where $u(.)$ is a strictly increasing and strictly concave utility function, and $u(0) = 0$. The parameters w_1, w_T, k are the weights (somtimes called discount factors) assigned to X_1, X_T and M in each option. Hereafter, we call the first option a "sequence option", and the second option a "single option". In a sequence option, the amount delivered immediately is called the "*front-end amount*", and the amount delivered later is called the "*back-end amount*".

In the sequence option, one unit change in $u(X_t)$ will yield a w_t unit change in the total value ($t \in \{1, T\}$). So, the weight w_t somehow reflects decision makers' sensitivity to changes in $u(X_t)$ in terms of valuating the certain sequence. In Section 2.4, we propose that paying less attention to $u(X_t)$ would make decision makers less sensitive to it, thereby decreasing w_t. Furthermore, there are two situations that can alter the volume of attention allocated to $u(X_t)$. The first is that the amount of another reward is increased by a sizeable level (value-driven attentional capture). The second is that we add a tiny value, e.g. $u(0)$, to some time point after t, but still in the sequence (hidden-zero effect). In either situation, decision makers' attention would be directed to somewhere other than the reward X_t and w_t should decrease.

A widely adopted assumption about time discounting is that the weights depend only on times. Several popular discounting theories, e.g. exponential and hyperbolic discounting, have adopted this assumption. However, our consideration about attention to small values predicts an interaction between the weights and reward amounts. Moreover, we predict the weight assigned to the current time, i.e. w_1, can also be discounted, and can be discounted more when there is a large T or X_T. In the following two subsections, we analyze what particular behavior, if being observed, will allow us to identify such an interaction.

3.2 Implication for Indifference Points

Suppose the decision maker is indifferent between the two options when $M = Y$. We call Y the "indifference point" in this context. In the additive discounted utility framework, we have

$$k \cdot u(Y) = w_1 \cdot u(X_1) + w_T \cdot u(X_T) \tag{1}$$

Assume all the weights depend only on times. In the given context, it implies we can set $k = w_1 = 1$. Let both T and X_T be constant, then under this assumption, $w_T \cdot u(X_T)$ should also be constant. Thus, to make Equation (1) hold true, $u(Y) - u(X_1)$ should be constant. Given that $u(.)$ is strictly concave, for any positive number Δ, we have $u(Y+\Delta)-u(X_1+\Delta) < u(Y) - u(X_1)$. We can decompose Y by $Y = X_1 + (Y - X_1)$. If X_1 is increased by Δ units, to make the equation hold true, Y should be increased by an amount larger than Δ. That is, if the weights depend only on times, $Y - X_1$ should always increase with X_1.

In reverse, under certain T and X_T, if $Y - X_1$ decreases with X_1, there must be an interaction between weights and amounts when applying the additive discounted utility framework. We test this in Experiment 2.

3.3 Implication for Probabilistic Choices

Consider the choice between the two options in a probabilistic choice framework. Keeping the others equal, when either X_1 or X_T increases, decision makers would be more likely to choose the sequence option. Let P denote the choice probability for the sequence option. It is usually assumed that P is determined by the difference in utility between options. Therefore,

$$P = \phi(w_1 \cdot u(X_1) + w_T \cdot u(X_T) - k \cdot u(M)) \tag{2}$$

where $\phi : R \rightarrow [0, 1]$ is a link function. We assume $\phi(.)$ is strictly increasing. When w_1 is smaller, for each unit increase in $u(X_1)$, there should be a smaller increase in P. In this case, the choices of the decision maker tends to appear more random. The same behavioral implication can apply to w_T.

Keeping the others equal, if the weights depend only on times, then w_1 and w_2 should be independent of X_1, X_T and T. The attention to small values, as we stated in Section 2.4, has two implications to these weights. First, based on value-driven attentional capture, we state a larger X_1 may reduce w_T and a larger X_T may reduce w_1. Second, based on the hidden-zero effect, we state a longer T may reduce not just w_T but also w_1. We test these implications in Experiment 3 by estimating a specification of Equation (2) and see whether there is an interaction between weights and different variables.

In summary, if people are (in-)attention to small values when valuating a reward sequence, changing the delay or amount of one reward would not just affect the weight assigned to itself, but should also interfere the weight assigned to the another reward within the sequence. Our Experiment 2-3 provide evidence for this.

4 Experiment 1: Causal Manipulation of Attention

4.1 Design

Experiment 1 aims to test whether directing people's attention to a reward can make them value that more, in the context of valuating reward sequences. We set up a series of choice tasks. The tasks are divided into four parts. Each task in Part 1-2 is called an intertemporal choice task. Each task in Part 3-4 is called a count-the-rabbits task. At each time there is only one task presented on the screen. The task screens are developed with HTML and Javascript, and we deploy the experiment through JATOS (Lange et al., 2015). Before each part begins, there are 2-3 example tasks to help participants get familiarized with the tasks in the corresponding part.

In Part 1-2, each task contains two options. The first option, presented on the top, is a single immediate monetary reward. The second option, presented on the bottom, is a sequence of two positive monetary rewards: one delivered immediately and the other delivered in some delay. Participants are required to choose the option they prefer. When each task begins, both options are not visible. Participants have to click a "Display" button to view the options. They are forced to view the options for at least 1.8s (during this time, their mouse pointer will be hidden) before they are able to make a choice.

In Part 1, after participants submit a choice, they can directly start the next task. In Part 2, after submitting a choice, an additional question will appear on the same screen. This additional question has three options, and participants have to identify which one among the three options is the sequence option for the current task. We inform participants that the additional question is to test their understanding and attention to the choice task, and ask them to try their best to correctly answer this question. We name any task followed by such an additional question as a task in the "question" part, and any task without such a question as a task in the "no question" part. Figure 2(a) demonstrates an example intertemporal choice task.

Tasks in Part 3 follow the same format as in Part 1, while tasks in Part 4 follow the same format as in Part 2. Nevertheless, in Part 3-4 we replace the monetary rewards by some rabbit symbols. In each count-the-rabbits task, we have one option containing a single set of rabbit symbols, and another option containing two sets of rabbit symbols. Participants need to identify which option has more "rabbits". In Part 3, participants can directly move to the next task once finishing the choice; In Part 4, following each choice, there is an additional question asking them the exact number of rabbits in the sequence option. Figure 2(b) demonstrates an example count-the-rabbits task.[2]

Participants are randomly assigned to two groups. In one group, in each task once both options become visible, they remain visible until the participants move to the next task. We call this group the "full-exposure" group (control group). In the other group, after both options have been displayed for 1.8s, the right half of each option will be blocked out. The participants need to make choices in the case that only part of the information is visible

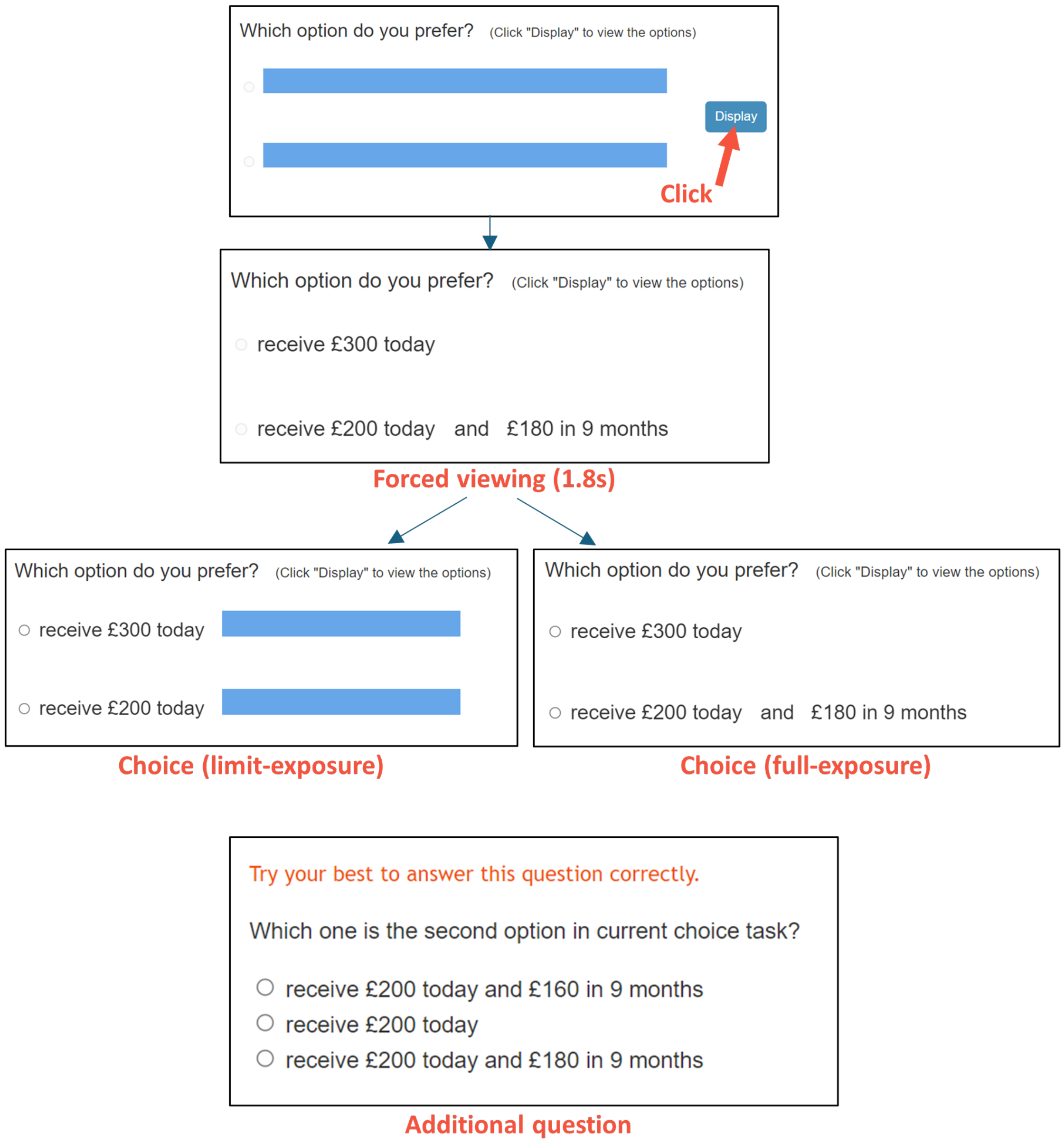
[2] Given the format of count-the-rabbits tasks are the same as intertemporal choice tasks, in Figure 2(b), we only demonstrate the screen that the participants face when being asked tp making a choice.

