Individual differences in the delay-reward heuristic: An exploratory study of socioeconomic status, subjective status, and personal relative deprivation

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April 30, 2021

Abstract

Recent research has examined the role of inference in intertemporal choice: when a future financial reward is ambiguous, people’s inferences about its value depend upon the delay until its delivery, and inferences about ambiguous delays depend upon the size of the stated reward. Here we report an exploratory study of individual differences in this *delay-reward heuristic* by examining whether people’s inferences about ambiguous future rewards correlate with objective and subjective indicators of socio-economic status: annual household income, education, self-placement in a national hierarchy of social status (SSS), and self-reported personal relative deprivation (PRD). Participants were presented with a hypothetical choice between receiving £10 now and an ambiguous reward in 1 year’s time, and had to infer the missing value. In multiple regression analyses, age and household income emerged as unique predictors that were negatively associated with (log-transformed) estimates, although the effect of income became unreliable when this variable was log-transformed; the effects of SSS and PRD were not reliably different from zero. When participants were subsequently asked to assume that their inferences of the missing value were correct and choose between the immediate and delayed option, larger estimates were positively associated with greater willingness to wait; choices were also predicted by age, income and SSS although the latter two effects were not unambiguously non-zero, and in multiple regression analysis only participants’ estimates of the reward emerged as a reliable predictor of preference. Taken together, these results support previous work suggesting that age is a meaningful predictor of inferences about ambiguous rewards and delays, and provide initial evidence that such inferences may also be associated with income.

People often have to choose between small rewards in the near future and larger rewards in the more distant future. Economists, psychologists and neuroscientists study this kind of intertemporal choice by examining how people respond to simplified financial decisions such as the choice between receiving £10 now and receiving £20 in one year from now (e.g., Matthews, 2012). By studying how people respond to changes in the monetary values and time intervals that define each option, researchers develop sophisticated mathematical models of the mapping between money, time and preference, and these models reflect different ideas about the mental processes by which people choose between “smaller, sooner” and “larger, later” outcomes (see e.g., Doyle, 2013, for a review). The overarching finding is that people typically value a given reward less the further it is shifted into the future, and that this *delay discounting* is steeper over the near future than over longer time horizons, contrary to the prescriptions of (supposedly) rational economic behaviour (e.g., Green & Myerson, 1996; Myerson & Green, 1995).

Researchers also study the factors that modulate or correlate with people’s preferences for more immediate rewards. Sometimes this involves experimentally manipu-

lating the decision context (e.g., by inducing a particular emotional state, Lerner et al., 2013); sometimes it involves examining whether demographic, personality, and socio-economic variables predict people’s willingness to wait for larger rewards (e.g., Du et al., 2002; Mahalingam et al., 2015; Reimers et al., 2009).

Outside the laboratory, the attributes that define intertemporal choice options are often ambiguous. That is, decision-makers do not know exactly when a delayed reward will arrive, or exactly how big it will be. This kind of decision under ambiguity has received relatively little attention (see Dai et al., 2019, for a recent review). Building on work by Pleskac and colleagues in the domain of risky choice (where rewards are immediate but probabilistic; Leuker et al., 2018; Pleskac & Hertwig, 2014), Skylark and colleagues have suggested that, when confronted with ambiguous intertemporal options, people employ a *delay-reward heuristic*, such that ambiguous rewards are inferred to be larger when the explicitly-stated delay is longer, and infer ambiguous delays to be longer when explicitly-stated rewards are larger. In a series of experiments, Skylark et al. (2020, 2021) have found that people’s inferences of missing attributes follow these predictions. In addition, people’s estimates of the ambiguous values predict their choices. For example, the larger participants’ estimates of an ambiguous delay, the more likely they are to choose the delayed option when the true delay is revealed (Sky-

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lark et al., 2021); and when people were told to assume that their estimate of an ambiguous reward was correct, larger estimates were associated with greater probability of choosing the delayed option (implying that people are not using their indifference point as the basis for their inferences; Skylark et al., 2020).

