Explorations in Human Decision Making

By

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Author attribution

The works contained in the body of this thesis, except otherwise acknowledged, is the result of my own investigations.

Chapter 1 is being prepared for submission. Cid Campos, Prof. Agnieszka Tymula and Prof. Paul Glimcher designed the experiment. Cid Campos conducted the experiment and analysed the data. Cid Campos wrote the chapter.

Chapter 2 is being prepared for submission. Cid Campos, Dr. Stephen Cheung Prof. Agnieszka Tymula and Dr. Xueting Wang designed the study. Cid Campos created the database and analysed the data. Cid Campos wrote the chapter.

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Statement of Originality

I certify that the intellectual content of this thesis is the product of my worn work and that all the assistance received in preparing this thesis and sources have been acknowledged. I certify that AI, specifically ChatGPT, was used for the grammatical correction of some of the sections.

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Abstract

Human decision making, even when it involves simple everyday choices has been revealed to have layers of complexity to it in recent years (P. W. Glimcher & Fehr, 2013; Rangel et al., 2008; Rushworth & Walton, 2009). The works contained in this thesis aim at exploring some of those layers, from designing procedures to improve decisions, conducting a meta-analysis on probability weighting, and looking at being hungry and how it affects decisions.

In the first chapter, we designed three choice procedures to improve choice quality without reducing the options available or using nudges. Using a within-subject experiment, we tested how our procedures compare to simply picking the preferred option. We find that each of our choice procedures increased the probability that a participant will correctly choose their independently identified highest valued option from the choice set.

In the second chapter, we present a meta-analysis of the sensitivity parameter, γ , of probability weighting functions used in models of decision-making under risk. Using 721 parameter estimates from 176 empirical papers, we examined the meta-analytic means, sources of heterogeneity, and domain dependence of γ across gains and losses, as well as when papers did not differentiate between the two (undifferentiated). We found that the meta-analytic mean of γ is significantly below one in all domains and found that estimates are lowest for gains, highest for losses, with undifferentiated estimates lying between the two.

In the third chapter, using the decision noise framework proposed by (Shen et al., 2025) we examined whether short term hunger influences simple food related decision-making through changes in early noise and or late noise. Contrary to our first hypotheses, we found that short term hunger does not reduce early noise, but we did find that it does not affect late noise which supported our second hypothesis.

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Designing Smart Choice Procedures for Better Decision Making

1. Introduction

"Learning to choose is hard. Learning to choose well is harder. And learning to choose well in a world of unlimited possibilities is harder still, perhaps too hard."

- Barry Schwartz, The Paradox of Choice

Modern living, it can be argued, is full of everyday choices involving a plethora of options. Want a loaf of standard white bread? You have more than 7 brands to choose from. How about a medication to help with your seasonal flu allergies? Well, you have 8 or more brands on the same shelf promising to be your cure. When faced with such options people often want to pick the best one, the best tasting cheap white bread or that one nasal spray that finally makes breathing so much easier. People don't want to buy multiple options of the same type of good just to find out only one meets there need. The potential waste than can be avoided if we can help people make better decisions can be of great interest to economic policy. Helping people pick the good that they value the most from a set, however, is much harder than it seems and one of the reasons for that is choice overload.

First empirically tested by Iyengar & Lepper (2000), one of the implications of choice overload is that when the number of available options increases people become worse at selecting the option with the highest value. This finding challenged the prevailing assumption that "more choice is always better" (Baumol & Ide, 1956; Hotelling, 1929). Subsequent studies reinforced this by observing that as choice set size increased the likelihood of people picking the objectively highest valued option declined (Payne, Bettman, & Johnson 1993, Tanius et al., 2009; Schram & Sonnemans, 2011; Hanoch et al., 2011; Besedes et al., 2012a, 2012b; Iyengar & Kamenica, 2010; Heiss et al., 2013). It was also demonstrated that choice overload arises across a variety of contexts whenever cognitive demands are sufficiently high (Caplin et al., 2011; Redelmeier & Shafir, 1995; Roswarski & Murray, 2006; Sanjurjo, 2015). The costs are substantial: beyond reduced welfare and forgone value (Caplin et al., 2011), choice overload is also associated with lower satisfaction (Redelmeier & Shafir, 1995; Roswarski & Murray, 2006), heightened anxiety during and after the decision (Bagshaw, 2010), and even decision paralysis (Manolică et al., 2021). These costs are not just confined to simple decisions as choice overload was also found to result in people either making worse decisions or avoiding making them despite faced with crucial life decisions with long term consequences such as with which insurance to get (Sethi-Iyengar et al., 2005). Further Chernev (2003) and Fasolo et al. (2007) similarly found that having a smaller choice set size, and therefore less overall number of options available, avoided decision paralysis.

In response, researchers have proposed two broad classes of solutions. The first if of these proposed reducing the number of available options. For example, Iyengar & Lepper (2000) argued that people are unable to undertake exhaustive comparisons when faced with many options, suggesting that choice sets should be smaller. (Cronqvist & Thaler, 2004) proposed that people should be given smaller choice set sizes with regard to investments, even going to the extent of giving only one option, since many people would end up choosing a default option in the first place. Kling et al. 2011 took it further by proposing that health care providers should provide only a small choice set size comprising of options that a person is most likely to prefer.

A second line of research advocated “libertarian paternalism” through nudges (Thaler & Sunstein, 2003). For instance, Sethi-Iyengar et al. (2005) proposed displaying only a small subset of options as a default while allowing people to view all options if desired. Van Gestel et al. (2020) proposed nudges that make use of placement position, accessibility and visibility while Sharma & Nair (2023) and Valentine et al. (2023) proposed sorting all options into categories based on common attributes and only displaying one category to the decision maker.

Although these approaches are effective in settings where policymakers wish to steer people toward socially desirable choices (e.g., healthier foods), they suffer from a fundamental limitation when applied to everyday consumer decisions. In such settings, a person’s objective is to select their own highest valued option and maximize personal utility. Both limiting options and nudging implicitly rely on externally predetermined judgments about which options should be emphasized or excluded. If these externally defined structures do not align with a person’s actual preference, they may divert attention from the person’s preferred option—or even remove it from the choice set entirely—thereby reducing welfare. Evidence supports this concern: nudges do not always improve individual welfare Click or tap here to enter text. and limiting assortments can reduce satisfaction in choices made even in countries that commonly employ them (Reutskaja et al., 2022).

This highlights the need for alternative approaches to mitigating choice overload and consequently helping people pick their highest valued options without restricting options or relying on preference-misaligned nudges. To do so, in this paper, we look to neuroeconomics for a framework to better understand why people are less able to choose the highest valued option when given larger choice set sizes. Based on this, we present different procedures which improve the likelihood of people picking the highest valued option from a set without having to use nudges or limit options. Theoretically, these procedures work by reducing distortions in the value representation of options in the human brain thus reducing the likelihood of lower valued options being chosen over higher valued ones. This is done by reducing the number of options being presented to a person to a minimum at crucial moments of the decision-making process while still allowing a person to go through all options across the entire process.

This improves upon the existing related literature, such as Besedes et al. (2015) and Dellaert et al. (2017), which sought to improve people's ability to pick the highest valued option by using sequential procedures which displayed subsets of all options at a time while not restricting the total number of options. Besedes et al., (2015) used procedures which displayed subsets of four options at a time from which participants had to select the option they wanted. Selected options were either carried over to the next succeeding subset or were presented in the final subset along with other selected options. Dellaert et al. (2017), on the other hand, presented a subset of three options as a default and allowed participants to view the full list of options. Participants then selected the option they wanted. A key difference between our approach and the existing literature is that they only reduced the number of options being presented based of the reasoning that reducing the number of options presented would be sufficient at increasing the likelihood of picking the highest valued option. Based on the neuroeconomic model we used, this may not be sufficient as value representations in the brain can still be distorted in small choice set sizes, like three or four used by the other two studies, leading to high likelihoods of participants picking lower valued options over higher valued ones. With our procedures, the number of options presented was kept at a minimum either at the final stages of the decision-making procedure or all throughout which theoretically reduce distortions in value representation of options in the brain allowing a clearer comparison of options which increase the likelihood of picking the highest valued option. This may explain why our results show greater improvement in the likelihood of picking the highest valued options when compared to the existing literature while still not restricting the number of options or relying on nudges.

2. Theoretical framework

Traditional economic theories do not account for the phenomenon that as choice sets increase people are less likely to pick the highest valued options, in dollar terms. To see this, note that in a standard random utility model (RUM) (Mariel et al., 2025), the utility of an option *i* is:

$$U(x_i) = v(x_i) + \varepsilon_i \tag{1}$$

where v_i denotes the deterministic component of the utility of option i and ε_i captures stochastic noise. Under this framework, the probability of selecting the option *i* from a set of options when a person picks as how they normally do, by simply picking one choice from the whole set is

$$P\big(u(x_i)\big) = \int 1\,[v(x_i) - v(x_j) > \varepsilon_j - \varepsilon_i, \forall j \neq i\,]d\varepsilon \tag{2}$$

The RUM structure implies that as long as the value gap between the highest valued option and second-best alternative is sufficiently large relative to noise, the highest valued option will be chosen—even as the number of options grows. This is because all other alternatives would be strictly dominated by the second-best option and therefore these alternatives would not matter in determining the final option being chosen in the RUM as implied by the regularity axiom (Hjorth, 2005). Thus, a standard RUM does *not* inherently generate a decline in choice accuracy as choice sets become larger as those additional alternatives would not matter. Therefore, to understand choice overload and how increased choice set sizes reduce the likelihood of the highest valued option being picked, we need a model that explicitly links the likelihood of choosing the highest valued option to set size.

Recent developments in neuroscience offer such a framework through **divisive normalization**, a canonical neural computation widely observed in sensory and decision-related brain areas (Carandini & Heeger, 2012). Initially documented in visual processing, where neurons represent stimuli relative to surrounding inputs (Carandini et al., 1997; Schwartz & Simoncelli, 2001), divisive normalization has since been shown to influence value-based decision making. It provides a mechanism through which the assessed value of an option depends on the magnitude and composition of the entire choice set (Glimcher, 2014; Louie et al., 2015; Webb et al., 2021). Under divisive normalization, the subjective value of an option i is given by

$$U_i(x) = \frac{x_i}{\delta + \omega(\sum {x_n}^{\beta})^{\frac{1}{\beta}}} + \varepsilon_i \tag{3}$$

where δ represents a baseline neural firing rate, ω and β control the strength and form of normalization, and $\sum {x_n}^{\beta}$ summarizes the overall sum of values of the choice set. As this sum increases when more alternatives are present in the choice set the denominator increases and subjective values collapse towards each other and subjective value differences decrease. This yields the following expression for the probability of selecting the highest valued option under the condition that a person is simply picking their one choice from a set of options:

$$P_i\,\big(u(x)\big) = \int 1\,[\frac{x_i - x_j}{\delta + \omega(\sum {x_n}^{\beta})^{\frac{1}{\beta}}} > \varepsilon_j - \varepsilon_i, \forall j \neq i\,]\,d\varepsilon \tag{4}$$

The implication is clear: as $\sum x_n{}^{\beta}$ increases, the gap between subjective values of a highest valued option and all other options decreases relative to noise as seen on the right-hand side of the equation. This results in a decline in the likelihood of the highest valued option being chosen characteristic of choice overload.

A more detailed consideration of the term $\sum x_n{}^{\beta}$ reveals two distinct mechanisms through which choice overload can arise. The sum increases when (1) the number of options increases and when (2) the values of the other options increase. Consequently:

1. Proposition 1: Decreasing the number of options presented at a given time increases likelihood of choosing the highest valued option (Figure 1 A – 1 B).

Proposition 1 can be illustrated in equation 4. As the sum $\sum x^{\beta}$ decreases asa consequence of decreasing the number of options the denominator of the expression $\frac{x_i - x_j}{\delta + \omega(\sum x_n{}^{\beta})^{\frac{1}{\beta}}}$ decreases resulting in a higher value relative to the difference in errors $\varepsilon_j - \varepsilon_i$ This would indicate a higher likelihood of picking the higher valued option, x_i over x_j.

To illustrate, consider a simple case with three options:

where x_1 is the highest valued option and x_3 to x_{12} are lower-valued options with values below x_2. These may function as a *distractors* given that they should not affect the likelihood of the highest valued option being selected given its value. As the choice set of presented options increases from only having three options, x_1 to x_3, to a larger one, x_1 to x_{12}, the higher value in the denominator of equation 4 increases making differentiating between options difficult.

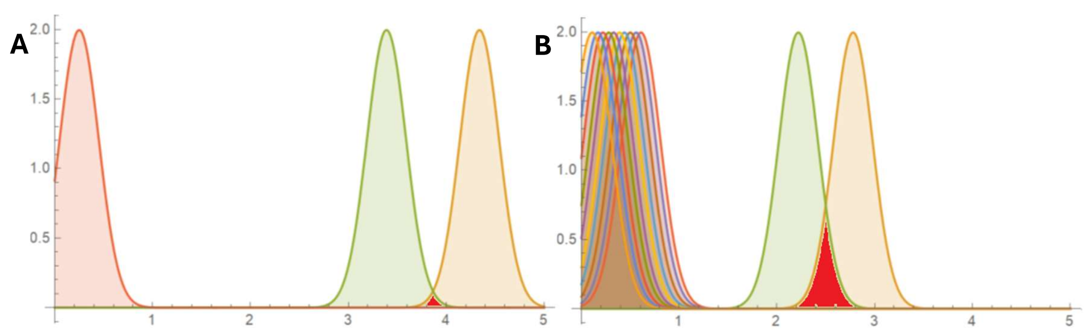

Figure 1. Implication of Divisive Normalization on Choice Overload. Each Distribution is the Valuation of One Option in a Set. The Red Area Where the Two Options with the Highest Values Overlap is the Likelihood of a Person Not Picking Their Highest Valued Option. A and B: As the Number of Options Displayed Increases, the Likelihood of Not Picking the Highest Valued

Option Increases. C and D: As the Value of the Distractor Increases, the Likelihood of Not Picking the Highest Valued Option Increases.

3. Experimental design

Using divisive normalization as our theoretical framework we hypothesize that choice procedures should visually present the smallest number of options to avoid subjective values of options collapsing towards each other. This in turn reduces the likelihood of participants making a mistake and choosing a lower valued option over a higher valued one. This follows directly from the model's implication that whenever more than two options are displayed, a distractor with a sufficiently high value can cause the subjective values of options to collapse towards each other as the denominator in equation three increases. This in turn causes the differences in subjective values of options to decrease leading to a lower likelihood of the top option being picked as in equation 4. Guided by this reasoning, we developed three simple and easily implementable procedures that satisfy these criteria, which we refer to as **Smart Choice Procedures (SCPs)**. The first, *Elimination–Remain* (ER), involves sequentially eliminating options one at a time until only two options remain. Eliminated options remain visible but are marked with an "X," making it explicit that they are no longer choice-relevant. The second, *Elimination–Disappear* (ED), is structurally similar but removes eliminated options from view entirely, which should further reduce their visual salience and, therefore, their contribution to normalization. The final procedure, *Binary Choice* (BC), presents only two options at every stage of the decision process, fully eliminating the presence of distractors in all intermediate steps.

3.1 General procedure

To test whether the Smart Choice Procedures increased the likelihood of participants picking their highest valued snack, we conducted a within-subject experiment which comprised of two stages. The first was a valuation task which we used to obtain each participant's snack valuations. The second stage was a choice task in which each participant selected one snack out of 12 options using Smart Choice Procedures. The choice task allowed us to verify in which procedure participants are most likely to select their highest valued snack.

We used 34 snacks commonly found in Australia, with prices ranging from $0.50 to $5. We included both sweet and savory snacks to get a diverse range of valuations from participants. All snacks were displayed on a table at the entrance to the laboratory to ensure that participants were familiar with the type and size of snacks on offer. The placements of the snacks were randomized across the sessions to avoid any effects of display order.

We asked participants to fast for a minimum of four hours prior to the start of each experimental session to ensure that participants were interested in the snacks that we were offering. In addition, we conducted each session at 11:30 am when participants were most likely to be hungry. Finally, we told participants that they had to stay in the lab for 30 minutes after the experiment finished and during that time they were only allowed to eat the snack that they received as part of their payment.

We allowed participants to proceed with the experiment at their own pace. Each session lasted around 90 minutes which included completing both tasks and a demographic questionnaire. We conducted all sessions at the Sydney Experiment Economics Laboratory. All procedures were approved by the University of Sydney Human Research Ethics Committee and all participants gave informed consent. The experiment was programmed using Qualtrics.

3.2 Participant Recruitment

85 participants completed our experiment. They were all University of Sydney students and were recruited from the University of Sydney research volunteer database using ORSEE (Greiner, 2015). 40.47 % of the participants were females. Their average age was 23.21 (SD = 4.44). With this sample size, assuming $\alpha = 0.05$ and power = 0.80, we can detect medium effect sizes (Cohen's d= 0.58) in a paired t-test.

3.3 Payment

We paid each participant based on one of their decisions in either the valuation or choice task, randomly selected. If a decision from the valuation task was chosen for payment, we determined the payoff following the BDM (Becker et al., 1964) procedure using a randomly generated price ranging from $0 to $5, in $0.10 increments. This price was not revealed to participants at the time of choice. If a participant's valuation for a snack was higher than or equal to the generated price, then it showed that they were willing to pay this price for the snack. Therefore, they bought the snack from the experimenter at the generated price. As payment, they received the snack and an amount in dollars equal to $15 minus the price. If a participant's valuation for a snack was below the generated price, then it showed that they were unwilling to pay this price for the snack. They did not buy the snack and received $15 as payment. If a decision from the choice task was chosen for payment, participants received the snack they chose and an additional $10.

In addition, all participants received a $10 participation fee. All monetary payments were made in cash after participants completed the experiment.

3.4 Valuation task

We elicited each participant's valuation of each of the 34 snacks using a Becker-DeGroot-Marshak (BDM) procedure (Becker et al., 1964). Each snack was shown on the screen one at a time (Figure 2). Participants entered their valuations (in $0.10 increments) using a slider bounded between $0 and $5. We adopted instructions from Healy (2020) to explain the BDM procedure to participants (Figure A 5). Participants proceeded at their own pace and there was no time limit on providing a response. In each trial, participants received $15 as an endowment that they could use towards purchasing a snack.

If participants were paid for this task, they would be paid for only one valuation. To ensure that we had reliable valuations, participants valued each snack twice. We used the average of these valuations to determine a snack ranking for each participant and determine their highest valued snack for each decision scenario in the choice task. From now on, we refer to the snack with the highest valuation in any decision scenario in the choice task, as established by the valuation task, as participant's highest valued snack in this decision scenario.

Figure 2. Valuation Task

3.5 Choice task

In the choice task, participants picked a snack they would like to receive using four different choice procedures. In each procedure, participants completed ten decision scenarios. In each decision scenario, there were twelve snacks available to choose from. These were randomly picked from the 34 snacks in each decision scenario for each participant. We chose a set size of twelve because it is large enough to make it difficult to choose (Webb et al., 2021). At the same time, the likelihood of the snack with the highest valuation out of all 34 appearing in all ten decision scenarios is low (0.003% chance) ensuring varied choice sets in each decision scenario. The order in which participants completed each treatment was randomized across participants.

3.5.1 Direct choice procedure

As a benchmark, we asked participants to simply choose one snack from a set of twelve snacks displayed on screen by clicking on it (Figure 3) after which they proceeded to the next decision scenario. We included this treatment because it mimics how decisions are usually made outside the lab. It served as a benchmark to measure if there was improvement in the ability to pick the snack they would like to receive in the other Smart Choice Procedures.

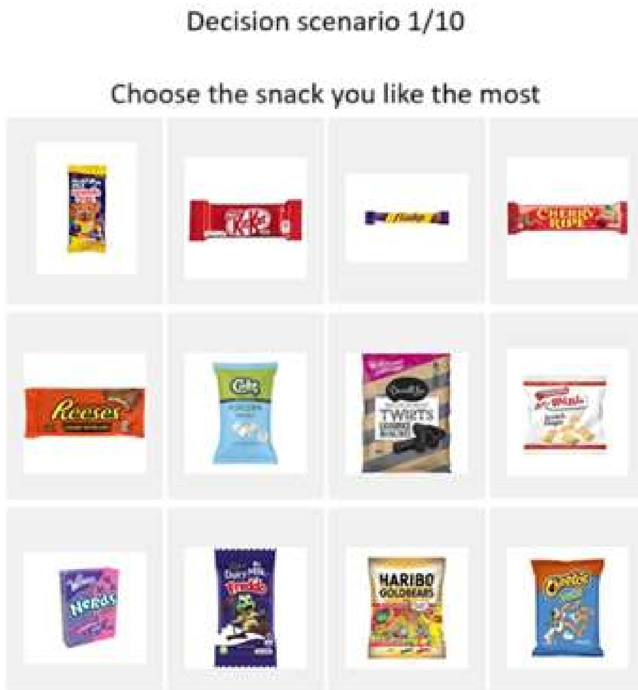

Figure 3. Direct Choice

3.5.2 Elimination remain procedure

In the Elimination Remain choice procedure, we told participants to eliminate snacks by clicking on them, one by one, until only one, the one they would like to receive was left. The eliminated snacks remained on screen with a black “X” beside it. Figure 4A shows an example screen with one snack eliminated. Participants continued eliminating snacks until only one snack was left (Figure 4B). The last remaining snack (Reese’s in Figure 4B) was recorded as their choice. We included this treatment to test whether the elimination of irrelevant alternatives increased the likelihood of choosing highest valued snack. The idea is that the elimination of the least preferred alternatives frees the cognitive resources for the participant to choose from the top alternatives with less noise.

Figures 4A and 4B. Elimination Remain

3.5.3 Elimination disappear procedure

The Elimination Disappear procedure was exactly like the Elimination Remain procedure except that each eliminated snack disappeared from screen after being clicked. Figure 5A shows an example screen with one snack eliminated. Participants continued eliminating snacks until only one snack was left (Figure 5B). The last remaining snack (Bueno in Figure 5b). We included this treatment because it is possible that placing an "X" next to an eliminated snack is not enough for the choosers to completely disregard this alternative. Possibly, when the snacks are visible, even if they are eliminated, they may be considered as alternatives, leading to choice overload. Including the Elimination Disappear procedure allows us to test whether it is necessary to remove the eliminated snacks from the field of vision to increase the likelihood of choosing the snack they wanted to receive.

Figure 5A and 5B. Elimination Disappear

3.5.4 Binary choice procedure

In the Binary Choice procedure, we showed participants two snacks at a time and told them to click on a snack they would like to receive. Like in the other procedures, each decision scenario consisted of twelve snacks. To complete one decision scenario participants made eleven binary choices. Within a binary choice, the computer excluded unchosen snacks from previous binary choices from that decision scenario. As such, each binary choice consisted of two snacks randomly selected from those that were still available out of the original twelve. The snack selected from the last pair was recorded as the snack they would like to receive. We included this treatment because by presenting only two options at a time, it reduces the cognitive load of each choice to a minimum.

Figure 6. Binary Choice

Elimination Remain, Elimination Disappear, and Binary Choice procedures were designed to improve participants' choices. Therefore, henceforth, we refer to the collectively as Smart Choice Procedures.

3.6 Questionnaires

Participants completed an exit questionnaire at the end of the study (Appendix C). It included demographic questions, questions about the study, health and hunger questions.

4. Results

4.1 Preliminary results: valuation task

We first established whether the valuations we elicited were reliable. To establish whether the two valuations that a participant provided for the same snack were consistent, we correlated the first and second round snack valuations and observed a very high correlation (Pearson correlation r = 0.86, p = 0.00). We illustrate this in Figure 7 A, where each dot represents the two valuations of the same snack by the same participant. If the participants provided the same valuation in both rounds, the dots fall on the orange 45- degree line. Most dots are on or close to the 45-degree line and the valuation-based snack rankings across the two rounds are highly correlated (Spearman correlation r = 0.84, p = 0.00). To get a better sense of the inconsistencies in valuations, we additionally calculated the difference between the second and first round valuations for each snack-participants pair. We found that the absolute value of the difference between second and first valuations for all 34 snacks had a mean of \$0.06 with 10% falling under \$0.005 and 75% under \$0.14. These are plotted in Figure 7B. On average, the absolute value of this difference is equal to \$0.26 and the median is \$0.10.

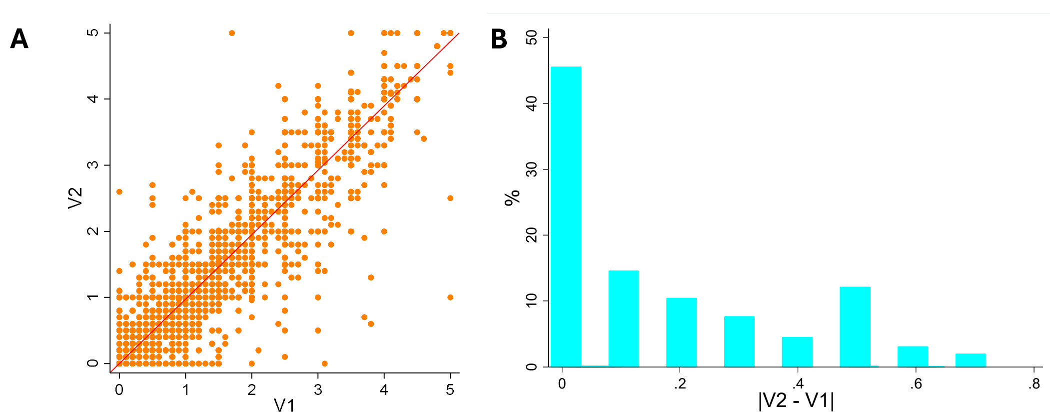

Figure 7. Consistency in Snack Valuations. A: Each Dot Represents Round One (v_1) and Round Two (v_2) Valuations of the Same Snack by the Same Participant. B: Distribution of Differences in Snack Valuations Between the Rounds.

There is some heterogeneity across participants in the consistency of their valuations and rankings. Participants' individual snack valuations Pearson correlation coefficients range from 0.54 to 1.00, with 90% of participants having a strong correlation with Pearson correlation coefficient above 0.76. Spearman correlations of snack rankings range from 0.26 to 1.00, with 90% of participants having strong correlations of above 0.70.

We conclude that the valuations were subsequently consistent and consequently generally could be reliably used to determine the snack rankings. We used each participant's average of the two valuations for each snack to determine their individual snack valuation and ranking. Given that we have a complete ranking of all snacks, for all choice sets that a participant encounters in the Choice Task, we can determine what snack was each participant's highest valued snack and should be selected in every set. In section 4.4.3, we present robustness checks where we exclude participants whose valuations and rankings were not strongly correlated.

4.2 Choice quality in different choice procedures

One way to evaluate a choice procedure is to check how often participants picked their highest valued snack. Averaging across all ten decision scenarios in each choice procedure, we find that our Smart Choice Procedures increased the probability of choosing the highest valued snack relative to Direct Choice. In Figure 8 A, we illustrate the probability of choosing the highest valued snack in each treatment. The horizontal red line at 8.33% indicates the probability of picking the highest valued snack for a completely random chooser. In all choice procedures, participants performed well above the random chooser. In Direct Choice, they selected their highest valued snack in 40.47% of all decision scenarios. The likelihood of picking highest valued snack was significantly higher ($p < 0.001$ in a paired t-test) and at around 58% across all in Smart Choice Procedures. This can be interpreted as participants choosing their highest valued snack in approximately 18% more decision scenarios. There was no difference in the probability of picking the highest valued snack across our Smart Choice Procedures ($p>0.7$ in all paired t-tests).