(see Figure 2). We call this second group the "limit-exposure" group (treatment group). Notably, since each option has a different length of content, only in the sequence option will a part of the information be actually blocked out. For the single option, we only block out a blank space. In an intertemporal choice task, the information being blocked is the delayed reward in the sequence option; in a count-the-rabbit task, the information being blocked is the second set of the rabbit symbols in the sequence option.

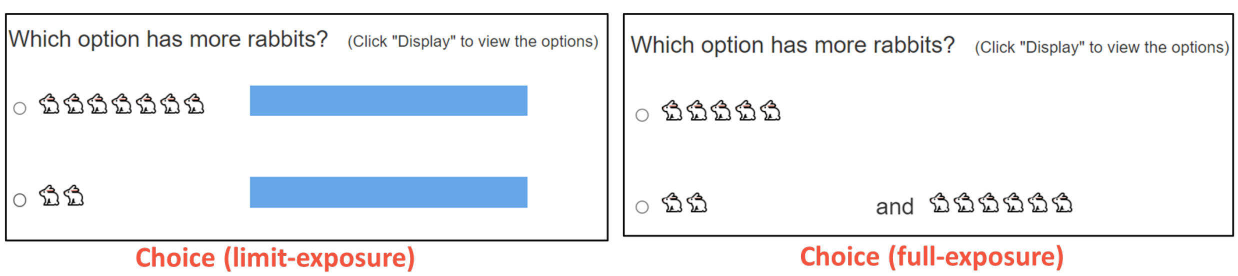
In each intertemporal choice task, the single option can be denoted by "receive η today" and the sequence option by "receive $\rho\eta$ today and $1.5(1-\rho)\eta$ in 12 months". In other words, by choosing the single option, a decision maker would get an amount $(1-\rho)\eta$ more today than the front-end amount in the sequence option; by choosing the sequence option, the same amount $(1-\rho)\eta$ would be invested in a riskless bond and the decision maker would get an interest of 50% in one year later. Thus, the preference for the sequence option is an indicator of patience. We select η from {£200, £240, £280, £320} and ρ from {0.1, 0.2, 0.3, 0.4, 0.5, 0.6}. Overall, Part 1-2 contain 24 main tasks. We randomly and evenly assign these tasks to each part. Except that, we add an attention check task in each part and participants who fail one of them will be excluded from the sample.[3]

In each count-the-rabbits task, suppose the single option contains r_1 rabbits, the first set of the sequence option contains r_2 rabbits, and the second set contains r_3 rabbits. We select r_1 from {7, 8}, r_2 from {1, 2, 3}. In half of these tasks, the sequence option has one more rabbit than the single option ($r_2 + r_3 = r_1 + 1$); for the other half, the single option has one more rabbit than the sequence option ($r_2 + r_3 = r_1 - 1$). Overall, there are 12 main tasks in Part 3-4. Similar to the intertemporal choice tasks, we randomly and evenly assign these tasks to each part.

[3] In one attention check task, each amount in the sequence option is £300 and the amount in the single option is £10. In the other attention check task, each amount in the sequence option is £80 and the amount in the single option is £300. Therefore, participants should definitely choose the sequence option in the former task and the single option in the latter task.



(a) Intertemporal Choice Task



(b) Count-the-Rabbits Task

Figure 2: Example tasks in Experiment 1

4.2 Altering Attention through Goals

The difference between the two groups (limit-exposure/full-exposure) lies in the information participants were exposed to when making choices. Each participant experienced two parts (no question/question). As is pointed out by Chun et al. (2011), a critical function of attention mechanisms is to "focus limited processing capacity on the most important information relevant to ongoing goals". In the "limit-exposure" group, to achieve the goal of correctly answering the additional questions, in each task participants have to remember the (only) information being blocked out. Thus, in an intertemporal choice task, during the forced viewing period they have to prioritize the processing of the back-end amount in the sequence option, as this information will never be accessible after that. By contrast, in the "full-exposure" group, all relevant information is visible when participants answer the additional question, so they do not need to specifically focus on that back-end amount.

Given the back-end amount is sizable, paying more attention to it should make participants value the sequence option more. Therefore, for intertemporal choice tasks, our hypothesis is that being required to answer the additional question would increase participants' preference for the sequence option within the "limit-exposure" group, and would not have much impact on the choices of those within the "full-exposure" group.

The count-the-rabbits tasks help us understand the mechanisms by which attention influences choices. As is pointed out by Pleskac et al. (2023), attention can alter choices by two possible processes: one is through valuation, the other is through perception. The latter implies attention may increase the perceived salience of an object and people intuitively tend to choose the more salient option. In specific preferential and perceptual choice tasks, Pleskac et al. (2023) find evidence supporting the valuation process and contradicting the perception process. For our experiment, the count-the-rabbits tasks (perceptual choice) serve as an analog to the intertemporal choice tasks (preferential choice). If attention alters choice through perception, the groups and additional questions should influence the choices in the same way for both kind of tasks. Indeed, the results in Section 4.4.1 and Section 4.4.2 suggest they influence the choices in each kind of tasks in different ways, thus supports the valuation process.

4.3 Sample

We recruited 300 UK residents via Prolific (female: 152; mean age: 43.6). The median completion time is 10.1 minutes. Each participant was paid £1.5 (on average £8.1 per hour). Four participants failed the attention check. Besides, there were two participants for whom the tasks were not displayed in the correct order.[4] We drop the participants who fail the attention check and those for whom the tasks were not displayed correctly. In the end, there are 148 participants in the "full-exposure" group and 146 participants in the "limit-exposure" group. We obtain 7,065 observations for intertemporal choice tasks and 3,504 observations for count-the-rabbits tasks.

The accuracy rate for the additional questions in "question" parts is high for each kind of tasks. For intertemporal choice tasks in Part 2, the overall accuracy rate is 94.0%, and 208 participants correctly answered all questions. For count-the-rabbit tasks in Part 4, the overall accuracy rate is 96.7%, and 259 participants correctly answered all questions.

4.4 Results

4.4.1 Intertemporal Choice Tasks

Table 1 illustrates how choices for the sequence option vary across different kinds of tasks, groups and parts. For intertemporal choice tasks, the proportion of choices for the sequence option in the "question" part is 5.5% higher than the "no question" part within the "limit-exposure" group, while within the "full-exposure" group, this difference is 2.1%. For count-the-rabbits tasks, the difference is 0.6% within the "limit-exposure" group and 2.2% within the "full-exposure" group. Results of χ^2-tests suggest the first difference, i.e. the difference for intertemporal choices in the "limit-exposure" group, is significant at the significance level 0.1% while the others are not significant.

Further, we examine the impact of groups and questions on intertemporal choices through

[4] For one of them, the data collected for main tasks in Part 2 ended up being the counterpart example tasks. For the other participant, the data collected for the example count-the-rabbit tasks in Part 3 ended up being intertemporal choice tasks.

Table 1: Comparing choices across parts in Experiment 3

Task	Group	Part: question	Part: no question	χ^2
Intertemporal Choice	limit-exposure	0.523	0.468	10.303 (p=0.001)
Intertemporal Choice	full-exposure	0.469	0.448	1.470 (p=0.225)
Count-the-Rabbits	limit-exposure	0.463	0.474	0.147 (p=0.702)
Count-the-Rabbits	full-exposure	0.515	0.476	2.470 (p=0.116)

Note: For each kind of tasks and each group, the proportion of choices for the sequence option in each part (question/no question) is reported in separate columns. In each row, we test whether the choices between parts follow the same distribution through χ^2-test. p-values are reported in parentheses.

a set of logistic linear regressions. Each regression model is estimated through the maximum likelihood method. Table 2 illustrates the key fixed-effect estimates in the results. The dependent variable is 1 if a participant choose the sequence option in a task and 0 otherwise. The variable Group is 1 if the participant is in the "limit-exposure" group and 0 otherwise; Question is 1 if the task is within the "question" part and 0 otherwise. We construct a dummy variable for each individual task and include these dummies as intercepts in regression models. For analysis, we first assume the error is homoscedastic across the participants and run a pooled regression on the full sample. Column (1) in Table 2 show the results of this pooled regression. Then, we add participant-specific dummies to the regression model. In intertemporal choice tasks, there are some participants whose choices are fixed at one option.[5] Including these participants in the regression with participant-specific dummies will make the design matrix singular. We apply two remedies to this. In Column (2), we run the regression on the sample in which each participant has changed her choice at least once across all intertemporal choice tasks. In Column (3), we run the regression on the full sample, but represent the participants fixing at one option with two only dummies: one for those always choose the sequence option, and the other for those always choose the single option.

[5] In the "limit-exposure" group, 23 participants always choose the single-amount option and 21 participants always choose the sequence option. In the "full-exposure" group, 31 participants always choose the single-amount option and 35 participants always choose the sequence option.

Table 2: Regression results for intertemporal choice tasks

	(1) Pooled	(2) FE	(3) FE
Group	0.085	0.047	-0.096
	(0.19)	(0.533)	(0.154)
Question$\cdot 1\{\text{Group} = 0\}$	0.085	0.301	0.301
	(0.059)	(0.189)	(0.187)
Question$\cdot 1\{\text{Group} = 1\}$	0.218***	0.53***	0.53***
	(0.067)	(0.164)	(0.163)
observations	7056	4416	7056
AIC	9625.349	4253.529	4259.531

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Standard errors are clustered at the subject level and are reported in the parentheses. The p-values are calculated based on Wald tests. Each model includes task-sepcific dummies as intercepts. Models for Column (2)-(3) include participant-specific dummies for those having changed their choices at least once across all intertemporal choice tasks. In addition, the model for Column (3) includes two dummies capture whether a participant always chooses the sequence option, and the single option.

As is consistent with our hypothesis, in the "limit-exposure" group (i.e. Group = 1), participants are significantly more likely to choose the sequence option within the "question" part than within the "no question" part (For each column, $p = 0.001$). By contrast, in the "full-exposure" group (i.e. Group = 0), the additional questions do not increase the preference for the sequence option by any significant level.

4.4.2 Count-the-Rabbits Tasks

In count-the-rabbits tasks, 226 participants correctly choose the option with more rabbits for every task, and the overall accuracy rate is 97.0%. There are only 105 wrong choices. As is illustrated in Figure 3, the wrong choices in count-the-rabbits tasks are disproportionally biased to the single option. In all conditions except when participants do the "question" part within the "full-exposure" group, they are more likely to choose the single option by mistake. A possible explanation for this is, in the "full-exposure" group, to answer the additional questions, participants need to (and they can) count the rabbits within each bunch, which helps eliminating the choice mistake.