These studies also found that participants' inferences about ambiguous options correlated with their age: compared to younger participants, older participants inferred that ambiguous rewards would be smaller, and ambiguous delays would be longer (Skylark et al., 2020, 2021). The finding that a demographic variable predicts people's expectations about the delay-reward trade-offs that they will encounter opens several lines of enquiry. For example, do these differences reflect different ecological experiences of delay-reward associations? Do the differences translate into different real-world decisions when options are ambiguous? And do the different expectations contribute to differences in preference when options are fully explicated (i.e., there is no ambiguity)? To the extent that older adults have more pessimistic expectations, any particular delay will presumably appear more attractive (or less unattractive) to an older adult than to a younger one, because it is shorter than expected (or not as much longer than expected) — which might partially explain putative associations between age and delay-discounting (e.g., Green et al., 1994; Jimura et al., 2011), although the evidence regarding age-related differences in discounting is mixed (e.g., Albert & Duffy, 2012; Löckenhoff & Samanez-Larkin, 2020).

The present report builds on the foregoing studies by further investigating individual differences in the delay-reward heuristic. Specifically, we report an exploratory study that examines whether inferences about ambiguous delayed rewards are associated with objective and subjective indicators of socio-economic status. Like age, social status is an important correlate of a wide range of economic behaviours and, as such, provides a natural place to start when looking at individual differences in the delay-reward heuristic. Indeed, because age is often correlated with social class, it is possible that the previously-reported age effects are proxies for socio-economic status effects. In addition, social status has been found to predict intertemporal preference in choice tasks where the options are unambiguous, further supporting the possibility that it will account for some of the inter-individual variation in expectations about the value of ambiguous attributes when the choice options are not fully explicated.

We consider three constructs. First, objective socio-economic status (SES), as indexed by household income and highest level of educational attainment. SES correlates with many socio-economic behaviours (e.g., Welte et al., 2002), and previous work has found that higher SES is associated with greater willingness to wait for delayed options in financial intertemporal choice tasks (e.g., Brown et al., 2015; Reimers et al., 2009). Second, subjective social status (SSS) — that is, where a person puts him or herself on a national “ladder” of social class. Research has found that SSS is often at least as important as objective SES in predicting behaviours and outcomes (e.g., Adler et al., 2000), and SSS has been found to

negatively correlate with willingness to wait in financial intertemporal choice (e.g., Ishii, 2015; Ishii et al., 2017). Third, personal relative deprivation (PRD) — the extent to which a person feels unfairly deprived of material outcomes relative to other people who are “like them” (Smith et al., 2012, 2020). PRD is similar to SSS in capturing a person's subjective status, but it differs in that it focuses on the decision-maker's self-selected comparison group of peers (rather than a national hierarchy) and relates to the feelings of injustice and resentment that are associated with feeling comparatively, and unfairly, badly-off. Over and above SES and SSS, higher PRD predicts a range of socio-economic behaviours and outcomes, (e.g., Callan et al., 2015, 2017; Kim et al., 2017; Mishra & Carleton, 2015), including a reduced willingness to wait in intertemporal choice tasks (Callan et al., 2008, 2011).

To investigate the links between these variables and inferences about ambiguous rewards during intertemporal choice, we employed a task used by Skylark et al. (2020, 2021), itself modelled on approach taken by Pleskac & Hertwig (2014). Participants were asked to suppose that they were taking part in a psychology experiment in which they were offered a choice between receiving £10 now and receiving an ambiguous reward in one year's time. After estimating the missing reward value, participants were asked to assume that their estimate was correct and indicate whether they would prefer the immediate or delayed option. They subsequently completed indicators of their objective and subjective socio-economic status and relative deprivation. Our primary interest was in people's inferences about the ambiguous reward (our interest in the choice data was somewhat secondary), and we did not have strong predictions. To the extent that more pessimistic expectations about the size of the future reward imply greater willingness to wait for any actual reward, we might expect people of higher (relative) status to produce smaller reward estimates (because higher status has previously been associated with greater willingness to wait). Alternatively, to the extent that greater status entails a greater familiarity with large monetary values (and perhaps more experience with rapid growth in value over time), we might expect higher status to be associated with larger estimates. The experiment was therefore conducted in a spirit of enquiry, rather than seeking to confirm a hypothesis.

Method

The study was conducted on-line via Qualtrics (www.qualtrics.com). A copy of the survey is included in the Supplementary Materials, available from <https://osf.io/wt25j/>.

Materials

Participants first completed the delay-reward task used by Skylark et al. (2020). The instruction page informed participants that they would be asked to consider a simple financial decision, and that, although the scenario was hypothetical, they should answer carefully, accurately, and

honestly. They were informed that there are no right or wrong answers. On the following page, participants were told:

Suppose that you take part in a Psychology experiment in which the experimenter offers you a choice between two financial options. Due to a random printing error, part of one of the options is missing, so you can't see the value that is meant to be displayed. The choice that the experimenter presents you with is shown below, with the missing value replaced by an "X".

