NeuroImage 185 (2019) 236–244

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Time ambiguity during intertemporal decision-making is aversive, impacting choice and neural value coding

Iris Ikink [a,b,*], Jan B. Engelmann [c], Wouter van den Bos [d,e], Karin Roelofs [a,b], Bernd Figner [a,b,**]

[a] Behavioural Science Institute, Radboud University Nijmegen, the Netherlands
[b] Donders Institute for Brain, Cognition and Behaviour, Radboud University Nijmegen, the Netherlands
[c] University of Amsterdam, Amsterdam School of Economics (CREED) and Tinbergen Institute, Amsterdam, the Netherlands
[d] Center for Adaptive Rationality, Max Planck Institute for Human Development, Berlin, Germany
[e] University of Amsterdam, Department of Developmental Psychology, Amsterdam, the Netherlands

ARTICLE INFO

Keywords:
Ambiguity
Intertemporal choice
Decision-making
fMRI
Modeling

ABSTRACT

We are often presented with choices that differ in their more immediate versus future consequences. Interestingly, in everyday-life, ambiguity about the exact timing of such consequences frequently occurs, yet it remains unknown whether and how time-ambiguity influences decisions and their underlying neural correlates. We developed a novel intertemporal fMRI choice task in which participants make choices between sooner-smaller (SS) versus later-larger (LL) monetary rewards with systematically varying levels of time-ambiguity. Across trials, delay information of the SS, the LL, or both rewards was either exact (e.g., in 5 weeks), of low ambiguity (4 week range: e.g., in 3–7 weeks), or of high ambiguity (8 week range: e.g., in 1–9 weeks). Choice behavior showed that the majority of participants preferred options with exact delays over those with ambiguous delays, indicating time-ambiguity *aversion*. Consistent with these results, the ventromedial prefrontal cortex showed *decreased* activation during ambiguous versus exact trials. In contrast, intraparietal sulcus activation *increased* during ambiguous versus exact trials. Furthermore, exploratory analyses suggest that more time-ambiguity averse participants show more insula and dorsolateral prefrontal cortex activation during subjective value (SV)-coding of ambiguous versus exact trials. Lastly, the best-fitting computational choice models indicate that ambiguity impacts the SV of options via time perception or via an additive ambiguity-related penalty term. Together, these results provide the first behavioral and neural signatures of time-ambiguity, pointing towards a unique profile that is distinct from impatience. Since time-ambiguity is ubiquitous in real-life, it likely contributes to shortsighted decisions above and beyond delay-discounting.

1. Introduction

In everyday life, decision-makers are often presented with choices that differ in their more immediate versus future consequences. For instance, would you prefer to have a relatively well-paying teaching job now, or continue your research in a less well-paying post-doc position so you can earn more money later? These types of choices present a trade-off between sooner-smaller (SS) versus later-larger (LL) rewards, with decision-makers trading off anticipated benefits and/or costs of outcomes that occur at different points in time (Kalenscher and Pennartz, 2008; Scheres et al., 2013). Over the past decades, these choices have been studied successfully using intertemporal choice tasks, which ask participants to choose between two amounts, each delivered at an exact time point (e.g., €10 today vs. €15 in four weeks). It is relevant to advance insight into the involved decision processes, as impatient choices in such tasks have been linked to problematic health and social outcomes, as well as clinical conditions associated with impulsivity (see e.g., Reynolds, 2006; Yoon et al., 2007; Mischel et al., 2011; Reimers et al., 2009; Scheres et al., 2010).

Despite the success of these experimental paradigms, they have overlooked one key feature until now: Real-life intertemporal choices are rarely precise in the timing of their outcomes. Instead, they are typically more or less ambiguous in terms of when a specific outcome would be obtained. For example, we know that investment in our careers may pay-off at some point in the future, but we do not know when exactly. Furthermore, some real-life intertemporal choices lack a discrete

* Corresponding author. Montessorilaan 3, 6525, HR, Nijmegen, the Netherlands.
** Corresponding author. Montessorilaan 3, 6525, HR, Nijmegen, the Netherlands.
E-mail addresses: i.ikink@donders.ru.nl (I. Ikink), b.figner@psych.ru.nl (B. Figner).

https://doi.org/10.1016/j.neuroimage.2018.10.008
Received 20 April 2018; Received in revised form 1 September 2018; Accepted 4 October 2018
Available online 5 October 2018
1053-8119/© 2018 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

moment of realization altogether (such as when considering the long-term benefits of eating healthy, or saving for retirement). The term ambiguity refers to a situation where a certain relevant choice characteristic is partly or completely unknown (Ellsberg, 1961), such as—in this case—the precise waiting time. To the best of our knowledge, no study to date has directly investigated how *time-ambiguity* influences intertemporal decisions and the underlying neural processes.