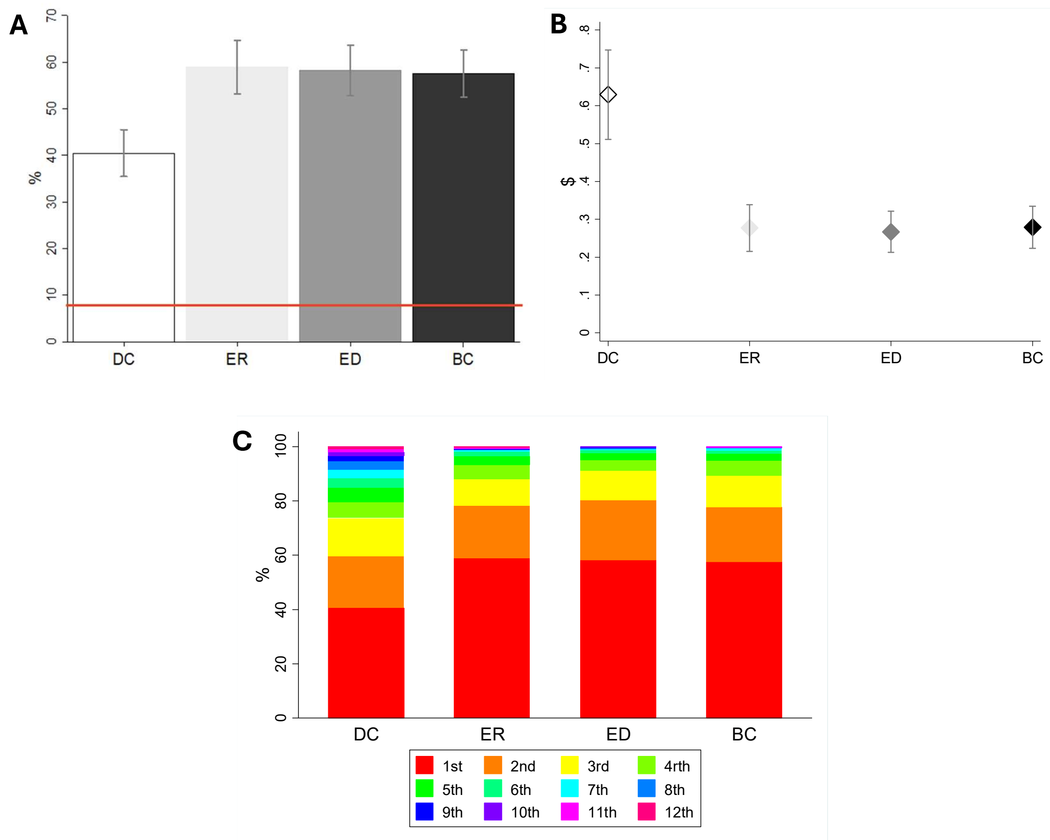

Figure 8. Choice Quality Across Choice Procedures. A: The Likelihood of Picking Highest Valued Snack B: Average Cost of Mistakes C: Likelihood of Picking nth-ranked Snack.

There is a possibility that due to slight differences across the two rounds of valuations, we misclassified a snack as second or third best, while it was a participant's highest valued snack. Therefore, we expanded our analysis by additionally calculating how often participants picked second, third, and all the way to the bottom ranked snack in each treatment. Figure 8 C sums up our findings. In our Smart Choice Procedures, in approximately 90% of the decision scenarios, participants picked one of their top three highest valued snacks.[1] It is significantly ($p < 0.05$) more often than in Direct Choice where participants picked one of the top three snacks in 75% of decision scenarios on average. Another comparison that illustrates the improvement of Smart Choice Procedures over Direct Choice, is that in the Smart Choice Procedures the probability of picking one of the top three alternatives was approximately equivalent to the cumulative likelihood of picking one of the top six snacks in Direct Choice. We also found that there were no instances of participants picking their lowest-ranked snack in the Elimination Disappear and Binary Choice treatments while Direct Choice had the highest incidences at 0.94%.

1 The exact values are 88.23% for Elimination Remain, 91.06% for Elimination Disappear, and 89.3% for Binary Choice.

Another way to evaluate choice procedures is to calculate their associated costs of mistakes as the forgone dollar value whenever participants picked a snack that was not their highest valued snack. To do this, in each decision scenario, we calculated the cost of a mistake as the difference between the valuation of the highest valued snack and the snack that was chosen. Thus, if a participant picked their highest valued snack, they then would have incurred a cost of 0. We then calculated an average cost of mistakes per decision scenario for each participant in each treatment. Figure 8 B presents these results. On average, participants lost $0.63 per decision scenario in Direct Choice. This cost dropped by approximately $0.35, thus by 50.72%, in Smart Choice Procedures, reducing to $0.28 in Elimination Remain and Binary Choice, and $0.27 in Elimination Disappear. These savings are sizable considering that the average valuation of a snack in our study was $3.15 and thus mistakes in Direct Choice were costlier by approximately 11.11% of the average snack valuation when compared to the Smart Choice Procedures.

Overall, we conclude that our Smart Choice Procedures resulted in a higher likelihood of participants picking higher-ranked snacks and less costly mistakes.

4.4 Robustness checks

4.4.1 Better choices by eliminating distractors

Our Smart Choice Procedures were designed to eliminate the effect of distractors (i.e. strictly dominated alternatives) on choice quality in a cognitively constrained chooser. According to the divisive normalization model, for a cognitively constrained chooser, as we reduce the number of irrelevant snacks in their choice set, they should make fewer mistakes. To verify the above logic, we test two predictions. First, we check whether the value of the irrelevant snacks influenced the propensity to make a mistake in the Direct Choice procedure. Second, we check whether in our Smart Choice Procedures that effect was reduced or eliminated.

To test how the valuation of all the snacks influenced the probability of a mistake in the Direct Choice procedure as well as the Smart Choice Procedures, we created a binary variable that is equal to one if a participant picked their highest valued snack in a given decision scenario (and zero otherwise). We then ranked all twelve snacks in each decision scenario based on their valuation, the highest being the first and the lowest being the twelfth. From this we created one variable for each rank showing the value of the snack for that rank in that decision scenario. This resulted in twelve variables x_1 to x_{12}. Table A 1 summarizes the means and standard deviations for each.

It is worthy to note that this ranking, however, does not fully capture the inherent differences and similarities between the valuation of each snack. For instance, if three snacks had the same highest value, then x_1, x_2 and x_3 would have the same values despite these rankings. In the event that this occurred, consecutive differently ranked variables would display the same value and picking any would count as picking the highest valued snack. This was, however, uncommon in our data as 86% of all decision scenarios had only one highest valued snack while 11% had two and 3% had three. Recognizing that it is easier to pick highest valued snack when there is more than one, in our model, we include a regressor equal to the number of snacks with the highest valued in a given decision scenario.

Using these variables, we then ran the following fixed effects regressions for both Direct Choice and each of the Smart Choice Procedures, where $Fav$is the binary variable on weather a participant picked their highest valued snack or not, x_1 to x_{12} are the values of the top to the lowest ranked snack in a decision scenario, and $nsvdr1$ as the number of snacks with the same value as the highest ranked snack. We chose to run a fixed effects regression in order to control for possible unobserved time-invariant heterogeneity across participants such as say personal traits of a participant that influence their decision-making.

$$Fav = \beta_0 + \sum_{i=1}^{12} \beta_i x_i + \beta_{13} nsvdr + u_1 + e_1 \quad (5)$$

In these regressions we expect that coefficient for x_1 will be significant and positive indicating that as the value of the highest ranked snack increased participants were more likely to pick their highest valued snack. In addition, we expect that the coefficient on x_2 will be significant and negative as this would indicate that as the value of the second snack increased participants may be less able to discern which of the top two snacks are their highest valued snack and therefore decreasing the likelihood of picking their highest valued snack. We also expect that with the Direct Choice Procedure one or several of the coefficients on the distractors, x_3 to x_{12}, will be significant and negative showing that distractors do have an effect under normal decision making. Finally, we expect that with the Smart Choice Procedures either none of the coefficients of the distractors are significant or that some may still be significant but have reduced significance or effect size.

In line with the predictions of the neuroeconomic framework, we find that this is the case as shown in Table 1. With the Direct Choice Procedure we find that the coefficient for the highest values distractor x_3 is significant ($p < 0.01$) and negative showing that some distractors reduce the likelihood of choosing the highest valued snack under normal decision-making circumstances. Further, we find that with all Smart Choice procedure the coefficient of x_3 as well as all the other distractors are not significant. This shows that our Smart Choice Procedures are able to either reduce or eliminate the effect of distractors and consequently increases the likelihood that participants were able to pick their highest valued snack. We also found an interesting observation where in the Elimination Remain Procedure x_2 was not significant and in the Elimination Disappear and Binary Choice procedure a flip seems to have occurred where x_3 is no longer significant while x_2 is. This may be because when the distractor, x_3, was significant normalization caused the subjective values of x_1 and x_2 to converge. Put in another way participants may have been less able to discern between x_1 and x_2 when x_3 was significant, therefore resulting in x_2 being insignificant. Finally, we find that these results were still consistent even when controlling for decision scenarios with multiple snacks having the highest value (Table 2). This shows that the effect of the Smart Choice Procedures on the distractors still held even when controlling for decision scenarios where it was easier to select the highest valued snack since there were multiple of them.

Table 1. The Effect of Irrelevant Snacks' Value on the Probability of Choosing the Highest Valued Snack in Direct and Smart Choice Procedures.

	DC	**ER**	**ED**	**BC**
x_1	0.245^{***}	0.251^{***}	0.329^{***}	0.344^{***}
	(0.059)	(0.051)	(0.051)	(0.053)
x_2	-0.022	-0.040	-0.222^{***}	-0.169^{*}
	(0.071)	(0.045)	(0.064)	(0.076)
x_3	-0.235^{**}	-0.111	-0.056	-0.006
	(0.073)	(0.080)	(0.086)	(0.086)
x_4	-0.021	-0.132	0.043	-0.025
	(0.071)	(0.091)	(0.116)	(0.080)
x_5	0.065	0.014	-0.105	-0.121
	(0.096)	(0.084)	(0.126)	(0.071)
x_6	-0.068	-0.074	-0.034	-0.018
	(0.106)	(0.127)	(0.102)	(0.105)
x_7	0.091	-0.016	0.017	0.179
	(0.091)	(0.111)	(0.115)	(0.127)
x_8	0.040	0.068	0.036	-0.192
	(0.112)	(0.151)	(0.123)	(0.129)
x_9	-0.012	0.095	0.053	0.069
	(0.144)	(0.109)	(0.116)	(0.145)
x_{10}	-0.119	-0.108	-0.097	-0.135
	(0.147)	(0.132)	(0.098)	(0.126)
x_{11}	0.056	0.153	0.073	0.146
	(0.118)	(0.132)	(0.090)	(0.140)
x_{12}	-0.048	-0.181	-0.140	-0.046
	(0.054)	(0.087)	(0.083)	(0.087)
# of snacks with the highest value	0.191^{***}	0.060	0.244^{***}	0.178^{***}
	(0.044)	(0.039)	(0.048)	(0.048)
Constant	-0.016	0.371^{***}	0.101	0.027
	(0.144)	(0.143)	(0.160)	(0.150)
N	850	850	850	850
adj. R^2	0.051	0.060	0.085	0.080

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. The Effect of Irrelevant Snacks' Value on the Probability of Choosing the Highest Valued Snack in Direct and Smart Choice Procedures in Decisions without Multiple Snacks with the Highest Value

	DC	ER	ED	BC
x_1	0.230***	0.323***	0.335***	0.388***
	(0.064)	(0.055)	(0.054)	(0.054)
x_2	-0.028	-0.050	-0.250***	-0.227*
	(0.078)	(0.045)	(0.072)	(0.086)
x_3	-0.260**	-0.166	-0.020	0.036
	(0.078)	(0.087)	(0.100)	(0.086)
x_4	0.070	-0.102	0.027	-0.020
	(0.069)	(0.095)	(0.122)	(0.086)
x_5	-0.014	0.0342	-0.111	-0.141
	(0.105)	(0.085)	(0.133)	(0.095)
x_6	0.033	-0.199	-0.013	0.048
	(0.109)	(0.118)	(0.109)	(0.125)
x_7	0.037	0.001	-0.022	0.201
	(0.095)	(0.112)	(0.123)	(0.139)
x_8	0.007	0.127	0.018	-0.285
	(0.112)	(0.174)	(0.140)	(0.152)
x_9	0.102	0.069	0.119	0.172
	(0.157)	(0.150)	(0.154)	(0.192)
x_{10}	-0.199	-0.083	-0.099	-0.160
	(0.166)	(0.144)	(0.146)	(0.161)
x_{11}	0.110	0.0977	0.103	0.127
	(0.139)	(0.158)	(0.123)	(0.149)
x_{12}	-0.090	-0.114	-0.136	-0.107
	(0.080)	(0.099)	(0.101)	(0.111)
Constant	0.152	0.341*	0.313*	0.087
	(0.142)	(0.153)	(0.156)	(0.160)
N	737	734	730	734
adj. R^2	0.040	0.097	0.075	0.092

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.2 Response times

Our Smart Choice Procedures led to better choices. However, they also required participants to spend more time to arrive at a decision in each decision scenario than in direct choice. Indeed, participants spent an average of 6.43 seconds choosing a snack in Direct Choice and 23.63, 20.49, and 17.46 in Elimination Remain, Elimination Disappear, and Binary Choice Procedures respectively (Figure A 4 B). Did participants make better decisions in the Smart

Choice Procedures because they simply took more time to consider their choices or because of the choice procedures themselves?

To answer this question, we first used fixed effect regressions to determine whether the probability of choosing the highest valued snack snack increases in Smart Choice Procedures even after we control for response time. In Table 3, we summarize the results. Model 1 replicates our analysis from Section 4.2 in a regression format. As our reference category is Direct Choice, the constant indicates that we estimate that in Direct Choice participants selected their highest valued snack in 40% of decision scenarios and the coefficients on each of the Smart Procedures indicate an improvement in the range of 17-18%. Model 2 is the same model but with an additional control variable for response time in each decision scenario. It is evident that, if anything, controlling for response time results in larger coefficients on the Smart Procedures dummy variables. In addition, we also controlled for decision scenario difficulty using the difference in valuations for the highest valued snack and second-best, x_1 - x_2 ,to further show that participants did better because of Smart Choice Procedures and not because decision scenarios were easier and we find that this does not change the result (model 3). Further, we ran all the same regressions while controlling for decision scenarios which had multiple snacks with the highest value since it would be easier to select the highest valued snack in these scenarios. With this, we found that our results were still consistent, showing that participants did better due to our Smart Choice Procedures and not simply because decision scenarios were easier (Tables A 4 and 5). Thus, we conclude that response times and decision scenario difficulty are not a good alternative explanation for our findings.

Table 3. Response Time and the Probability of Choosing the Highest Valued Snack. Dependent Variable Equals to One if a Participant Picked their Highest Valued Snack. Elimination Remain, Elimination Disappear and Binary Choice are Categorical Variables for each treatment. Time is the Time in Seconds Spent per Decision. $x_1 – x_2$ is the Difference in Values of the Highest Valued Snack and Second-Best Snack. Average Response Time is the Average Time a Participant Spent for All Decisions.

	(1)	(2)	(3)
ER	0.179***	0.218***	0.213***
	(0.030)	(0.033)	(0.033)
ED	0.178***	0.210***	0.201***
	(0.030)	(0.032)	(0.032)
BC	0.169***	0.202***	0.195***
	(0.027)	(0.030)	(0.030)
Time		-0.002**	-0.002*
		(0.001)	(0.001)
$x_1 – x_2$			0.187***
			(0.028)
Constant	0.405***	0.420***	0.330***

	(0.020)	(0.020)	(0.025)
N	3400	3400	3400
adj. R^2	0.027	0.029	0.055

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.3 Excluding participants with inconsistent valuations

Despite high consistency in snack valuations (see Section 4.1), we did note a few participants who had less consistent snack valuations and rankings across the two valuation rounds. Therefore, we sought to check whether our results still hold when we exclude participants with inconsistent valuations. To do this, for each participant, we calculated Pearson correlation for all their snack valuations and Spearman correlation of all their snack rankings from the two valuation rounds. We then excluded from the analysis 12 participants for whom at least of these correlations were lower than 0.7[2] and replicated our main results in Figure 8 and Table 3. As shown in Figure A 1, the quality of choices remained consistent with our main results as participants picked their highest valued snack around 40% of the time for Direct Choice while around 58% for all Smart Choice Procedures. Participants also incurred similar costs of mistakes with participants having $0.63 in Direct Choice and around $0.28 in the Smart Choice Procedures. As shown in Table A 3, after excluding these participants, we find that our Smart Choice Procedures improved the likelihood of choosing the highest valued snack and time spent by participants I each decision scenario and that response times and decision scenario difficulty are not a good alternative explanation for our findings.

4.4.4 Higher-value goods

As usually done in laboratory experiments, the choice objects in our study are of relatively low value. Would Smart Choice Procedures still lead to better choices when participants are choosing between goods with higher dollar values? One could imagine that in such situations, participants make better decisions simply because of the higher stakes and therefore no longer benefit from our procedures. To test this, we re-ran the entire experiment using the same procedures and replacing 34 snacks with 34 higher-valued consumer products. We also recruited a different pool of participants, all of which were university of Sydney students recruited from the University of Sydney research volunteer database using ORSEE.

The products included clothing, electronics, kitchenware and accessories (see Figure A 2 for images of all products) and had a market value that ranged from $20 to $158. The average value of products used in this treatment is around 15 times higher than in the main experiment that uses snacks. Due to higher costs, we ran this version of the experiment with a smaller sample of 20 participants. With this sample size, assuming $\alpha = 0.05$ and power = 0.80, we can still detect moderate effect sizes (Cohen's d= 0.68) in a paired t-test. Consistent

[2] Four participants had Pearson correlation coefficient below 0.7, eight participants had Spearman correlation coefficient below 0.7 and four participants had both correlation coefficients below 0.7

with main experiment, we ensured that all participants were told to fast for the same period, all sessions were held at 11:30 and all products were immediately given to participants after the experiment.

In line with our intention, participants valued products in this treatment more than snacks. The average valuation in this treatment was \$37.85 (SD = 1.54) which is significantly ($p<0.001$) more than the average valuation (\$1.29) in the main treatment that used snacks.

We find that our Smart Choice Procedures increased the probability of choosing the highest valued snack and decreased the cost of mistakes also when participants were choosing from high-value products (see Figure 9). In Direct Choice, participants selected their highest valued snack in 45.5% of all decision scenarios. The likelihood of picking highest valued snack was significantly higher ($p < 0.001$ in a paired t-test) and at around 58% in all Smart Choice Procedures. On average, participants lost \$14.58 per decision scenario due to mistakes in Direct Choice. This cost dropped by approximately \$9.87 on average, thus by 52.19%, in Smart Choice Procedures, reducing to \$8.65 in Elimination Remain, \$9.54 in Elimination Disappear, and \$11.44 in Binary Choice. This is similar percentage improvement in the main experiment when participants made decisions over snacks that have much lower value. These savings are sizable considering that the average valuation of a product in our study was \$52.5 and thus mistakes in Direct Choice were costlier by approximately 27.77% of the average product valuation when compared to the Smart Choice Procedures.

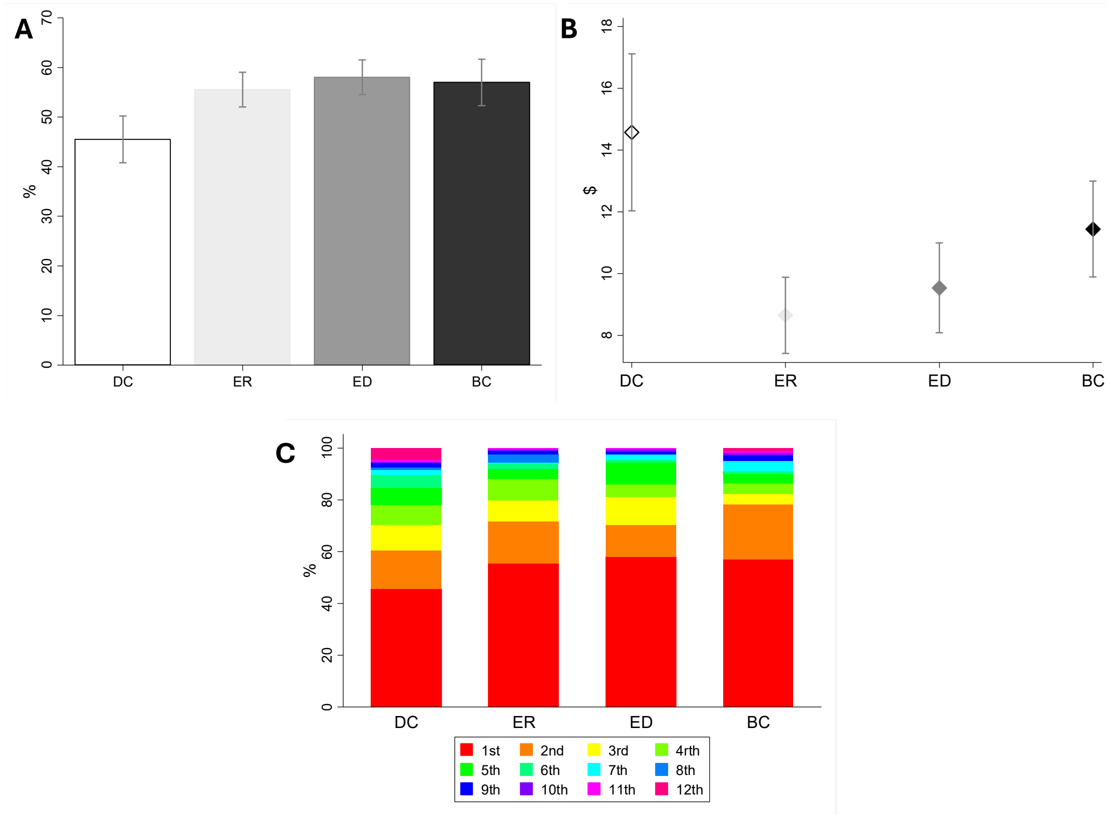

Figure 9. Choice Quality for High-Valued Products across Choice Procedures. A: The Likelihood of Picking the Highest Valued Snack B: Average Cost of Mistakes C: Likelihood of Picking nth-ranked for Higher Valued Goods Snack.

We also confirmed that the improvement in choice quality when using Smart Choice Procedures is due to the fact that they eliminate the effect of the value of distractors has on the probability of choosing the highest valued snack (see Table A 4 and 5). As with snacks, we found that as the value of the third-ranked snack increased, x_3, participants were less likely to pick their highest valued snack in the Direct Choice Treatment. As expected, this effect vanished in our Smart Choice Procedures.

4.5 Preferred Procedures and Time per Procedure

At the end of the experiment, we asked participants to rank each of the four procedures, four being the highest and one being the lowest, to ascertain each participant's preferred procedure. We found that participants preferred the Direct Choice procedure the most followed by the Binary Choice procedure (Figure A 4 A). Participants were also mostly indifferent between the Elimination Remain and Elimination Disappear procedures. This showed that participants preferred the procedure that did not necessarily result in highest likelihood of picking the highest valued snack. A similar trend was also found in the experiment for higher valued goods (Figure A 4 C). This means that despite the fact that Smart Choice Procedures improved choice quality, participants did not prefer them to other procedures.

5. Discussion

Choice overload, specifically the inability of people to pick their highest valued option from a set as more options become available should be of great concern to policy makers as it poses costs to people in their daily decisions. In the past, its existence was put into question (Scheibehenne et al., 2010) however other works (Chernev et al., 2010) including a more recent meta-analysis (Chernev et al., 2012a) found that choice overload occurs under different contexts and is more observable when we look at choice overload as a phenomenon that reduces the likelihood of people picking the their highest valued option rather than focussing on other measures such as anxiety. This is further supported by the existing literature that showed it occurs under different contexts (Caplin et al., 2011; Redelmeier & Shafir, 1995; Roswarski & Murray, 2006; Sanjurjo, 2015) and it does reduce welfare (Caplin et al., 2011). Furthermore, a recent study (Dean et al. 2025) found that the costs of choice overload in the form of decreased welfare may be greater than what had previously been estimated. This is because people end up choosing a default option rather than looking for their highest valued option when choice sets increase.

As was shown by the meta-analysis by Chernev et al. (2012), much of the existing literature regarding choice overload and how it reduces the likelihood of people picking their highest valued option focus on identifying when it happens and the factors that cause it. They found that these factors can be generalized into four main categories 1) difficulty of the decision task, 2) choice set complexity, 3) preference uncertainty and 4) the decision goal. Most of these however only modulate the existing likelihood of picking the highest value option with any given choice set size and do not provide an explanation on how that likelihood changes as the choice set size increases. Furthermore, it was pointed out by the meta-analysis that much of literature makes use of the concept that larger choice set sizes pose larger cognitive costs which lead to reduced likelihoods of people picking their highest valued option. As such, solutions proposed for choice overload which also seek to not limit the number of options available to people or use nudges, such as by Besedes et al. (2015) and Dellaert et al. (2017), operate around the premise that simply reducing the number of options presented at a given time would be enough to improve the likelihood of people picking their highest valued option.

We expanded on this literature in two ways. First, we looked to neuroeconomics, specifically divisive normalization and how it affects people's decisions (Louie et al., 2013, 2014; Webb et al., 2021) for a framework to understand how choice set sizes affect the likelihood of people picking their highest valued option. Second, based of that framework, we identified and tested three Smart Choice Procedures that had a key feature. Our three Smart Choice Procedures presented the minimal number of options either at the end of the decision-making process or all throughout. This was crucial because, based of the neuroeconomic model we used, when presented with more than the minimal number of options the value representation of options may still collapse towards each other if distractor values are high enough. This in turn would reduce the likelihood of a person picking their highest valued option even if the number of options presented was few such as three or four. This was a feature that other solutions, such as presented by Besedes et al. (2015) and Dellaert et al. (2017) did not have.

In line with the predictions of the neuroeconomic framework we used, we found that our Smart Choice Procedures (Elimination Remain, Elimination Disappear and Binary Choice increased the likelihood of participants choosing their highest valued option. Our tests showed that these increased that likelihood by as much as 20 percentage points compared to a baseline where participants simply picked an option directly from the whole set of twelve. Further we found that our Smart Choice Procedures increased the likelihood of picking the highest valued option more than the procedures used by the related literature. This is also in line with the predictions of our neuroeconomic framework which showed that our procedures would work better since they minimized the number of options presented at some point in the decision-making process. Besedes et al. (2015) used procedures wherein a subset of four options was presented one at a time to participants. In each subset, participants had to choose one option they wanted to receive and this continued until the final choice was made. These procedures resulted increased likelihoods by 2 and 13 percentage points compared to a similar baseline as ours. Dellaert et al. (2017), on the other hand, showed subsets of three options to participants with the option to view the entire choice set. These subsets varied in terms of sorting quality. A high sorting quality showed recommended options while low sorting qualities had randomly chosen options. With low sorting quality, these procedures did not improve likelihoods and with high sorting quality likelihoods increased by 10 percentage points. It is also worthy to note that such sorting is similar to a form of default nudge.

We also found that Smart Choice also reduced cost of mistakes of participants. This cost can be thought of as the foregone value when participants weren't able to pick their highest valued option. Our tests showed these costs were reduced by around 50% when participants used our Smart Choice Procedures when compared to when they simply picked one option from the entire choice set. This showed that our procedures may improve the welfare of our participants not just by increasing the likelihood of picking their highest valued option but also reducing the cost of their mistakes.

In addition to these, we also expanded on the literature on by looking at the likelihood of choosing the highest valued option across low and high valued goods. Much of the literature as summarized by Chernev et al. (2012) saw having higher valued options as a potential factor that could lead to choice overload in general. However, when it comes specifically to the likelihood of people picking their highest valued option the literature is less clear. We however found that the likelihood participants picking their highest valued option when they simply picked one from the whole set was slightly higher for the higher valued goods versus the lower valued ones. However, we still found that our Smart Choice Procedures still increased the likelihood of picking the highest valued option and reduced the cost of mistakes for both low and high valued goods. We also noted that these procedures worked across different domains of goods, as the first experiment we conducted involved low valued snacks and the second one involved high value consumer goods such as gadgets and clothes.

A potential challenge however is that, despite these results, we also noted that participants tended to prefer simply picking an option from the whole set rather than using our Smart Choice Procedures. We also noted that this was consistent for both low value and high value goods. This is similar to what Dellaert et al. (2017) found. Their participants had an almost inverse relationship between how much a procedure increased the likelihood of picking the highest valued option and how much a participant preferred that procedure. Similar to them we hypothesized that these preferences across procedures may be due to the amount of time each participant had to spend in each one.

Finally, we take note that some structural differences in the procedures we used such as the number of steps it takes to make a final decision and different attention demands for participants could have influenced the efficacy of each procedure. These though may not have a strong effect. For instance, the direct choice procedure would have the lowest number of steps and would be expected to have the least attention demand on participants. Thus, if these structural differences had a stronger effect on the likelihood of choosing the highest valued option than what our neuroeconomic model predicted then likelihoods should be higher with direct choice. This is because a higher number of steps would mean a greater probability of making a mistake across the entire decision-making process and higher attention demands should create a greater cognitive load on participants, both of which might reduce the likelihood of picking the highest valued snack. However, we do not find this to be the case indicating that our procedures worked aligned with the prediction of the neuroeconomic model.

Chapter 2: A Meta-Analysis of the Sensitivity Parameter of Probability Weighting Functions Across Domains

A Meta-Analysis of the Sensitivity Parameter of Probability Weighting Functions Across Gains and Losses

1. Introduction

It has been observed that people do not treat objective probabilities linearly. Instead, they overweight small probabilities and underweight large probabilities (Fehr-Duda & Epper, 2012; Gonzalez & Wu, 1999; Lattimore et al., 1992, Prelec, 1998; Tversky & Kahneman, 1992). Several models, such as the Tversky-Kahneman (TK) model in cumulative prospect theory (CPT) (Tversky & Kahneman, 1992), the Prelec I and 2 models (Prelec, 1998), and the Linear-in-Odds (LLO) model (Lattimore et al., 1992) , illustrate such behaviour through probability weighting functions which show how probabilities, p, are weighted by people, $w(p)$. In these functions, the overweighting of small probabilities and underweighting of large ones leads to the classic inverse-S shaped probability weighting function.