Option A: Receive £10 now
Option B: Receive £X in 1 year's time

What do you think the missing value, X, is?
Enter a number in the box below.

(The explanation of the missing value as being due to a random printing error is intended to reduce the likelihood of the participant inferring that it is obscured because, for example, it is unusual or unattractive.) There followed a text box that accepted numeric responses.

On the following page, participants were told:

Suppose that your estimate of the missing value is correct. That is, suppose that the experimenter is offering you a choice between::

Option A: receive £10 now
Option B: receive £[participant's estimate] in 1 year's time

Which would you choose?"

Followed by radio buttons for Option A and Option B.

In addition to completing the Delay-Reward task, participants completed the following measures/items:

- **Income (INC):** Participants were asked: "What is your annual household income (before taxes)? That is, how much does your household make each year, before tax? Please be as accurate as you can" followed by 23 response options: £10,000 or less, £10,001–£15,000, £15,001–£20,000, and so on in £5000 steps until £80,001–£90,000 and so on in £10,000 steps until the top category, "More than £150,000". We coded each response by the mid-point of the response category, in thousands of pounds (i.e., 5, 12.5, 17.5...); for the top category we used the median-based estimator described by Parker and Fenwick (1983; see e.g., Matthews et al., 2016).
- **Education (EDU):** Participants were asked: "What is the highest level of education you have completed?" with 6 options (No formal qualifications or equivalent (e.g., did not finish school); Secondary school qualifications or equivalent (e.g., GCSEs); Post-16 education or equivalent (e.g., A-levels, BTEC); Bachelor's degree or equivalent (e.g., BA, BSc); Master's degree or equivalent (e.g., MA, MSc, MPhil); Doctoral

degree or equivalent (e.g., PhD). Responses were coded 1 to 6.

- **SES:** For some analyses, we computed an overall measure of socio-economic status by computing, for each participant, the average of their z-scored income and z-scored education.
- **PRD:** Participants completed Callan et al.'s (2011) 5-item PRD scale, answering each question on a 7-point scale ranging from "Strongly agree" to "Strongly disagree" (coded 7 to 1, with 2 items reverse-coded).
- **SSS:** Participants were presented with a cartoon ladder with 10 rungs and asked to think of it as representing where people stand in the United Kingdom, with those who are the "best off – those who have the most money, the most education and the most respected jobs" at the top and those who are "worst off" at the bottom. Participants selected a rung to indicate where they thought they stood in this hierarchy.
- **Demographics:** Participants were asked "Which of the following best describes you?" (response options: This is the first time I have completed this survey; I have previously started the survey but did not finish it (e.g., the browser crashed, I lost progress and restarted); This is not the first time I have completed this survey; I have previously completed it). They were also asked for their age (indicated via a slider ranging from 0–100) and sex (response options: male, female, prefer not to say, coded -0.5, 0.5, 0, respectively).

Design and Procedure

Upon starting the survey, participants were presented with a landing page that asked them to maximize their browser, switch off their phone/music/email so that they could focus, to work on their own, and to complete the survey in one go. There followed an information sheet and consent form; participants who answered "no" to any of the consent questions were redirected to a page asking them to return the survey. Participants completed the delay-reward task first, followed by the SES (education followed by income, on the same page), PRD, and SSS measures in random order (each measure on a separate page), and finally the demographic questions followed by a debriefing page. All questions required an answer before the participant could progress to the next page, and the back button was disabled.

Participants

Participants were recruited via Prolific (www.prolific.co). We requested participants who were using a desktop computer, resident in the UK, aged 19–100 (see below) with an approval rate of 95% or higher. We requested 274 participants (the number was based on budgetary considerations) and paid £0.80 for each completion of