In contrast, in the probability domain, ambiguity about probabilities is well known to affect choice. Here, participants are typically asked to choose between a safe option (e.g., €10 for sure) and a gamble. This type of choices is called 'risky choices'. In a typical study investigating probability-ambiguity, participants might encounter two kinds of gambles, related to two different forms of uncertainty: When the probability of winning the gamble is known to participants (e.g., €15 with 50% chance), we speak of risk, whereas when this probability is unknown or only partly known (e.g., €15 with 20–80% chance) we speak of (probability-) ambiguity (Knight, 1921; Huettel et al., 2006). Thus, both risk and probability-ambiguity entail uncertainty about the outcome, but under risk the decision-maker can make an informed decision (having all relevant information), while under ambiguity the decision-maker misses some relevant information (Tymula et al., 2012).

Perhaps not too surprising, people typically show probability-ambiguity aversion, preferring certain options and options with known probabilities to options with unknown or partly unknown probabilities (see, e.g., Ellsberg, 1961; Kahneman and Tversky, 1979). Ambiguity preferences in the probability domain cannot be explained by risk preferences, as the two are often found to be uncorrelated (Cohen et al., 1985; Di Mauro and Maffioletti, 2004; van den Bos and Hertwig, 2017, but see Chakravarty and Roy, 2009) and have an at least partly distinct neural signature: A meta-analysis by Krain et al. (2006) identified *increased* dorsolateral prefrontal cortex (dlPFC) and posterior parietal cortex (PPC) activation under probability-ambiguity compared to risk, both key nodes of the central executive control network (Seeley et al., 2007). Possibly, the evaluation of ambiguous (compared to risky) choice options requires more executive control (Platt and Huettel, 2008). Krain et al.'s meta-analysis further identified *decreased* activation in the orbitofrontal cortex (OFC) during probability-ambiguity compared to risk. The OFC is commonly implicated in subjective value (SV) coding (Peters and Büchel, 2010; Sescousse et al., 2013), thus likely representing the decrease in SV under ambiguity. Finally, Krain et al.'s meta-analysis identified largely overlapping frontal and parietal activations for probability-ambiguity and risk. Similarly, Levy et al. (2009) found a common system to encode SV under probability-ambiguity and risk, making it plausible that we also find shared neural substrates across time-ambiguous and time-exact trials.

Using research on probability-ambiguity as starting point, we developed a novel intertemporal choice task that systematically varied time-ambiguity across trials. On each trial, one or both of the presented options had an exact (e.g., 5 weeks from now) or ambiguous (e.g., 1–9 weeks from now) outcome timing (see Fig. 1). The level of time-ambiguity was 4 or 8 weeks, added to the SS, the LL, or both options. To gain further insight in how time-ambiguity impacts choice, we estimated and formally compared different computational models and measured neural signals using fMRI while participants made intertemporal choices in the presence and absence of varying levels of time-ambiguity.

Based on work in the probability domain, we expected ambiguity-*aversion* in the domain of intertemporal decisions. Specifically, we expected participants to prefer options with exact delays over those offering ambiguous delays, and stronger time-ambiguity aversion for the larger (8 weeks) compared to the smaller (4 weeks) level of time-ambiguity. At the neural level, we assumed that time-exact and time-ambiguous intertemporal choices likely share computational substrates. Accordingly, we expected to find partly overlapping activations in frontal and parietal regions (see Bartra et al., 2013; McClure et al., 2004). Importantly, given the possible greater need of executive control processes for decisions involving ambiguity (Platt and Huettel, 2008), we expected *increased* activation in the dlPFC and PPC during time-ambiguous relative to standard intertemporal decisions, whereas regions encoding SV (in intertemporal choice: ventromedial prefrontal cortex (vmPFC), posterior cingulate cortex (PCC), and ventral striatum (vStr); see Kable and Glimcher, 2007; Bartra et al., 2013) were expected to show *decreased* activation under time-ambiguity, reflecting the value-reduction. Lastly, studies in the probability-domain found that individual differences in ambiguity and risk preferences were associated with brain activity in SV, executive control, and salience regions (respectively, the OFC, dlPFC, and amygdala; Huettel et al., 2006; Hsu et al., 2005; Blankenstein et al., 2017). Accordingly, we expected individual differences in time-ambiguity preferences to be associated with brain activations in at least some of these regions (i.e., more time-ambiguity averse participants might show stronger decreases in SV-regions and stronger increases in executive control and salience regions during time-ambiguous compared to time-exact trials).