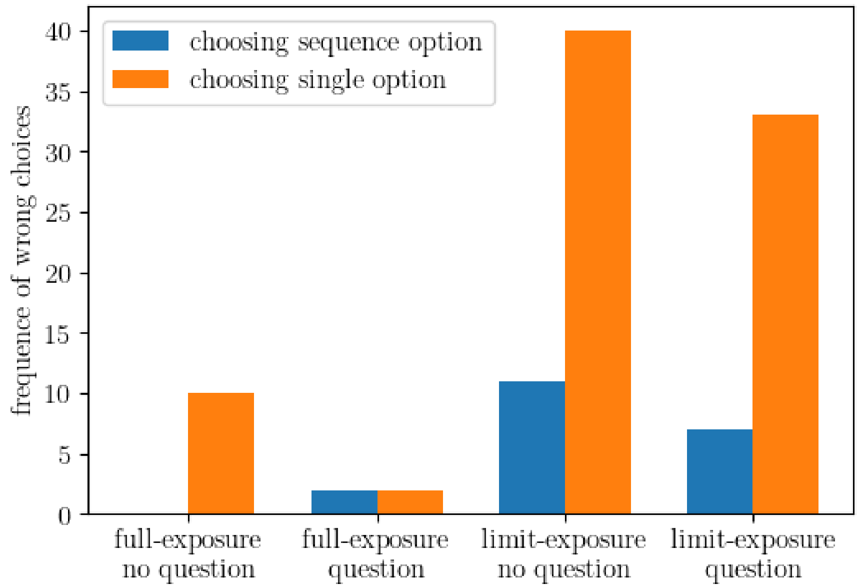


Figure 3: Frequence of wrong choices in count-the-rabbits tasks

We conduct a set of logistic linear regressions upon the choices in the count-the-rabbits tasks. Table 3 illustrates the key fixed-effect estimates. The dependent variable, and the variable Group as well as Question are the same as for the intertemporal choice tasks. Each task is treated as a dummy variable and set as an intercept. Column (1) in Table 3 reports the results of a pooled regression, while Column (2)-(4) report the results of a model with participant-specific dummies. Column (2) is estimated on the full sample, Column (3) is estimated on the sample in which each participant has changed her choice at least once in intertemporal choice tasks, Column (4) is estimated on the sample in which each participant has made at least one wrong choice in count-the-rabbits tasks. Each column is estimated through the maximum likelihood method.

The impact of additional questions on participants' choices, in count-the-rabbits tasks, exihibits an opposite pattern to the intertemporal choice tasks within each group. For count-the-rabbits tasks, within the "limit-exposure" group, the additional questions have no significant effect on choices; within the "full-exposure" group, the additional questions increase the increase the likelihood of the sequence option being selected by a significant level (for Column (1)-(4), the p-values are 0.011, 0.025, 0.017 and 0.009 respectively). By contrast,

Table 3: Regression results for count-the-rabbits tasks

	(1) Pooled	(2) FE	(3) FE	(4) FE
Group	-0.732*	-4.466*	-0.21	-0.964***
	(0.331)	(1.789)	(1.771)	(0.312)
Question$\cdot 1\{\text{Group} = 0\}$	0.581*	1.357*	1.618*	2.032**
	(0.228)	(0.606)	(0.681)	(0.778)
Questsion$\cdot 1\{\text{Group} = 1\}$	0.07	0.225	0.466	0.214
	(0.319)	(0.376)	(0.444)	(0.352)
observations	3504	3504	2190	810
AIC	883.789	1103.793	752.785	586.582

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Standard errors are clustered at the subject level and are reported in the parentheses. The p-values are calculated based on Wald tests. FE indicates a fixed-effect model (containing participant-specific dummies). Column (1)-(2) are estimated on the full sample, Column (3) contains the participants who have changed choices at least once in intertemporal choice tasks, Column (4) contains those having made at least one wrong choice in count-the-rabbits tasks. Each model includes task-specific dummies as intercepts.

in intertemporal choice tasks, the additional questions significantly increase the preference for the sequence option for the "limit-exposure" group but not for the "full-exposure" group.

4.4.3 Decision Times

To examine the participants' decision processes, we record the participants' mouse position at the moment when they are prompted to make a choice, i.e. at the end of the forced viewing period, and their response time in each choice task. The mouse position data suggest that participants may form their intention to choose an option during the forced viewing period, and the response times suggest blocking out information in the sequence option may facilitate their choice for the that option (though according to 2, this has no impact on their time preferences).

First, the mouse position data indicate, during the forced viewing period in each task, many participants tend to move their mouses toward the option they eventually choose, though the mouse pointer is invisible at that period.[6] Note the single option is presented above the sequence option. As is illustrated in Figure 2, when a participant click the "Display" button to view the content of options, her mouse pointer should lie in the middle between the two options. After that, she can move mouse freely until being asked to make a choice. In intertemporal choice tasks, the average distance from the top of the screen to the mouse pointer is 218px for those choosing the single option (on the top) but 264px for those choosing the sequence option (on the bottom). In count-the-rabbit tasks, this average distance is 214px for those choosing the single option and 248px for those choosing the sequence option. Mann-Whitney U tests suggest, in each kind of tasks, the vertical positions of mouse pointer for those choosing the single option are significantly higher than those choosing the sequence option (for intertemporal choice tasks, $U = 9397658.5$, $p < 0.0001$; for count-the-rabbits tasks, $U = 2122489.0$, $p < 0.0001$). In Appendix, we show in Figure B.1 that, at the end of the forced viewing period, the vertical positions of mouse pointer are clustered exactly at the position of the option being chosen subsequently. Therefore, we can infer that many participants are developing their choices before some information is being block out, and if our experimental conditions has a causal effect on choices, it is highly likely that it occurs in the forced viewing period.

Second, we analyze the response times.[7] For intertemporal choice tasks, the average response time is 3.41s for choosing the single option and 3.62s for choosing the sequence option. For count-the-rabbits tasks, the average response times are 3.80s and 4.88s respectively. Mann-Whitney U tests suggest response times for choosing the single option are significantly shorter than for choosing the sequence option (for intertemporal choice tasks, $U = 2528314.5$, $p < 0.003$; for count-the-rabbits tasks, $U = 739393.5$, $p < 0.0001$). Furthermore, we analyze the relationship between response times (in second) and choices as well as experimental conditions through linear regressions. The results suggest choices for the single option take significantly less time, at the significance level 0.5%. Table A.1 of the Appendix

[6] Studies have suggested there is a strong relationship between the direction of mouse movements and subsequent decisions. For evidence, see Freeman and Ambady (2010) and Freeman (2018).

[7] There are outliers in the response time data. For example, the longest time that a participant spent in an intertemporal choice is 349.39s while the average response time is 3.64s. To reduce the impact of outliers on our analysis, we remove the highest 0.5% response times.

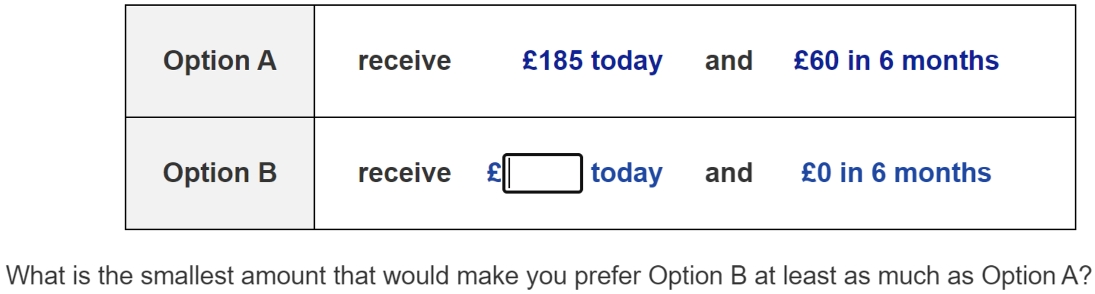
provide more details of these regressions. Therefore, choosing the single option might be more intuitive in our tasks. This also explains why participants tend to choose the single option by mistake in count-the-rabbits tasks.

5 Experiment 2: Indifference Point

5.1 Design

In Experiment 2, we examine the impact of inattention to time attribute and to small values on valuation of a reward sequence. We designed a survey of 19 questions: it contains 14 fill-in-the-blank questions as the main task, 4 choice questions for consistency check, and one additional choice question measuring participants' impatience. For the question measuring impatience, we use the "Preference for Earlier vs Later Income" (PELI) task in Burro et al. (2022). The survey begins with the consistency check questions, continues with the fill-in-the-blank questions, and ends with the PELI question. At each time, there is only one question on the screen. The questions are developed with HTML and Javascript. We use JATOS (Lange et al., 2015) to deploy the survey.

Each fill-in-the-blank question in the main task contains two options - Option A and Option B - framed as reward sequences. Option A offers two positive rewards at two specific times: one is delivered today and the other is delivered after a certain delay (e.g. "receive £185 today and £60 in 6 months"). Option B offers an unknown amount today and zero amount after the same delay. Participants have to identify which level of this unknown amount would make them value the two options equally, and fill in their answer in a box. Figure 4 presents an fill-in-the-blank question in the main task. Before participants start the main task, there is an example question helping them get familiarized with the question format. Throughout the survey, the back-end amount in Option A is fixed at £60. We set up two levels for the sequence length (6 months, 12 months), and seven levels for the front-end amount in Option A (£25, £105, £185, £265, £345, £425, £505) . Overall, there are 14 fill-in-the-blank questions, presented in a random order.



Option A	receive £185 today and £60 in 6 months
Option B	receive £ ☐ today and £0 in 6 months

What is the smallest amount that would make you prefer Option B at least as much as Option A?

Figure 4: An fill-in-the-blank question in Experiment 2

Each consistency check question also contains two options: one is the same as the Option A of a subsequent fill-in-the-blank question, and the other offers a specific amount today and zero amount in the future. The amount offered today in the latter option, is either the same as the back-end amount of the former option, or above the total money of the former option. Participants are required to choose the option they prefer. We exclude the participants whose choices are inconsistent with their answers in the corresponding fill-in-the-blank questions. For example, a participant may face a choice between "receive £185 today and £60 in 6 months" and "receive £300 today and £0 in 6 months". Suppose she chooses the latter, then it indicates she values the latter option more, and for the corresponding fill-in-the-blank question, she should fill in an amount smaller than £300.

5.2 Sample

We recruited 200 UK residents (female: 100; mean age: 40.5) via Prolific. Three participants failed to complete the survey. For those who completed the full survey, the median completion time is 5 minutes. We pay each participant £1.2 (on average £14.26 per hour). There were 161 participants passing the consistency check. We remain the participants passing the consistency check in our sample. Given that each of them completed 14 fill-in-the-blank questions, we construct a sample of 2,254 observations.