the study. Upon arrival at the survey web-page, the survey software checked whether the participant's IP address was from the United Kingdom and whether they were using a mobile device; participants from outside the UK and those on mobile devices were redirected to pages asking them to "return" the survey on Prolific (the latter group were invited to try again on a computer, if they wished); the software was also set to block participants whose IP address was already registered as having completed the task. After data collection was complete, we screened for past participation by checking whether respondents' IP addresses occurred in two earlier, similar studies (there were none) and within the current study (of the people who completed the task, 3 had IP addresses associated with earlier, or overlapping, attempts that had not produced complete data; these 3 participants were excluded). We then also screened for participants who were under 18 or who reported that this was not their first attempt; no participants were excluded on these grounds, leaving a final sample of 271 (92 male, 2 prefer not to say); we refer to this as the "lax" sample. We also prepared a "strict" sample, which consisted of the lax sample minus participants who indicated their age as exactly 18 (although our intention was to permit participants aged 18 and above, the recruitment platform was slightly mis-configured to request participants aged 19+; correspondingly, participants who reported their age to us as 18 may have mis-reported their age either to us or to the platform, which suggests they should perhaps be excluded) and those whose IP address was judged to be outside the UK by the maxmind function from the rgeolocate package for R (Keyes et al., 2020). There is a risk that these additional screening steps risk throwing out "good data" (we cannot be sure that the 18-year olds mis-reported their age, or that the IP geolocation is accurate) so we think it best to analyze both the lax and strict samples; the latter consisted of 259 individuals (86 male, 1 prefer not to say).

The sample characteristics for the Lax and Strict samples are shown in Table 1.

Results and Discussion

Analyses were conducted using R (R Core Team, 2020). The data and analysis script are included in the Supplementary Materials (<https://osf.io/wt25j/>).

As might be expected, participants' estimates of the missing reward value were positively skewed and were therefore transformed for all analyses as $\log_{10}(\text{Estimate})$ to improve normality (although the preference for certain round numbers meant that the distribution remained somewhat "lumpy" and rather heavy-tailed).

For all analyses, we sought to check that our inferences were not the consequence of arbitrary analytic decisions by running both conventional (parametric) and robust analyses for both the Lax and Strict datasets. Likewise, we ran a selection of analyses that differ in their treatment of income and education, because researchers often adopt different approaches to these variables (e.g., Callan et al., 2011; Ishii et al., 2017; Kim et al., 2018; Skylark & Baron-

Table 1: Sample characteristics.

	Lax		
	Min	Max	M (SD)
AGE	18	82	36.94 (12.46)
EDU	1	6	3.70 (1.01)
INC	5	163.38	41.56 (30.02)
SSS	1	9	5.10 (1.76)
PRD	1	7	3.53 (1.13)
EST	1	3650	75.60 (233.83)
LOGEST	0	3.56	39.03 (2.84)
CHOICE			0.63 (0.03)
	Strict		
	Min	Max	M (SD)
AGE	19	82	37.41 (12.38)
EDU	1	6	3.71 (1.01)
INC	5	163.38	41.20 (29.76)
SSS	1	9	5.08 (1.76)
PRD	1	7	3.52 (1.14)
EST	1	3650	72.71 (231.95)
LOGEST	0	3.56	38.48 (2.80)
CHOICE			0.63 (0.03)

Note: For both the Lax and the Strict sample, Cronbach's α for PRD is .81 (Revelle, 2020). EST = Estimate of the ambiguous reward; LOGEST = $\log_{10}(\text{EST})$. For LOGEST, the M and SD values indicate the geometric mean and SD (computed by exponentiating the arithmetic mean and SD of the $\log_{10}$ -transformed estimates). For the Choice variable, the mean is the proportion, p , who chose to wait and the the SD is $\sqrt{p * (1 - p) / N}$.

Cohen, 2017). In particular, as well as annual household income, we examined the results when income was $\log_{10}$ -transformed, when income and education were replaced by the combined SES variable described above, and (for regression analyses) when education was treated as a factor. Of course, other specifications/analyses would also be possible, and might yield different results.

Correlation analyses

Figure 1 shows the correlation coefficients and association 95% confidence intervals for the associations between (log-transformed) estimates (LOGEST) and the other variables; for each correlation we ran both conventional (Pearson) correlations and Kendall correlations (for the latter, confidence intervals were computed using the DescStats package for R (Signorell et al., 2021), using both the Lax and Strict datasets. In general, the results are similar across all analyses. As noted, different researchers have treated objective socio-economic indicators differently in previous research, so the plot shows the correlations between log-transformed estimates and income, log-transformed income (LOGINC) and the com-

Figure 1: Correlation coefficients. The y-axis labels indicate the pair of variables whose correlation is being tested; for each correlation, the four different points indicate the results of taking different approaches to data exclusion (lax vs strict) and to computing the correlation (Pearson vs Kendall).