2. Materials and methods

2.1. Participants

Thirty right-handed males participated after providing informed written consent. All participants had normal or corrected-to-normal vision, no MRI contra-indications, and no history of brain surgery, as indicated by self-report. Of the 30 participants, two were excluded because they showed minimal variation in choices (0 and 3 LL choices, respectively). Four more were excluded because our behavioral modeling

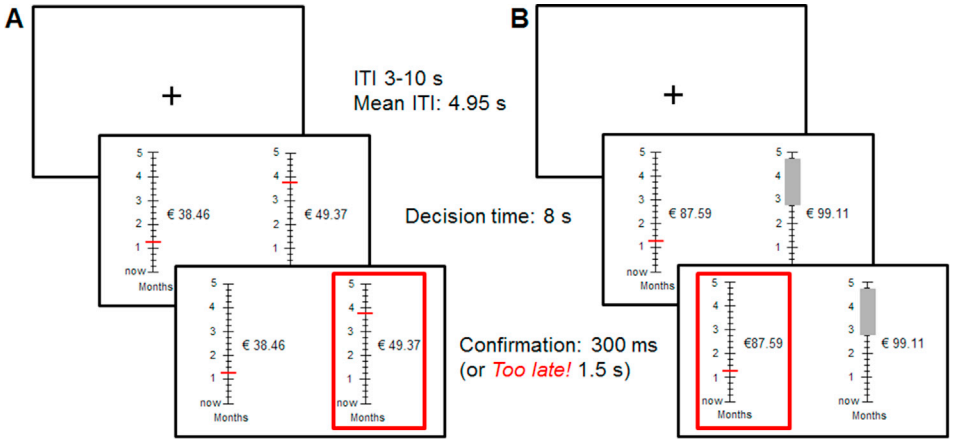

Fig. 1. The fMRI task. Participants first saw a fixation cross, and then the choice options were presented during which they had maximally 8 s to indicate their choice. In each trial, there was either no time-ambiguity (panel A), a time-exact SS and a time-ambiguous LL (panel B), a time-ambiguous SS and a time-exact LL, or both a time-ambiguous SS and a time-ambiguous LL. Time ambiguity was either 4 or 8 weeks. After choosing an option, participants received visual confirmation of their choice. If participants did not respond within the predefined period of 8 s, the message "*Too late*!" was displayed for 1.5 s and the trial was counted as a miss. Following the feedback, the next trial would start. Position of the SS and LL (left/right) was randomized across trials.

(details below) indicated that we could not predict their choices significantly above chance level in the fMRI task. Thus, the final sample included 24 males (18–34 years, $M_{age} = 23.83$).

Participants could choose to receive a flat-rate payment or course-credits for participation. To make the fMRI task incentive-compatible, participants were informed that they had a 10% chance that one of their choices would be randomly selected (a payout scheme as recommended by Charness et al., 2016) and the chosen option would be paid out for real via bank transfer (time-exact option: on the indicated day; time-ambiguous option: on a random time point within the specified time-range).

2.2. Behavioral measures

Participants completed the Monetary Choice Questionnaire (MCQ; Kirby et al., 1999) and an adaptive delay discounting task (ADDT; adjusted from Luo et al., 2009) before they went into the scanner. This was done to create two individualized indifference pairs between *time-exact* SS and LL options for the fMRI task (details in supplementary materials (SM) Appendix A). We used individualized indifference pairs—with non-ambiguous SS and LL options having equal subjective value—to maximize our design's power to detect time-ambiguity effects. That is, adding time-ambiguity to an option should have more impact on choices if both exact options have equal value, compared to when participants would prefer one exact option to the other. On average, our approach resulted in participants having a slight preference for LL rewards during exact fMRI trials ($M_{p(LLchoice)} = .58$; $p = .0002$; binomial test). However, across participants there was some variation (Q1 = .443; Q2 = .643; Q3 = .784), with several participants still showing a preference for the SS or LL choice option. Since we assume that ambiguity will affect choices most when the participant would be relatively indifferent between the respective options without ambiguity, we think that the true ambiguity effect might be underestimated for such participants. After the scanning session, participants completed a 36-item standard intertemporal choice task with time-exact SS and LL rewards (see Figner et al., 2010) to generate more trials for the modeling procedure.