5.3 Results

5.3.1 Heterogeneity in Decision-Making

In each question, Option A can be denoted by "receive X_1 today and X_T in delay T" and Option B can be denoted by "receive Y today and £0 in delay T". The amount Y is filled by participants and we call it the indifferent point between two options. Taking receiving X_1 now as the benchmark, by choosing the sequence option people can receive an additional amount of X_T in delay T, and by choosing the single option they can receive an additional amount of $Y - X_1$ now. Thus, the present value of X_T is revealed by $Y - X_1$. For a certain X_T, a smaller $Y - X_1$ indicates that people may discount the value of X_T more.

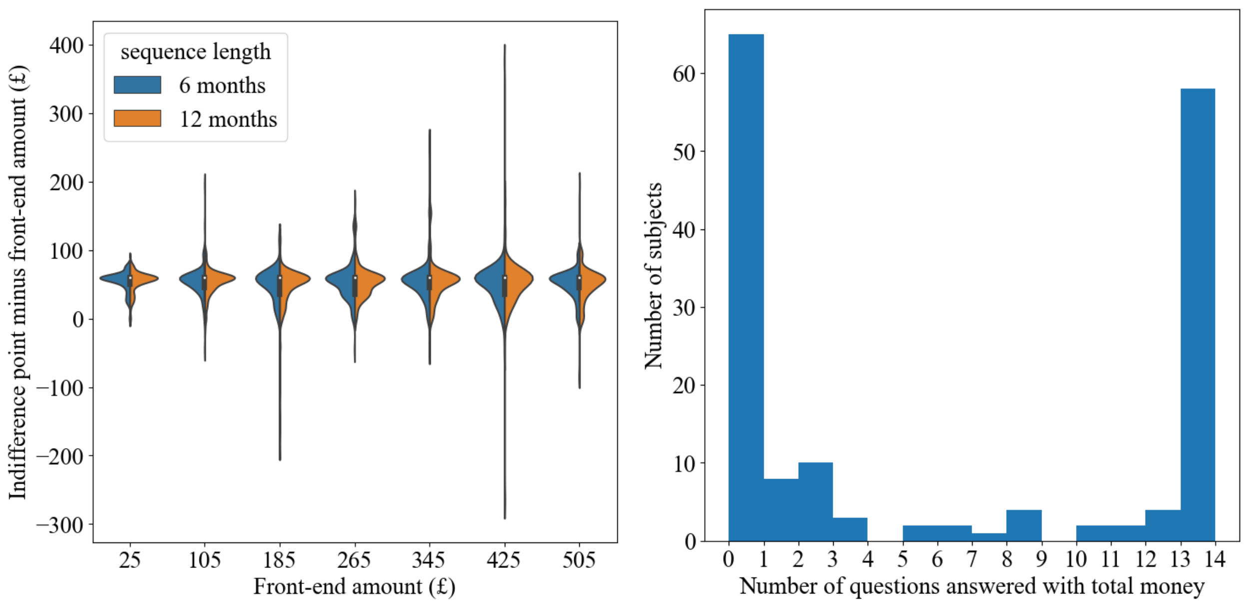
Figure 5(a) illustrates the distribution of indifference points for each question. Note in Option A, the back-end amount is fixed at £60. The y-axis of this subfigure is the indifference point minus front-end amount, i.e. $Y - X_1$. 86.4% of the observations lie in the range from £0 to £60; 12.8% of the observations are above £60, implying that some participants value Option A as much as receiving an amount greater than its total money today; 0.8% of the observations is negative, implying that some the participants value Option A as much as receiving an amount lower than its front-end amount today. The latter two could originate from various causes, e.g. the discount factor w_T is too large,[8] participants made mistakes or over-rounded when filling in answers. Some observations in the latter two cases should be viewed as outliers. For example, the maximum and minimum levels of $Y - X_1$ are £375 and -£265.[9]

In addition, a substantial proportion of indifference points (43.8%) are simply $X_1 + X_T$, i.e. the total money to be obtained in Option A. Such "*total money*" answers are highly likely to be a heuristic because on average these answers take less time (9.28s) than the other answers (10.88s), and the difference is significant (two-sample test: $t = 4.177$, $p < 0.0001$).

[8] Suppose in Equation (1), w_T is close to 1, then the decision maker needs a $u(Y)$ almost equal to $u(X_1) + u(X_T)$. Given $u(.)$ is strictly concave, it is not impossible that $Y > X_1 + X_T$.

[9] For the maximum case, the participant values "receive £425 today and £60 in 12 months" as much as receiving £800 today, but values "receive £505 today and £60 in 6 months" as much as receiving £505 today. For the minimum case, the participant values "receive £425 today and £60 in 12 months" as much as receiving £160 today, but for all the other questions, the $Y - X_1$ is ranged between £15 and £60. Thus, it is likely that such observations are mistakes.

Figure 5(b) illustrates the distribution of "total money" answers over the participants. There are two peaks in the distribution: of all 161 participants in our sample, 62 participants (38.5% of the participants) use the total money to answer every question, whereas 65 participants have never used the total money as an answer. This suggests, different people may use different approaches to value the sequence Option A, and the "total money" is one of those approaches. For those who consistently fill in the total money across the questions, their valuation of the sequence Option A cannot be explained by time discounting. As we illustrate above, we account for this behavior by inattention to the time attribute.



(a) (b)

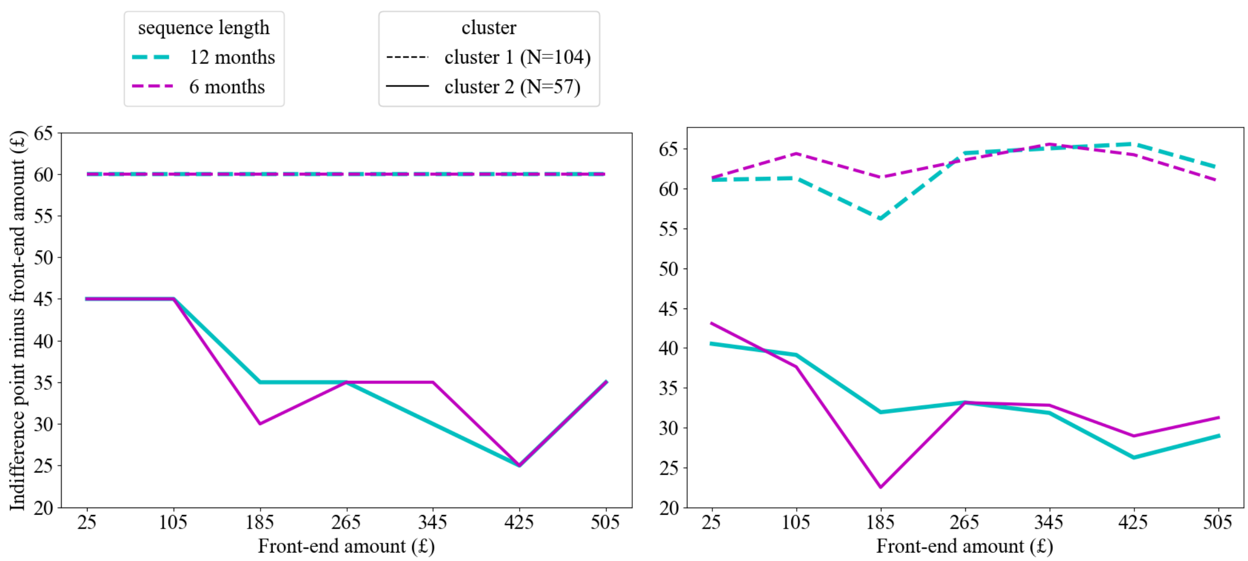
Figure 5: Distribution of responses in Experiment 2

We then use the k-means method to cluster participants into two groups, based on their answers in all questions. The first group (cluster 1) has 104 participants, and the second (cluster 2) has 57 participants.[10] The Mann-Whitney U test rejects the hypothesis that the two clusters are drawn from a same population ($U = 1059304.0$, $p < 0.0001$). The proportion of the "total money" answers is 63.1% in cluster 1, and is only 8.6% in cluster 2, and the difference is significant (Pearson's $\chi^2 = 619.040$, $p < 0.0001$). Over 79% of the observations

[10]In the case that there are three clusters, the number of participants in each cluster is 105, 55 and 1. In the case of four clusters, the number of participants in each cluster is 105, 46, 1 and 9. We only divide people into two groups because the size for the third (and fourth) group is too small.

in cluster 2 are above £0 and lower than £60. Thus, people in cluster 1 are disporportionally more likely to use total money to value a reward sequence, while those in cluster 2 are more likely to value it through time discounting approach.

Figure 6 shows the median and mean indifference point minus the back-end amount £60, for each question. The patterns of lines also suggest that people in cluster 1 tend to use the total money in answers, and for people in cluster 2, $Y - X_1$ is decreasing with X_1. The former is better explained by inattention to time attribute rather than by time discounting, as we discuss in Section 2.3. The latter violates the popular assumption that time discounting is solely dependent on times, as we discuss in Section 3.2.



(a) median (b) mean

Figure 6: Median and mean indifference point minus the front-end amount for each fill-in-the-blank question

5.3.2 Large Front-End Amount Devalues the Back-End Amount

We analyze the relationship between $Y - X_1$ and X_1 while taking into account the heterogeneity in participants' decision processes. The key question is, for people answer the questions in a way apart from "total money", whether $Y - X_1$ is decreasing in X_1. Notably, the sample contains outliers which may influence our results. We deal with the outliers in three ways. First, we use nonparametric methods for a preliminary analysis. Second, we validate the findings in linear regressions. The regression models are estimated through the OLS method. To reduce the impact of outliers, we remove the most extreme 0.5% of observations (the six largest and six smallest $Y - X_1$) from the sample. Third, we conduct robust regressions using Huber's M-estimators on the full sample, as such estimators are generally insensitive to outliers (Huber and Ronchetti, 2009).

We first look at the nonparametric analysis. The Spearman's ρ between $Y - X_1$ and X_1 is -0.049, which indicates a weak negative correlation between them ($p = 0.021$). For people in cluster 1, the Spearman's ρ is -0.015 ($p = 0.556$); for people in cluster 2, the Spearman's ρ is -0.189 ($p < 0.0001$). This indicates $Y - X_1$ is irrelevant to X_1 in cluster 1, but significantly decreasing in X_1 in cluster 2. Furthermore, the results from Kendall's τ coefficient is similar. For all participants, the Kendall's τ between $Y - X_1$ and X_1 is -0.038 ($p = 0.018$). For people in cluster 1, the Kendall's τ is -0.013 ($p = 0.552$); for people in cluster 2, the Kendall's τ is -0.148 ($p < 0.0001$).