Figure 2: Regression coefficients for models of log-transformed estimates. See main text for explanation of the predictor abbreviations and analyses.

Figure 3: Regression coefficients for single-predictor models of choices. See main text for explanation of the predictor abbreviations and analyses.

Figure 4: Regression coefficients for multiple regression models of choices. See main text for explanation of the predictor abbreviations and analyses.

bined SES measures. (For brevity, we do not plot the correlations between LOGINC and SES and the other variables.)

The labels to the left of the figure indicate the pair of variables whose association is being tested. The key relationships are those at the top, involving the estimates of the ambiguous reward. As in previous work (Skylark et al., 2020, 2021), there is a negative association between estimates and age. A novel finding is that estimates were negatively associated with household income (both raw and log-transformed). To the extent that the composite SES variable reflects income, this variable is also somewhat negatively associated with estimates; there is little indication that education is meaningfully associated with estimates. In addition, demographic and social-status indicators show some inter-relations (e.g., people with higher income place themselves higher on the social-status ladder and report less personal relative deprivation than do those with lower income).

Regression analyses of estimates

We regressed log-transformed estimates onto the social status and demographic variables, entered simultaneously. Unless otherwise noted, the dependent variable (log-transformed estimates) and all predictors apart from sex were z-scored prior to analysis. We used both ordinary least squares (OLS) and robust regression, the latter implemented via the `lmrob` function from the `robustbase` package for R (Maechler et al., 2020) using the recommended "KS2014" setting.

We ran 4 analyses that differed in their treatment of the socio-economic indicators: for Analyses 1 and 4, income and education were separate, continuous predictors; Analysis 2 used LOGINC in place of income; Analysis 3 replaced income and education with the combined SES measure; and for Analysis 4 education was treated as a factor with weighted-effect coding (implemented via the `wec` package version 0.4-1 for R; Grotenhuis et al., 2017). Analyses 1–4 used the Lax dataset; Analyses 5–6 were the same as Analyses 1–4, respectively, but used the Strict dataset.

The resulting regression coefficients are plotted in Figure 2; the figure does not show the coefficients for each level of education when this is treated as a factor, because the paucity of data means that the confidence intervals are often very wide and distort the scale.

The results are generally very consistent across model specifications, datasets, and robust vs conventional regression. Like the correlation analysis and previous work, the coefficient for age is negative with confidence intervals that exclude zero; after controlling for other variables, an increase of 1 standard deviation in age corresponds to a decrease of about a quarter of a standard deviation in log-transformed estimate.

The effects of PRD, SSS and education are all estimated to be very close to zero, with confidence intervals that imply that only small non-zero effects are plausible.

The effect of income is less clear-cut. When raw income is used as a predictor, the results mirror the correlation analysis and indicate that more affluent partici-

pants inferred smaller values for the ambiguous reward. But when income is log-transformed, the effect is smaller and has CIs that cover zero; the combined SES measure yields similar results. Notably, even for the "significant" effect of untransformed income, the CI only just misses zero. Taken together, the data indicate some reason to think that household income is associated with smaller estimates of the ambiguous reward, but the result is not clear-cut.

Predicting choices from individual variables

We ran logistic regression analyses that predicted choices (coded 0 for the immediate option and 1 for the delayed option) from log-transformed estimates and each of the other variables. In the first instance, each variable was considered separately (i.e., as the only predictor in the regression model). As before, unless otherwise noted the predictors (apart from sex) were z-scored. Figure 3 shows the regression coefficients for each predictor; for each coefficient we analysed both the Lax and Strict datasets using both conventional and robust logistic regression (the latter implemented via the `glmrob` function from the `robustbase` package for R; Maechler et al., 2020). Like for the regression analyses of estimates, we examined the effects of income, log-transformed income, and the combined SES variable. For brevity, the intercepts are not shown.

There is a substantial effect of estimates: people who inferred that the delayed reward was large were more likely to choose to wait than those who inferred that it was small. This implies that participants did not use their indifference point at the basis for their inferences.