2.3. fMRI task

The novel fMRI task[1] was programmed with Presentation® software (Neurobehavioral Systems, Inc., Berkeley, CA). Each trial showed a left and right option with a timeline ranging from now to five months (Fig. 1). SS and LL magnitudes were constructed based on the two estimated indifference pairs from the pre-scanning tests, with amounts jittered by up to ± €2 to create some variation across trials. Participants were informed that exact delivery times of the SS and LL were always specified by a red stripe on the timeline (for SS: 5 weeks from now, for LL: 15 weeks from now), but that in some trials (the ambiguous trials) exact delivery times were hidden behind a box, thereby creating a range of possible delivery times (design inspired by Levy et al., 2009). The range of time-ambiguity was 4 or 8 weeks.

Midpoints of the delivery times were always the same (5 weeks for the SS; 15 weeks for the LL). Thus, time-ambiguity on the SS resulted in an ambiguous SS in 3–7 weeks (low ambiguity level) or 1–9 weeks (high ambiguity level), and a time-ambiguous LL became 13–17 weeks or 11–19 weeks, respectively. Because of these equal midpoints, time-ambiguity neutral participants should treat time-ambiguous and exact trials the same, assuming that ambiguous delays have on average a delivery time around the midpoint of any given time range (this is somewhat of a simplification; see SM Figure A for more details). However, if participants are time-ambiguity averse or -seeking, exact and ambiguous trials should be treated differently.

We additionally included 44 *matched-ambiguity trials*, in which both options had identical amounts and midpoints, but one option had an exact delivery time (e.g., €41.71 in 15 weeks), and the other option an ambiguous delivery time (e.g., €41.71 in 13–17 weeks; SM Figure B). We originally included these trials to get a clear neural ambiguity signal, given that the other factors (amount, average time-of-delivery) remained identical within a trial. However, behavioral analyses showed that participants chose mostly ambiguity aversely during these trials, with little to no variation in choices and significantly reduced response times compared to all other trials. Although a preference for the unambiguous option was expected, the extreme choice proportions and fast RTs gave the trials limited use for imaging analyses and we therefore did not further use them in our analyses (more details in SM Appendix B).

Altogether, the task consisted of 22 time-exact trials, 132 time-ambiguous trials (22 × 3 (time-ambiguity type: on SS, LL, or both) x 2 (time-ambiguity level: 4 or 8 weeks)), and 44 matched-ambiguity trials, presented in four runs. On average, participants missed 1.33 trials (SD = 2.96; with 32 missed trials in total; 0.67%), and mean RT was 2709 ms ($SD = 1355$ ms). RTs did not significantly differ between exact and ambiguous trials ($M_{Ex} = 2663$ ms, $SD_{Ex} = 701$ ms, $M_{Amb} = 2724$ ms, $SD_{Amb} = 688$ ms, paired *t*-test, $p = .218$).

2.4. Behavioral analyses

Choice data were analyzed with a generalized linear mixed-effects model approach in R (R Core Team, 2013) using the *mixed* function of the package afex (Singmann et al., 2017), which calls the *glmer* function of the lme4 package (Bates et al., 2015). The dependent variable was choice (SS or LL) on each trial. We used a maximal random-effects structure with a participant-specific random intercept, random slopes for all within-subject predictors of interest, and correlations among all random effects (Barr et al., 2013). *P* values were determined using Likelihood Ratio Tests (Barr et al., 2013), as implemented in afex' *mixed* function. Continuous predictors were standardized and categorical predictors were sum-to-zero coded.

2.5. Behavioral modeling

To explore how time-ambiguity might influence SV-computations, we developed several novel discounting model candidates. Specifically, we built on the standard hyperbolic discounting model (Mazur, 1987):

$$SV = \frac{OV}{1 + k^{*}D} \quad (1)$$

where *SV* is subjective value, *OV* is objective monetary amount, *k* is discount rate, and *D* is delay. The parameter *k* quantifies the level of discounting, with $k = 0$ indicating no delay discounting and higher values indicating steeper discounting (impatience). We implemented a logistic choice rule that assumes that the probability of choosing the LL-option ($Pr_{LLchoice}$) is a function of the options' SV-difference:

$$Pr\ LLchoice = \frac{1}{1 + e^{-\theta^{*}(SVLL - SVSS)}} \quad (2)$$

where θ is a parameter that accounts for choice stochasticity. Higher values of θ indicate greater consistency (i.e., less noise) in participants' choices.