Then we run a set of linear regressions to predict $Y - X_1$. The independent variables are the front-end amount X_1 under each sequence length T, and participants' responses to the PELI question. The variable PELI is 1 if a participant chooses the large later income in the PELI question and 0 if she chooses the small earlier income. Meanwhile, we use variables CL1 and CL2 to represent clustering results, and construct interaction terms between them and X_1 under each sequence length T. The variable CL1 is 1 if a participant is in cluster 1 and 0 otherwise; CL2 is 1 if a participant is in cluster 2 and 0 otherwise.

Table 4 illustrates the regression results. Column (1)-(2) are the pooled OLS regressions run on the sample without outliers. The adjusted R^2 for the two columns indicates that incorporating clustering results in regression models improves the goodness of fit by a lot (from 0.001 to 0.335). Then we add participant-specific dummies into each model and run fixed-effect regressions. First, we estimate the models on the sample without outliers, using the OLS method. Second, we estimate the same models on the full sample, using Huber's M-estimator for loss function and Huber's proposal 2 estimator for scale estimator. Column (3)-(4) report the fixed-effect estimates obtained from the OLS regressions, and Column (5)-(6) report the estimates obtained from the Huber's robust regressions. Under each estimator,

Table 4: Regression results for Experiment 2

	(1) Pool	(2) Pool	(3) FE	(4) FE	(5) RLM	(6) RLM
$X_1 \cdot 1\{T = T_L\}$	-0.006***		-0.006**		-0.005***	
	(0.002)		(0.002)		(0.001)	
$X_1 \cdot 1\{T = T_H\}$	-0.006***		-0.006**		-0.007***	
	(0.002)		(0.002)		(0.001)	
$X_1 \cdot 1\{T = T_L\}$×CL1		0.023***		0.002		0.0
		(0.004)		(0.002)		(0.001)
$X_1 \cdot 1\{T = T_H\}$×CL1		0.024***		0.003		-0.0
		(0.004)		(0.002)		(0.001)
$X_1 \cdot 1\{T = T_L\}$×CL2		-0.06***		-0.02***		-0.018***
		(0.005)		(0.004)		(0.002)
$X_1 \cdot 1\{T = T_H\}$×CL2		-0.061***		-0.022***		-0.022***
		(0.005)		(0.004)		(0.002)
PELI	-0.705	-1.218	8.796***	6.52***	1.431***	1.439***
	(3.815)	(2.552)	(0.014)	(0.392)	(0.33)	(0.322)
Constant	54.194***	54.586***	46.971***	48.711***	52.766***	53.026***
	(3.461)	(2.603)	(0.507)	(0.449)	(0.375)	(0.365)
observations	2242	2242	2242	2242	2254	2254
adj-R^2	0.001	0.335	0.637	0.645		
Muller-Welsh					146.734	139.589

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Standard errors are reported in the parentheses. Column (1)-(2) are obtained from pooled OLS models, Column (3)-(4) are from fixed-effect OLS models, Column (5)-(6) are from fixed-effect robust linear models (RLM). For OLS, standard errors are clustered at the subject level, and p-values are calculated using t-tests. For RLM, each model is estimated using Huber's M-estimator (the threshold for loss function is set at 1.345) and the scale estimator is Huber's proposal 2 estimator. Each p-value for RLM is calculated based on a normal distribution with i.i.d. assumption. Y_1 and T denote the front-end amount and the sequence length in Option A. T_L and T_H are 6 months and 12 months, respectively. Clustering results are obtained through the k-means method.

these fixed-effect models yield similar results. Overall, $Y - X_1$ is slightly decreasing with the front-end amount X_1. For participants in cluster 1, an increase in X_1 has no significant impact on how people value the back-end amount. But for those in cluster 2, this increase significantly reduces $Y - X_1$, at the significance level 0.5%. It is also worth noting that, for people in cluster 2, according to Column (6), an £100 increase in X_1 reduces its revealed present value, $Y - X_1$, by £1.8 when the sequence is 6-month long, and by £2.2 when the sequence is 12-month long, which are 3.0% and 3.7% of the amount £60.[11]

For Column (5)-(6), in case the residuals are not normally distributed due to outliers, we obtain the confidence intervals of regression coefficients via a stratified bootstrap method, In Appendix, Figure B.2 illustrate the bootstrap 95% confidence intervals for key fixed-effect estimates. The results in Table 4 remain robust to this bootstrap method. Moreover, as a robustness check, we use the Gaussian mixture model, instead of k-means, to cluster participants into two groups. The Gaussian mixture model exactly groups the participants who answer every question with the "total money" (N=62) into cluster 1, and the remaining 99 participants into cluster 2. We run the same regressions based on the new clustering results. In Appendix, Figure B.3 illustrates the bootstrap 95% confidence intervals of the key fixed-effect estimates in a model corresponding to Column (6). Our results remain robust under this circumstance.

5.3.3 Correlation between Valuation Approach and Patience

The coefficients for PELI in Table 4 are all significantly positive at the significance level 0.5%. This suggest that people who choose the large later income rather than the small earlier income in the PELI question tend to value the back-end amount at a higher level. Thus, the PELI question provides a valid measure for patience in our experiment. The Mann-Whitney U test on $Y - X_1$ also rejects the hypothesis that participants choosing

[11] For robust regressions, we use the Muller-Welsh criterion to measure the model performance (Müller and Welsh, 2005). A smaller Mull-Welsh score implies a greater ability to parsimoniously fit the data and predict new independent observations. The calculation of the Muller-Welsh criterion requests applying stratified bootstrap. To construct bootstrap samples, we divide observations into three strata (the upper tail, the lower tail, the others), and draw observations with replacement within each stratum. Each bootstrap sample is 50% in size of the entire sample, and the process is repeated 1,000 times. Column (6) has a better performance in this criterion.

different options in the PELI question are drawn from the same population ($U = 421520.0$, $p = 0.004$).

The relationship between participants' choices in the PELI questions and how they value the sequence Option A is ambiguous. Putting the k-means clustering results and the variable PELI into a contingency table, we obtain $\chi^2 = 0.550$, $p = 0.458$, which indicates the clusters and PELI are not correlated. However, using the Gaussian mixture model as the clustering method lead to an opposite result. In the latter case, χ^2-test suggests those exhibiting more patience in the PELI question, i.e. choosing the large later income, are more likely to use the total money answering all questions in the main task ($\chi^2 = 11.063$, $p = 0.001$).

6 Experiment 3: Sensitivity of Choice Probability

6.1 Design

In Experiment 3, we further test how (in-)attention to small values may affect time discounting. Specifically, we test Proposition 1 and Proposition 2 with an online survey. The survey consists of 20 intertemporal choices questions and 3 risky choices questions. Each question is presented as a choice list. In an intertemporal choice question, there are 10 rows in the list. In each row, participants are required to choose between a single immediate reward ("option A") and a sequence of two positive rewards ("option B"). Option A is constant within a question, while option B varies from row to row. Participants need to actively state their preferences on each choice. The intertemporal choice questions are presented in a random order and two of them are used for attention check. Figure 7 present an intertemporal choice question in the survey. Before the survey begins, there is an example question helping participants get familiarized with this question format. The risky choice questions follow the same format. In each row of a risky choice question, participants can choose to get either a large reward with a 50% chance, or a small reward with certainty. The risky reward is constant within the question, while the safe reward varies across rows. We use these risky choice questions to characterize the participants' utility function for further analysis.[12]

The intertemporal choice questions are divided into two conditions: (1) *front-end amount varies*; (2) *back-end amount varies.* In each question under the "front-end amount varies" condition, the front-end amount in the sequence option increases by £10 with each row, starting from £10 and going up to £100, whereas the back-end amount remains constant for all rows. In each question under the "back-end amount varies" condition, the back-end amount varies across rows, following the same pattern as the first condition, while the front-end amount remains constant. Under each condition, the time length of the sequence option is also constant across rows in a choice list.

The amount of the single option is selected from {£100, £120}. Each of such amounts is paired with a combination of a amount constant across rows and a specific length of the sequence option. Under the "front-end amount varies" condition, the length of a sequence is selected from {1 month, 9 months, 18 months}, and the back-end amount, which is constant across rows, is selected from {£50, £70, £90}. The lowest level of the back-end amount (£50) is only combined with the shortest sequence length (1 month), the middle level of the back-end amount (£70) can be combined with the shortest or middle level of sequence length (1 month or 9 months), and the highest level of the back-end amount can be combined with any level of sequence length (1 month, 9 months or 18 months). By this approach, we ensure that in any question, most people would switch their preference in the middle of the choice list. Eventually, we obtain 6 combinations, and by pairing them with each amount of the single option, we obtain 12 questions for the first condition. Under the "back-end amount varies" condition, we only examine whether the impact of each unit change in the back-end amount on choices will be influenced by the other amount in the sequence. So, the sequence length is simply fixed at 3 months. Under this condition, the front-end amount, which is constant across rows, is selected from {£50, £70, £90} as well. Pairing them with each amount of the single option, we obtain 6 questions for the second condition. Overall, there are 18 intertemporal choice questions except for attention check questions.

[12] Each risky choice question has 7 rows and the safe reward amount increases by the same amount with each row. The amount in the risky reward option (constant across rows) is selected from {£50, £100, £180}. For amount £50, the safe reward amount varies from £3 to £27; for amount £100, the safe reward amount varies from £20 to £50; for amount £180, the safe reward amount varies from £30 to £90.