There is also a non-zero effect of age: older participants were less likely to wait. Of course, this bivariate analysis ignores the fact that older participants also tended to infer that the delayed reward was relatively small. As far as we know, the only previously-published work to use the decision task employed in the current paper (in which participants are asked to assume that their inference of the missing value is correct prior to choosing) is Skylark et al. (2020). Those authors did not examine the association between age and choice without also controlling for estimates of the ambiguous value. Skylark et al. (2021, Experiment 3a) did examine bivariate associations between age and choice in tasks where the ambiguous reward remained ambiguous (i.e., participants were not told to assume that their inference was correct) and, like the present experiment, found that older participants were less likely to choose the delayed option.¹

None of the other predictors have particularly large or reliably non-zero effects. There is some indication that higher SSS and income are associated with less propensity to choose the delayed option, but the CIs only just exclude zero (and in the case of income, whether they exclude zero or not depends on the analysis strategy/dataset). Like

¹The design of Skylark et al.'s study was complicated by the fact that some participants made their choices prior to giving their estimates, which makes direct comparison with the current work difficult.

for age, these effects do not take into account the fact that more affluent participants typically produced more pessimistic (i.e., smaller) estimates of the delayed reward.

Predicting choices via multiple regression

Our final analyses consist of multiple logistic regressions in which choices were predicted from the other variables entered simultaneously. As before, all predictors other than gender were z-scored, and we ran multiple analyses to check the robustness of our findings to alternative approaches. Analyses 1, 2, and 3 used the Lax dataset with income, log-transformed income, and combined SES, respectively; trying to treat education as a factor produced software error/warnings so we do not include that approach. Analyses 4–6 applied the same approaches as Analyses 1–3, respectively, to the Strict data set.

The resulting coefficient estimates are plotted in Figure 4. The findings are generally very similar across the different analytic strategies: there is a substantial positive intercept, indicating an overall tendency of participants to favour the delayed option; there is also a positive effect of estimated reward – the larger participants inferred the ambiguous reward to be, the more likely they were to choose the delayed option. (It is worth bearing in mind that the task instructions asked participants to assume that their estimate of the ambiguous value was correct when making their choice.) Most of the other predictors have point estimates that are very close to zero, with fairly tight confidence intervals. There is some indication that females were less willing to wait than males, but there is quite a lot of uncertainty attached to the estimate of the effect and the CIs do not consistently exclude zero across the different analytic strategies.

Unlike the single-predictor models, the effect of age is now small and not reliably different from zero; that is, after controlling for the other predictors, age is no longer meaningfully associated with the tendency to wait. (The aforementioned study by Skylark et al., 2021, Experiment 3a, also found that the association between age and choice effectively disappeared after controlling for estimates – but as noted, direct comparison with the current work is perhaps not appropriate.) One possible interpretation of this is that estimated reward mediates a link between age and willingness to wait (i.e., older participants make more pessimistic inferences about the missing value and, because of this, are less likely to choose the delayed option), but we do not formally test this possibility here.

Conclusions

The present data provide further evidence that older participants make more pessimistic inferences about ambiguous future rewards, and provide some indication that people with higher household income show a similar tendency to make more modest estimates. We found little indication that inferences were meaningfully associated with PRD, SSS, sex or education, after controlling for other variables. As in previous work, larger estimated

future rewards were associated with greater willingness to select the delayed option. Considered in isolation, age and reward-estimates both reliably predicted choices, with some indication that people with higher annual income and higher subjective status were more willing to wait, although the latter effects were not clear-cut. After controlling for other variables, only estimates emerged as a strong predictor of choices. Given the exploratory nature of this work, we refrain from speculating about the processes underlying our findings, or about their significance for studies of individual differences in delay-discounting in tasks for which all options are fully explicated. We think that it would be productive to replicate the present study using a larger, more nationally-representative sample, and to generalize beyond the specific decision-making domain (psychology experiments) explored here.