In these functions, the overall shape and how pronounced the curvature of probability weighting function is determined by the sensitivity parameter, often denoted as γ. Values of γ between 0 and 1 result in a probability weighting function that takes on an inverse-S shape, showing overweighting of small probabilities and underweighting of large ones. When γ is equal to 1 the probability weighting function is linear showing that no weighting occurs. And when γ is greater than 1 an S-shaped function is observed (Lattimore et al., 1992; Tversky & Kahneman, 1992) showing underweighting of small probabilities and overweighting of large ones. Furthermore, γ also shows how sharply the function veers away from linearity with values further from 1 indicating a greater disparity between the objective probability, p, and the weighted probability $w(p)$. An important feature of the sensitivity parameter, as was pointed out by Tversky-Kahneman (1992) and Prelec (1998), is that the same weighting functions may result in different estimates depending on whether estimations were done in the domains of gains or losses. As a consequence, estimating the sensitivity parameter must take into account these possible differences due to domains.

Understanding the sensitivity parameter, γ, is thus crucial to understanding how people make risky decisions wherein they are presented with different options of varying probabilities. Understanding γ can explain both beneficial behaviours, such as buying insurance (Barseghyan et al., 2013), as well as potentially harmful ones, such as gambling like decisions (Gurevich et al., 2009), as both could be the result of how an individual weighs the risk of an outcome. And, overall, γ is crucial at explaining whether people exhibit the fourfold pattern of behaviour characterized by risk seeking for small probability gains, risk aversion for large probability gains, risk aversion for small probability losses and risk seeking in large probability (Abdellaoui, 2000; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Consequently, understanding γ and estimating its value reliably would be crucial for predicting real-world choice, evaluating welfare implications, and designing.

Despite the importance of γ as well as multiple studies showing that probability weighting is non-linear (Fudenberg & Puri, 2022; Zilker & Pachur, 2022) findings on γ are mixed in different ways. First is regarding its value with many studies finding γ to be less than 1 however exact estimates differ. These ranged from as low as 0.05 and up to 0.96 with a few even finding values above 1 (Table 1). Second is regarding the domain dependence of γ. Several papers including Tversky-Kahneman (1992) and Prelec (1998) have argued that γ may not be the same when decisions are made with potential gains or losses, in other words γ may have different values across the domains of gains and losses even for the same individual. They further argued that estimations of γ should thus differentiate between the two domains as any estimation that does not do so may end up having a "mixed" estimate of the two. It is, however, unclear if this difference in γ across the two domains is systemic across studies and if this potential "mixing" of estimates from gains and losses when estimations are undifferentiated is reflected in most of the literature. Third is regarding the sensitivity of γ to certain study characteristics and estimation characteristics. Such characteristics, such type of rewards used to incentivise participants, could be resulting in different estimates of γ (Abdellaoui, 2000; Gonzalez & Wu, 1999; Booij et al., 2010; Fehr-Duda & Epper, 2012). Finally, is regarding whether these sensitivities to study characteristics and estimation characteristics are domain specific. Given that there may be a need to estimate γ separately for each domain, it would thus be important to know if using a certain study or estimation characteristic affects γ estimates in one domain and not in the other. For example, certain rewards may result in higher estimates of γ compared to others when losses are involved but there may be no effect in gains. Being unaware of such domain dependent sensitivities of γ to such characteristics may distort possible differences between estimates across domains.

We thus sought out to conduct a meta-analysis to address these. In this analysis we sought to achieve the following. First was to evaluate what the meta-analytic mean is for γ for the domains of gains, losses and for when papers did not differentiate between the two. The purpose of which is for us not only to identify what the meta-analytic means are from the literature but also to be able to compare the means across the domains. This would allow us to answer two questions: (1) Do the meta-analytic mean estimates of γ differ across the domains of gains and losses across the literature? and (2) Is there systemic evidence that estimating γ without differentiating between gains and losses results in a "mix" of the estimates for gains and losses? As such, would the meta-analytic mean of γ, for papers that did not differentiate between the two domains, systematically be between those for gains and losses? Second, was to test whether estimates of γ were sensitive to commonly employed study and estimation characteristics (reward types, estimation techniques, etc.) for the domains of gains, losses and when the two were undifferentiated. This would allow us to answer (3) What study and estimation characteristics are γ estimates sensitive to? And (4) are these sensitivities consistent across domains or are they domain dependent?

A recently published meta-analysis by Imai et al. (2025) on risk taking propensities had a section with a meta-analysis on the parameter γ. In it, they found a meta-analytic mean γ of 0.68 for their entire data set which comprised of estimates in the gains and loss domains as well as those that did not differentiate between the two. They also found meta-analytic means of 0.73 and 0.71 for gains and losses respectively. They also tested for the sensitivity of γ against a set of characteristics for their entire data set. We, however, expand on their work by answering our questions that were not explicitly covered by their paper: (2) Is there systemic evidence that estimating γ without differentiating between gains and losses results in a "mix" of the estimates for gains and losses? As such, would the meta-analytic mean of γ, for papers that did not differentiate between the two domains, systematically be between those for gains and losses? and (4) are these sensitivities consistent across domains or are they domain dependent?

2. Data and Methodology

2.1 Theoretical Framework

In decision-making models under risk, empirical evidence has shown that people weigh probabilities non-linearly (Fudenberg & Puri, 2022; Zilker & Pachur, 2022) and it was observed that people tend to both overweight small probabilities and underweight large ones (Tversky & Kahneman, 1992; Prelec, 1998; Lattimore et al., 1992; Gonzalez & Wu, 1999; Fehr-Duda & Epper, 2012). Several models have thus been proposed to illustrate this behaviour. Kahneman & Tversky (1992) introduced the TK model which assumes that a person's weighting of the probability of an outcome is determined by a parameter γ, often called the sensitivity parameter. This means that for every probability of an outcome, p, a person instead attaches a weighted probability $w(p)$, to that outcome as determined by γ.

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1 - p)^{\gamma})^{1/\gamma}} \tag{1}$$

An alternative to this model was the Prelec 1 model proposed by Prelec (1998). Similar to the TK model it solely relies on γ determine how a person would weight the probability of an outcome.

$$w(p) = \ exp(-\left(-log(p)\right)^{\gamma} \tag{2}$$

Two additional models are similar in form to the TK and Prelec 1 models however these include an additional parameter δ, often called the elevation parameter. These two are LLO model (Lattimore et al., 1992) which is a two parameter form of the TK model

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1 - p)^{\gamma}} \tag{3}$$

and the Prelec 2 model (Prelec, 1998) which is a two parameter form of the Prelec 1 model.

$$w(p) = \ \exp\left(-\delta\left(-log(p)\right)^{\gamma}\right) \tag{4}$$

For all of these models values of γ less than one would indicate that a person overweights small probabilities and underweights large probabilities and as a result the resulting probability weighting function would have an inverse-S shaped. Values of γ equal to 1 would indicate that a person has linear weighting for probabilities meaning that a person does not overweight or underweight any probabilities. Finally values of γ greater than one would indicate that a person underweights small probabilities and overweight large ones resulting in a S shaped probability weighting function. It is important to note that given the two main functional forms, TK and Prelec, a direct comparison of a particular value of γ may not be ideal across some models. This is because a value of γ in one form may result in a slightly different curve or shape in another (Figure A15).

It has been pointed out that the weighting of probabilities may not be the same when decisions are made with respect to gains or losses (Tversky & Kahneman, 1992; Prelec, 1998; Lattimore et al., 1992; Gonzalez & Wu, 1999). In other words, the sensitivity parameter γ may be specific to which domain, gains or losses, the decision is being made in. From these, we decided to look at whether this holds on a meta-analytic level. Specifically, we wanted to see if, (1) estimates for γ were indeed significantly different across gains, losses and when studies did not differentiate between the two and (2) if any of these probability weighting functions resulted in significantly different estimates from other probability weighting functions of gamma across domains. This is because some of these probability weighting functions may domain specific tendencies.

2.2 Identification and selection of relevant papers

We began our meta-analysis by casting a wide net for all relevant studies. Figure 10 shows this initial stage as well as all subsequent stages of our identification and selection process. We conducted our search using all the known major databases for published papers (Web of Science core, Scopus, PsychINFO, Econlit, Pubmed, Repec, SSRN and Google Scholar) and unpublished papers and theses (Repec, SSRN and Google Scholar) with sets of search terms (topic keywords and methodology keywords). This returned 6243 papers and four research assistants and a PhD student were part of a two-stage double-screening process for these papers. The authors then sampled the papers to verify correct coding.

For the title and abstract screening, we excluded papers that were not related to probability weighting and or had no empirical contents. This refined the number of papers down to 2123. For the full text screening, we excluded all papers that had no numerically reported estimate of γ and also papers whose data could not be used to estimate γ. This resulted in our list of 176 papers.

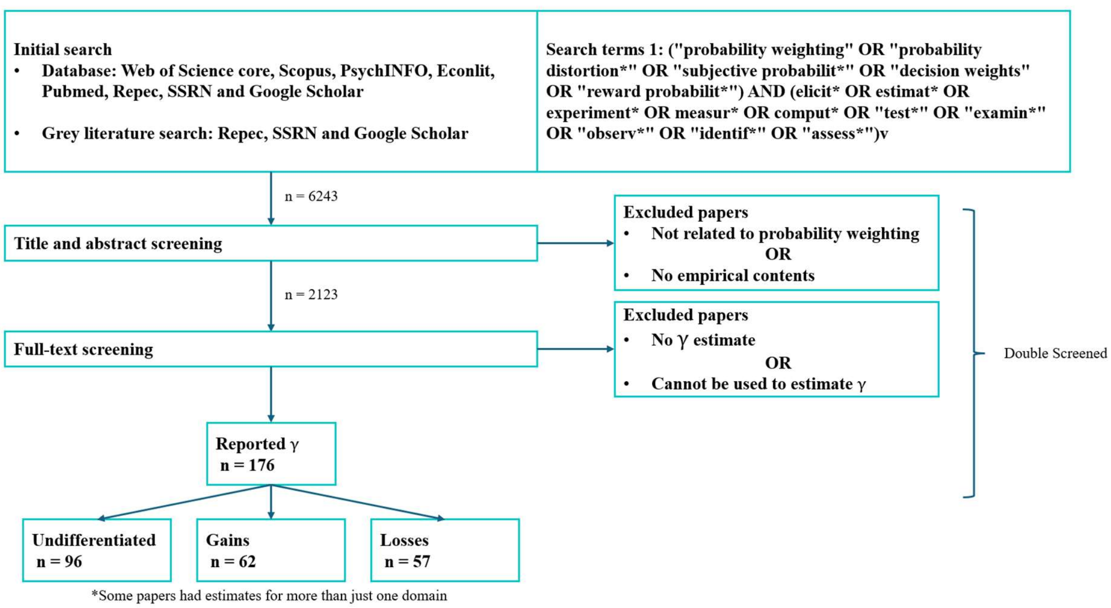

Figure 10. Paper Selection Procedure

2.3 Dataset Construction

We focussed on γ, the sensitiviry paramter of the probability weightig function, as the main variable of our study along with it's standard error (which determines the weight of an estimate of γ in the meta-analysis). There was, however, an issue in how studies report estimates of this paramater. Some studies report aggregate-level parameter estimates and others report individual-level parameter estimates. The former provides the standard error as well as the mean estimate while the latter provides summary statistics that can either include the mean or the median. To address this, if individual estimates were reported, we transformed the standard deviation of the individual estimates into the standard error of the mean estimate. Another issue was when aggregate estimates of γ did not report standard errors of which we found 21 had none. To address this we pooled all the avaialble standard errors in our data set and imputed that as the standard error for estimates with missing standard errors (Furukawa et al., 2006).

We also found that several papers had multiple estimates of γ. If a paper had separete estimates of γ for the domains of gains, losses or if they included an estimate that did not differentiate between the two, then we kept all those estimates as they allowed us to compare across any domain specific characterisctics of γ. If a paper had multiple estimates which used a full sample of participants and subsamples, we kept all the estimates for the subsamples and carefully noted the characteristics of participants involved with each. If a paper had multiple estimates, each involving the use of a different probability weighting functions and utility functions, then we kept all those estimates as as this allowed us to compare across differing probability weighting functions and utlity functions. If a paper also had different estimates, each using a different method of elicitation, estimation, reward, and how probabilites were presented, then we kept each as this allowed us compare across the different methods used for each of these. As a result of all of this, we collected a total of 721 estimates of γ of which 214 were in gains and 182 were in losses and 325 did not distinguish between the two.

Aside from the estimates of γ, we also collected data on the different characteristics of the paper from which an estimate was from as well as the different estimation characteristics used to create each estimate. For paper characteristics this included publication status (e.g. publishes paper, working paper), the field in which the paper was published in (e.g. economics/business, psychology), location of where the study was conducted (e.g. laboratory, field), and the type of data generated (e.g. observational, experimental). For estimation characteristics this included probability weighting function used (e.g. TK, Prelec 1), utility function used (e.g. linear, power utility), reward type (e.g. money, food), type of participants (e.g. university students, general population), probability presentation (e.g. numerical, visual/graphical), and elicitation methods (e.g. binary choice, price lists). All of which were crucial to allow us to test for possible sources of heterogeneity in γ estimates.

3. Results

We conducted all our analyses into three parts. Each part focussed on γ estimates that were made in the domains of gains, losses or estimates that did not distinguish between the two. We thus called each part of each analysis as undifferentiated, gains or losses in reference to the domains in which these estimates were from. This was in line with our goals of ascertaining if differences existed in the meta-analytic means for each domain, if there is evidence that γ estimates for undifferentiated are mixes of the ones for gains and losses and as such the meta-analytic mean for undifferentiated is between of those for gains and losses, and finally if γ estimates are sensitive to certain paper and estimate characteristics and if these sensitivities are domain sensitive.

3.1 Characteristics of papers and estimates

Table 4 summarizes the characteristics of the papers which we included in our analyses. We included a total of 176 papers in our study of which 96 of those had γ estimates that were undifferentiated, 62 which had estimates for gains and 57 had estimates for losses. It is important to note that a paper may have multiple estimates in different domains. As such, if a paper had estimates in say the gains and loss domains, then we counted it as one of the papers for both gains and losses.

In terms of publication status, for undifferentiated 92.71% of papers were published as of February 2026 while 5.21% were working papers. These included papers from various fields though most of them were concentrated in Economics or Business (84.38%) followed by Psychology (9.38%), Health and Medical Sciences (5.21%) and Neuroscience (1.04%). For gains, 90.32% were published papers and 9.68% were working papers distributed among Economics and Business (83.87%), Psychology (8.06%), Health and Medical Sciences (3.23%) and Neuroscience (1.61%). Finally for loss, 98.25% of papers were published while 1.75% were working papers distributed among Economics and Business (85.96%), Psychology (8.77%), Health and Medical Sciences (3.51%) and Neuroscience (1.75%).

Table 4. Paper Characteristics

	Undifferentiated		Gains		Losses		Total
	Frequency	Proportion	Frequency	Proportion	Frequency	Proportion	
	96	100.00	62	100.00	57	100.00	176
Publication Status							
Published Paper	89	92.71	56	90.32	56	98.25	
Unpublished	5	5.21	6	9.68	1	1.75	
Field							
Economics/Business	81	84.38	52	83.87	49	85.96	
Psychology	9	9.38	5	8.06	5	8.77	
Neuroscience	1	1.04	1	1.61	0	1.75	
Health/Medical	5	5.21	3	3.23	1	3.51	

Location						
Field	52	54.17	35	58.33	33	60.00
Lab	38	39.58	25	41.67	22	40.00
Online	4	4.17	0	0.00	0	0.00
Type of Data						
Experimental	94	97.92	57	93.44	52	92.86
Observational	2	2.08	3	4.92	3	5.36

Table 5, on the other hand summarizes the characteristics of the γ estimates we included from these papers. There was a total of 721 estimates included of which 325 were undifferentiated, 214 were in gains and 182 were in losses.

In terms of probability weighting functions used to estimate γ, four were the most used. For undifferentiated estimates, 27.69% used the TK model, 16.31% used Prelec I, 34.36% used LLO, and 16.92% used Prelec 2. For gains, 47.20% used TK, 8.88% used Prelec I, 20.56% used LLO and 15.42% used Prelec 2. Finally for loss, 55.49% used TK, 7.69% used Prelec I, 24.18% used LLO and 12.09% used Prelec 2. On the other hand, most estimates made use of one utility function the power utility function. For undifferentiated 88.00% used of power utility,1.85% used CARA and 2.77% used power expo. For gains 93.93% used power utility, 0.93% used CARA and 1.40% used power expo. Finally for loss, 90.11% used power utility, 1.10% used CARA and 3.85% used power expo.

In terms of other estimation characteristics, most estimations were done using similar study characteristics. Money was the most common form of reward type accounting for 94.51% for undifferentiated, 91.04% for gains and 88.17% for losses. University students were the most common participants with 80.1% for undifferentiated, 83.70% for gains and 84.07% for losses. Probabilities were mostly presented in numeric forms as part of the elicitation process with 76.00% for undifferentiated, 84.62% for gains, and 83.52% for loss with visual or graphical representations being a far second at 16.62%, 12.98% and 14.20% respectively. In terms of elicitation methods price lists and binary choices were the most common used with pricelists accounting for 51.08% for undifferentiated, 34.34% for gains and 37.85% for loss while binary choices accounting for 40.00% for undifferentiated, 62.20% for gains and 58.76% for loss.

Table 5. Estimation Characteristics

	Undifferentiated		Gains		Losses		Total
	Frequency	Proportion	Frequency	Proportion	Frequency	Proportion	

	325	100	214	100	182	100	721
Weighting Function							
$\frac{p^{\gamma}}{(p^{\gamma} + (1 - p)^{\gamma})^{1/\gamma}}$	90	27.69	101	47.20	101	55.49	
$exp(-(-log(p))^{\gamma})$	53	16.31	19	8.88	14	7.69	
$\frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1 - p)^{\gamma}}$	112	34.46	44	20.56	44	24.18	
$\exp(-\delta(-log(p))^{\gamma})$	55	16.92	33	15.42	22	12.09	
Utility Function							
x^{α}	286	88.00	201	93.93	164	90.11	
$\frac{1 - e^{-\alpha x}}{\alpha}$	6	1.85	2	0.93	2	1.10	
$-exp(-\beta x^{\alpha})$	9	2.77	3	1.40	7	3.85	
Reward Type							
Money	258	94.51	183	91.04	149	88.17	
Food	2	0.73	0	0.00	0	0.00	
Physical Item	6	2.20	0	0.00	0	0.00	
Health Outcome	6	2.20	1	8.46	1	0.59	
Participants							
University Students	260	80.10	179	83.70	153	84.07	
General Population	64	9.90	35	6.30	29	15.93	
Probability Presentation							
Numerical	247	76.00	176	84.62	147	83.52	
Visual Graphs	54	16.62	27	12.98	25	14.20	
Described in Words	2	0.62	0	0.00	0	0.00	
Learned	18	5.54	5	2.40	4	2.27	
Method of Elicitation							
Price List	160	51.08	72	34.45	67	37.85	
Binary Choices	130	40.00	130	62.20	104	58.76	
BDM	10	3.08	1	0.48	4	2.26	

3.2 Descriptive analysis of sensitivity parameter estimates

The earliest estimate of γ in our data set was from 1992 (Tversky & Kahneman 1992) and it remained the only estimate until 1996. We looked at the number of estimates per year for undifferentiated, gains and losses as shown in figure 11 where we saw a gradual rise in the number of estimates with a sudden peak around 2018 for all three. We plotted the estimated values from these across the years as seen figure 12A, 12B, and 12C for undifferentiated, gains and losses respectively. These showed that most estimates concentrated below the value of one which indicated inverse-S shaped probability weighting functions though some estimates not only had values higher than one but also showed increasing values above 1.5.

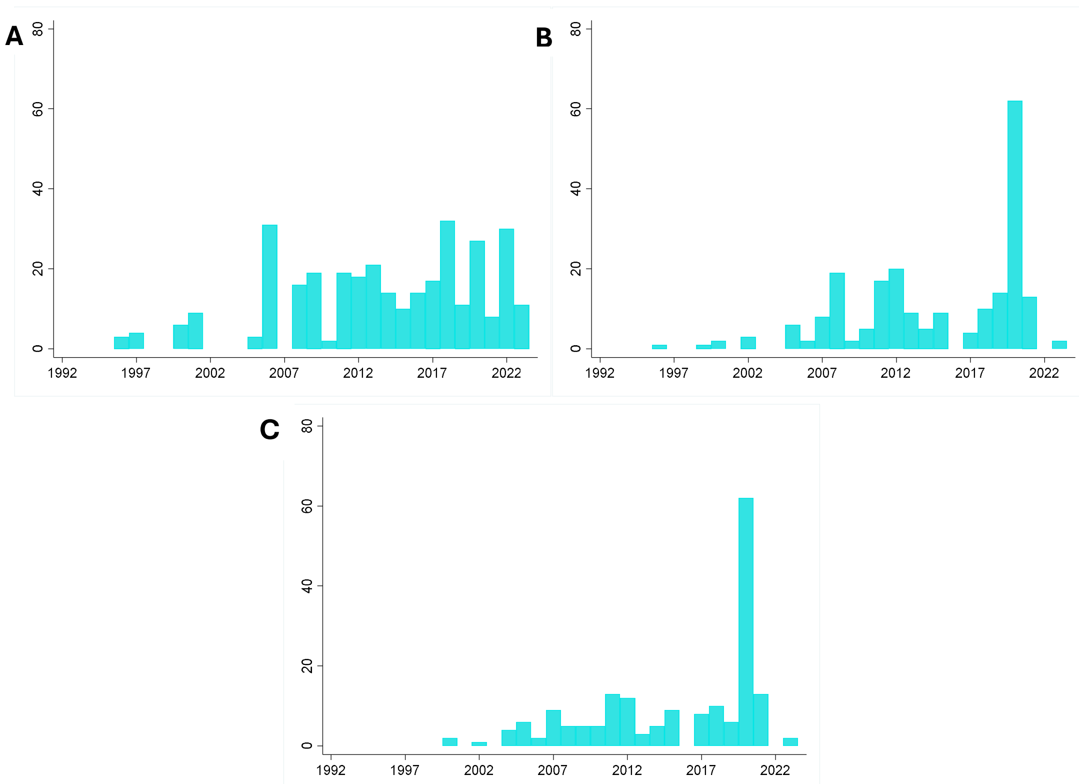

Figure 11. Histogram of γ Estimates for A: Undifferentiated, B: Gains, and C: Losses

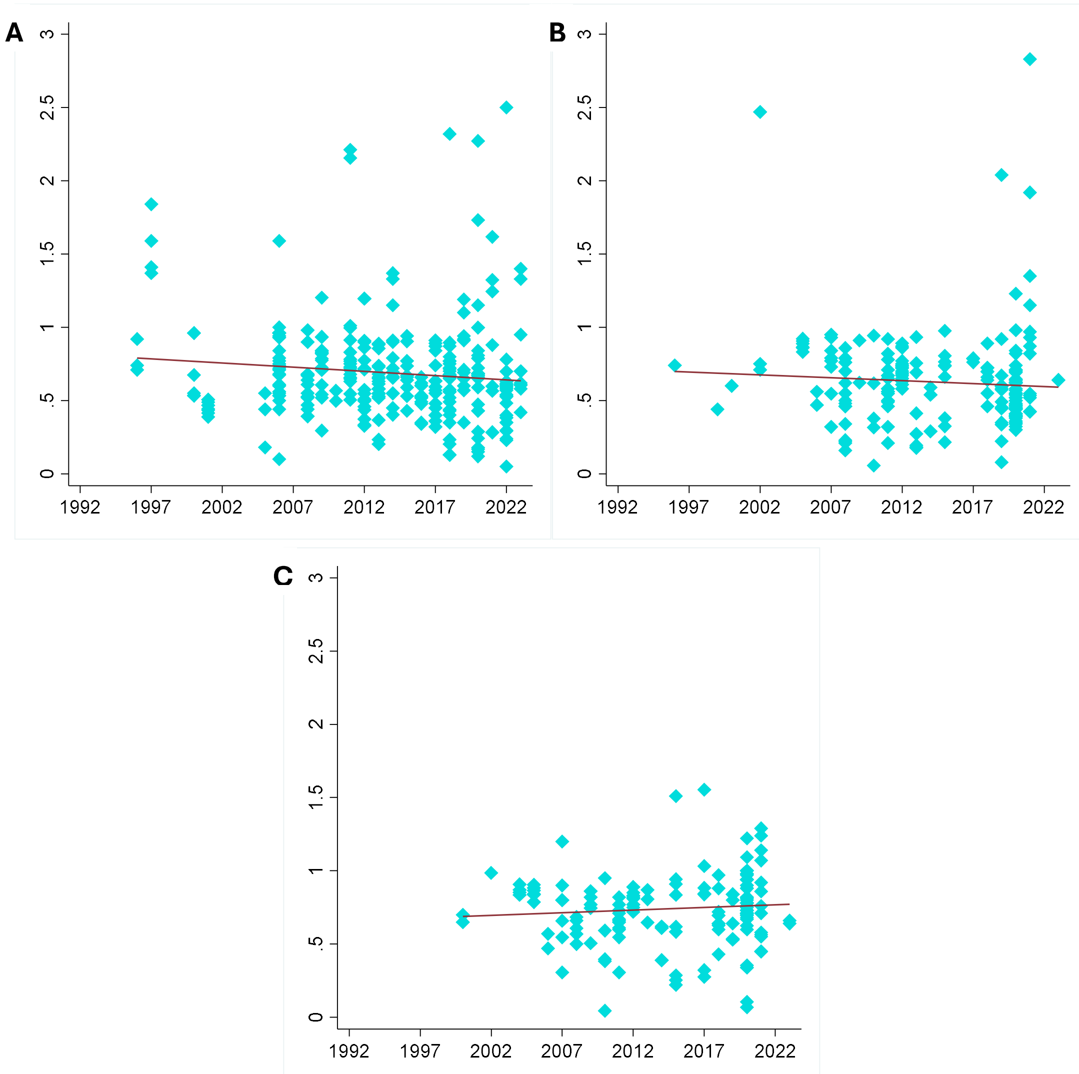

Figure 12. Scatter Plot of Estimated γ Values by Year for A: Undifferentiated, B: Gains, and C: Losses

Looking at the distribution of estimates for undifferentiated we found these had a mean of 0.69 with a leftward skew resulting in a median of 0.64 (Table 6 and Figure 13A). These indicated an inverse-S shape to the probability weighting function, and this is supported by majority of estimates with 90% having a value less than one.

For gains, we found a mean of 0.62 with a leftward skew resulting in a median of 0.60 (Table 6 and Figure 13B). These indicated an inverse-S shape to the probability weighting function, and this is supported by majority of estimates with 95% having a value less than one.

For losses, we found a mean of 0.74 with a slight rightward skew resulting in a median of 0.77 (Table 6 and Figure 13C). These indicated an inverse-S shape to the probability weighting function, and this is supported by majority of estimates with 90% having a value less than one.

Given these values, we found that the mean for undifferentiated was in the middle of the two means for gains and losses which supported the notion that undifferentiated estimates are a “mix” of estimates for gains and losses. Further, using two-sided t-tests to check if these means were statistically significant from one another, we found the mean for undifferentiated to be significantly greater than for gains ($p < 0.05$), the mean for undifferentiated to be slightly significantly less than for losses ($p = 0.049$) and the mean for losses was significantly greater than for gains ($P < 0.0001$).