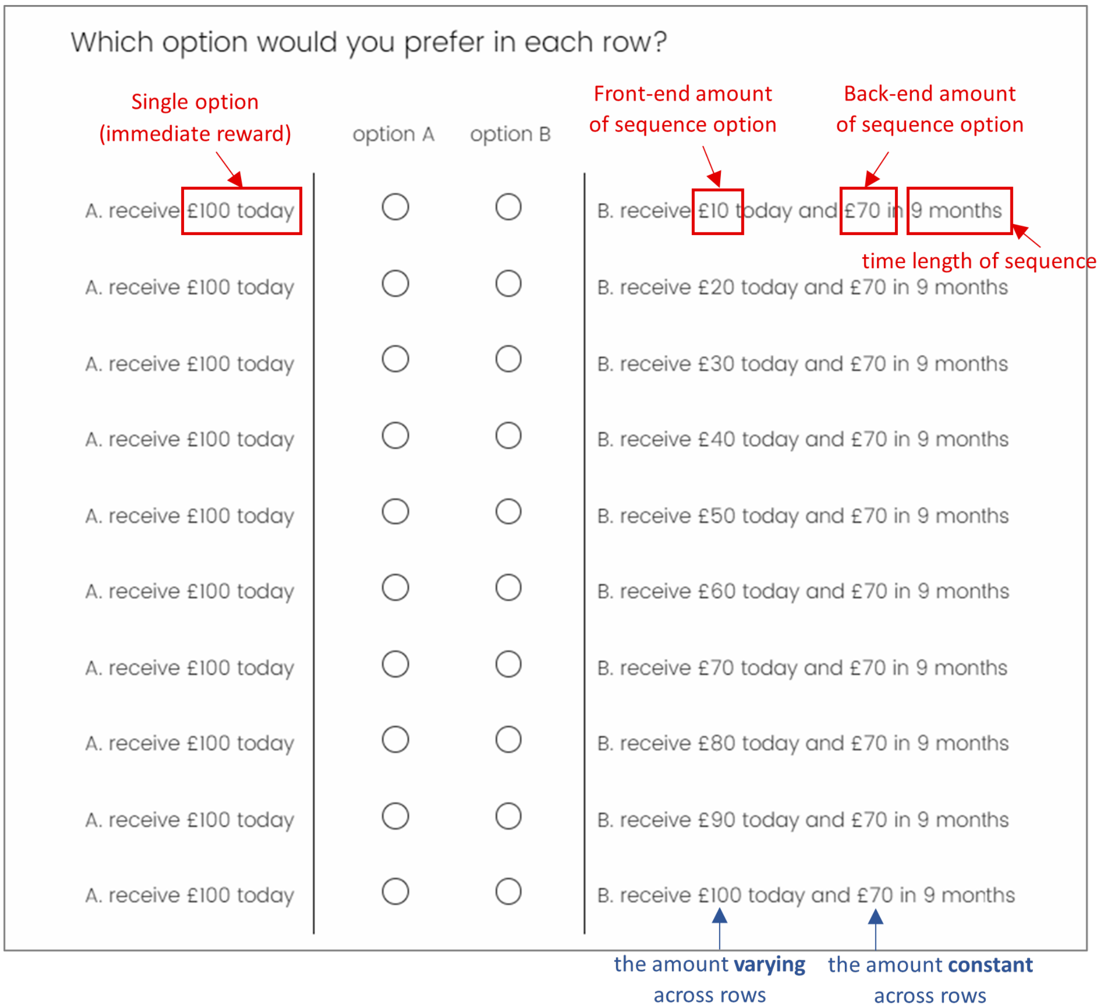


Figure 7: An intertemporal choice question in Experiment 1

6.2 Sample

We recruited 160 UK residents (female: 80, mean age: 41.9) via Prolific. The survey is developed and deployed with Qualtrics. The median survey completion time is 10 minutes. Each participants received £2 after completing the survey (on average £11.94 per hour). Three participants failed the attention check and we remove them from the sample. Eventually, there are 157 participants in the sample. Each participants completed 12 intertemporal choice questions under the "front-back amount varies" condition and 6 questions under the "back-end amount varies" condition. Each row in an intertemporal choice question is taken as an observation. Given that each intertemporal choice question contains 10 rows, we obtain 18,840 observations for the first condition and 9,420 observations for the second condition. For risky choice questions, we obtain 3,297 observations.

6.3 Results

6.3.1 Sensitivity to Front-End Amount Is Modulated by Back-End Amount

We start by presenting the results of descriptive analysis and then move on to regression analysis. For every choice list, we identify each participant's indifference point between the left and right sides by the median of the rows where she switches from choosing the single option to the sequence option. If the participants choose the single (sequence) option for every row in the choice list, we set the indifference point as the maximum (minimum) row. Note the single option and one amount in the sequence option are fixed in a choice list, hereafter we refer to the indifference point with the only amount varying across rows. Figure 8 shows the standard deviation of such indifference points for each question.

The standard deviation of indifference points provides a measure for participants' sensitivity to the amount varying across rows in each question. A smaller variance indicates a greater sensitivity of choice to changes in that amount. To illustrate, one can imagine an extreme case. Suppose all participants prefer "receive £100 today" (single option) to "receive £50 today and £70 in 1 month" (sequence option) in a question, but on the next row where the front-end amount increases from £50 to £60, they all prefer the sequence

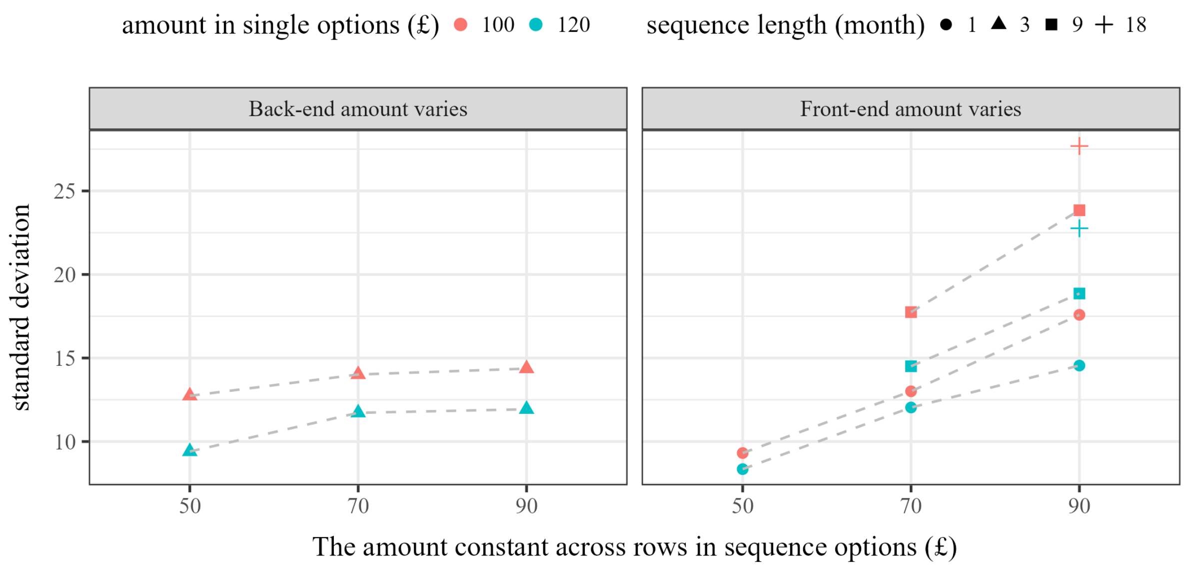


Figure 8: Standard deviation of indifference points in Experiment 3

option. Then, all of their indifference point will be £55 and there is no variance in their choices. In other words, they are extremely sensitive to this change in the front-end amount so that it increases their likelihood of choosing the sequence option by 100%. By contrast, each change in that amount only increases the likelihood by a small level, we should observe a great variance in their choices.

The right side of Figure 8 indicates, keeping the others equal, in the "front-end amount varies" condition, either increasing the back-end amount or delaying the delivering of this amount would result in a greater standard variance. Meanwhile, the left side of Figure 8 indicates, in the "back-end amount varies" condition, increasing the front-end amount also results in a greater standard variance in indifference points. All these implies that when valuing the sequence options, people are less sensitive to changes in an amount if the other amount gets larger, and they are less sensitive to changes in the front-end amount if delay of the back-end amount gets longer.

6.3.2 Model Estimation

For regression analysis, we draw the insights from Section 3.3 and construct a probabilistic choice model. Let "receive M today" denote the single option and "receive X_1 today and X_T

in delay T" denote the sequence option for any specific choice. Each condition is analyzed separately. In the "front-end amount varies" condition, only X_1 is varying across rows within each question. So, we focus on the variation of w_1 with other variables. Similarly, in the "back-end amount varies" condition, we only focus on w_T.

In each condition, let X_c denote the amount constant in the sequence options, X_v denote the amount varying across rows. Assuming the weights are independent of other variables, we can generalize Equation (2) by

$$P = \phi(w \cdot u(X_v) + g(M, X_c, T)) \tag{3}$$

where $w \cdot u(X_v)$ represents $w_1 \cdot u(X_1)$ in the "front-end amount varies" condition and represents $w_T \cdot u(X_T)$ in the "back-end amount varies" condition, and $g(M, X_c, T)$ represents all the other terms in Equation (2). We allow $g(M, X_c, T)$ to be a non-linear term. To construct it, we create a dummy variable for each question (each question has a unique combination of M, X_c and T) and take these dummies as random intercepts. We transfer M, X_c, and T to dummy variables, and set their minimum levels as the control levels. To examine how the coefficient of $u(X_v)$ would be affected by other variables, we construct the interactions between it and each level of X_c, M and T.

The link function is set to be $\phi(v) = 1/(1 + e^{-v})$. In other words, we predict participants' choices with logistic regressions. Following Andersen et al. (2008), we consider a concave utility function $u(x) = (\omega + x)^\gamma$, $0 < \gamma < 1$, $\omega \geq 0$, where γ denotes the risk aversion coefficient and ω denotes background consumption. To estimate γ and ω, we construct a probabilistic choice model and fit it with the data from risky choice questions. Appendix C provides more details about the estimation method. As a result, we obtain $\gamma = 0.695$ and $\omega \approx 0.000$.[13]

We report the model estimation results in Table 5. Each model is fitted with the maximum likelihood method. Column (1) and (3) reports the results of pooled regressions, and Column

[13]In Table A.2 of the Appendix, we also report the estimates obtained under risk-neutral utility function $u(x) = x$. The results suggest considering a concave utility function improves the goodness of fit (producing to a lower AIC).

(2) and (4) report the results of the models including participant-specific dummies as random intercepts. In general, the results suggest either a large X_c or a longer T can reduce the coefficient w in Equation (3).[14] For the "front-end amount varies" condition, increasing the back-end amount from the lowest level £50 to its middle level X_{mid} and highest level X_{high} (which is £70 and £90 respectively) could reduce the coefficient of $u(X_v)$, i.e. w_1, by 0.502 and 0.833 according to Column (2), with $p = 0.021$ for the former estimate and $p < 0.0001$ for the latter estimate. Meanwhile, as the delay of the back-end amount increases from its lowest level "1 month" to the middle level T_{mid} "9 months", and to the highest level T_{high} "18 months", the coefficient of $u(X_v)$ is reduced by 0.222 and 0.325 respectively, with $p < 0.0001$ for both estimates.