In total, we generated and tested 16 different computational models that describe how time-ambiguity preferences might influence choice via the value function (Eq. (1)), the choice rule (Eq. (2)), or both. We had three main types of models: Ambiguity influencing SV via (i) influencing how the time of delivery is estimated, (ii) an additive ambiguity bonus or penalty, or (iii) ambiguity influencing the noise term in the choice rule. Appendix C in the SM provides more details on the different models; Table A in the SM states all formulas and model-fits. The modeling results indicated that the two best-fitting models showed a comparably good fit to the behavioral data (as indicated by the two lowest BIC values; see

[1] The design of the task was piloted behaviorally beforehand.

Table 1
Overview of the 2 best-fitting models and the standard hyperbolic discounting model in terms of mean BIC (lower values indicate better fit) and mean Accuracy (proportion accurately predicted choices in the fMRI task; higher values indicate better fit), with $N = 24$.

	BIC	Accuracy
Additive model	226.9248	.8155
Time perception model	227.1083	.8197
Standard discounting model	236.7281	.7906

Table 1); thus we report results for both. Both models incorporate two separate time-ambiguity preference parameters, namely β_{SV} and β_{noise}, affecting the value function and choice rule, respectively.

In model 1, the *time perception model*, time-ambiguity influences SV by influencing the perception of delay D:

$$\text{SV (time perception model)} = \frac{\text{OV}}{1 + \text{k} * (\text{D} + \beta\text{sv} * \text{A})} \quad (3)$$

where β_{SV} is the time-ambiguity preference and A the time-ambiguity level (0 for exact trials). D was the midpoint of ambiguous delays, thus β_{SV}-values of 0 indicate ambiguity neutrality, β_{SV}-values > 0 indicate ambiguity aversion (i.e., subjective delays longer than the delay midpoint), and β_{SV}-values < 0 indicate ambiguity seeking (i.e., subjective delays shorter than the delay midpoint). Mean β_{SV} was significantly above 0, indicating time-ambiguity aversion ($p = .007$ with $M = 0.353$; one-sample Wilcoxon-test).

In model 2, the *additive model*, time-ambiguity influences SV via a component that is added to the hyperbolically discounted value (i.e., a bonus or penalty, depending on whether the participant is ambiguity-seeking or -averse):

$$\text{SV (additive model)} = \frac{\text{OV}}{1 + \text{k} * \text{D}} - \beta\text{sv} * \text{A} \quad (4)$$

Mean β_{SV} was again significantly higher than 0, indicating time-ambiguity aversion ($p = .015$ with $M = 8.312$; one-sample Wilcoxon-test).

The second time-ambiguity parameter, β_{noise}, was the same in both models: β_{noise} interacted with θ in the logistic choice function when time-ambiguity was present:

$$\Pr LLchoice = \frac{1}{1 + e^{-\theta * \beta noise * (SVLL - SVss)}} \quad (5)$$

Here, β_{noise}-values of 1 indicate neutrality (i.e., not affecting θ), whereas β_{noise}-values < 1 indicate that participants become less consistent (i.e., noisier) with time-ambiguity present, and β_{noise}-values > 1 indicate that participants become more consistent. Interestingly, mean β_{noise} was significantly higher than 1 in both models (time perception model: $p = .0002$ with $M_{\beta noise} = 2.392$; additive model: $p = .0004$ with $M_{\beta noise} = 2.448$; one-sample Wilcoxon-tests), indicating that time-ambiguity made participants less noisy. This is perhaps not too surprising given that we used indifference pairs: When adding ambiguity to one option, this might make choice easier (and thus less stochastic or noisy) as subjective values between the two options differ more compared to when both options are exact and of equal subjective value.

Interestingly, estimated discount rates k and β_{SV} parameters *within* each model showed quite some variability and were not significantly correlated ($r = -0.13$, $p = .554$ for the time perception model; $r = 0.20$, $p = .345$ for the additive model; Spearman rank-order correlations given the non-normal distributions. For other correlations between estimated parameters, see SM Appendix D and Table C). This suggests that there might be no strong association between participants' level of discounting and their time-ambiguity preference. Because these parameter estimates were both variable and uncorrelated, we decided to include them in the fMRI analysis. Most importantly, these models and estimated parameters enabled us to generate a SV-predictor for the fMRI models. At a more exploratory level, it allowed us to investigate brain-behavior associations with time-ambiguity and discounting preferences, and to further arbitrate between the models. For more details on and results of these exploratory analyses, see SM Appendix E, Figure C, and Tables D and E.