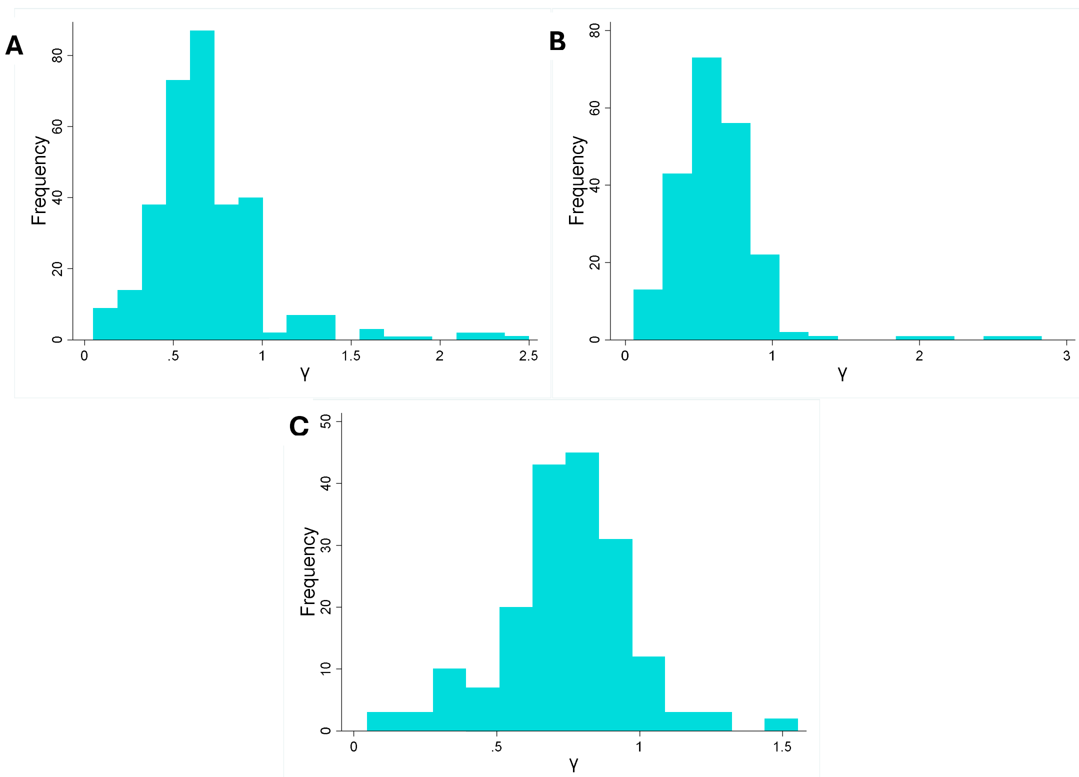

Figure 13. Frequency Distribution of γ Estimates for A: Undifferentiated, B: Gains, and C: Losses

Table 6. Summary Statistics of γ Estimates for Undifferentiated, Gains and Losses

	N	Mean	SD	Q25	Median	Q75	Min	Max
Undifferentiated	325	0.69	0.34	0.52	0.64	0.80	0.05	2.5
Gains	214	0.62	0.32	0.45	0.60	0.74	0.06	2.83
Losses	182	0.74	0.23	0.64	0.77	0.88	0.05	1.55

3.3 Meta-analytic estimates of γ

To obtain a proper meta-analysis of γ we made use of a random effects model that made use of the standard error for each estimate for undifferentiated, gains and loss estimates. To this effect we made use of the DerSimonian & Laird (1986) random effects model as summarized below:

$$\gamma_j = \gamma_0 + \xi_j + \varepsilon_j \tag{5}$$

where γ_j is the *j*th estimate of the sensitivity parameter, and the observed sensitivity parameter estimates are comprised of the "true" sensitivity parameter common to all estimates, the sampling errors $\xi_j \sim \mathrm{N}(0, \tau^2)$ and $\varepsilon_j \sim \mathrm{N}(0, v_j^2)$, wherein τ^2 captures the unknown between-observation heterogeneity, beyond mere sampling variance, while the sampling variance v_j^2 is known. The random-effects estimate $\overline{\gamma_0}$ is a weighted average of individuals γ_j estimates and the weights are given by $w_j = 1/(v_j^2 + \hat{\tau}^2)$ where $\hat{\tau}^2$ is the estimate of τ^2 using the DerSimonian and Laird method (Dersimonian & Laird, 1986):

$$\overline{\gamma_0} = \frac{\sum_{j=1}^{m} w_j \gamma_j}{\sum_{j=1}^{m} w_j} \tag{6}$$

With this, estimates with smaller standard errors are given larger weights. Furthermore, given that our data set included multiple estimates of γ from a single study in some cases, we accounted for this by using cluster-robust variance estimation by clustering standard errors on a per study level (Pustejovsky & Tipton, 2022).

Figure A4, A5, A6 show the forest plots (Hedges & Olkin, 1985) of the estimates for undifferentiated, gains and losses respectively, with the overall meta-analytic mean at the bottom. The rows of the forest plot each shows a different undifferentiated estimate some of which are from the same paper while the size of each diamond represents the weight of that estimate. Horizontal lines indicate the 95% confidence interval for that estimate.

Using these we found that, for undifferentiated (Figure A1), the estimated overall mean γ was 0.66 with a 95% confidence interval of [0.74, 0.90]. This mean supports an inverted-S shape probability weighting. For gains (Figure A2), the estimated overall mean γ was 0.57 with a 95% confidence interval of [0.55, 0.85]. For losses (Figure A3), the estimated overall mean was 0.74 with a 95% confidence interval of [0.51, 0.85]. Both these means also support an inverted-S shape probability weighting. We also found that like our previous means from Section 3.2 the meta-analytic mean for undifferentiated estimates is in between the estimates for gains and losses supporting the notion that undifferentiated estimates are possible mixes of estimates from both the gains and loss domains across the literature.

3.4 Selective reporting and publication bias

The meta-analytic estimates for γ that we found may not be a true reflection of the sensitivity parameter due to the possible presence of two types of biases. The first could be selective reporting biases wherein, for some reason, authors chose to report only particular values for γ. The second would be publication biases wherein journals may have chosen to only publish papers with particular values of for γ. To address these, we conducted funnel plots each for undifferentiated, gains and losses. This method is an effective method for detecting both forms of biases (Egger et al., 1997) and is a scatter plot of estimates against their standard errors with estimates with smaller standard errors at the top. This is put on top of a cone representing the 95% confidence interval that fans out from the estimated overall mean. Any asymmetry of the estimates along this cone and about the mean would suggest "missing studies" indicating either selective reporting or publication bias. Figure 14A, 14B, and 14C shows the funnel plots for undifferentiated, gains and losses. Visual inspection of these plots showed that for undifferentiated and gains there seemed to be asymmetry towards values above the mean due clear outliers that are outside the 95% confidence interval. For losses, however, there seemed to be only slight asymmetry with less pronounced outliers outside 95% confidence interval above the mean.

To further investigate these, we made use of the Egger test which is a simple meta-regression of each estimate on its standard error (Egger et al. 1997):

$$\gamma_{ij} = \alpha_0 + \alpha_1 * SE_{ij} + \varepsilon_{ij} \tag{7}$$

where α_0 is the "true" effect when there is no selective reporting and $\alpha_1 \neq 0$ indicating the existence of bias. To account for heteroskedasticity, we used least squares with the inverse of the variance $1/SE_{ij}^2$ as the weight. If the noted asymmetry for losses in the forests plots is correct, then α_1 should be significant and have a positive value indicating a bias for values above the mean. We found this was the case, for undifferentiated ($\alpha_1 = 0.62, \mathrm{p} < 0.001$) and gains ($\alpha_1 = 1.26, \mathrm{p} < 0.001$) since results of the egger tests showed significant bias but for losses ($\alpha_1 = 0.37, \mathrm{p} > 0.05$) tests found no significant bias.

Correcting for this, we made use of a trim-and-fill technique (Duval & Tweedie, 2000; Sutton et al., 2000) which involved trimming the studies that caused the asymmetry so that the overall mean estimate produced by the remaining studies could be considered minimally impacted by the bias. The minimally impacted overall mean estimate was then used to fill the imputed missing studies. This resulted in a new overall mean estimate for undifferentiated of 0.62 with a 95% confidence interval of [0.59, 0.64] and a mean of 0.55 with a 95% confidence interval of [0.55, 0.59] for gains. We found that these new means though were statistically indistinct from their original ones after testing using two sided t-tests.

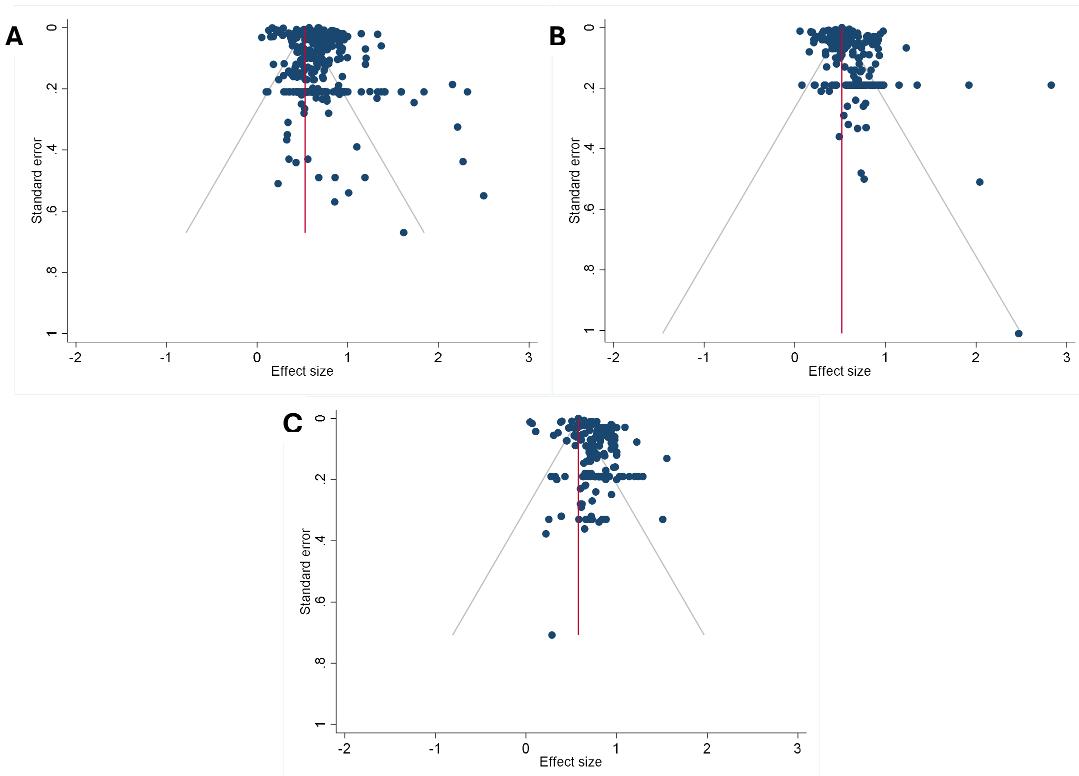

Figure 14. Funnel Plots of γ Estimates for A: Undifferentiated, B: Gains, and C: Losses. Red lines are the meta-analytic mean and cones show the 95% confidence interval.

3.5 Sources of heterogeneity

Heterogeneity in our γ estimates for undifferentiated, gains and losses are quantified by the I^2 statistic in each forest plot. This statistic is computed as:

$$I^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + s^2} 100 \tag{8}$$

wherein $\hat{\tau}^2$ is the estimated value of τ^2 , the unknown in between-estimate heterogeneity and $s^2 = \frac{(m-1)\sum w_j}{(\sum w_j)^2 + \sum w_j{}^2}$ which is the common sampling variance of the overserved effect size with m as the number of estimates and $w_j = \frac{1}{v_j^2}$ is the weight of each estimate.

Using these, we found that there was high heterogeneity among estimates for undifferentiated (I^2 = 99.85%), gains (I^2 = 97.81%), and losses (I^2 = 97.76%). These indicated that variance across estimates may be driven by unobserved between-estimate heterogeneity and not just sampling variance which was explored in the previous section. To explore this, we conducted the following meta-regression model for undifferentiated, gains and losses separately:

$$\gamma_{ij} = \alpha_0 + \alpha_1 * SE_{ij} + \beta X_{ij} + \varepsilon_{ij} \tag{9}$$

where X_{ij} is a vector of observable characteristics of the jth estimate from study I, and β is the coefficient vector. Characteristics included as variables in X_{ij} include (1) paper characteristics which include: publication status (baseline category was published papers), field in which the study was conducted (baseline category was economics/business), location (baseline category was conducted in the laboratory), and type of data (baseline category was experimental data), and (2) estimate characteristics which include: probability weighing function used (baseline category was the LLO model), utility function used (baseline category was the linear utility function), reward type (baseline category was monetary rewards), probability presentation (baseline category was numerical), and method of elicitation (baseline category was using binary choices). We categorized these variables into these two groups to further clarify if estimate heterogeneity was due to estimation methodologies employed or due to the nature of the papers.

It is important to note that we only included probability weighting functions as a variable in X_{ij} as a control. We did not compare across the four probability weighting functions that were most used in papers. The reason for this, as was pointed out by section 2.1, is because each functional form, TK or Prelec, implies different curvatures for the same value of γ. To illustrate this, we graphed the probability weighting functions for the same values of γ, 0.33, 0.5 and 0.83, with the purple line illustrating the TK functional form and the red line for the Prelec functional form (Figure A7A, A7B, A7C). We observed that the two curves diverge from one another the less γ was compared to one. In addition, we also looked at the meta-analytic means for estimates that only used the TK functional form, as well as the 25th, 50th and 75th percentiles of estimates, and from those calculated the equivalent values of γ that would generate a similar curvature and shape for the Prelec functional form. We computed these equivalent values by minimizing the mean squared error between the two functional forms and we calculated these for undifferentiated, gains and losses (Tables A3, A4 and A5). From these we observed a similar pattern wherein the two functional forms diverged the less the value of γ was relative to one.

Tables 7, 8, and 9 show the results for undifferentiated, gains and losses respectively. For each, we show the meta-regression for each individual characteristic separately (Models 1 – 9) and for all characteristics (Model 10). The baseline is consisted of an estimate for γ obtained from a published paper, in the field of economics/business which was conducted in the laboratory, resulting in experimental data. Furthermore, this baseline made use of the LLO probability weighting function, a linear utility function, monetary rewards for participants, numerical presentations of probabilities, and binary choices as an elicitation method.

We found that two patterns worthy of note. First, we noted that field experiments resulted in higher γ estimates in both the reduced (Model 8) and whole model (Model 10) but only for losses. This hinted at possible differences on how people treat real world losses versus how they treat lab induced ones. Second, we noted that food rewards resulted in higher estimates for γ when compared to monetary rewards in the reduced (Model 3) and full model (Model 10) however it is worth noting that studies that made use of food rewards were confined to just undifferentiated. This implied that people react to food rewards differently to monetary ones resulting in weighting functions with more pronounced curvatures.

Aside from these three main patterns we also noted the following. For undifferentiated, we found learned probability presentations and matching task elicitations lead to lower estimates of γ for the reduced models (Models 4 and 5) and price list elicitations lead to higher estimates of γ in the full model (Model 10). For gains, that price list elicitations increased the estimates for γ for the reduced model (Model 5) but not for the complete model (Model 10). Estimates in the field of psychology were higher than in economics/business both in the reduced model (Model 7) and complete model (Model 10) while estimates in Neuroscience were lower than in economics/business for both the reduced (Model 7) and complete models (Model 10).

Table 7. Meta-regression for γ for Undifferentiated. The baseline is an estimate of γ from a published paper, in the field of economics/business which was conducted in the laboratory, resulting in experimental data, that used the LLO probability weighting function, a linear utility function, monetary rewards for participants, numerical presentations of probabilities, and binary choices as an elicitation method.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimate Characteristics										
Weighting Function										
$\frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}$	0.054									0.067
	(0.038)									(0.049)
$exp(-(-log(p))^{\gamma})$	-0.016									0.037
	(0.048)									(0.059)
$\frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}$	Baseline									Baseline
	(.)									(.)
$\exp(-\delta(-log(p))^{\gamma})$	0.027									0.004
	(0.044)									(0.056)
Utility Function										
x^{α}		0.143^{*}								0.168^{*}
		(0.072)								(0.084)
$\frac{1-e^{-\alpha x}}{\alpha}$		0.049								0.114
		(0.135)								(0.137)
$-exp(-\beta x^{\alpha})$		0.107								0.039
		(0.114)								(0.113)
βx		Baseline								Baseline
		(.)								(.)
Reward Type										
Money			Baseline							Baseline
			(.)							(.)
Food			1.515^{***}							1.723^{***}
			(0.262)							(0.325)
Physical Item			-0.057							-0.057
			(0.106)							(0.137)
Health Outcome			0.077							-0.015
			(0.123)							(0.188)
Probability Presentation										
Numerical				Baseline						Baseline
				(.)						(.)

Visual Graphs	0.016						-0.047
	(0.046)						(0.057)
Described in Words	0.138						0.066
	(0.184)						(0.197)
Learned	-0.220**						-0.179
	(0.067)						(0.161)
Method of Elicitation							
Price List		-0.063					-0.146***
		(0.034)					(0.044)
Binary Choices		Baseline					Baseline
		(.)					(.)
Matching Task		-0.173*					-0.151
		(0.086)					(0.131)
BDM		-0.113					-0.183
		(0.326)					(0.413)
Paper Characteristics							
Publication Status							
Published Paper			Baseline				Baseline
			(.)				(.)
Unpublished			-0.131				0.017
			(0.111)				(0.412)
Field							
Economics/Business				Baseline			Baseline
				(.)			(.)
Psychology				0.001			-0.098
				(0.075)			(0.089)
Neuroscience				0.309*			0.133
				(0.150)			(0.137)
Health/Medical				0.065			-0.031
				(0.073)			(0.073)
Location							
Field					0.044		-0.004
					(0.033)		(0.045)
Lab					Baseline		Baseline
					(.)		(.)
Online					-0.028		-0.123
					(0.094)		(0.083)
Type of Data							
Experimental						Baseline	Baseline
						(.)	(.)
Observational						0.090	-0.371
						(0.124)	(0.194)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.633***	0.533***	0.660***	0.677***	0.719***	0.667***	0.656***	0.645***	0.663***	0.605***
	(0.027)	(0.070)	(0.018)	(0.018)	(0.026)	(0.017)	(0.017)	(0.023)	(0.016)	(0.072)
Observations	325	325	273	325	325	325	325	325	325	273

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. Meta-regression for γ for Gains. The baseline is an estimate of γ from a published paper, in the field of economics/business which was conducted in the laboratory, resulting in experimental data, that used the LLO probability weighting function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimate Characteristics										
Weighting Function										
$\frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}$	-0.045									0.021
	(0.044)									(0.066)
$exp(-(-log(p))^\gamma)$	0.175*									0.269***
	(0.070)									(0.075)
$\frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}$	0.000									0.000
	(.)									(.)
$\exp(-\delta(-log(p))^\gamma)$	-0.128*									0.019
	(0.057)									(0.083)
Utility Function										
x^α		-0.154								-0.151
		(0.217)								(0.208)
$\frac{1-e^{-\alpha x}}{\alpha}$		0.060								0.000
		(0.263)								(.)
$-exp(-\beta x^\alpha)$		0.158								0.211
		(0.250)								(0.233)
βx		Baseline								Baseline
		(.)								(0.)
Reward Type										
Money			Baseline							Baseline
			(.)							(.)
Physical Item			0.000							0.000

	(.)						(.)
Health Outcome	-0.088						-0.530
	(0.364)						(0.429)
Probability Presentation							
Numerical		Baseline					Baseline
		(.)					(.)
Visual Graphs		-0.098					0.015
		(0.053)					(0.073)
Described in Words		0.000					0.000
		(.)					(.)
Learned		0.091					0.203
		(0.110)					(0.155)
Method of Elicitation							
Price List			0.130^{***}				0.054
			(0.038)				(0.052)
Binary Choices			Baseline				Baseline
			(.)				(.)
Matching Task			-0.090				-0.514^{*}
			(0.203)				(0.200)
BDM			0.000				0.000
			(.)				(.)
Paper Characteristics							
Publication Status							
Published Paper				0.000			0.000
				(.)			(.)
Unpublished				0.160			0.206
				(0.346)			(0.306)
Field							
Economics/Business					0.000		0.000
					(.)		(.)
Psychology					0.207^{**}		0.193^{*}
					(0.062)		(0.084)
Neuroscience					-0.334^{***}		-0.320^{**}
					(0.078)		(0.111)
Health/Medical					0.156		0.479
					(0.242)		(0.298)
Location							
Field						0.047	-0.012
						(0.035)	(0.059)
Lab						0.000	0.000
						(.)	(.)
Online						0.000	0.000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
								(.)		(.)
Type of Data										
Experimental									0.000	0.000
									(.)	(.)
Observational									0.268*	0.318
									(0.104)	(0.180)
Constant	0.618***	0.713**	0.548***	0.571***	0.530***	0.580***	0.564***	0.543***	0.553***	0.643**
	(0.037)	(0.216)	(0.018)	(0.019)	(0.021)	(0.020)	(0.017)	(0.026)	(0.017)	(0.214)
Observations	213	213	200	207	208	213	213	208	210	196

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9. Meta-regression for γ for Losses. The baseline is an estimate of γ from a published paper, in the field of economics/business which was conducted in the laboratory, resulting in experimental data, that used the LLO probability weighting function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimate Characteristics										
Weighting Function										
$\frac{p^{\gamma}}{(p^{\gamma} + (1 - p)^{\gamma})^{1/\gamma}}$	0.120**									0.071
	(0.038)									(0.054)
$exp(-(-log(p))^{\gamma})$	0.191**									0.252**
	(0.071)									(0.081)
$\frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1 - p)^{\gamma}}$	Baseline									Baseline
	(.)									(.)
$\exp(-\delta(-log(p))^{\gamma})$	0.063									0.133*
	(0.056)									(0.064)
Utility Function										
x^{α}		0.008								-0.026
		(0.097)								(0.155)
$\frac{1 - e^{-\alpha x}}{\alpha}$		0.010								0.000
		(0.160)								(.)
$-exp(-\beta x^{\alpha})$		0.216								0.353

	(0.119)								(0.184)
βx	Baseline								Baseline
	(.)								(.)
Reward Type									
Money		Baseline							Baseline
		(.)							(.)
Physical Item		0.000							0.000
		(.)							(.)
Health Outcome		-0.105							-0.279
		(0.286)							(0.318)
Probability Presentation									
Numerical			Baseline						Baseline
			(.)						(.)
Visual Graphs			-0.093						-0.179*
			(0.048)						(0.070)
Described in Words			0.000						0.000
			(.)						(.)
Learned			-0.119						0.010
			(0.109)						(0.170)
Method of Elicitation									
Price List				-0.044					-0.098*
				(0.036)					(0.044)
Binary Choices				Baseline					Baseline
				(.)					(.)
Matching Task				0.000					0.000
				(.)					(.)
BDM				0.000					0.000
				(.)					(.)
Paper Characteristics									
Publication Status									
Published Paper					Baseline				Baseline
					(.)				(.)
Unpublished					0.165				0.255
					(0.280)				(0.237)
Field									
Economics/Business						Baseline			Baseline
						(.)			(.)
Psychology						0.058			0.017
						(0.055)			(0.063)
Neuroscience						-0.049			0.000
						(0.280)			(.)
Health/Medical						0.086			0.147

							(0.189)			(0.211)
Location										
Field								0.130***		0.113*
								(0.031)		(0.049)
Lab								Baseline		Baseline
								(.)		(.)
Online								0.000		0.000
								(.)		(.)
Type of Data										
Experimental									Baseline	Baseline
									(.)	(.)
Observational									-0.123	0.058
									(0.085)	(0.139)
Constant	0.653***	0.722***	0.745***	0.761***	0.760***	0.745***	0.734***	0.665***	0.749***	0.665***
	(0.031)	(0.095)	(0.018)	(0.018)	(0.021)	(0.017)	(0.018)	(0.024)	(0.016)	(0.161)
Observations	182	182	169	176	177	182	182	177	179	165

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4. Discussion

In this meta-analysis we provided comprehensive synthesis of empirical estimates of the sensitivity parameter γ that determines the curvature of probability weighting functions in risky choice. Three findings stood out. First, across domains, we found that the meta-analytic mean of γ was robustly below one, reaffirming the notion that people overweight small probabilities and underweight large ones in the literature. Further, we found that this pattern was mostly persisted across three decades, across paper characteristics and estimation characteristics. This adds evidence that non-linear probability weighting is a feature of human decision-making under risk.

Second, and more importantly, our results provided systematic evidence for domain dependence in γ. We found that γ estimates differ between gains and losses, with lower values observed for gains (γ = 0.57) and higher values for losses (γ = 0.74) a pattern that several papers had started to point out (Zeisberger et al., 2012; Goyal & Miyapuram, 2019) but had not been observed from a meta-analytic perspective. This implies that people display stronger curvature when evaluating risky gains than when evaluating risky losses. This, however, contradicts what Imai et al. (2025) found, with their meta-analytic estimates for gains at 0.73 and 0.71 for losses. Thus, we contribute to the literature by providing more evidence showing that there is a difference in γ estimates across the two domains wherein γ is larger in losses than in gains. In addition, we found that γ estimates for undifferentiated fall between those for the domains of gains and losses. Thus, we added to the literature by providing meta-analytic support and evidence to concerns raised by some papers including Tversky and Kahneman (1992) and Prelec (1998) that pooling gains and losses may obscure asymmetries between the two domains by giving an estimate that seems to be a "mix" of estimates from both domains. This then further, supports that studies, in order to reliably estimate γ, might have to do so separately for gains and losses.

Third, we found high heterogeneity in γ estimates across studies, even after accounting for sampling variance. This was partially explained by differences in study and estimation characteristics used by papers. Analysing these allowed us to note two patterns from a meta-analytic perspective which further added to our contribution to the literature. First, was that field studies resulted in systematically higher γ estimates for losses relative to laboratory studies, suggesting that real-world loss contexts may increase probability weighting compared to controlled experimental settings. This could raise some questions about external validity: particularly regarding comparing laboratory estimates and field estimates of in the loss domain. Second, was that food related rewards resulted in higher estimates of γ for undifferentiated. This, along with the effect that field experiments have verses laboratory ones have in the loss domain seem to provide some evidence that salience, context and how concrete a loss is affects how people weigh probabilities attached to potential outcomes. Aside from these three patterns we also noted other possible domain dependent effects of some paper and estimate characteristics on γ estimates.

We did note several limitations of our meta-analysis. Despite having an extensive number of papers, a large proportion of heterogeneity remains unexplained. This implies that unobserved factors—such as task complexity, stakes size, cultural context, or individual differences in numeracy and risk literacy—may play an important role in shaping γ. This heterogeneity across all three domains still remained even after correcting for asymmetry in the data. Future papers, not just meta-analytic work could benefit from exploring these potential unobserved factors providing deeper insights on what shaped probability weighting.

Chapter 3: An Exploration on Hunger's Effects on Decision Noise

An Exploration on Hunger's Effects on Decision Noise

1. Introduction and Theory

We have all experienced being hungry at one point in our lives. The irritability, the pains, the inability to concentrate and the brain fog should be familiar to all of us. It thus comes as no surprise that studies have long provided evidence for the effects of hunger on people. Hormonal and metabolic changes, when a person is hungry, affect motivation and mechanical (Berthoud et al., 2011; Morton et al., 2006), increased dopamine sensitivity result in increased experienced saliency of rewards (Goldstone et al., 2009; van der Laan et al., 2011), reduced activity in the prefrontal cortex which impairs control and planning (Arnsten, 2009; Bass & Nussbaum, 2010; Bechara, 2005) and increased stress and irritability (Tomiyama et al., 2010) are just some of the commonly known effects. Taking all of this into account, one would expect that being hungry should consequently have an effect on a person's ability to make decisions. Some papers touched on this, such as the well-known paper by Danziger et al. (2011) which found that extraneous factors affect how severe Judges rulings would be. However, in this case, the paper did not single out hunger as a main factor but rather it focused on a possible cumulation of factors that lead to mental fatigue as the cause.

The literature that directly looked at the effects of short term hunger on decision making mostly focused on intertemporal choices, risky choices or complex tasks. For instance, Skrynka & Vincent (2019) found that hunger increases people's impatience resulting in immediate smaller rewards being preferred to larger delayed rewards. This was further reinforced by Wang & Dvorak (2010) who found that hunger reduces delay discounting. Other studies such as van Swieten et al. (2023) found that hunger affects risk taking depending on whether risk was learned or described. van de Ridder et al. (2015), on the other hand, found that hunger affects gambling decisions wherein hunger increased the likelihood of people making more strategic bets. This however has been put to question by other papers such as Festjens et al. (2018) and Shabat-Simon et al. (2018).

However, with regard to the effect of hunger on simple decisions that involve picking an option from a set either to consume or use, the existing literature provides no clear answer. Addressing this is important as many everyday choices, such as what to buy and eat, involve such simple decisions and many these do not involve risk or intertemporal choice. A single simple decision may not have large consequences on its own but considering how frequent they are, then those consequences quickly accrue.

A possible framework for understanding how hunger may affect simple decision-making is provided by Shen et al. (2025). They pointed out that in decisions involving picking an option from a set, two types of noise are present namely early and late noise. They defined early noise as the variability inherent in the input values feeding into the decision-making process. Put in another way, one can think of this as the uncertainty in how a person values each option in a set which results in inconsistent valuations. For example, if a person were unfamiliar with an option or uncertain about an option's attributes such as size, quality, flavor or appearance then they would be uncertain about how much they value it resulting in inconsistent valuations of that option. This is shown in figure 15 wherein early noise affects the affects the decision-making process at the stage prior when valuations of each option is formed. They then defined late noise as to represent the variability in the firing rates of value-coding neurons independent from the inputs. Taken another way, one can think of late noise as the stochasticity affecting the decision-making process after the valuations have been formed resulting in inconsistencies in the final decision made. For example, if a person picked their top valued option in one set and didn't do so in another, then that inconsistency could be attributed to late noise affecting the decision-making process. This is shown in figure 15 wherein late noise occurs after the valuations have been formed but occurring before the final choice is made.