Under the "back-end amount varies" condition, note the back-end amount is delivered in 3 months for each question. In this case, increasing the front-end amount from the lowest level to its middle level X_{mid} and highest level X_{high} could reduce the coefficient of $u(X_v)$, i.e. w_2, by 0.284 and 0.501 according to Column (4), with $p = 0.009$ for the former estimate and $p < 0.0001$ for the latter estimate. This result is consistent with the behavior of a certain proportion of participants in Experiment 2: they discount the value of the back-end amount more when there is a larger front-end amount.

Our results also suggest an increase in M, i.e. the amount in single option, would increase the participants' sensitivity to the amount varying across rows. In Figure 8, the indifference points have a smaller variance under the higher level of M (which is £120). In Table 5, the coefficient of $u(X_v)$ is significantly increased when $M = M_{high}$, with $p < 0.0001$ for each column. This indicates the reference points may also have an effect on time discounting. A relevant evidence to this might be the magnitude effect, i.e. people exhibit more patience in choices between larger amounts. To illustrate, suppose the front-end amount in each question is always 0 and thus the choice is between receiving M today and receiving X_v later. If we assume the utility of each amount is determined by our estimated utility function, the magnitude effect would predict that an increase in M from £100 to £120 can result in $u(X_v)$ being less discounted (Andersen et al., 2013). This exactly implies the coefficient of $u(X_v)$

[14] In Table A.3 of the Appendix, we remove the rows where all participants choose the same option and then run the same regressions. These results are still valid.

Table 5: Regression Results for Experiment 3

	Front-end amount varies		Back-end amount varires	
	(1) Pooled	(2) FE	(1) Pooled	(2) FE
$u(X_v)$	0.921***	1.605***	0.72***	1.657***
	(0.121)	(0.243)	(0.057)	(0.154)
$u(X_v) \cdot 1\{M = M_{high}\}$	0.129***	0.206***	0.246***	0.504***
	(0.016)	(0.031)	(0.034)	(0.078)
$u(X_v) \cdot 1\{X_c = X_{mid}\}$	-0.294*	-0.502*	-0.141***	-0.284**
	(0.12)	(0.217)	(0.045)	(0.109)
$u(X_v) \cdot 1\{X_c = X_{high}\}$	-0.498***	-0.833***	-0.257***	-0.501***
	(0.119)	(0.223)	(0.046)	(0.109)
$u(X_v) \cdot 1\{T = T_{mid}\}$	-0.129***	-0.222***		
	(0.029)	(0.048)		
$u(X_v) \cdot 1\{T = T_{high}\}$	-0.181***	-0.325***		
	(0.037)	(0.06)		
observations	18840	18840	9420	9420
AIC	11310.724	6824.27	4150.095	2099.21

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Standard errors are clustered at the subject level and are reported in the parentheses. The p-values are calculated based on Wald tests. X_c denotes the amount constant in a choice list, and its middle and highest levels are X_{mid} and X_{high}. T denotes the delay of the back-end amount, and its middle and highest levels are T_{mid} and T_{high}. M denotes amount in the single option, and its higher level is M_{high}. X_v denotes the amount varying across rows. The utility function is $u(x) = x^{0.695}$. Every model includes question-specific dummies as random intercepts. Column (2) and (4) come from a model including participant-specific dummies as random intercepts.

in our analytic framework should be increasing with M.

7 Discussion

In this section, we discus the relationship between the results of Experiment 1-3 and some theories about time discounting. In Experiment 1, we exogenously manipulate attention and find this effectively alters participants' time preferences. In Experiment 2, a substantial portion of participants valuate any reward sequence simply by its total money. To the best of our knowledge, both results cannot be accounted for by the existing time discounting theories.

In Experiment 2-3, we also find evidence supporting our arguments about (in-)attention to small values. In Experiment 2, we find when people valuate a sequence of two positive rewards, an increase in the front-end amount could make (some of) them discount the value of the back-end amount more. In Experiment 3, our model estimation results suggest an increase in one reward or in sequence length could make the total value of sequence less sensitive to another reward, which may indicate people discount the value of the another reward more. These results can be (partially) generated by certain theories related to attention.

First, the salience theory (Bordalo et al., 2012, 2013) proposes that a reward stimulus would look more salient if it differs more greatly from a reference point. When people valuate a reward sequence, they tend to overweight the salient rewards and underweight the non-salient rewards. Taking zero as the reference point, when there is a large reward in the sequence, the salience theory would predict that it can attract much attention and therefore reduce the weights assigned to other rewards, i.e. making them more discounted. Nevetheless, the salience theory cannot account for the hidden-zero effect and our finding that a longer delay of the back-end amount could make the value of the front-end amount more discounted. To incorporate such evidence, adding zero values into the sequence should reduce the "salience" of positive rewards. This may require us to add an extra constraint on the total volume of weights. For example, fixing the sum of weights at a certain level so that allocating weights to new zero values would definitely reduce the weights for other rewards.

Second, Noor and Takeoka (2022, 2024) propose a theory related to optimal allocation of attention across time points. In their theory, decision makers originally focus on the current time, but to process a reward sequence, they should allocate attention weights to future times, which incurs a cognitive cost. The decision makers' objective is to maximize the total value of the sequence minus the incurred cognitive cost. Their theory also predicts that people tend to assign greater weights to larger rewards. Under certain cognitive cost functions and constraints, the theory can produce the results of our experiments.

Apart from attention theories, there are also other theories that can explain some of our results. For example, the intertemporal trade-off model (Read and Scholten, 2012; Scholten et al., 2016, 2024) proposes that when valuating a reward sequence, people would value the amounts and the times separately. The total value of the sequence is the utility of the total money minus a delay cost. Increasing an earlier amount in the sequence can reduce the delay cost, while increasing a later amount can increase the delay cost. According to the most recent version of this model, for sequence options in our experiments, a large back-end amount would make each unit increase in the front-end amount reduces the delay cost by a greater degree, and a large front-end amount would make each unit increase in the back-end amount increases the delay cost by a smaller degree. Meanwhile, in either case, the utility of total money should increase by a smaller degree due to the concavity of utility function. When the latter effect exceeds the former effect, a large reward can make the total value less sensitive to the other amount. However, under a longer delay of the back-end amount, increasing the front-end amount should reduce the delay cost by a greater degree. Therefore, under this circumstance, the intertemporal trade-off model predicts people are more sensitive to the front-end amount, while the results of Experiment 3 indicate the reverse.

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Appendix

A. Additional Tables

Table A.1: Predicting response times with choices and conditions in Experiment 1

	Intertemporal Choice	Count-the-Rabbits
Group	-0.684***	-0.792***
	(0.141)	(0.144)
Question$\cdot 1\{\text{Group} = 0\}$	-0.165	0.912***
	(0.174)	(0.199)
Question$\cdot 1\{\text{Group} = 1\}$	0.457***	0.849***
	(0.101)	(0.132)
Choice	0.954*	1.291***
	(0.399)	(0.456)
Choice$\times$Group	-0.762*	-1.265***
	(0.304)	(0.229)
Choice$\times$Question$\cdot 1\{\text{Group} = 0\}$	0.001	-0.138
	(0.257)	(0.23)
Choice$\times$Question$\cdot 1\{\text{Group} = 1\}$	-0.12	0.263
	(0.195)	(0.175)
observations	4393	2179
AIC	18560.034	8711.872
adj-R^2	0.381	0.55

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Both models are estimated through 2SLS method. For first-stage regression, we use the model for Column (2) in Table 2 to predict intertemporal choices, and the model for Column (3) in Table 3 to predict count-the-rabbits choices. The variable Choice which is 1 if the predicted choice is the sequence option and is 0 otherwise. For second-stage regression, indepdent variables are the predictors shown in the table plus task-specific dummies and their interactions with Choice, and participant-specific dummies. Standard errors (in the parentheses) are clustered at the subject level. p-values are calculated based on t-tests.

Table A.2: Regression results with risk-neutral utility function for Experiment 3

	Front-end amount varies		Back-end amount varires	
	(1) Pooled	(2) FE	(1) Pooled	(2) FE
X_v	0.181	0.316***	0.139***	0.318***
	(0.339)	(0.044)	(0.011)	(0.03)
$X_v \cdot 1\{M = M_{high}\}$	0.022***	0.031***	0.039***	0.071***
	(0.006)	(0.006)	(0.007)	(0.017)
$X_v \cdot 1\{X_c = X_{mid}\}$	-0.047	-0.079*	-0.015	-0.024
	(0.032)	(0.04)	(0.009)	(0.023)
$X_v \cdot 1\{X_c = X_{high}\}$	-0.083**	-0.135***	-0.026**	-0.031
	(0.031)	(0.041)	(0.01)	(0.023)
$X_v \cdot 1\{T = T_{mid}\}$	-0.033***	-0.058***		
	(0.006)	(0.012)		
$X_v \cdot 1\{T = T_{high}\}$	-0.046***	-0.085***		
	(0.012)	(0.015)		
observations	18840	18840	9420	9420
AIC	11455.38	6963.578	4215.293	2158.83

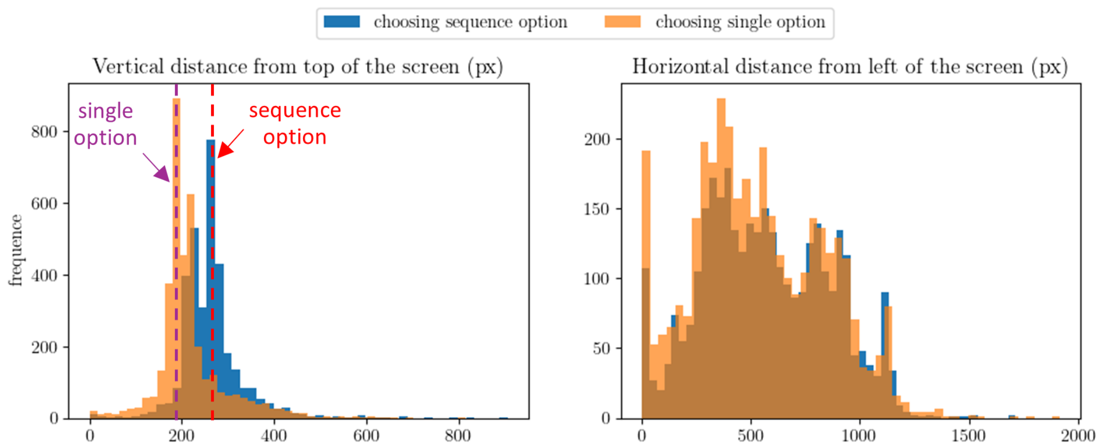
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Standard errors are clustered at the subject level and are reported in the parentheses. The p-values are calculated based on Wald tests. X_c denotes the amount constant in a choice list, and its middle and highest levels are X_{mid} and X_{high}. T denotes the delay of the back-end amount, and its middle and highest levels are T_{mid} and T_{high}. M denotes amount in the single option, and its higher level is M_{high}. X_v denotes the amount varying across rows. Every model includes question-specific dummies as random intercepts. Column (2) and (4) come from a model including participant-specific dummies as random intercepts.