References

- Adler, N. E., Epel, E. S., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy white women. *Health Psychology, 19*(6), 586–592. <https://doi.org/10.1037/0278-6133.19.6.586>
- Albert, S. M., & Duffy, J. (2012). Differences in risk aversion between young and older adults. *Neuroscience and Neuroeconomics, 1*, 3–9. <https://doi.org/10.2147/NAN.S27184>
- Brown, J.R., Ivković, Z., & Weisbenner, S. (2015). Empirical determinants of intertemporal choice. *Journal of Financial Economics, 116*, 473–486. <http://dx.doi.org/10.1016/j.jfineco.2015.04.004>
- Callan, M.J., Ellard, J.H., Shead, N.W., & Hodgins, D.C. (2008). Gambling as a search for justice: Examining the role of personal relative deprivation in gambling urges and gambling behavior. *Personality and Social Psychology Bulletin, 34*(11), 1514–1529. <http://dx.doi.org/10.1177/0146167208322956>
- Callan, M.J., Shead, N.W., & Olson, J.M. (2011). Personal relative deprivation, delay discounting, and gambling. *Journal of Personality and Social Psychology, 101*(5), 955–973. <http://dx.doi.org/10.1037/a0024778>
- Callan, M.J., Kim, H., Gheorghiu, A.I., & Matthews, W.J. (2017). The interrelations between social class, personal relative deprivation, and prosociality. *Social Psychological and Personality Science, 8*(6), 660–669. <http://dx.doi.org/10.1177/1948550616673877>
- Callan, M.J., Kim, H., & Matthews, W.J. (2015). Predicting self-rated mental and physical health: The contributions of subjective socioeconomic status and personal relative deprivation. *Frontiers in Psychology, 6*. Article 1415. 1–14. <http://dx.doi.org/10.3389/fpsyg.2015.01415>
- Dai, J., Pachur, T., Pleskac, T. J., & Hertwig, R. (2019). Tomorrow never knows: Why and how uncertainty matters in intertemporal choice. In R. Hertwig, T. J. Pleskac, & T. Pachur (Eds.), *Taming Uncertainty*. MIT Press.