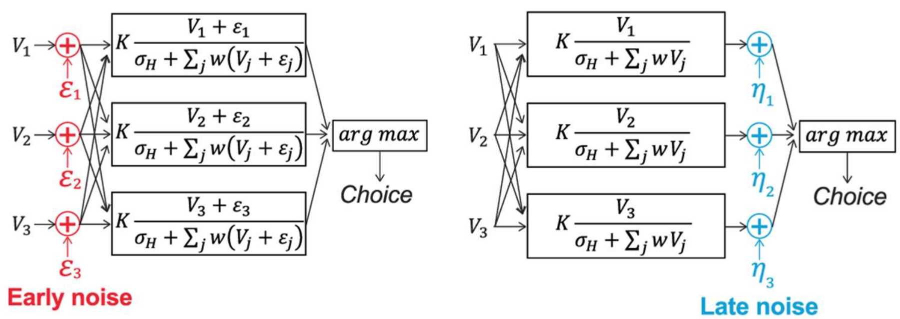

Figure 15. Early and Late Noise as Depicted in the Decision-Making Process by Shen et al. (2025)

We hypothesize that hunger has the potential to affect both types of noise and its final effect on simple decision-making involving food would depend on how it affects each of these noises and the veracity of each effect. We looked at two main strands of research to help inform our hypothesis. The first of these strands of research identified that hunger increases people's attention to food related options as opposed to non-food related options (Marchiori & Papies, 2014). Further research also identified that people also focussed more on a narrower set of attributes when evaluating options, attributes often associated with food such as flavor and portion size (Hare et al., 2009; March & Gluth, 2025; Papies, 2020). The second of these strands of research identified that hunger, particularly short term self-reported hunger, had mixed or no effects on people's performance in cognitive tasks (Bamberg & Moreau, 2025; Landini et al., 2024). From these, we hypothesize the following. First is that hunger decreases early noise when people are making simple decisions regarding food as the increased attention on food options and the narrowing of attributes being evaluated makes people more certain about their valuations. Second is that hunger has no effect on late noise in simple decision-making similar to how hunger has been found to have no effect on other simple cognitive tasks.

2. Methodology

To test these hypotheses, we collected data for this study during a within-subject experiment we conducted on Smart Choice Procedures and their effect on the likelihood of participants picking their highest valued snack as was seen in Chapter 1. In that experiment, we had 85 participants perform two main tasks, each task involved 34 different snacks. The snacks used in both tasks consisted of 34 snacks commonly found in Australia, with prices ranging from $0.50 to $5 and included both sweet and savory snacks. We also had participants fill out hunger and demographic questionnaires at the end of the experiment. All participants were students from the University of Sydney.

The first of these tasks was a valuation task which we used to elicit each participant's valuation for each snack from which we could create our measure for early noise. The second task was a choice task where we asked participants to pick their highest valued snack from a set for total of 40 decision rounds. We used this to determine how often participants were able to pick their highest valued snack from which we could measure late noise. Finally, in the hunger and demographic questionnaires we had participants self-report their hunger levels by answering different questions regarding hunger as well as other demographic questions.

For each experimental session, we asked participants to fast for a minimum of four hours prior to the start of the experiment. It is important to note that it was made clear to participants that they were free to fast for longer periods. The purpose of this was so that we could observe the effects of varying levels of hunger on the performance of participants on the valuation task and the choice task. To further ensure that participants were most likely hungry, we conducted each session at 11:30 am. All snacks were displayed on a table at the entrance of the laboratory at the beginning of each experimental session. This was to ensure that participants were familiar with the portion size and appearance of each snack. The placement of these snacks was randomized to avoid any display order effects.

2.1 Valuation Task

We used a Becker-DeGroot-Marshak (BDM) procedure (Becker et al., 1964) to elicit each participant's valuation of the 34 snacks. For this, we showed each snack on the screen one at a time (Figure 16). Participants entered their valuations (in $0.10 increments) using a slider bounded between $0 and $5. We adopted instructions from Healy (2020) to explain the BDM procedure to participants (Figure A5). Participants proceeded at their own pace and there was no time limit on providing a response. In each trial, participants received $15 as an endowment that they could use towards purchasing a snack. If participants were paid for this task, they would be paid for only one decision. To ensure that we had reliable valuations, participants valued each snack twice. We also used the average of these two valuations to determine a snack ranking for each participant

Figure 16. Valuation Task

2.2 Choice Task

In the choice task, we asked participants to pick a snack they would like to receive using four different choice procedures. In each procedure, participants completed ten decision scenarios totalling 40 decision scenarios. In each decision scenario, there were twelve snacks available to choose from. These were randomly picked from the 34 snacks in each decision scenario for each participant. Using the snack rankings we obtained from the valuation task, we then determined which of those twelve snacks was their top snack for a decision scenario. From now on, we refer to the top snack in any decision scenario, as established by the valuation task, as participant's highest valued snack in a decision scenario. We then counted the number of instances that each participant picked their highest valued snack.

We chose a set size of twelve because it is large enough to make it difficult to choose (Webb et al., 2021). At the same time, the likelihood of a snack with the highest valuation out of all 34 appearing in all ten decision scenarios is low (0.003% chance). The order in which participants completed each treatment was randomized across participants. These four choice procedures were Direct Choice (DC), Elimination Remain (ER), Elimination Disappear (ED) and Binary choice. For this study, we used all forty decision scenarios from all four procedures to determine how often participants were able to pick their highest valued snack as their final choice.

2.2.1 Direct Choice Procedure

As a benchmark, we asked participants to simply choose one snack from a set of twelve snacks displayed on screen by clicking on it (Figure 17) after which they proceeded to the next decision scenario. We included this treatment because it mimics how decisions are usually made outside the lab. It served as a benchmark to measure if there was improvement in the ability to pick the snack they would like to receive in the other Smart Choice Procedures.

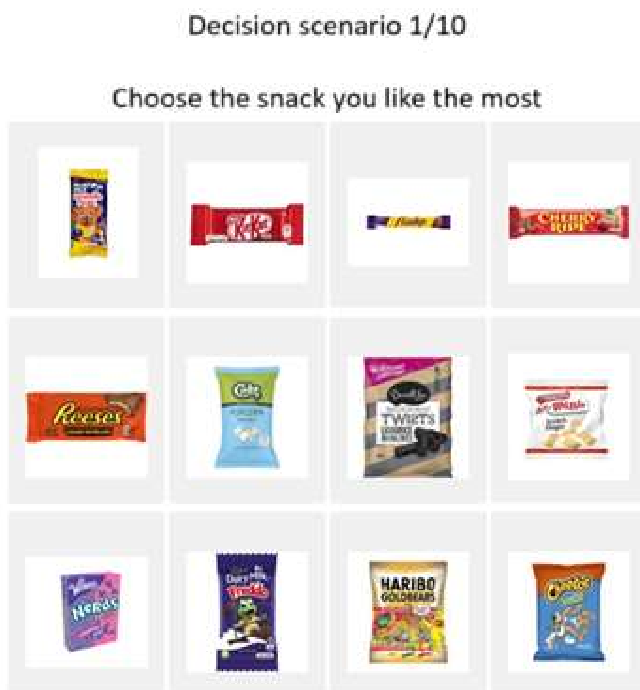

Figure 17. Direct Choice

2.2.2 Elimination Remain Procedure

In the Elimination Remain choice procedure, we told participants to eliminate snacks by clicking on them, one by one, until only one, the one they would like to receive was left. The eliminated snacks remained on screen with a black “X” beside it. Figure 18A shows an example screen with one snack eliminated. Participants continued eliminating snacks until only one snack was left (Figure 18B). The last remaining snack (Reese’s in Figure 18B) was recorded as their choice. We included this treatment to test whether the elimination of irrelevant alternatives increased the likelihood of choosing highest valued snack. The idea is that the elimination of the least preferred alternatives frees the cognitive resources for the participant to choose from the top alternatives with less noise.

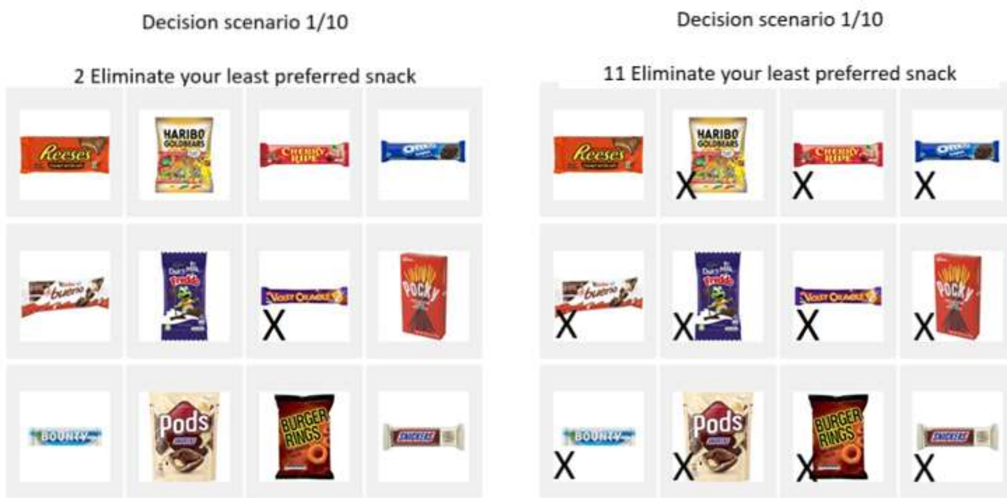

Figure 18A and 18B. Elimination Remain

2.2.3 Elimination Disappear Procedure

The Elimination Disappear procedure was exactly like the Elimination Remain procedure except that each eliminated snack disappeared from screen after being clicked. Figure 19A shows an example screen with one snack eliminated. Participants continued eliminating snacks until only one snack was left (Figure 19B). The last remaining snack (Bueno in Figure 19B). We included this treatment because it is possible that placing an "X" next to an eliminated snack is not enough for the choosers to consider them as eliminated. Possibly, when the snacks are visible, even if they are eliminated, they may be considered as alternatives, leading to choice overload. Including the Elimination Disappear procedure allows us to test whether it is necessary to remove the eliminated snacks from the field of vision to increase the likelihood of choosing the snack they wanted to receive.

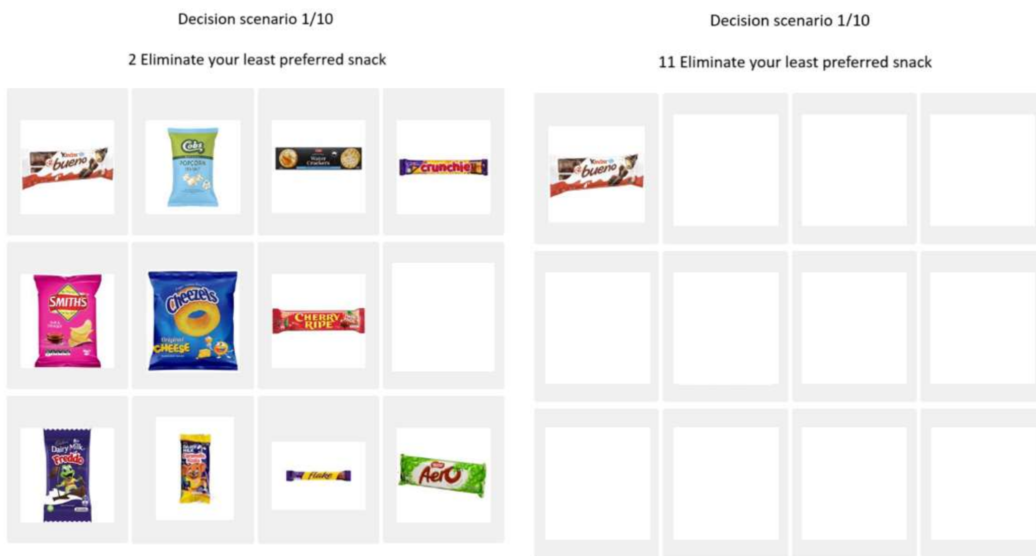

Figure 19A and 19B. Elimination Disappear

2.2.4 Binary Choice Procedure

In the Binary Choice procedure, we showed participants two snacks at a time and told them to click on a snack they would like to receive. Like in the other procedures, each decision scenario consisted of twelve snacks. To complete one decision scenario participants made eleven Binary Choices. Within a decision scenario, the computer excluded snacks from previous pairs that were not chosen. As such, each Binary Choice consisted of two snacks randomly selected from those that were still available out of the original twelve. The snack selected from the last pair was recorded as the snack they would like to receive. We included this treatment because by presenting only two options at a time, it reduces the cognitive load of each choice to a minimum.

Figure 20. Binary Choice

2.3 Payment

We paid each participant based on one of their decisions in either the valuation or choice task, randomly selected. If a decision from the valuation task was chosen for payment, we determined the payoff following the BDM procedure using a randomly generated price ranging from \$0 to \$5, in \$0.10 increments. This price was not revealed to participants at the time of choice. If a participant's valuation for a snack was higher than or equal to the generated price, then it showed that they were willing to pay this price for the snack. Therefore, they bought the snack from the experimenter at the generated price. As payment, they received the snack and an amount in dollars equal to \$15 minus the price. If a participant's valuation for a snack was below the generated price, then it showed that they were unwilling to pay this price for the snack. They did not buy the snack and received \$15 as payment. If a decision from the choice task was chosen for payment, participants received the snack they chose and an additional \$10.

In addition, all participants received a \$10 participation fee. All monetary payments were made in cash after participants completed the experiment.

2.4 Hunger and Demographic Questionnaires

To elicit each participant's self-reported hunger, we asked two questions as part of the hunger questionnaire (Figure A11) at the end of the experiment. We referred to them as the hunger question, appetite question and the hours fasted question. These two questions asked participants to input their responses using a slider bounded between 1 to 10 (in increments of 1). These two questions were designed to elicit a participant's self-reported hunger from different perspectives. These questions were stated as:

Hunger Question: *How hungry do you feel right now? Please rate it with 1 for not hungry at all and 10 for you've never felt this hungry before.*

Appetite Question: *How much can you eat right now? Please rate it with 1 for none at all and 10 for more than a whole meal*.

In addition to these we also had participants answer demographic questions regarding their weight, weekly allowance on snacks, and how familiar they were with each snack (1 not at all, 5 being very familiar) (Figure A10)

3. Results

3.1 Hunger Data

From our two main questions in the hunger questionnaire, we were able to elicit two self-reported measures of hunger. We referred to these two measures as hunger and appetite measures after the questions used to elicit them. These comprised self-reported hunger with 1 being the least hungry and 10 being the most. We obtained both measures in order to establish if each participant's self-reported hunger was consistent and therefore could be used to test the effect of hunger on both early and late noise. We found that this was the case after looking at the Pearson correlation between Hunger and Appetite ($r = 0.602$) which showed a medium to strong correlation. Figure 21 shows weighted scatter plots showing the correlation of these measures with each. We therefore determined that our participants had consistent self-reported measures of hunger which could be used.

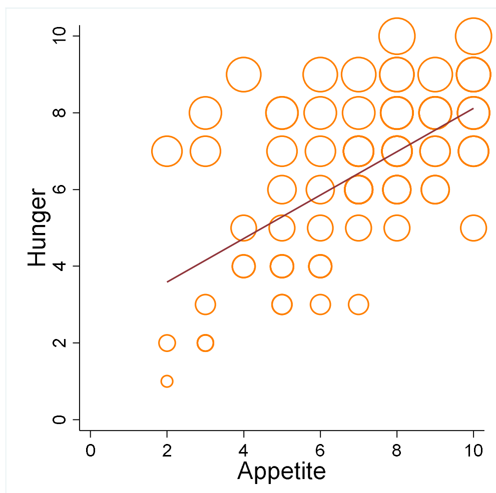

Figure 21A and 21B. Correlations Between Two Hunger Measures

Next, we had to determine if there was enough variation in the measures to ensure that we could see the effect of different levels of hunger on the two types of noise. We found that this was the case with hunger ($SD = 2.06$, $\sigma^2 = 4.23$), and appetite ($SD = 2.19$, $\sigma^2 = 4.78$) having significant variation. Figure 22A and 22B show the distribution of each of these measures. From these we determined to use hunger and appetite as our measures of hunger to test against the two types of noise.

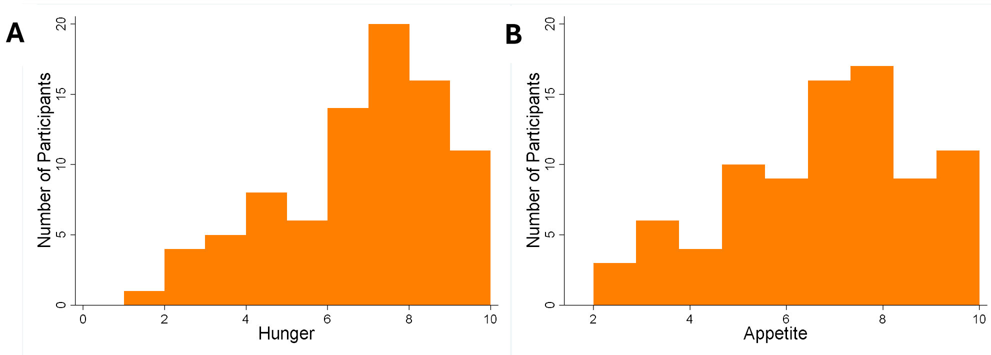

Figure 22A and 22B. Distribution of Two Hunger Measures

3.2 Valuation and Hunger

Before we proceeded to look at the effects of hunger on both types of noise, we decided to first look at the effect of hunger on how participants valued each snack. The reason for this is because any measure of early noise and late noise would be based on these valuations for this study. Therefore, we needed to identify any direct effect that hunger may have on each snack's valuation so that we could avoid confounding these with what we may observe with early and late noise. Any pattern observed on how hunger affects valuations may also help explain what we may observe regarding hunger's effects on early and late noise.

To do so, we first looked at the correlation between all valuations for the first round of valuations with either the hunger or appetite levels per participant. We then looked at the same correlation for all the valuations in the second round per participant. Equations 1 and 2 show the regression models we used where $\boldsymbol{V_1}$ and $\boldsymbol{V_2}$.were the valuations of a snack by a participant for either the first or second round and $\boldsymbol{hunger}$ was either the hunger measure or the appetite measure. We also ran similar regression which further controlled for how long participants took to make each valuation in seconds.

$$V_1 = \beta_0 + \beta_1 hunger + \varepsilon \quad (1)$$

$$V_2 = \alpha_0 + \alpha_1 hunger + \xi \quad (2)$$

We found that participants with higher self-reported hunger valued snacks more than ones which ones with lower self-reported hunger. These results held for both the first (Table 10, Models 1 and 2) and second (Table 11, Models 1 and 2) rounds of valuations and also held even when we controlled for the how long participants took to value each snack (Tables 10 and 11, Models 3 and 4).

Table 10. Hunger's Effect on Valuations for the First Round

	(1)	(2)	(3)	(4)
Hunger	0.039^{***}		0.038^{***}	
	(0.010)		(0.010)	
Time			0.040^{***}	0.039^{***}
			(0.004)	(0.004)
Appetite		0.045^{***}		0.041^{***}
		(0.010)		(0.010)
Constant	0.943^{***}	0.882^{***}	0.675^{***}	0.633^{***}
	(0.069)	(0.070)	(0.073)	(0.073)
Observations	2890	2890	2890	2890
Adjusted R^2	0.004	0.007	0.037	0.039

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11. Hunger's Effect on Valuations for the Second Round

	(1)	(2)	(3)	(4)
Hunger	0.042^{***}		0.043^{***}	
	(0.010)		(0.010)	
Time			0.054^{***}	0.053^{***}
			(0.006)	(0.006)
Appetite		0.049^{***}		0.045^{***}
		(0.010)		(0.010)
Constant	0.879^{***}	0.813^{***}	0.625^{***}	0.593^{***}
	(0.069)	(0.070)	(0.073)	(0.073)
Observations	2890	2890	2890	2890
Adjusted R^2	0.005	0.008	0.034	0.035

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We then addressed whether this correlation between hunger and valuations held evenly for all snacks or if it depended on how much a participant liked a snack. The reason for this is because if hungrier participants valued snacks unevenly, such as if they only valued their top ten snacks more, then that uneven effect of hunger on snack valuations might make it appear that hunger was either increasing or decreasing late noise. To test for this, we grouped all snacks into the top 11 snacks, middle 11 snacks and bottom 12 snacks per participant. We chose this grouping as we noted that the average valuation of snacks by ranking for all participants had a consistent rate of decline across rankings. This meant that on average, there were no substantial jumps in valuations across adjacently ranked snacks which would affect the regression on the group that it is put in. Therefore grouping the snacks into these three groups were sufficient to observe if hunger had any effect on how a participant valued a snack based on how much a participant liked a snack. We then ran the same regressions as equations 1 and 2 for each group. We found that this pattern of increasing snack valuations held for all three groups for both first and second rounds of valuations (Tables 12 and 13) however the increases in value were uneven.

T tests across all three groups for the regressions that used the hunger measure and first round valuations confirmed this with the middle group (M = 0.047, SD = 0.014) being significantly higher than the top group (M = 0.032, SD = 0.009), $t(1593.37) = -27.56$, $p < .001$, the bottom group (M = 0.035, SD = 0.011) being significantly higher than the Top group (M = 0.032, SD = 0.009), $t(1928.61) = -6.62$, $p < .001$ and the middle group (M = 0.047, SD = 0.014) being significantly higher than the Bottom group (M = 0.035, SD = 0.011), $t(1770.51) = 20.94$, $p < .001$. T-tests across all three groups using the appetite measure also found uneven increases to valuations due to hunger with middle group (M = 0.041, SD = 0.013) being significantly higher than the top group (M = 0.014, SD = 0.003), t(1033.20) = −61.88, p < .001, the bottom group (M = 0.070, SD = 0.017) being significantly higher than the top group (M = 0.014, SD = 0.003), $t(1088.04) = -103.46$, $p < .001$ and the bottom group (M = 0.070, SD = 0.017) being significantly higher than the middle group (M = 0.041, SD = 0.013), $t(1893.22) = -42.57$, $p < .001$. The same patterns also held for all second round valuations. We did note however that the coefficient sizes were small. For instance, the coefficient 0.035 for the hunger measure in the bottom group would indicate that hunger only increased snack valuations by 3.5 cents. Considering that the highest possible value for a snack in the experiment was 5 dollars then that increase only amounts to just 0.7%.

Table 12. Hunger's Effect on Valuations for the First Round Across Top, Middle and Bottom Ranked Snacks

	Top	Middle	Bottom	Top	Middle	Bottom
Hunger	0.032^{***}	0.047^{***}	0.035*			
	(0.009)	(0.014)	(0.011)			
Time	0.028^{***}	0.022^{***}	0.030^{***}	0.028^{***}	0.022^{***}	0.030^{***}
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)
Appetite				0.014*	0.041^{**}	0.070^{***}
				(0.003)	(0.013)	(0.017)
Constant	0.063	0.551^{***}	1.593^{***}	0.171^{**}	0.576^{***}	1.335^{***}
	(0.061)	(0.098)	(0.130)	(0.062)	(0.098)	(0.131)
Observations	935	935	1020	935	935	1020
Adjusted R^2	0.066	0.030	0.021	0.055	0.028	0.034

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13. Hunger's Effect on Valuations for the Second Round Across Top, Middle and Bottom Ranked Snacks

	Top	Middle	Bottom	Top	Middle	Bottom
Hunger	0.038***	0.047**	0.042*			
	(0.010)	(0.015)	(0.019)			
Time	0.058***	0.031***	0.036***	0.058***	0.030***	0.033***
	(0.007)	(0.008)	(0.010)	(0.008)	(0.008)	(0.010)
Appetite				0.013*	0.042**	0.081***
				(0.006)	(0.014)	(0.018)
Constant	0.031	0.520***	1.443***	0.185*	0.535***	1.175***
	(0.074)	(0.104)	(0.136)	(0.075)	(0.105)	(0.134)
Observations	935	935	1020	935	935	1020
Adjusted R^2	0.072	0.025	0.016	0.060	0.024	0.031

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.3 Early Noise and Hunger

Following the definitions provided by Shen et al. (2025), wherein early noise can be thought of as uncertainty with regard to how much a person values a particular option that results in inconsistencies in the valuation of said option, we created two measures of early noise. The first of which comprised of the difference between the first and second valuation of a snack by a participant, V_1- V_2. The reason for this is that any difference between the two would capture any inconsistencies brought about by uncertainties in how much participants value a snack, consequently capturing early noise. If a participant thus experienced no early noise then one would expect this difference to be zero. The second measure consisted of the predicted residuals between first and second round of valuations per snack per participant. The reason for this is because these residuals show the nconsistencies between the predicted relationship between the both rounds of valuations and thus could be thought of as representing the noise in valuations, early noise. Thus, a participant with no early noise should be expected to have no residuals between the two valuations. To obtain this we ran regressions between first and second rounds of valuations for all snacks per participant and used those to generate the predicted residuals for every snack per participant. The reason for this second measure is to provide an alternative representation of early noise.

Using these two measures, we then looked at the effect of self-reported hunger on early noise by running regressions following equations 3 and 4 for all participants for all snacks wherein V_1- V_2 was the difference between the first and second valuation of a snack by a participant, $Residual$ was the predicted residual noise between the first and second valuation of a snack by a participant, $hunger$ was either the hunger or appetite measure,

$familiar$ is a self-reported measure of how familiar a participant was with a snack, $allowance$ was the weekly allowance of a participant for snacks and $time$ was the number of seconds it took a participant to do both valuations for a snack. We included the crucial control for how familiar a participant was with a snack as this could directly affect early noise independent of hunger.

$$V_1 - V_2 = \beta_0 + \beta_1 hunger + \beta_2 familiar + \beta_3 allowance + \beta_4 time + \varepsilon \quad (3)$$

$$Residual = \alpha_0 + \alpha_1 hunger + \alpha_2 familiar + \alpha_3 allowance + \alpha_4 time + \xi \quad (4)$$

We found that both measures, hunger and appetite had no effect on either measure of early noise (Tables 14 and 15). Not only were the estimated coefficients insignificant but the coefficients using the predicted residuals as the dependent variable showed no correlation whatsoever. This was despite finding hunger increased the valuations of all snacks. Based on the previous literature that found increased attention on food items as hunger increased (Marchiori & Papies, 2014), these findings suggest that increased attention may have only increased how participants valued snacks but did not affect any uncertainties they had regarding how much they value a snack.

Table 14. Hunger's Effect on Both Measures of Early Noise

	V1 - V2	Residual
Hunger	-0.006	-0.000
	(0.004)	(0.004)
Familiarity	-0.014*	0.006
	(0.006)	(0.006)
Allowance	-0.000	0.000
	(0.000)	(0.000)
Time	0.003*	0.004***
	(0.001)	(0.001)
Constant	-0.004	-0.061
	(0.045)	(0.040)
Observations	2890	2890
Adjusted R^2	0.006	0.003

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15. Appetite's Effect on Both Measures of Early Noise

	V1 - V2	Residual

Appetite	-0.005	-0.001
	(0.004)	(0.003)
Familiarity	-0.014*	0.006
	(0.006)	(0.006)
Allowance	-0.000	0.000
	(0.000)	(0.000)
Time	0.003*	0.004***
	(0.001)	(0.001)
Constant	-0.004	-0.057
	(0.044)	(0.039)
Observations	2890	2890
Adjusted R^2	0.006	0.003

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4 Late Noise and Hunger

Using the definition provided by Shen et al. (2025) for late noise, as variability in the firing rates of the brain result in inconsistencies indecision outcomes, we chose two measures for late noise. The first consisted of the number of times a participant picked their highest valued snack for all of the decision scenarios across all choice procedures. The reason for this is because one may assume that participants would want to pick their highest valued snack from each decision scenario as that would increase the likelihood of them getting a snack that they like as part of the payoff. Therefore, inconsistencies between instances wherein participants picked their highest valued snack and when they did not would capture inconsistencies in decision outcomes due to late noise. It is important to note that if a participant had multiple snacks with the same highest value in that decision scenario and the participant picked any of them, then we counted that as the participant picking their highest valued snack. The second measure of late noise consisted of the cost incurred by a participant whenever they did not pick their highest valued snack. Put in another way, it would be the difference between the value of the highest valued snack and the snack that was chosen. This meant that if a participant picked their highest valued snack then they incurred zero costs. The reason for this as a measure is because when participants are consistently picked their highest valued snack across decision scenarios then that difference would be consistently zero. However, any inconsistencies if decision outcomes, such as picking the highest valued snack, would result in varying differences between decision scenarios. It is important to note that these measures of late noise, are not completely independent from early noise as inconsistencies in valuations could have an impact on the consistency in which participants may have picked their highest valued snack. However, given our findings as shown in figure 7 most of the valuations we obtained were consistent and therefore any variability in the decision outcomes in each decision scenario due to inconsistencies in valuations would be expected to be minimal if any.