Table A.3: Regression results on the censored data in Experiment 3

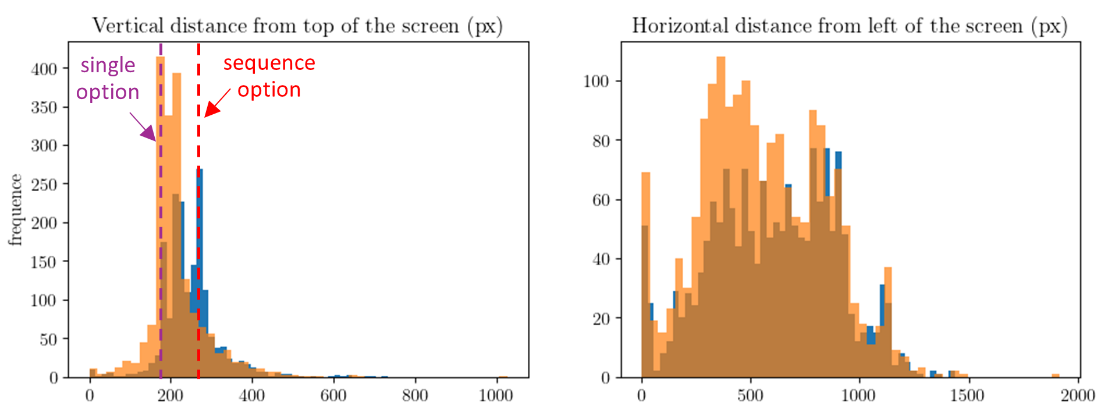
	Front-end amount varies		Back-end amount varires	
	(1) Pooled	(2) FE	(1) Pooled	(2) FE
$u(X_v)$	0.914**	1.584***	0.712***	1.65***
	(0.342)	(0.247)	(0.059)	(0.155)
$u(X_v) \cdot 1\{M = M_{high}\}$	0.107*	0.193***	0.187***	0.484***
	(0.053)	(0.03)	(0.037)	(0.08)
$u(X_v) \cdot 1\{X_c = X_{mid}\}$	-0.314*	-0.499*	-0.134***	-0.281*
	(0.129)	(0.226)	(0.047)	(0.111)
$u(X_v) \cdot 1\{X_c = X_{high}\}$	-0.509***	-0.828***	-0.248***	-0.5***
	(0.127)	(0.231)	(0.048)	(0.111)
$u(X_v) \cdot 1\{T = T_{mid}\}$	-0.115***	-0.212***		
	(0.03)	(0.049)		
$u(X_v) \cdot 1\{T = T_{high}\}$	-0.163***	-0.312***		
	(0.036)	(0.061)		
observations	14915	14915	6594	6594
AIC	11226.482	6797.682	4120.484	2094.364

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. FE denotes a model including participant-specific dummies as random intercepts. Each model and the estimation method are the same as Table 5. However, for each question, the rows where all participants choose the same option are removed from the sample.

B. Additional Figures



(a) Intertemporal Choice Task



(b) Count-the-Rabbits Task

Figure B.1: Mouse positions recorded at the end of the forced viewing period

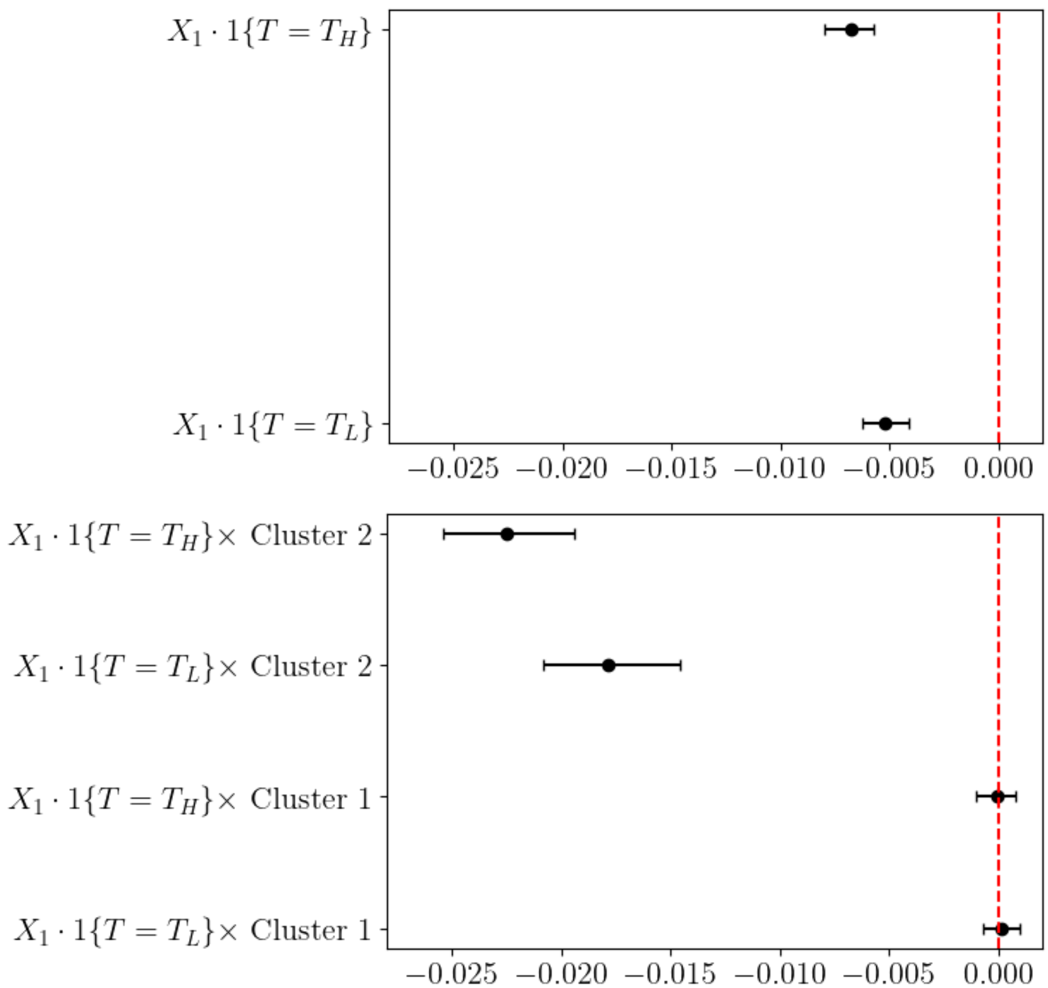


Figure B.2: Bootstrap 95% confidence intervals for coefficients in the robust regressions

Note: The subfigures on the top and the bottom correspond to Column (5) and (6) in Table 4 respectively. The dots are the original estimates and the error bars indicate the confidence intervals. To approximate the distribution for each coefficient, we use the stratified bootstrap method. The observations are divided into three strata based on RLM results: the upper tail (with high residuals and a weight of 1), the lower tail (with low residuals and a weight of 1), and the others. We draw observations with replacement within each stratum and use them to estimate the coefficients. Each bootstrap sample is the same size as the original sample, and the process is repeated 1,000 times.

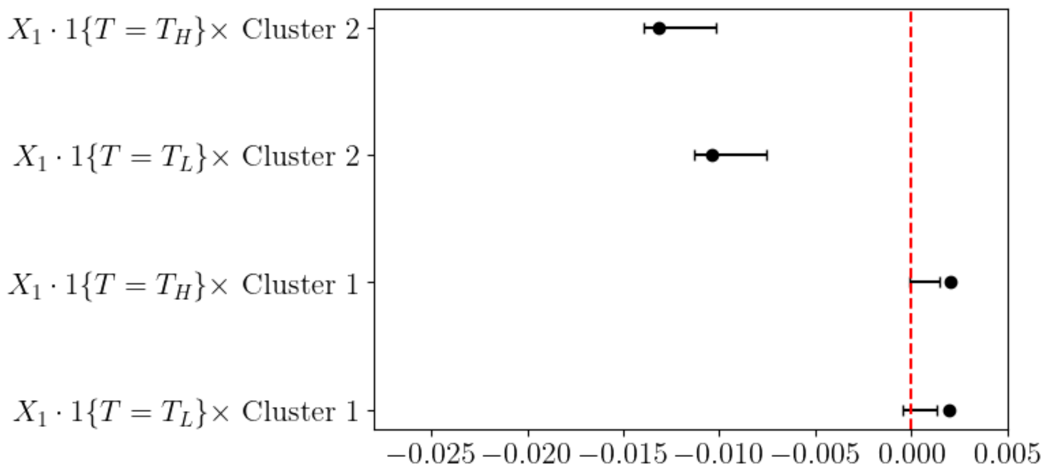


Figure B.3: Regression coefficients - using Gaussian mixture model for clustering

Note: The regression model is the same as Column (6) in Table 4. Estimation method is the same as Figure B.2. The dots are the original estimates and the error bars indicate the boostrap 95% confidence intervals.

C. Method to estimate risk aversion coefficient

For any risky choice i, let "get X_i^R with a 50% chance" denote the risky option and "get X_i^S with certainty" denote the safe option. Note X_i^R is constant within a choice list while X_i^S is varying across rows. Assume that participants choose the safe option with probability P_i^{risk}, and

$$P_i^{\text{risk}} = \frac{1}{1 + e^{-\frac{\Delta U}{\lambda}}} \tag{4}$$

where $\Delta U = u(X_i^S) - 0.5 \cdot u(X_i^R)$ and λ ($\lambda > 0$) is a temperature parameter that controls the randomness of choice. The utility function is $u(x) = (\omega + x)^\gamma$, $0 < \gamma < 1$, $\omega \geq 0$. We fit the model with the maximum likelihood method. The log-likelihood function is

$$LL(\gamma, \lambda) = \sum_{i=1}^{N} \xi_i \ln(P_i^{\text{risk}}) + (1 - \xi_i) \ln(1 - P_i^{\text{risk}}) \tag{5}$$

We use $\gamma = 1$, $\lambda = 1$ as the initial values and maximize the log-likelihood function with the SLSQP algorithm. The model is fitted on the 3,297 observations of the risky choices. In the solution, $LL = -1711.87$, $\gamma = 0.695$, $\lambda = 1.904$, $\omega \approx 2.245 \times 10^{-13}$.