- Doyle, J. R. (2013). Survey of time preference, delay discounting models. *Judgment and Decision Making*, 8(2), 116–135.
- Du, W., Green, L., & Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychological Record*, 52, 479–492. <https://doi.org/10.1007/BF03395199>
- Green, L., Fry, A.F., & Myerson, J. (1994). Discounting of delayed rewards. *Psychological Science*, 5(1), 33–36.
- Green, L., & Myerson, J. (1996). Exponential versus hyperbolic discounting of delayed outcomes: Risk and waiting time. *American Zoologist*, 36(4), 496–505.
- Jimura, K., Myerson, J., Hilgard, J., Keighley, J., Braver, T. S., & Green, L. (2011). Domain independence and stability in young and older adults' discounting of delayed rewards. *Behavioural Processes*, 87(3), 253–259. doi:10.1016/j.beproc.2011.04.006
- Grotenhuis, M., Ben Pelzer, Eisinga, R., Nieuwenhuis, R., Schmidt-Catran, A., & Konig, R. (2017). When size matters: advantages of weighted effect coding in observational studies. *International Journal of Public Health*, 62, 163–167. <https://doi.org/10.1007/s00038-016-0901-1>
- Ishii, K. (2015). Subjective socioeconomic status and cigarette smoking interact to delay discounting. *SpringerPlus*, 4:560, 1–5. <https://doi.org/10.1186/s40064-015-1361-4>
- Ishii, K., Eisen, C., & Hitokoto, H. (2017). The effects of social status and culture on delay discounting. *Japanese Psychological Research*, 59(3), 230–237. <https://doi.org/10.1111/jpr.12154>
- Keyes, O., Schmidt, D., Robinson, D., Davis, C., Rudis, B., Maxmind, Inc., Gloor, P. & IP2Location.com (2020). rgeolocate: IP Address Geolocation. R package version 1.3.1. <https://CRAN.R-project.org/package=rgeolocate>
- Kim, H., Callan, M.J., Gheorghiu, A.I., & Matthews, W.J. (2017). Social comparison, personal relative deprivation, and materialism. *British Journal of Social Psychology*, 56, 373–392. <https://doi.org/10.1111/bjso.12176>
- Kim, H., Callan, M.J., Gheorghiu, A.I., & Skylark, W.J. (2018). Social comparison processes in the experience of personal relative deprivation. *Journal of Applied Social Psychology*, 48(9), 519–532. <https://doi.org/10.1111/jasp.12531>
- Lerner, J.S., Li, Y., & Weber, E.U. (2013). The financial costs of sadness. *Psychological Science*, 24(1), 72–79. <https://doi.org/10.1177/0956797612450302>
- Leuker, C., Pachur, T., Hertwig, R., & Pleskac, T. J. (2018). Exploiting risk-reward structures in decision making under uncertainty. *Cognition*, 175, 186–200. <https://doi.org/10.1016/j.cognition.2018.02.019>
- Löckenhoff, C. E., & Samanez-Larkin, G. R. (2020). Age differences in intertemporal choice: The role of task type, outcome characteristics, and covariates. *Journals of Gerontology: Psychological Sciences*, 75(1), 85–95. <https://doi.org/10.1093/geronb/gbz097>
- Maechler, M., Rousseeuw, P., Croux, C., Todorov, V., Ruckstuhl, A., Salibian-Barrera, M., Verbeke, T., Koller, M., Conceicao, E.L.T., & di Palma, M.A. (2020). robustbase: Basic Robust Statistics. R package version 0.93-6. <http://CRAN.R-project.org/package=robustbase>
- Mahalingam, V., Stillwell, D., Kosinski, M., Rust, J., & Kogan, A. (2014). Who can wait for the future? A personality perspective. *Social Psychological and Personality Science*, 5(5), 573–583. <https://doi.org/10.1177/1948550613515007>
- Matthews, W. J. (2012). How much do incidental values affect the judgment of time? *Psychological Science*, 23, 1432–1434. <https://doi.org/10.1177/0956797612441609>
- Matthews, W.J., Gheorghiu, A.I., & Callan, M.J. (2016). Why do we overestimate others' willingness to pay? *Judgment and Decision Making*, 11(1), 21–39.
- Mishra, S., & Carleton, N. (2015). Subjective relative deprivation is associated with poorer physical and mental health. *Social Science and Medicine*, 147, 144–149. <https://doi.org/10.1016/j.socscimed.2015.10.030>
- Myerson, J., & Green, L., (1995). Discounting of delayed rewards: models of individual choice. *Journal of the Experimental Analysis of Behavior*, 64, 263–276. <https://doi.org/10.1901/jeab.1995.64--263>
- Parker, R. N., & Fenwick, R. (1983). The Pareto curve and its utility for open-ended income distributions in survey research. *Social Forces*, 61(3), 872–885.
- Pleskac, T. J., & Hertwig, R. (2014). Ecologically rational choice and the structure of the environment. *Journal of Experimental Psychology: General*, 143(5), 2000–2019. <https://doi.org/10.1037/xge0000013>
- R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Version 4.0.3. <https://www.R-project.org/>
- Reimers, S., Maylor, E. A., Stewart, N., & Chater, N. (2009). Associations between a one-shot delay discounting measure and age, income, education and real-world impulsive behavior. *Personality and Individual Differences*, 47(8), 973–978. <https://doi.org/10.1016/j.paid.2009.07.026>
- Revelle, W. (2020). psych: Procedures for personality and psychological research. R package version 2.0.12. <https://CRAN.R-project.org/package=psych>
- Signorell, A. et al. (2021). DescTools: Tools for descriptive statistics. R package version 0.99.40. <https://cran.r-project.org/package=DescTools>
- Skylark, W.J., & Baron-Cohen, S. (2017). Initial evidence that non-clinical autistic traits are associated with lower income. *Molecular Autism*, 8, 61, 1–11. <https://doi.org/10.1186/s13229-017-0179-z>
- Skylark, W.J., Chan, K.T.F., Farmer, G.D., Gaskin, K.W., & Miller, A.R. (2020). The delay-reward heuristic: What do people expect in intertemporal choice tasks? *Judgment and Decision Making*, 15(5), 611–629
- Skylark, W.J., Farmer, G.D., & Bahemia, N. (2021). Inference and preference in intertemporal choice. *Judgment and Decision Making*, 15(5), 611–629

- ment and Decision Making*, 16(2), 422–459.
- Skylark, W. J., & Prabhu-Naik, S. (2018). A new test of the risk-reward heuristic. *Judgment and Decision Making*, 13, 73–78.
- Smith, H.J., Pettigrew, T.F., Pippin, G.M., & Bialosiewicz, S. (2012). Relative deprivation: A theoretical and meta-analytic review. *Personality and Social Psychology Review*, 16(3), 203–232. <https://doi.org/10.1177/1088868311430825>
- Smith, H.J., Ryan, D.A., Jaurique, A., & Duffau, E. (2020). Personal relative deprivation and mental health among university students: Cross-sectional and longitudinal evidence. *Analyses of Social Issues and Public Policy*, 20(1), 287–314. <https://doi.org/10.1111/asap.12201>
- Welte, J.W., Barnes, G.M., Wierczorek, W.F., Tidwell, M-C., & Parker, J. (2002). Gambling participation in the U.S. – Results from a national survey. *Journal of Gambling Studies*, 18, 313–337.