Using these measures for late noise we then ran the following regressions, based on equations 5 and 6, for all participants for each decision scenario wherein Fav was the number of times a participant picked their highest valued snack, $Cost$ was the cost of not choosing the highest valued snack, $hunger$ was either the hunger or appetite measure, $treat$ was a control for which choice procedure was used for a decision scenario, $allowance$ was the weekly allowance of a participant for snacks and $time$ was the number of seconds it took a participant to choose in a decision scenario. It was crucial that we included a control for the choice procedures used as those were found to have significant effects on both measures.

$$Fav = \beta_0 + \beta_1 hunger + \beta_2 time + \beta_3 treat + \beta_4 allowance + \beta_5 time + \varepsilon \quad (5)$$

$$Cost = \alpha_0 + \alpha_1 hunger + \alpha_2 time + \alpha_3 treat + \alpha_4 allowance + \alpha_5 time + \xi \quad (6)$$

We found that both hunger measures, hunger and appetite also had no effect on both measures of late noise (tables 16 and 17). This was despite finding that hunger increased the valuation of snacks and it did so unevenly, depending on how much a participant liked a snack. This supported our initial hypothesis that hunger had no effect on late noise similar to how it had no clear effect on simple cognitive tasks. These results further implied that, despite hunger increasing the valuation of some snacks more than others, these uneven increases were not enough to change how likely participants were able to pick their highest valued snack from a set or how costly it was for them whenever they were not able to pick their highest valued snack.

Table 16. Hunger's Effect on Late Noise (Number of Times the Highest Valued Snack was Picked)

Hunger	0.003	
	(0.004)	
Time	0.001	0.001
	(0.001)	(0.001)
ER	0.187***	0.187***
	(0.024)	(0.024)
ED	0.179***	0.179***
	(0.024)	(0.024)
BC	0.170***	0.170***
	(0.024)	(0.024)
Allowance	-0.000	-0.000
	(0.000)	(0.000)
Appetite		0.005
		(0.004)

Constant	0.357***	0.344***
	(0.042)	(0.043)
Observations	3400	3400
Adjusted R^2	0.023	0.024

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17. Hunger's Effect on Late Noise (Cost of Not Picking the Highest Valued Snack)

Hunger	0.018	
	(0.011)	
Time	0.000	0.000
	(0.001)	(0.001)
ER	0.357***	0.357***
	(0.031)	(0.031)
ED	0.363***	0.363***
	(0.031)	(0.031)
BC	0.350***	0.350***
	(0.031)	(0.031)
Allowance	-0.000***	-0.000***
	(0.000)	(0.000)
Appetite		0.010
		(0.005)
Constant	-0.729***	-0.635***
	(0.054)	(0.055)
Observations	3400	3400
Adjusted R^2	0.062	0.059

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4. Discussion

In this study, we examined whether short term hunger affects simple food-related decision-making through the perspective of early and late noise defined by Shen et al. (2025). Using the variability in the differences of how participants valued 34 snacks and how consistently they were able to pick their highest valued snack from varying sets of 12 snacks, we were able to establish our measures of early and late noise. Analyses of these measures showed little evidence that short term hunger affected either early or late noise which led us to reject our first hypothesis, that hunger decreases early noise, while confirming our second, that hunger has no effect on late noise. This consequently showed that being hungry had no impact on how certain participants were in how they valued snacks and their ability to pick their highest valued snack from a set consistently. We therefore noted that, at least from the perspective of early and late noise, hunger had no impact on simple food related decision-making. We did, however find that hunger significantly increased snack valuations, meaning hungrier participants ended up valuing snacks more. These increased valuations though had no impact on early and late noise and consequently had no impact on how certain participants were in how much they valued the snacks and how consistently they were able to pick their highest valued snack.

This finding, that hunger raises snack valuations, is consistent with previous papers (Hare et al., 2009; March & Gluth, 2025; Marchiori & Papies, 2014; Papies, 2020) that showed that hunger heightens attention to food-related stimuli and, as one may assume, that the heightened attention would coincide with people valuing food items more. We did note, however, that these increases in food valuation were small, amounting to only a few cents, considering that the maximum value of a snack was 5 dollars. We found that these increases were uneven across groups of preferences, with middle and lower ranked snacks experiencing larger relative valuation increases than top ranked snacks. Despite this uneven pattern, hunger had no effect on participants' ability to identify and choose their highest valued snack snack from a choice set, suggesting that the increases were not large enough to have an effect or change preference orderings.

Our finding, that hunger had no effect on how consistently participants were able to pick their highest valued snack and how costly mistakes were whenever participants did not pick their highest valued snack align with previous findings that showed that short-term hunger has little or no effect on simple cognitive tests (Bamberg & Moreau, 2025; Landini et al., 2024). This makes sense since, one may assume that simple cognitive tests, such as Raven's Progressive Matrices test, and picking a highest valued snack from a randomly generated set of 12 snacks may require similar cognitive resources.

Taken together, our results suggest that hunger's impact on simple decisions is more limited. While we found that hunger alters how much individuals' value food, it does not appear to compromise their ability to make consistent or welfare-maximizing choices when selecting from a set of food options. This could have implications for understanding consumer behaviour in that being hungry may increase spending levels or willingness to pay without causing confusion on how much consumers value a food item or increasing their decision errors.

We did note several limitations of our study. Our study only looked at short term hunger however one may expect that long term or chronic hunger may have completely different if not dire consequences on decision making as these may lead to drastic decreases in cognitive capacity or available cognitive resources such as blood glucose levels. Also, we focussed on looking at the effect of being hungry from the perspective of early and late noise. It is possible that even short term hunger may have an effect that a different model maybe more apt at detecting. Future research can expand on both these lines of inquiry.

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Appendix

Chapter 1 Appendix

Appendix A Figures and Tables

Table A 1. Mean and Standard Deviation of Each of the nth Ranked Snacks Across All Decision Scenario. x_1 being the highest ranked snack and x_{12} being the lowest.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
Mean	2.55	2.08	1.78	1.53	1.315	1.12	0.94	0.79	0.66	0.54	0.42	0.29
SD	(1.27)	(1.18)	(1.12)	(1.06)	(0.98)	(0.91)	(0.83)	(0.76)	(0.69)	(0.61)	(0.53)	(0.42)

Table A 2. Response Time and the Probability of Choosing the Highest Valued Snack in Decisions Without Multiple Snacks with the Highest Value. Dependent Variable Equals to One if a Participant Picked their Highest Valued Snack. Elimination Remain, Elimination Dis

	(1)	(2)	(3)
ER	0.182***	0.232***	0.226***
	(0.032)	(0.036)	(0.034)
ED	0.165***	0.206***	0.189***
	(0.032)	(0.035)	(0.033)
BC	0.164***	0.206***	0.191***
	(0.031)	(0.034)	(0.033)
Time		-0.003**	-0.002*
		(0.001)	(0.001)
$x_1 - x_2$			0.283***
			(0.031)
Constant	0.385***	0.403***	0.248***
	(0.022)	(0.022)	(0.029)
N	2935	2935	2935
adj. R^2	0.026	0.029	0.086

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A 1. Robustness Checks. Figure A and B: Controlling for Participants with Pearson Coefficients Less then 0.7. Figure C and D: Controlling for Participants Spearman Coefficients Less then 0.7

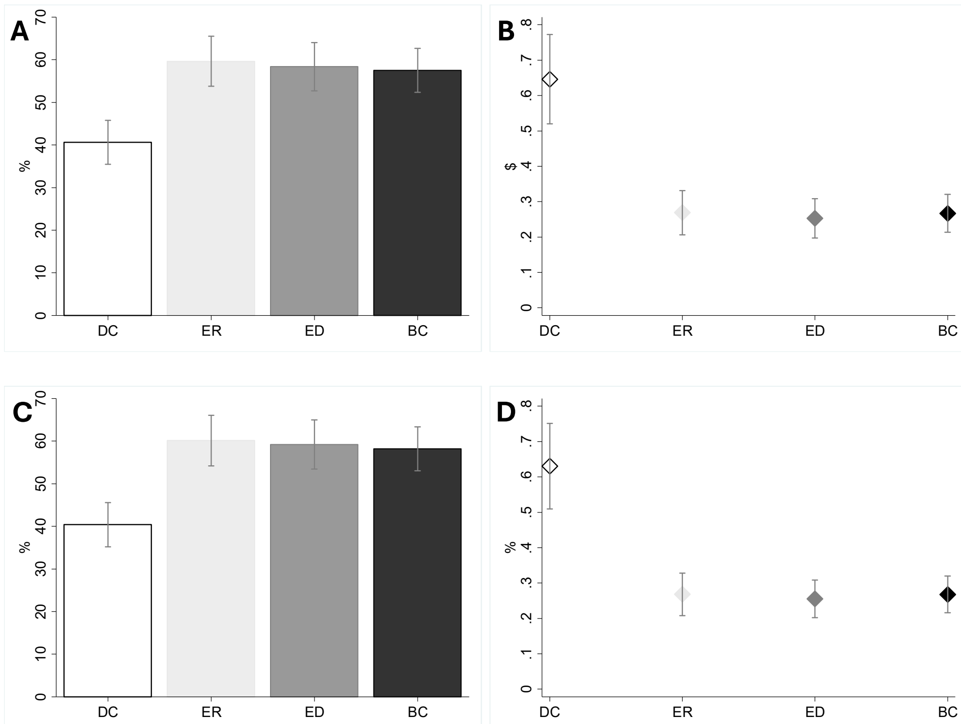


Table A 3. Replicating Table 1. M1 to M3: Removed for Participants with Pearson Coefficients Less then 0.7. M4 to M6: Removed for Participants with Spearman Coefficients Less then 0.7

	(1)	(2)	(3)	(4)	(5)	(6)
ER	0.267***	0.281***	0.239***	0.273***	0.285***	0.250***
	(0.039)	(0.040)	(0.037)	(0.039)	(0.039)	(0.036)
ED	0.239***	0.246***	0.212***	0.250***	0.256***	0.228***
	(0.037)	(0.038)	(0.035)	(0.038)	(0.038)	(0.036)
BC	0.230***	0.236***	0.203***	0.238***	0.244***	0.216***
	(0.034)	(0.035)	(0.032)	(0.035)	(0.036)	(0.032)
Time	-0.004**	-0.004**	-0.002*	-0.004**	-0.004**	-0.002*

	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Constant	0.541*	0.546***	0.547***	0.546**	0.550***	0.551***
	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)
$X_1 - X_2$		0.261***	0.277***		0.257***	0.269***
		(0.048)	(0.048)		(0.048)	(0.047)
Ave Response Time			-0.011*			-0.009*
			(0.005)			(0.005)
Observations	3240	3240	3240	3080	3080	3080
Wald	52.87	102.37	97.73	56.62	107.71	104.26

Standard errors in parentheses, * p<0.05, ** p<0.01, ***p<0.001

Figure A 2. Images of Products Used in Higher Value Experiment

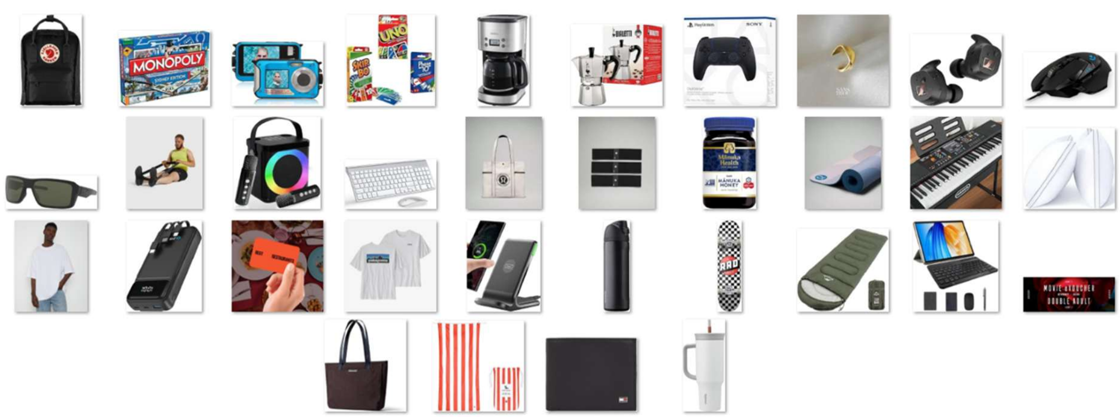


Table A 4. The Effect of Irrelevant Snacks' Value on the Probability of Choosing the Highest Valued Snack in Direct and Smart Choice Procedures with Response Time Control with Higher-value Goods.

	(1)	(2)	(3)	(4)
x_1	0.382**	0.204*	0.229*	0.267***
	(0.099)	(0.065)	(0.094)	(0.053)
x_2	-0.310	-0.0738	-0.182	-0.184*
	(0.184)	(0.122)	(0.118)	(0.057)
x_3	-0.119*	-0.112	-0.106	-0.121
	(0.018)	(0.127)	(0.121)	(0.098)
x_4	0.249	0.132	0.273	-0.224
	(0.214)	(0.259)	(0.153)	(0.125)
x_5	-0.150	-0.0567	-0.432	0.314
	(0.166)	(0.135)	(0.281)	(0.236)
x_6	0.163	0.160	0.209	-0.254
	(0.207)	(0.218)	(0.213)	(0.187)
x_7	0.225	0.099	0.114	0.068
	(0.256)	(0.364)	(0.260)	(0.170)
x_8	-0.166	-0.052	-0.216	0.216
	(0.223)	(0.312)	(0.343)	(0.309)
x_9	0.175	-0.003	-0.139	-0.070
	(0.204)	(0.084)	(0.224)	(0.280)
x_{10}	-0.303	-0.163	0.129	-0.278
	(0.220)	(0.187)	(0.278)	(0.211)
x_{11}	0.043	-0.025	-0.230	0.353
	(0.240)	(0.174)	(0.198)	(0.218)
x_{12}	0.094	0.091	0.111	-0.180
	(0.209)	(0.165)	(0.191)	(0.086)
# of snacks with the highest value	-0.021	0.030	-0.079	-0.076
	(0.059)	(0.053)	(0.065)	(0.123)
Time	-0.001	0.000	-0.005*	0.002
	(0.002)	(0.001)	(0.002)	(0.003)
Constant	-0.216	0.283	0.839*	0.556*
	(0.310)	(0.338)	(0.280)	(0.232)
N	200	200	200	200
adj. R^2	0.070	0.015	0.058	0.121

Standard errors in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 5. The Effect of Irrelevant Snacks' Value on the Probability of Choosing the Highest Valued Snack in Direct and Smart Choice Procedures with Response Time

Control with Higher-value Goods in Decisions without Multiple Snacks with the Highest Value.

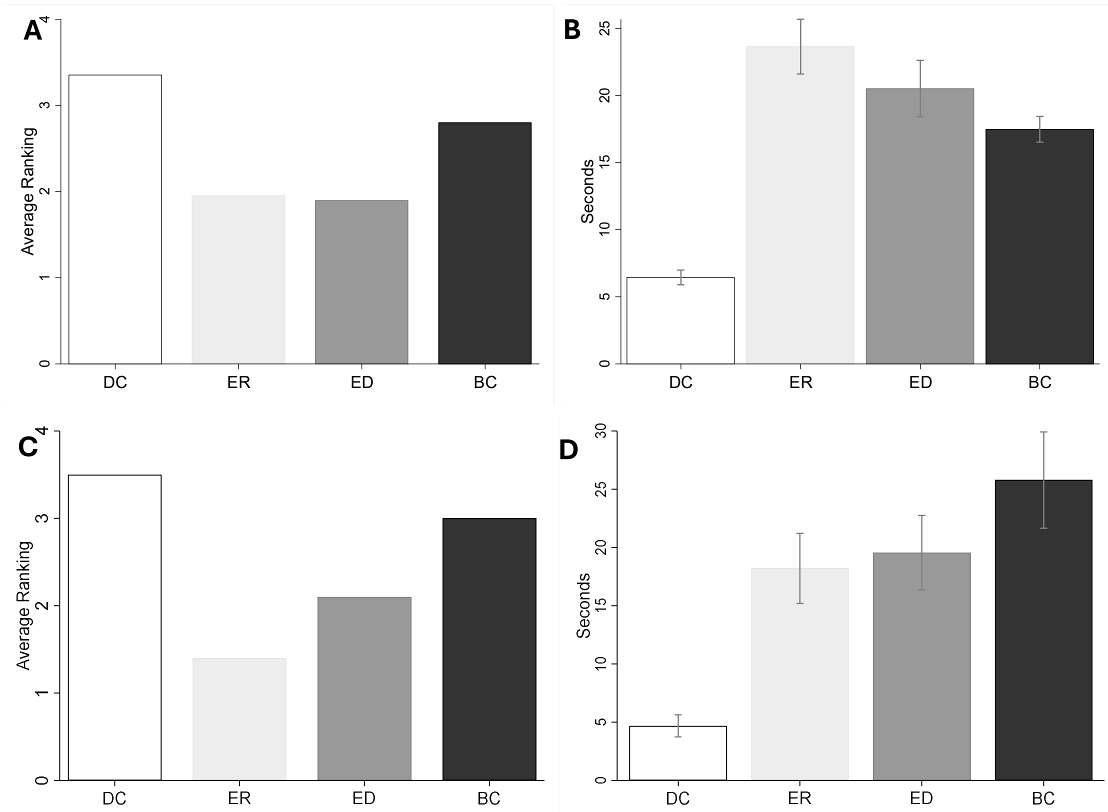
	(1)	(2)	(3)	(4)
x_1	0.388**	0.195	0.219	0.292***
	(0.092)	(0.097)	(0.099)	(0.053)
x_2	-0.272	-0.043	-0.141	-0.203*
	(0.197)	(0.131)	(0.163)	(0.0714)
x_3	-0.189*	-0.286	-0.065	-0.087
	(0.014)	(0.139)	(0.115)	(0.103)
x_4	0.347	0.118	0.169	-0.290
	(0.216)	(0.276)	(0.159)	(0.202)
x_5	-0.138	-0.235	-0.346	0.379
	(0.186)	(0.139)	(0.184)	(0.214)
x_6	0.173	0.300	0.247	-0.336
	(0.203)	(0.204)	(0.221)	(0.182)
x_7	0.091	0.130	-0.067	0.066
	(0.215)	(0.371)	(0.289)	(0.185)
x_8	-0.033	-0.027	-0.023	0.243
	(0.189)	(0.339)	(0.397)	(0.327)
x_9	0.265	-0.059	-0.202	-0.024
	(0.194)	(0.059)	(0.243)	(0.278)
x_{10}	-0.482	-0.016	0.055	-0.152
	(0.224)	(0.226)	(0.255)	(0.111)
x_{11}	0.014	-0.189	-0.226	0.258*
	(0.203)	(0.184)	(0.199)	(0.086)
x_{12}	0.141	0.215	0.084	-0.218
	(0.201)	(0.198)	(0.196)	(0.115)
Time	-0.001	0.001	-0.006	0.003
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	-0.356	0.298	0.765	0.371
	(0.305)	(0.399)	(0.390)	(0.185)
N	174	174	177	178
adj. R^2	0.090	0.019	0.044	0.128

Standard errors in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A 3. Imaged of 34 Snacks Used in the Snack Study

Figure A 4. Preferred Procedures and Time per Decisions in Each Procedure. A: Average Ranking of Each Procedure by All Participants, Four Being the Highest. B: Average Number of

Seconds Spent by Participants to Arrive at Final Choice per Decision Scenario Using Each Procedure



Appendix B Instructions

Welcome.

Thank you for participating in our study! In the study, you will complete two tasks and a questionnaire. You will receive $10 for your participation and some additional payoff which depends on the decisions you make in two tasks. This payoff will consist of money and/or food. After completing both tasks and the questionnaire, the computer will randomly select one of your decisions and you will receive it as your payment. You will then have to stay in this room for 30 mins longer. During that time, no external food is allowed - you can eat only the snacks you received as a payment for this study. If you received a drink such as tea, then water will be provided to you after the experiment. Please pay attention to the instructions so that you understand how your decisions affect your payment. If at any time you have questions, raise your hand and the experimenter will come to talk to you. Do not communicate with other participants or make noise during the study. On this screen when you are ready to continue, click the plate button

Valuation Task

You start the valuation task with an additional $15 that you received from the experimenter. You should think about this money as yours.

Your task is to tell us the maximum price you would pay for different snacks. On each screen you will enter your maximum price for each snack using a slider, ranging from $0 to $5 in 0.10 increments.

To understand this valuation task let us start with the following example for one snack, Mochis:

Q#			
1	**Buy for $ 0.10**	**Yes**	**No**
2	**Buy for $ 0.20**	**Yes**	**No**
3	**Buy for $ 0.20**	**Yes**	**No**
…	**…**	**…**	**…**
50	**Buy for $ 5.00**	**Yes**	**No**

In the table above, each row represents a question where you decide whether to buy Mochis or not at the stated price. In row 1 you are asked if you would buy Mochis for $0.10. In each row you pick either Yes (you buy the mochis for the stated price) or No (you do not buy the mochis at that price). After you answer in all 50 rows, suppose the computer randomly picks one row and pays you the option you chose there. This means that if in that question, you said you would purchase Mochis, you will buy the Mochis from the experimenter at the price listed in this question. If on the other hand, you said you do not want to buy, you will not have the opportunity to buy mochis from us. Each row is equally likely to be chosen for payment. Obviously, you have no incentive to lie on any row, because if that row is chosen for payment, then you would end up with the option you like less.

We assume you are going to choose the Yes in the first few rows, but at some point, you will switch to choosing No. So, to save time, you can just tell at which dollar value you would switch. In other words, you tell at which dollar amount do you feel exactly the same about the two options that is at what price you are indifferent between buying mochis or not. This is the same as the maximum price you are willing to pay for the snack on offer.

The computer can then 'fill out' your answers to all 50 questions based on your maximum price (choosing Yes for all questions with prices below the maximum price you would pay, and No for all questions with prices at or above the maximum price you would pay). At the end of today's session, after you finish the whole experiment, the computer may randomly choose one of these rows for payment. If you lie about the true maximum price you are willing to pay, you might end up getting paid an option that you like less.

Now that you know the 50 rows you are choosing from for each snack, we won't keep showing them visually for every question. The same question can equivalently be written like this:

What is the maximum price you would pay?

Let's consider some concrete examples:

Example:

Below is an example of the valuation task.

In this example, mochis are on the screen.

You will indicate the maximum price you would pay for mochis by moving the slider to the correct position. Then click the plate to move to the next decision scenario.

Scenario 1 - Suppose the maximum price you would pay is 4.6 and the price in the selected row is $3.2. Since you value mochis more than they cost, you buy them. If this decision is randomly chosen as your payoff you get:

- $10 show-up fee
- The mochis
- $11.8 ($15 - $3.2 price)

Scenario 2 - Suppose your maximum price you would pay is $1.70 and the price in the selected decision row is still $3.2. Since you value mochi less than they cost, you do not buy them. If this decision row is randomly chosen as your payoff you get:

- $10 show-up fee
- $15

There are 34 snacks in this task and you will provide your valuation for each twice.

IMPORTANT: If at the end of the study, the computer picks a decision row from the valuation task to count towards payment, you will be paid for one decision row only. This means that in every valuation decision, you should assume you have all $15 to spend. You should not redistribute or save $15 across the snacks because if you are paid from the valuation task, only one decision row will count. In other words, you will never buy more than one snack from the experimenter.

You should always report how much you value the snack.

Please raise your hand if you have any questions.

Choice Task

You start the choice task with an additional $10 that you received from the experimenter. You should think about this money as yours.

Your task is to choose the snack you like most out of the snacks displayed on the screen. You will do this using different procedures that we will explain before you start each.

If the computer randomly selects one of your decisions from this task for your payoff, in addition to the show-up fee, you get:

- The snack you picked in this decision
- $10

Please raise your hand if you have any questions.

BC

You start the procedure with an additional $10 that you received from the experimenter. You should think about this money as yours.

In this procedure, you will again choose your preferred snack out of 12 but you will see only two at a time. Simply pick the snack you like most by clicking on it.

Clicking on a snack will indicate that you like it the most. Once you click on a snack you like the most you will be moved automatically to the next screen. The snack you did not pick will no longer appear. You will continue picking the snack you like until only one snack is left. This last snack that remains will be considered the one you like the most. You will complete decision scenarios.

Example:

In this example, there are three snacks to choose from: mochis, licorice cats, and rice crackers. (In the real task there will be 12 snacks to choose from.) In this procedure, you see two snacks at a time out of all the snacks.

In this example you are shown licorice cats and rice crackers.

Let’s say the snack you like most out of the two is licorice cats. You then click on the licorice cats, which is highlighted for this example.

On the new screen, you will see two snacks again but the snack you did not pick in the previous screen will no longer appear. In this case you are shown mochis and licorice cats and rice crackers no longer appear.

Let’s say you click on licorice cats next and move to the next screen. Licorice cats will then be the snack you like the most for this decision.

If this decision is randomly chosen as your payoff you get:

- $10 show-up fee
- Licorice Cats
- $10

Please raise your hand if you have any questions.

ED

You start the procedure with an additional $10 that you received from the experimenter. You should think about this money as yours.

In this procedure, you will see 12 snacks on the screen. Eliminate the snack you like least by clicking on it, one at a time, until only one is left.

Clicking on a snack will indicate that you like it the least. Once you click on a snack you like the least that snack will be eliminated and you will be moved automatically to the next screen. On the next screen, the snack you eliminated will disappear. You will continue eliminating until only one snack is left. This last snack that remains will be considered the one you like most. You will complete 10 decision scenarios.

Example:

In this example, there are three snacks: mochis, licorice cats, and rice crackers. (In the real task there will be 12 snacks to choose from.)

Let’s say the snack you like least out of the three is rice crackers. You should click on the rice crackers, which is highlighted for this example.

On the new screen, the snack you eliminated will no longer appear. In this case, rice crackers will disappear.

Let’s say you want to eliminate licorice cats next. You click on them and move to the next screen. On the final screen, only one snack is left - mochis. Mochis will then be considered the snack you liked the most in this decision scenario.

If this decision is randomly chosen as your payoff you get:

- $10 show-up fee
- Mochis
- $10

Please raise your hand if you have any questions.

ER

You start the procedure with an additional $10 that you received from the experimenter. You should think about this money as yours. In this procedure, you will see 12 snacks on the screen. Eliminate the snack you like least by clicking on it, one at a time, until only one is left.

Clicking on a snack will indicate that you like it the least. Once you click on a snack you like the least that snack will be eliminated and you will be moved automatically to the next screen. On the next screen, the snack you eliminated will have an X mark beside it. You will continue eliminating until only one snack is left. This last snack that remains will be considered the one you like most. You will complete 10 decision scenarios.

Example:

In this example, there are three snacks: mochis, licorice cats, and rice crackers. (In the real task there will be 12 snacks to choose from.)

Let’s say the snack you like least out of the three is rice crackers. You should click on the rice crackers, which is highlighted for this example, to eliminate it.

On the new screen, the snack you eliminated is indicated by an X mark meaning it is eliminated. In this case, there will be an X mark beside rice crackers.

Let’s say you want to eliminate licorice cats next. You click on them and move to the next screen. On the final screen, only one snack is left – mochis. Mochis will then be considered the snack you liked the most in this decision scenario.

If this decision is randomly chosen as your payoff you get:

- $10 show-up fee
- Mochis
- $10

Please raise your hand if you have any questions.

DC

You start the procedure with an additional $10 that you received from the experimenter. You should think about this money as yours. In this procedure, you will see 12 different snacks on the screen. Simply pick the snack you like most by clicking on it.

Clicking on a snack will indicate that you like it the most. Once you click on a snack you like the most you will be moved automatically to the next screen. You will complete 10 decision scenarios.

Example:

In the example, there are only three snacks: mochis, licorice cats, and rice crackers. (In the real task there will be 12 snacks to choose from.)

Let’s say the snack you like most out of these three is mochis. You should click on the mochis, which is highlighted for this example.

If this decision is randomly chosen as your payoff you get:

- $10 show-up fee
- Mochis
- $10

Please raise your hand if you have any questions.

Appendix C Questionnaires

You have now completed the main part of the experiment. Complete the following demographic questions to proceed.

Participant Number (number given to you at the beginning)

Age

Gender at birth

Do you consider yourself ____ ?

a. Very Wealthy

b. Wealthy

c. Neither Poor or Wealthy

d. Poor

e. Very Poor

Weekly budget on entertainment, fun and eating out (in AUD): ______

Do you consider yourself: __________

a. Underweight

b. Slightly Underweight

c. Neither Underweight or Overweight

d. Overweight

f. Obese

Were you familiar with these snack goods before the experiment? Select your response to each one

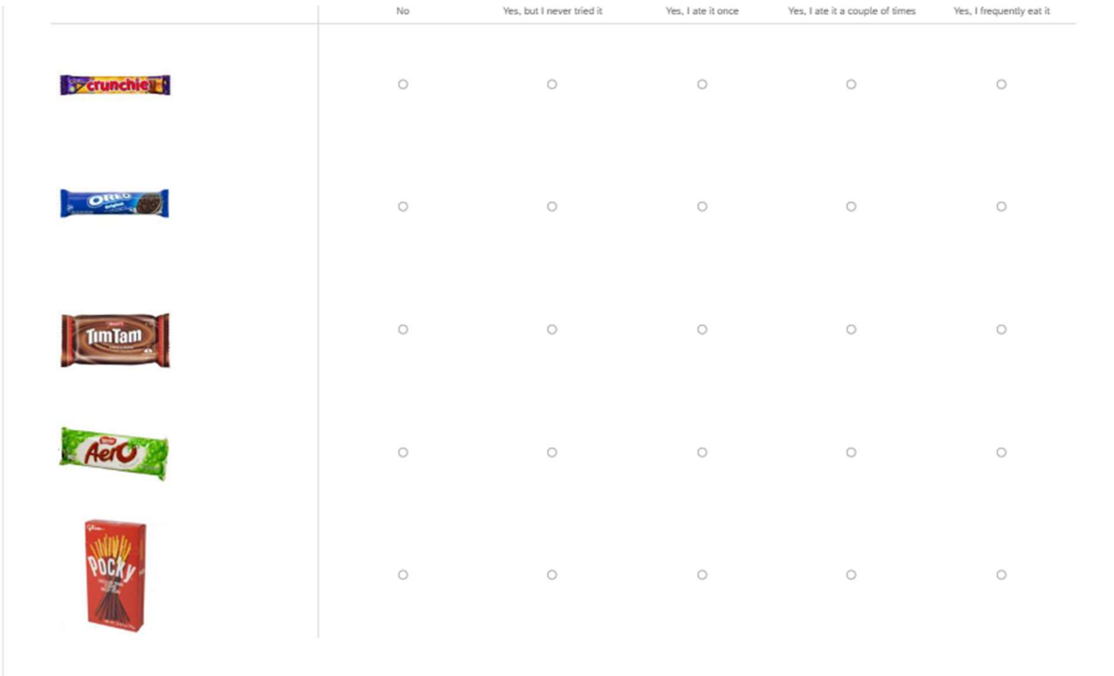
	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○

	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○

	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○

	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○

	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○
	○	○	○	○	○



	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
crunchie	○	○	○	○	○
OREO	○	○	○	○	○
TimTam	○	○	○	○	○
Aero	○	○	○	○	○
POCKY	○	○	○	○	○

	No	Yes, but I never tried it	Yes, I ate it once	Yes, I ate it a couple of times	Yes, I frequently eat it
Cheetos	○	○	○	○	○
Twisties	○	○	○	○	○
Nerds	○	○	○	○	○
SNICKERS	○	○	○	○	○

What would you do if you got a snack? You can answer whether you got a snack as a reward or not in this study. Select all that apply

Eat it right after I receive it

Eat it later

Give it to somebody

Resell

Share

Other

Which of the four methods did you like the most? Rank them from one to five with one being the best by dragging the bars below to the top or bottom positions.

Picking your favorite directly

Eliminating snacks by comparing two at a time

Eliminating snacks from the whole set with the eliminated options disappearing

Eliminating snacks from the whole set with the eliminated options having x beside them

What do you think was the experiment was about?

For how long have you been fasting before this experiment (put in the number of hours):

Did you eat any food within four hours of coming to this experiment? (Y/N):

Did you drink any water or drinks within four hours of coming to this experiment? (Y/N)

How hungry do you feel right now? Please rate it with 1 for not hungry at all and 10 for you've never felt this hungry before.

How full do you feel right now? Please rate it with 1 for not at all full and 10 for totally full. Put a check under your rating.

How much can you eat right now? Please rate it with 1 for none at all and 10 for more than a whole meal.

Chapter 2 Appendix

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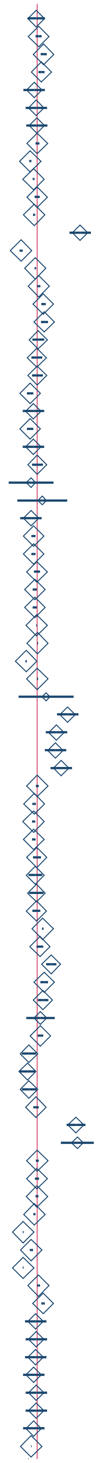
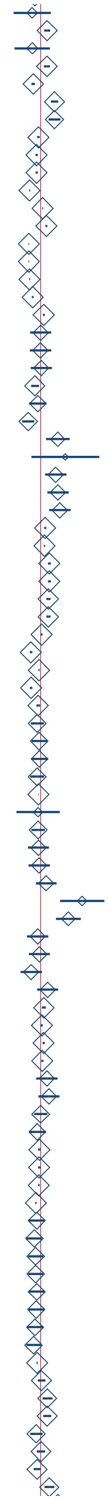
Lists and Tables

1



Study	Effect size with 95% CI	
Abdellaoui et al. (2011)	0.63 [0.30, 0.96]	
Abdellaoui et al. (2011)	0.72 [0.61, 0.84]	0.40
Abdellaoui et al. (2011)	0.91 [0.80, 1.03]	0.40
Abdellaoui et al. (2011)	0.83 [0.71, 0.95]	0.39
Abdellaoui et al. (2013)	0.55 [0.14, 0.96]	0.22
Abdellaoui et al. (2013)	0.63 [0.22, 1.04]	0.22
Abdellaoui et al. (2013)	0.65 [0.24, 1.06]	0.22
Abdellaoui et al. (2018)	0.68 [0.60, 0.75]	0.41
Abdellaoui et al. (2022)	0.40 [0.36, 0.44]	0.42
Abdellaoui et al. (2022)	0.53 [0.49, 0.57]	0.42
Andersen (2014)	0.66 [0.56, 0.77]	0.40
Andersen et al. (2014)	0.55 [0.51, 0.59]	0.42
Andersen et al. (2018)	2.32 [1.91, 2.73]	0.22
Anderson et al. (2022)	0.05 [-0.01, 0.11]	0.42
Anderson et al. (2022)	0.60 [0.57, 0.63]	0.42
Andreoni et al. (2011)	0.73 [0.67, 0.79]	0.42
Astebro et al. (2015)	0.90 [0.82, 0.99]	0.41
Astebro et al. (2015)	0.94 [0.81, 1.07]	0.39
Attema et al. (2019)	0.71 [0.48, 0.94]	0.33
Attema et al. (2019)	0.65 [0.44, 0.86]	0.34
Ayako & Kume (2008)	0.68 [0.47, 0.89]	0.34
Ayako & Kume (2008)	0.39 [0.27, 0.51]	0.39
Ayako & Kume (2008)	0.53 [0.11, 0.94]	0.22
Ayako & Kume (2008)	0.39 [0.27, 0.51]	0.39
Ayako & Kume (2008)	0.53 [0.11, 0.94]	0.22
Ayako & Kume (2008)	0.68 [0.47, 0.89]	0.34
Aydogan et al. (2020)	0.43 [-0.43, 1.29]	0.08
Baillon et al. (2012)	0.86 [-0.10, 1.82]	0.07
Baillon et al.(2020)	0.43 [0.02, 0.84]	0.22
Balaz et al. (2013)	0.53 [0.45, 0.61]	0.41
Balaz et al. (2013)	0.53 [0.45, 0.61]	0.41
Balaz et al. (2013)	0.66 [0.54, 0.78]	0.39
Balaz et al. (2013)	0.58 [0.50, 0.66]	0.41
Balaz et al. (2013)	0.58 [0.50, 0.66]	0.41
Barreda-Tarrazona et al. (2011)	0.65 [0.63, 0.67]	0.42
Barreda-Tarrazona et al. (2011)	0.68 [0.66, 0.70]	0.42
Bauchamp et al. (2020)	0.24 [0.21, 0.27]	0.42
Bernheim et al. (2020)	0.67 [0.65, 0.70]	0.42
Birchby et al. (2011)	1.01 [-0.05, 2.07]	0.06
Birnbaum & Chavez (1997)	1.84 [1.43, 2.25]	0.22
Birnbaum & Chavez (1997)	1.41 [1.00, 1.82]	0.22
Birnbaum & Chavez (1997)	1.37 [0.96, 1.78]	0.22
Birnbaum & Chavez (1997)	1.59 [1.18, 2.00]	0.22
Bleichrodt & Pinto (2000)	0.67 [0.62, 0.73]	0.42
Bleichrodt & Pinto (2000)	0.55 [0.48, 0.62]	0.41
Bleichrodt & Pinto (2000)	0.53 [0.47, 0.59]	0.42
Bleichrodt & Pinto (2000)	0.53 [0.46, 0.61]	0.41
Bocquého et al. (2014)	0.66 [0.50, 0.81]	0.38
Bouchouicha et al. (2017)	0.59 [0.33, 0.86]	0.31
Bouchouicha et al. (2017)	0.64 [0.35, 0.92]	0.30
Bouchouicha et al. (2017)	0.63 [0.48, 0.79]	0.37
Bougherara et al. (2021)	0.88 [0.85, 0.91]	0.42
Bruhin et al. (2018)	0.77 [0.64, 0.90]	0.39
Bruner (2009)	1.20 [1.01, 1.40]	0.35
Bruner (2009)	0.94 [0.79, 1.08]	0.38
Capra et al. (2013)	0.89 [0.68, 1.09]	0.35
Cheung (2020)	0.79 [0.24, 1.34]	0.16
Cheung (2020)	0.79 [0.69, 0.89]	0.40
Choi et al. (2022)	0.35 [0.07, 0.63]	0.30
Choi et al. (2022)	0.29 [-0.02, 0.60]	0.28
Choi et al. (2022)	0.35 [0.07, 0.64]	0.29
Choi et al. (2022)	0.61 [0.51, 0.72]	0.40
Clarke & Kalani (2011)	2.16 [1.79, 2.52]	0.24
Clarke & Kalani (2011)	2.21 [1.57, 2.85]	0.13
Comeig et al. (2015)	0.67 [0.61, 0.73]	
Comeig et al. (2015)	0.66 [0.58, 0.74]	
Conte et al. (2018)	0.66 [0.61, 0.71]	
Conte et al. (2018)	0.56 [0.51, 0.60]	
Conte et al. (2018)	0.13 [0.11, 0.15]	
Conte et al. (2018)	0.44 [0.37, 0.50]	
Conte et al. (2018)	0.13 [0.11, 0.15]	
Conte et al. (2018)	0.72 [0.66, 0.77]	
Conte et al. (2018)	0.90 [0.83, 0.97]	
Cubitt et al. (2022)	0.61 [0.20, 1.02]	
Cubitt et al. (2022)	0.63 [0.22, 1.04]	
Cubitt et al. (2022)	0.61 [0.20, 1.02]	
Cubitt et al. (2022)	0.54 [0.13, 0.95]	
Cubitt et al. (2022)	0.63 [0.22, 1.04]	
Cubitt et al. (2022)	0.63 [0.22, 1.04]	
Cubitt et al. (2022)	0.54 [0.13, 0.95]	
Donkers et al. (2001)	0.43 [0.42, 0.45]	

2



Drichoutis et al. (2012)	0.33 [-0.39, 1.05]
Drichoutis et al. (2012)	0.91 [0.79, 1.03]
Drichoutis et al. (2012)	0.33 [-0.35, 1.02]
Drichoutis et al. (2012)	0.90 [0.79, 1.01]
Drichoutis et al. (2012)	0.37 [0.30, 0.44]
Engelmann et al. (2012)	1.20 [1.06, 1.33]
Engelmann et al. (2012)	1.20 [0.96, 1.43]
Engelmann et al. (2012)	0.57 [0.52, 0.62]
Epper et al. (2011)	0.51 [0.46, 0.55]
Epper et al. (2012)	0.50 [0.45, 0.54]
Foster et al. (2013)	0.23 [0.22, 0.25]
Foster et al. (2013)	0.74 [0.72, 0.75]
Foster et al. (2013)	0.88 [0.85, 0.92]
Foster et al. (2013)	0.20 [0.19, 0.22]
Foster et al. (2018)	0.20 [0.19, 0.22]
Foster et al. (2018)	0.23 [0.22, 0.25]
Foster et al. (2018)	0.35 [0.31, 0.38]
Freudenreich & Musshoff (2022)	0.78 [0.74, 0.82]
Gajweski & Meunier (2020)	0.66 [0.25, 1.07]
Gajweski & Meunier (2020)	0.65 [0.24, 1.06]
Gajweski & Meunier (2020)	0.68 [0.27, 1.09]
Galarza (2005)	0.44 [0.28, 0.60]
Galarza (2005)	0.55 [0.22, 0.88]
Galarza (2005)	0.18 [-0.06, 0.42]
Gao et al. (2021)	1.32 [0.87, 1.78]
Gao et al. (2021)	1.62 [0.30, 2.93]
Gao et al. (2021)	1.24 [0.83, 1.65]
Gao et al. (2023)	1.33 [0.92, 1.74]
Gao et al. (2023)	1.40 [0.99, 1.81]
Glockner et al. (2020)	0.84 [0.80, 0.88]
Glockner et al. (2020)	0.81 [0.78, 0.84]
Glockner et al. (2020)	1.00 [0.94, 1.05]
Glockner et al. (2020)	1.00 [0.94, 1.05]
Goeree et al. (2000)	0.96 [0.88, 1.04]
Goeree et al. (2000)	0.96 [0.88, 1.04]
Gonzalez & Wu (2022)	0.70 [0.66, 0.73]
González-Jiménez (2021)	0.28 [0.23, 0.33]
González-Jiménez (2021)	0.60 [0.57, 0.63]
González-Jiménez (2021)	0.28 [0.24, 0.33]
González-Jiménez (2021)	0.57 [0.50, 0.64]
Guth et al. (2016)	0.53 [0.27, 0.78]
Guth et al. (2016)	0.60 [0.31, 0.90]
Guth et al. (2016)	0.62 [0.29, 0.95]
Guth et al. (2016)	0.52 [0.25, 0.80]
Hajimoladarvish (2018)	0.57 [0.57, 0.58]
Harrison & Swarthout (2018)	0.56 [-0.28, 1.40]
Harrison & Swarthout (2018)	0.56 [0.31, 0.81]
Harrison & Swarthout (2019)	0.57 [0.16, 0.98]
Harrison & Swarthout (2019)	0.60 [0.19, 1.01]
Harrison et al. (2018)	0.87 [0.47, 1.27]
Harrison et al. (2020)	2.27 [1.41, 3.13]
Harrison et al. (2020)	1.73 [1.25, 2.21]
Hey et al.(2009)	0.54 [0.13, 0.95]
Hey et al.(2009)	0.61 [0.19, 1.02]
Hey et al.(2009)	0.29 [-0.12, 0.71]
Hey et al.(2009)	0.93 [0.52, 1.34]
Hsu et al. (2009)	0.79 [0.71, 0.86]
Hsu et al. (2009)	0.71 [0.66, 0.75]
Hsu et al. (2009)	0.77 [0.73, 0.82]
Hsu et al. (2009)	0.72 [0.68, 0.77]
Jessup (2008)	0.90 [0.49, 1.31]
Jessup (2008)	0.98 [0.57, 1.39]
Kellen et al. (2016)	0.66 [0.41, 0.91]
Kellen et al. (2016)	0.53 [0.20, 0.86]
Kemel & Paraschiv (2023)	0.61 [0.56, 0.66]
Kemel & Paraschiv (2023)	0.60 [0.55, 0.66]
Kemel et al. (2020)	0.59 [0.55, 0.63]
Kemel et al. (2020)	0.47 [0.45, 0.50]
Kilka & Weber (2001)	0.51 [0.19, 0.82]
Kilka & Weber (2001)	0.41 [0.12, 0.71]
Kilka & Weber (2001)	0.47 [0.18, 0.76]
Kilka & Weber (2001)	0.47 [0.18, 0.76]
Kilka & Weber (2001)	0.51 [0.19, 0.82]
Kilka & Weber (2001)	0.49 [0.19, 0.79]
Kilka & Weber (2001)	0.44 [0.12, 0.76]
Kilka & Weber (2001)	0.39 [0.10, 0.67]
Kliger & Levy (2009)	0.52 [0.50, 0.54]
Konigsheim et al. (2019)	0.69 [0.54, 0.84]
Kontek & Birnbaum (2019)	0.92 [0.72, 1.12]
Kontek & Birnbaum (2019)	0.91 [0.75, 1.07]
Kopsacheilis (2018)	0.49 [0.25, 0.73]
Kopsacheilis (2018)	0.67 [0.51, 0.83]
Kopsacheilis (2018)	0.52 [0.38, 0.66]
Laury (2011)	1.00 [0.80, 1.19]

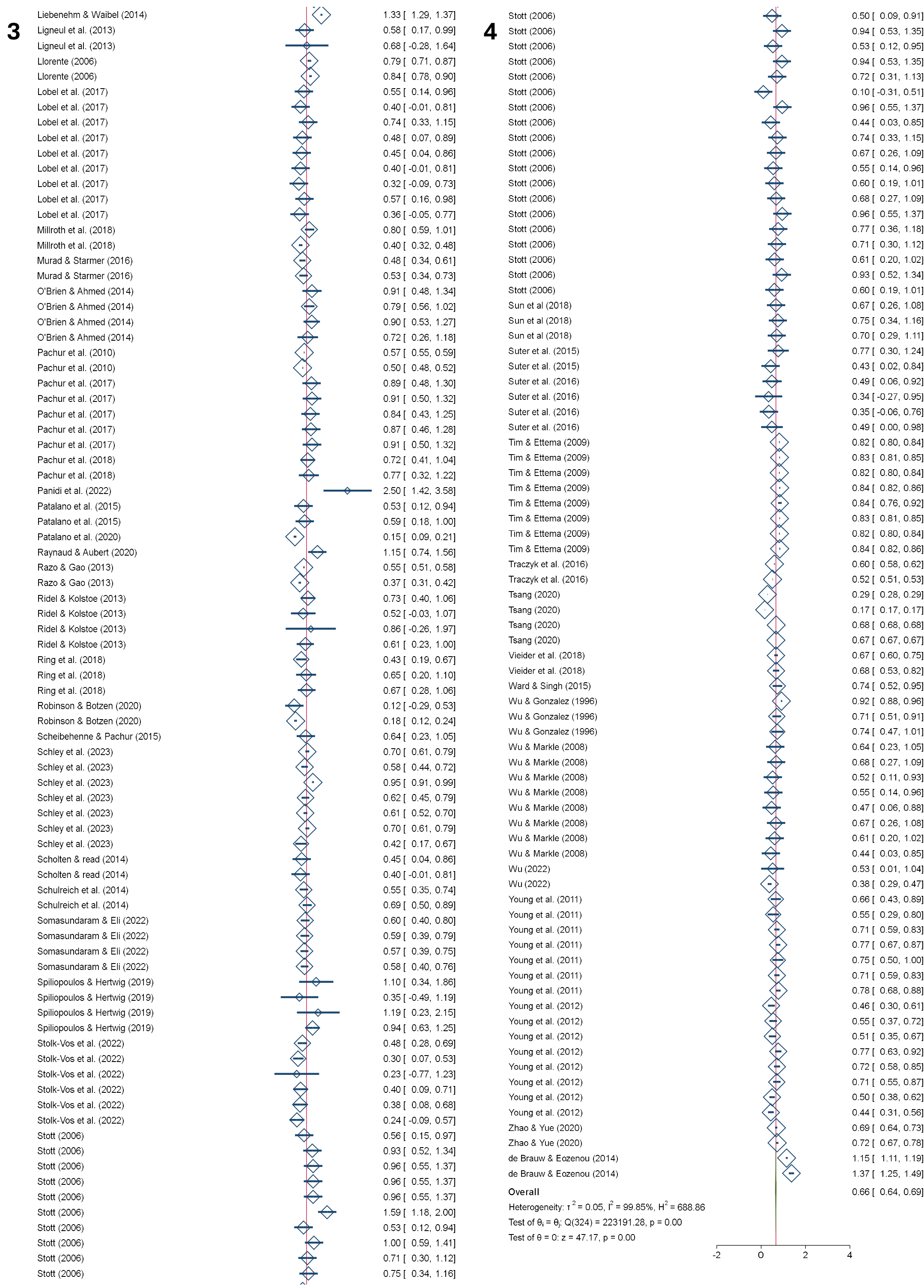
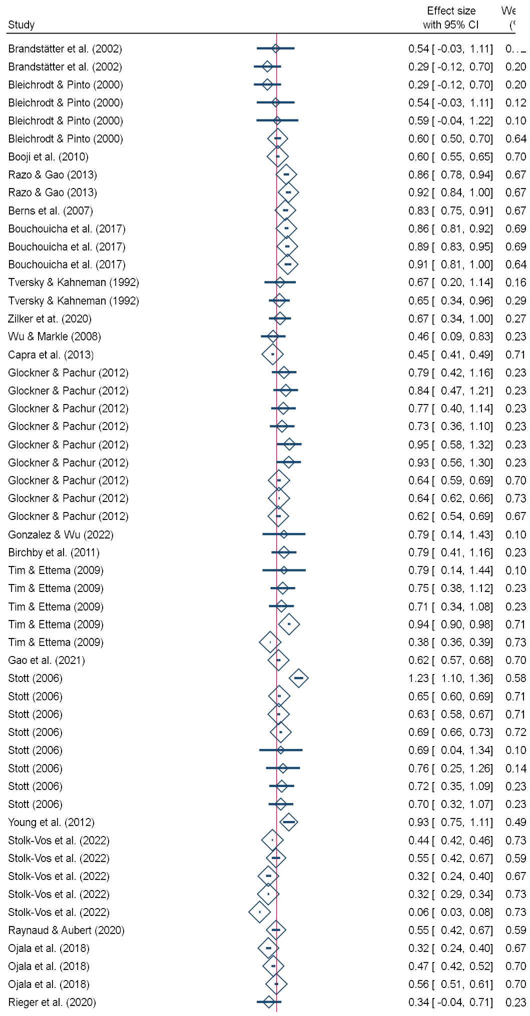
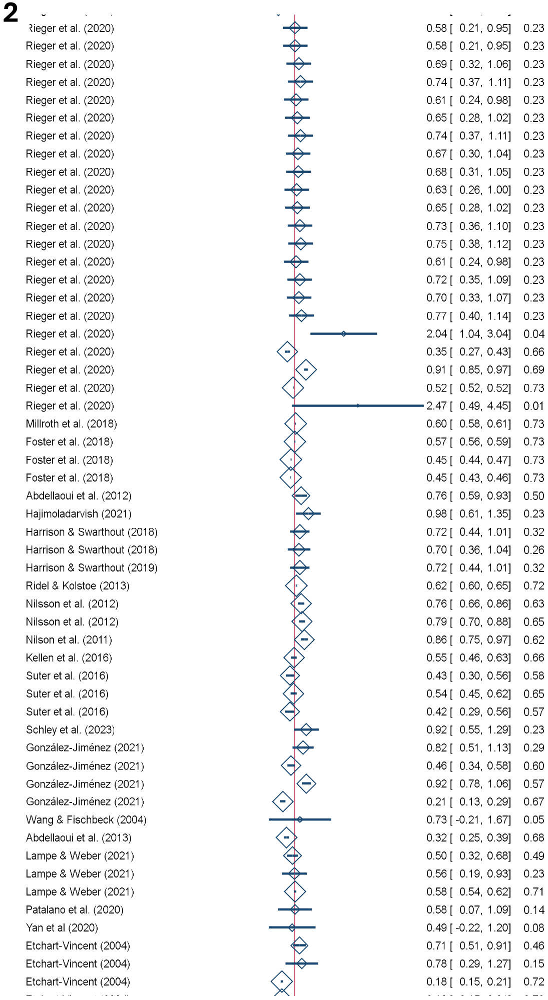


Figure A 5. Forest Plot for Undifferentiated. The red line is the meta-analytic mean; diamonds indicate weight of each estimate and bars show the 95% confidence interval per estimate.

1


Study
Effect size with 95% CI
We
Brandstätter et al. (2002) 0.54 [-0.03, 1.11]
Brandstätter et al. (2002) 0.29 [-0.12, 0.70] 0.20
Bleichrodt & Pinto (2000) 0.29 [-0.12, 0.70] 0.20
Bleichrodt & Pinto (2000) 0.54 [-0.03, 1.11] 0.12
Bleichrodt & Pinto (2000) 0.59 [-0.04, 1.22] 0.10
Bleichrodt & Pinto (2000) 0.60 [0.50, 0.70] 0.64
Booji et al. (2010) 0.60 [0.55, 0.65] 0.70
Razo & Gao (2013) 0.86 [0.78, 0.94] 0.67
Razo & Gao (2013) 0.92 [0.84, 1.00] 0.67
Berns et al. (2007) 0.83 [0.75, 0.91] 0.67
Bouchouicha et al. (2017) 0.86 [0.81, 0.92] 0.69
Bouchouicha et al. (2017) 0.89 [0.83, 0.95] 0.69
Bouchouicha et al. (2017) 0.91 [0.81, 1.00] 0.64
Tversky & Kahneman (1992) 0.67 [0.20, 1.14] 0.16
Tversky & Kahneman (1992) 0.65 [0.34, 0.96] 0.29
Zilker et at. (2020) 0.67 [0.34, 1.00] 0.27
Wu & Markle (2008) 0.46 [0.09, 0.83] 0.23
Capra et al. (2013) 0.45 [0.41, 0.49] 0.71
Glockner & Pachur (2012) 0.79 [0.42, 1.16] 0.23
Glockner & Pachur (2012) 0.84 [0.47, 1.21] 0.23
Glockner & Pachur (2012) 0.77 [0.40, 1.14] 0.23
Glockner & Pachur (2012) 0.73 [0.36, 1.10] 0.23
Glockner & Pachur (2012) 0.95 [0.58, 1.32] 0.23
Glockner & Pachur (2012) 0.93 [0.56, 1.30] 0.23
Glockner & Pachur (2012) 0.64 [0.59, 0.69] 0.70
Glockner & Pachur (2012) 0.64 [0.62, 0.66] 0.73
Glockner & Pachur (2012) 0.62 [0.54, 0.69] 0.67
Gonzalez & Wu (2022) 0.79 [0.14, 1.43] 0.10
Birchby et al. (2011) 0.79 [0.41, 1.16] 0.23
Tim & Ettema (2009) 0.79 [0.14, 1.44] 0.10
Tim & Ettema (2009) 0.75 [0.38, 1.12] 0.23
Tim & Ettema (2009) 0.71 [0.34, 1.08] 0.23
Tim & Ettema (2009) 0.94 [0.90, 0.98] 0.71
Tim & Ettema (2009) 0.38 [0.36, 0.39] 0.73
Gao et al. (2021) 0.62 [0.57, 0.68] 0.70
Stott (2006) 1.23 [1.10, 1.36] 0.58
Stott (2006) 0.65 [0.60, 0.69] 0.71
Stott (2006) 0.63 [0.58, 0.67] 0.71
Stott (2006) 0.69 [0.66, 0.73] 0.72
Stott (2006) 0.69 [0.04, 1.34] 0.10
Stott (2006) 0.76 [0.25, 1.26] 0.14
Stott (2006) 0.72 [0.35, 1.09] 0.23
Stott (2006) 0.70 [0.32, 1.07] 0.23
Young et al. (2012) 0.93 [0.75, 1.11] 0.49
Stolk-Vos et al. (2022) 0.44 [0.42, 0.46] 0.73
Stolk-Vos et al. (2022) 0.55 [0.42, 0.67] 0.59
Stolk-Vos et al. (2022) 0.32 [0.24, 0.40] 0.67
Stolk-Vos et al. (2022) 0.32 [0.29, 0.34] 0.73
Stolk-Vos et al. (2022) 0.06 [0.03, 0.08] 0.73
Raynaud & Aubert (2020) 0.55 [0.42, 0.67] 0.59
Ojala et al. (2018) 0.32 [0.24, 0.40] 0.67
Ojala et al. (2018) 0.47 [0.42, 0.52] 0.70
Ojala et al. (2018) 0.56 [0.51, 0.61] 0.70
Rieger et al. (2020) 0.34 [-0.04, 0.71] 0.23

2


Rieger et al. (2020) 0.58 [0.21, 0.95] 0.23
Rieger et al. (2020) 0.58 [0.21, 0.95] 0.23
Rieger et al. (2020) 0.69 [0.32, 1.06] 0.23
Rieger et al. (2020) 0.74 [0.37, 1.11] 0.23
Rieger et al. (2020) 0.61 [0.24, 0.98] 0.23
Rieger et al. (2020) 0.65 [0.28, 1.02] 0.23
Rieger et al. (2020) 0.74 [0.37, 1.11] 0.23
Rieger et al. (2020) 0.67 [0.30, 1.04] 0.23
Rieger et al. (2020) 0.68 [0.31, 1.05] 0.23
Rieger et al. (2020) 0.63 [0.26, 1.00] 0.23
Rieger et al. (2020) 0.65 [0.28, 1.02] 0.23
Rieger et al. (2020) 0.73 [0.36, 1.10] 0.23
Rieger et al. (2020) 0.75 [0.38, 1.12] 0.23
Rieger et al. (2020) 0.61 [0.24, 0.98] 0.23
Rieger et al. (2020) 0.72 [0.35, 1.09] 0.23
Rieger et al. (2020) 0.70 [0.33, 1.07] 0.23
Rieger et al. (2020) 0.77 [0.40, 1.14] 0.23
Rieger et al. (2020) 2.04 [1.04, 3.04] 0.04
Rieger et al. (2020) 0.35 [0.27, 0.43] 0.66
Rieger et al. (2020) 0.91 [0.85, 0.97] 0.69
Rieger et al. (2020) 0.52 [0.52, 0.52] 0.73
Rieger et al. (2020) 2.47 [0.49, 4.45] 0.01
Millroth et al. (2018) 0.60 [0.58, 0.61] 0.73
Foster et al. (2018) 0.57 [0.56, 0.59] 0.73
Foster et al. (2018) 0.45 [0.44, 0.47] 0.73
Foster et al. (2018) 0.45 [0.43, 0.46] 0.73
Abdellaoui et al. (2012) 0.76 [0.59, 0.93] 0.50
Hajimoladarvish (2021) 0.98 [0.61, 1.35] 0.23
Harrison & Swarthout (2018) 0.72 [0.44, 1.01] 0.32
Harrison & Swarthout (2018) 0.70 [0.36, 1.04] 0.26
Harrison & Swarthout (2019) 0.72 [0.44, 1.01] 0.32
Ridel & Kolstoe (2013) 0.62 [0.60, 0.65] 0.72
Nilsson et al. (2012) 0.76 [0.66, 0.86] 0.63
Nilsson et al. (2012) 0.79 [0.70, 0.88] 0.65
Nilson et al. (2011) 0.86 [0.75, 0.97] 0.62
Kellen et al. (2016) 0.55 [0.46, 0.63] 0.66
Suter et al. (2016) 0.43 [0.30, 0.56] 0.58
Suter et al. (2016) 0.54 [0.45, 0.62] 0.65
Suter et al. (2016) 0.42 [0.29, 0.56] 0.57
Schley et al. (2023) 0.92 [0.55, 1.29] 0.23
González-Jiménez (2021) 0.82 [0.51, 1.13] 0.29
González-Jiménez (2021) 0.46 [0.34, 0.58] 0.60
González-Jiménez (2021) 0.92 [0.78, 1.06] 0.57
González-Jiménez (2021) 0.21 [0.13, 0.29] 0.67
Wang & Fischbeck (2004) 0.73 [-0.21, 1.67] 0.05
Abdellaoui et al. (2013) 0.32 [0.25, 0.39] 0.68
Lampe & Weber (2021) 0.50 [0.32, 0.68] 0.49
Lampe & Weber (2021) 0.56 [0.19, 0.93] 0.23
Lampe & Weber (2021) 0.58 [0.54, 0.62] 0.71
Patalano et al. (2020) 0.58 [0.07, 1.09] 0.14
Yan et al (2020) 0.49 [-0.22, 1.20] 0.08
Etchart-Vincent (2004) 0.71 [0.51, 0.91] 0.46
Etchart-Vincent (2004) 0.78 [0.29, 1.27] 0.15
Etchart-Vincent (2004) 0.18 [0.15, 0.21] 0.72

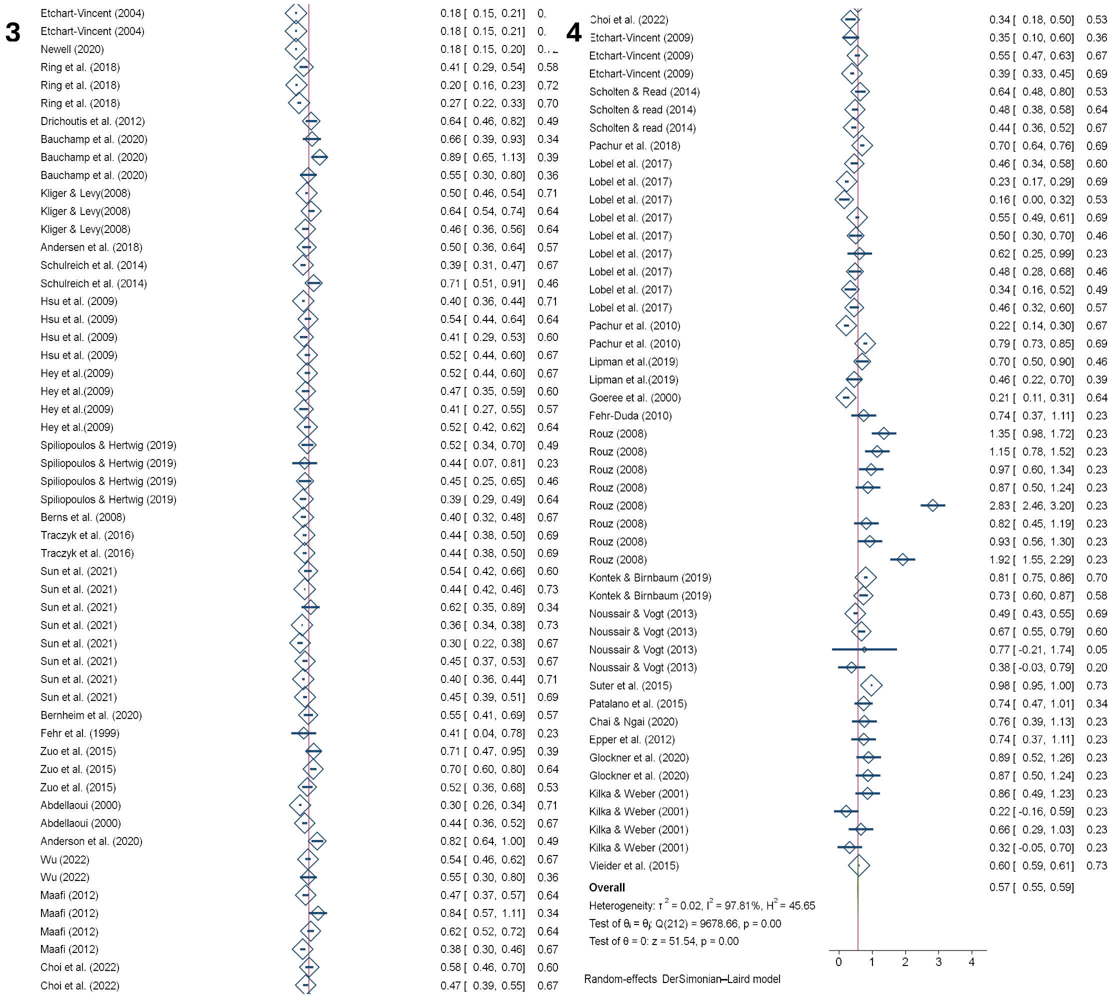
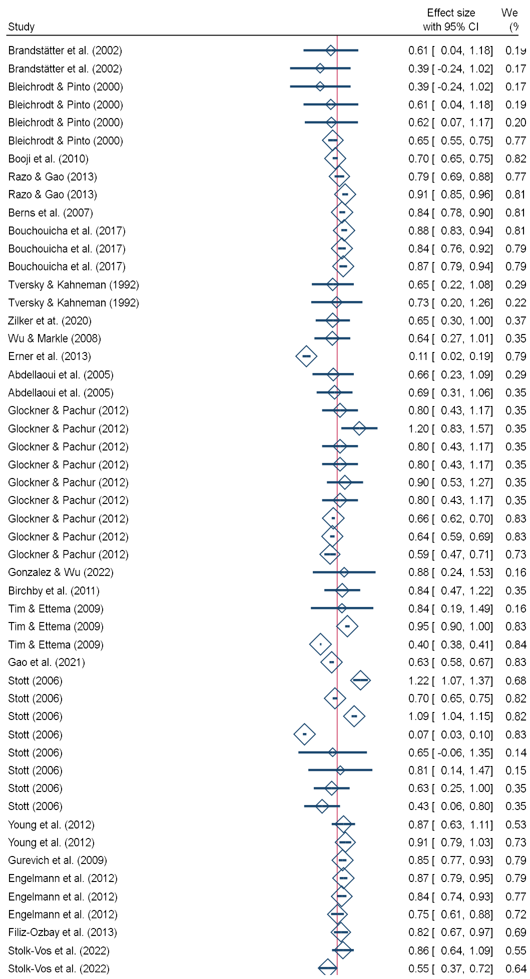


Figure A 6. Forest Plot for Gains The red line is the meta-analytic mean; diamonds indicate weight of each estimate and bars show the 95% confidence interval per estimate.

1


Study
Effect size with 95% CI
We (%
Brandstätter et al. (2002) 0.61 [0.04, 1.18] 0.19
Brandstätter et al. (2002) 0.39 [-0.24, 1.02] 0.17
Bleichrodt & Pinto (2000) 0.39 [-0.24, 1.02] 0.17
Bleichrodt & Pinto (2000) 0.61 [0.04, 1.18] 0.19
Bleichrodt & Pinto (2000) 0.62 [0.07, 1.17] 0.20
Bleichrodt & Pinto (2000) 0.65 [0.55, 0.75] 0.77
Booji et al. (2010) 0.70 [0.65, 0.75] 0.82
Razo & Gao (2013) 0.79 [0.69, 0.88] 0.77
Razo & Gao (2013) 0.91 [0.85, 0.96] 0.81
Berns et al. (2007) 0.84 [0.78, 0.90] 0.81
Bouchouicha et al. (2017) 0.88 [0.83, 0.94] 0.81
Bouchouicha et al. (2017) 0.84 [0.76, 0.92] 0.79
Bouchouicha et al. (2017) 0.87 [0.79, 0.94] 0.79
Tversky & Kahneman (1992) 0.65 [0.22, 1.08] 0.29
Tversky & Kahneman (1992) 0.73 [0.20, 1.26] 0.22
Zilker et at. (2020) 0.65 [0.30, 1.00] 0.37
Wu & Markle (2008) 0.64 [0.27, 1.01] 0.35
Erner et al. (2013) 0.11 [0.02, 0.19] 0.79
Abdellaoui et al. (2005) 0.66 [0.23, 1.09] 0.29
Abdellaoui et al. (2005) 0.69 [0.31, 1.06] 0.35
Glockner & Pachur (2012) 0.80 [0.43, 1.17] 0.35
Glockner & Pachur (2012) 1.20 [0.83, 1.57] 0.35
Glockner & Pachur (2012) 0.80 [0.43, 1.17] 0.35
Glockner & Pachur (2012) 0.80 [0.43, 1.17] 0.35
Glockner & Pachur (2012) 0.90 [0.53, 1.27] 0.35
Glockner & Pachur (2012) 0.80 [0.43, 1.17] 0.35
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Glockner & Pachur (2012) 0.64 [0.59, 0.69] 0.83
Glockner & Pachur (2012) 0.59 [0.47, 0.71] 0.73
Gonzalez & Wu (2022) 0.88 [0.24, 1.53] 0.16
Birchby et al. (2011) 0.84 [0.47, 1.22] 0.35
Tim & Ettema (2009) 0.84 [0.19, 1.49] 0.16
Tim & Ettema (2009) 0.95 [0.90, 1.00] 0.83
Tim & Ettema (2009) 0.40 [0.38, 0.41] 0.84
Gao et al. (2021) 0.63 [0.58, 0.67] 0.83
Stott (2006) 1.22 [1.07, 1.37] 0.68
Stott (2006) 0.70 [0.65, 0.75] 0.82
Stott (2006) 1.09 [1.04, 1.15] 0.82
Stott (2006) 0.07 [0.03, 0.10] 0.83
Stott (2006) 0.65 [-0.06, 1.35] 0.14
Stott (2006) 0.81 [0.14, 1.47] 0.15
Stott (2006) 0.63 [0.25, 1.00] 0.35
Stott (2006) 0.43 [0.06, 0.80] 0.35
Young et al. (2012) 0.87 [0.63, 1.11] 0.53
Young et al. (2012) 0.91 [0.79, 1.03] 0.73
Gurevich et al. (2009) 0.85 [0.77, 0.93] 0.79
Engelmann et al. (2012) 0.87 [0.79, 0.95] 0.79
Engelmann et al. (2012) 0.84 [0.74, 0.93] 0.77
Engelmann et al. (2012) 0.75 [0.61, 0.88] 0.72
Filiz-Ozbay et al. (2013) 0.82 [0.67, 0.97] 0.69
Stolk-Vos et al. (2022) 0.86 [0.64, 1.09] 0.55
Stolk-Vos et al. (2022) 0.55 [0.37, 0.72] 0.64

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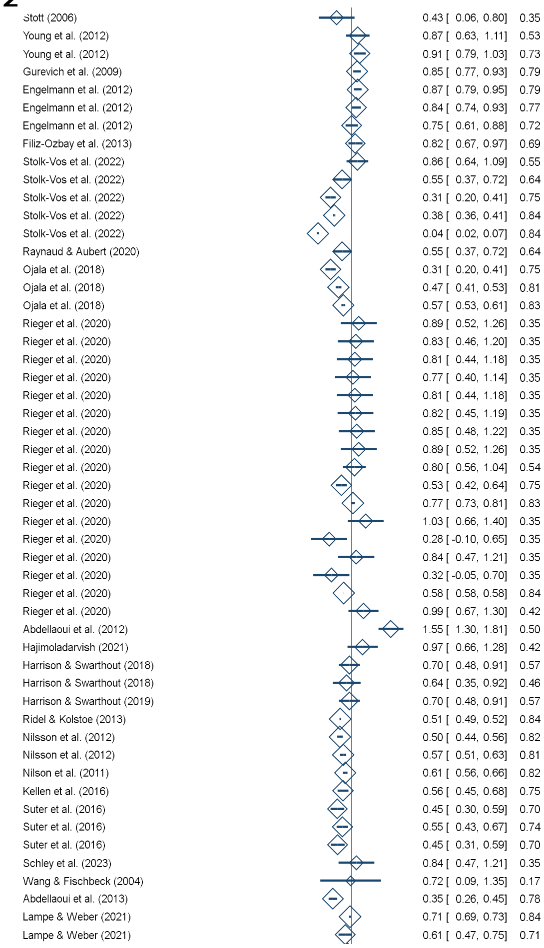
Stott (2006) 0.43 [0.06, 0.80] 0.35
Young et al. (2012) 0.87 [0.63, 1.11] 0.53
Young et al. (2012) 0.91 [0.79, 1.03] 0.73
Gurevich et al. (2009) 0.85 [0.77, 0.93] 0.79
Engelmann et al. (2012) 0.87 [0.79, 0.95] 0.79
Engelmann et al. (2012) 0.84 [0.74, 0.93] 0.77
Engelmann et al. (2012) 0.75 [0.61, 0.88] 0.72
Filiz-Ozbay et al. (2013) 0.82 [0.67, 0.97] 0.69
Stolk-Vos et al. (2022) 0.86 [0.64, 1.09] 0.55
Stolk-Vos et al. (2022) 0.55 [0.37, 0.72] 0.64
Stolk-Vos et al. (2022) 0.31 [0.20, 0.41] 0.75
Stolk-Vos et al. (2022) 0.38 [0.36, 0.41] 0.84
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Ojala et al. (2018) 0.31 [0.20, 0.41] 0.75
Ojala et al. (2018) 0.47 [0.41, 0.53] 0.81
Ojala et al. (2018) 0.57 [0.53, 0.61] 0.83
Rieger et al. (2020) 0.89 [0.52, 1.26] 0.35
Rieger et al. (2020) 0.83 [0.46, 1.20] 0.35
Rieger et al. (2020) 0.81 [0.44, 1.18] 0.35
Rieger et al. (2020) 0.77 [0.40, 1.14] 0.35
Rieger et al. (2020) 0.81 [0.44, 1.18] 0.35
Rieger et al. (2020) 0.82 [0.45, 1.19] 0.35
Rieger et al. (2020) 0.85 [0.48, 1.22] 0.35
Rieger et al. (2020) 0.89 [0.52, 1.26] 0.35
Rieger et al. (2020) 0.80 [0.56, 1.04] 0.54
Rieger et al. (2020) 0.53 [0.42, 0.64] 0.75
Rieger et al. (2020) 0.77 [0.73, 0.81] 0.83
Rieger et al. (2020) 1.03 [0.66, 1.40] 0.35
Rieger et al. (2020) 0.28 [-0.10, 0.65] 0.35
Rieger et al. (2020) 0.84 [0.47, 1.21] 0.35
Rieger et al. (2020) 0.32 [-0.05, 0.70] 0.35
Rieger et al. (2020) 0.58 [0.58, 0.58] 0.84
Rieger et al. (2020) 0.99 [0.67, 1.30] 0.42
Abdellaoui et al. (2012) 1.55 [1.30, 1.81] 0.50
Hajimoladarvish (2021) 0.97 [0.66, 1.28] 0.42
Harrison & Swarthout (2018) 0.70 [0.48, 0.91] 0.57
Harrison & Swarthout (2018) 0.64 [0.35, 0.92] 0.46
Harrison & Swarthout (2019) 0.70 [0.48, 0.91] 0.57
Ridel & Kolstoe (2013) 0.51 [0.49, 0.52] 0.84
Nilsson et al. (2012) 0.50 [0.44, 0.56] 0.82
Nilsson et al. (2012) 0.57 [0.51, 0.63] 0.81
Nilson et al. (2011) 0.61 [0.56, 0.66] 0.82
Kellen et al. (2016) 0.56 [0.45, 0.68] 0.75
Suter et al. (2016) 0.45 [0.30, 0.59] 0.70
Suter et al. (2016) 0.55 [0.43, 0.67] 0.74
Suter et al. (2016) 0.45 [0.31, 0.59] 0.70
Schley et al. (2023) 0.84 [0.47, 1.21] 0.35
Wang & Fischbeck (2004) 0.72 [0.09, 1.35] 0.17
Abdellaoui et al. (2013) 0.35 [0.26, 0.45] 0.78
Lampe & Weber (2021) 0.71 [0.69, 0.73] 0.84
Lampe & Weber (2021) 0.61 [0.47, 0.75] 0.71

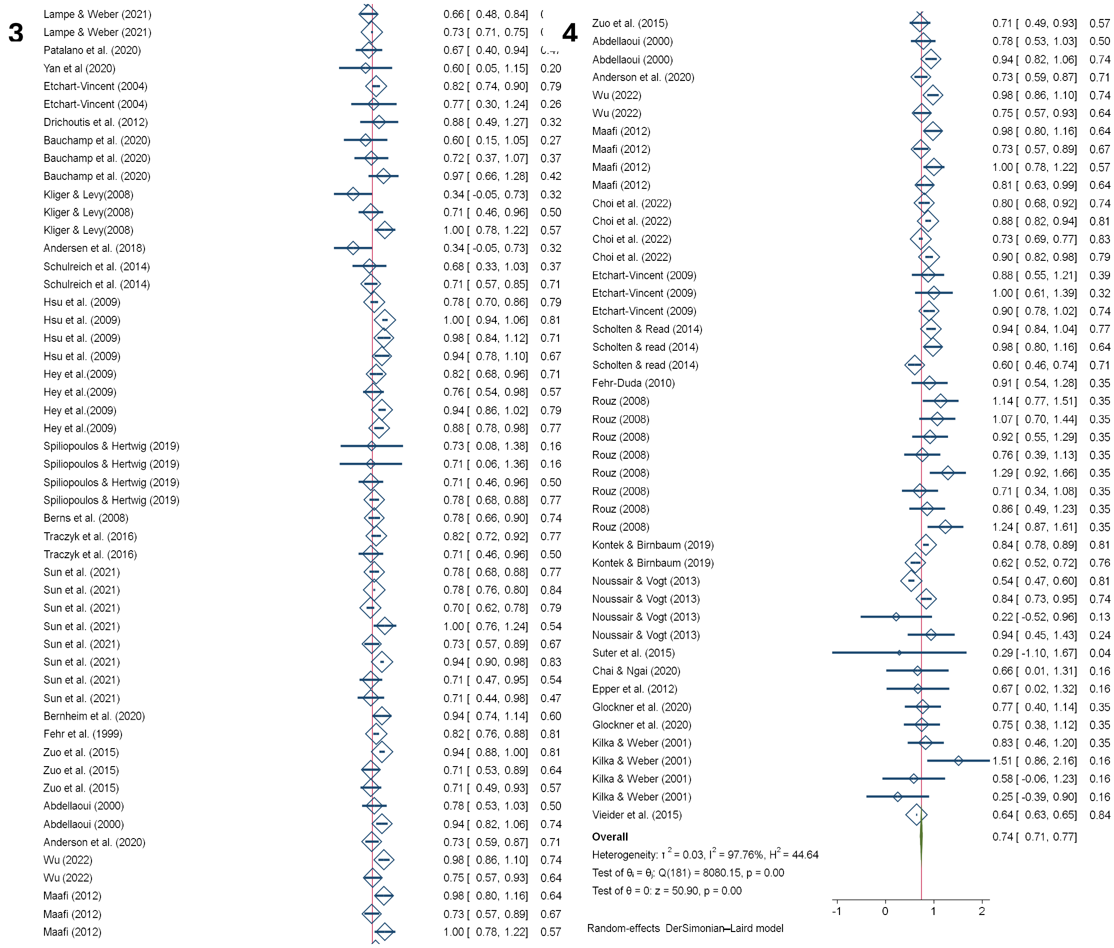

Figure A 7. Forest Plot for Losses. The red line is the meta-analytic mean; diamonds indicate weight of each estimate and bars show the 95% confidence interval per estimate.

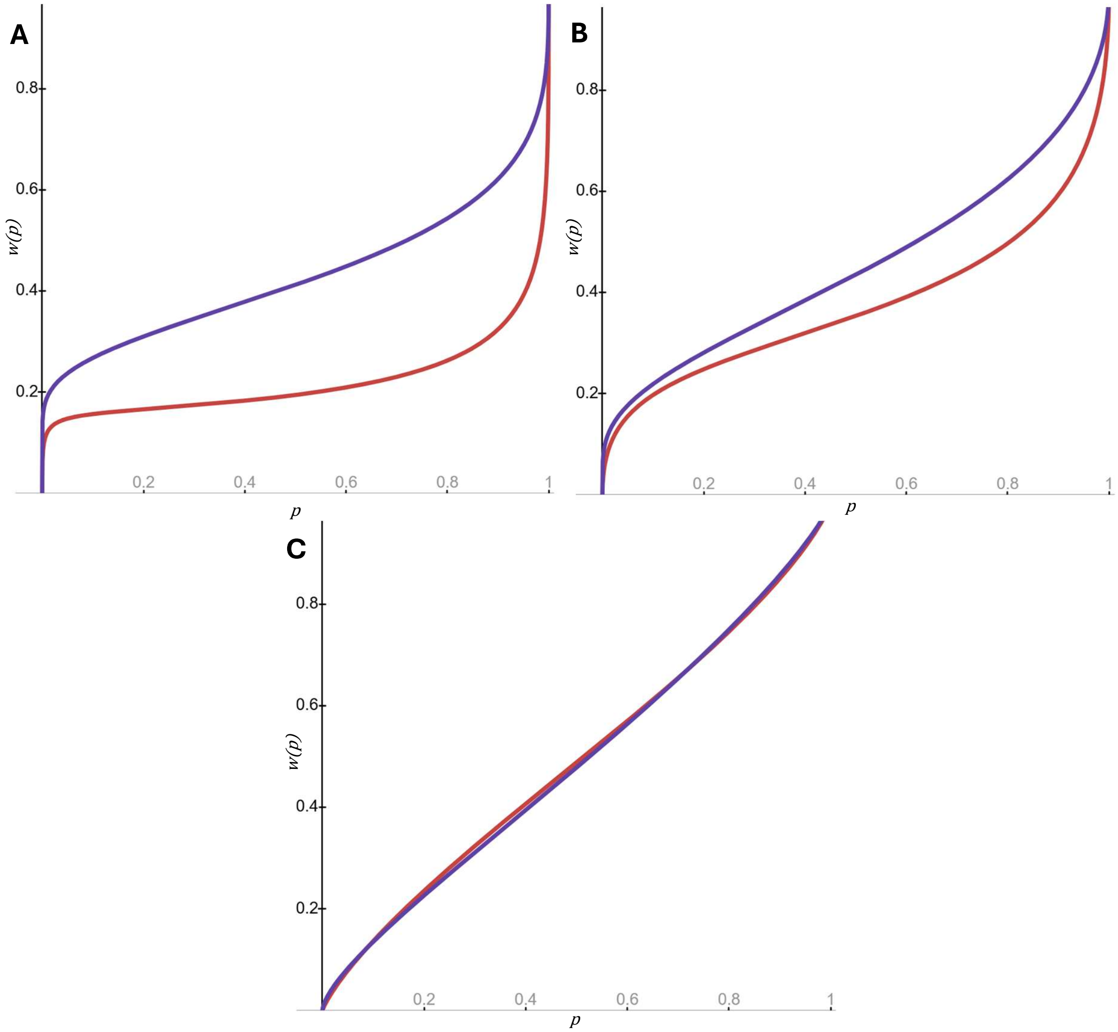

Figure A 8. Comparison of TK and Prelec Functional Forms Using for A: $\gamma = 0.33$, B: $\gamma = 0.33$ and C: $\gamma = 0.33$. Purple lines are for the TK functional form and red lines for the Prelec functional form.

Table A 6. Equivalent Values of γ for the Prelec Functional Form Calculated from Meta-analytic Means of Estimates that Used the TK Functional Form for Undifferentiated.

Percentile	TK	Prelec Equivalent
25%	0.55	0.40
50%	0.67	0.60
75%	0.82	0.81
Meta Mean	0.68	0.61

Table A 7. Equivalent Values of γ for the Prelec Functional Form Calculated from Meta-analytic Means of Estimates that Used the TK Functional Form for Gains.

Percentile	TK γ	P1 & P2 Equivalent
25%	0.45	0.23
50%	0.57	0.43
75%	0.74	0.70
Meta Mean	0.57	0.43

Table A 8. Equivalent Values of γ for the Prelec Functional Form Calculated from Meta-analytic Means of Estimates that Used the TK Functional Form for Losses.

Percentile	TK γ	P1 & P2 Equivalent
25%	0.71	0.66
50%	0.78	0.76
75%	0.88	0.88
Meta Mean	0.77	0.75

Table A 9. Coding Strategy

Variable Name	Variable Type	Codes/Description
Probability Weighting Function	Categorical	1 – TK 2 – Prelec 1 3 – LLO 4 – Prelect 2 5 - Others
Utility Function	Categorical	1 – Linear 2 - Power utility 3 – CARA 4 - Power expo 5 - Others
Reward Type	Categorical	1 – Money 2 – Food 3 – Physical item 4 – Health outcome 5 - Others
Participants	Categorical	1 -University students 2 – General population 3 - Others
Probability Presentation	Categorical	1 – Numerical 2 – Visual graphs 3 – Describes in words 4 – Learned 5 - Others
Method of Elicitation	Categorical	1 – Price list 2 – Binary choice 3 – Matching task 4 – BDM 5 - Others

Publication Status	Dummy	0 – Published paper 1 – Unpublished
Field	Categorical	1 – Economics/business 2 – Psychology 3 – Neuroscience 4 – Health/medical 5 - Others
Location	Categorical	1 – Field 2 – Lab 3 – Online 4 - Others
Type of Data	Dummy	0 – Experimental 1 - Observational
Estimation Level	Categorical	1 – Aggregate 2 – Individual 3 - Both
Domain	Categorical	1 – Undifferentiated 2 – Gains 3 - Losses
Aggregate γ		Reported γ at aggregate level, blank if not reported
Aggregate γ se		Reported γ standard error at aggregate level, blank if not reported
Individual γ mean		Reported γ mean at individual level, blank if not reported
Individual γ median		Reported γ median at individual level, blank if not reported
Individual γ sd		Reported γ standard deviation at individual level, blank if not reported
Individual γ range		Reported γ percentile at individual level, blank if not reported
SCImago ranking	Continuous	SCImago quartile ranking
SCImago H index	Continuous	SCImago H index
SCImago score	Continuous	SCImago SJR score