2.6. fMRI data acquisition

fMRI images were collected using a 1.5T Siemens Avanto MRI scanner with a 32-channel coil. Functional scans were acquired using a multi-echo GRAPPA MR sequence (TR = 2330 ms; TEs[5] = 9.3, 20.9, 33, 44, and 56 ms; flip angle = 90°; 37 transversal slices; 3×3x3mm voxels; FOV = 192 mm; Poser et al., 2006) in four separate runs. Before the first functional run, 30 volumes (prescans) were collected while participants viewed a countdown from 30 to 0 on the screen. After the functional runs, high-resolution structural T1-weighted images were acquired (TR = 2250 ms; TE: 2.95 ms; 176 sagittal slices, 1 × 1x1mm voxels, FoV = 256 mm).

2.7. fMRI preprocessing and analysis

Imaging data were pre-processed and analyzed using the Matlab toolbox SPM12 (Wellcome Department of Imaging Neuroscience, London, UK). We used a standard preprocessing approach (details in SM Appendix F). The fMRI time series of each participant were analyzed using an event-related approach in the context of the general linear model (GLM).

As regressors of interest we included exact trials (Ex), ambiguity on SS, ambiguity on LL, and ambiguity on both. The regressors were modeled using canonical hemodynamic response functions temporally aligned with the onset of the events of interest. To best capture the decision period, minimize distortions due to time on task effects, and implicitly account for choice latencies, we modeled decisions from trial onset until the button press indicating choice using a boxcar with length RT (variable epoch model; Grinband et al., 2006; Yarkoni et al., 2009). The fixation cross commencing each trial (displayed for three to 10 s, with $M_{ITI} = 4.95$s) served as jitter to dissociate trials and was not explicitly modeled, thus serving as null event per trial (176% of time relative to explicitly modeled decision events). Time and dispersion derivatives were added to account for subject-to-subject and voxel-to-voxel variation in response peak and dispersion (Henson et al., 2001). As parametric modulator we included the subjective value of the chosen option ($SV_{ChosenOption}$), calculated by transforming the objective value of the chosen option on each trial to the subjective value using participant-specific parameter estimates. We did this once for the time perception model and once for the additive model (SV-formulas (3) and (4), respectively), as these were our winning behavioral models. Thus, we ran two separate GLMs, the "time perception GLM" for the time perception model, and the "additive GLM" for the additive model, which differed in their $SV_{ChosenOption}$-values (as well as their individual k and β_{SV} covariate-values at the second level; see also below). In both models, separate regressors of no interest included trials in which no decision was recorded, feedback after each trial, matched-ambiguity trials (see SM Appendix B), as well as six movement parameters (estimated with the spatial realignment procedure) to account for residual head-movement related effects. Finally, the fMRI time series were high-pass filtered (cut-off 120 Hz).

When estimating contrasts of interest, we collapsed across the 3 separate ambiguity regressors (ambiguity on SS, LL, and both) to create an overall ambiguity contrast (Amb). We did this, as the behavioral results indicated no differences between ambiguity on SS, LL, and both, making us mainly interested in contrasting exact (Ex) versus ambiguous (Amb) trials. Contrast images of the effects of interest (Amb versus Ex; SV_{Amb} versus SV_{Ex}, the latter representing $SV_{ChosenOption}$ during ambiguous versus exact trials) were then generated per participant. Individual values of parameters k (discount rate) and β_{SV} (time-ambiguity preference) were included as covariates of interest at the second level

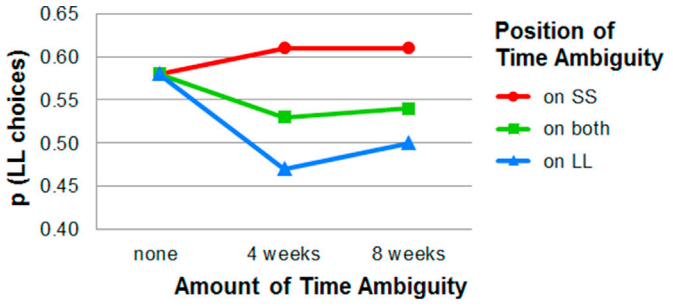

Fig. 2. Proportion of LL choices for each of the 7 different combinations of exact and ambiguous timing information of the SS and LL choice options.

(separately for the time perception and additive GLM). Using the grey matter mask from the tpm folder in SPM12 (with a cutoff of P > .15), we then carried out simple *t*-tests. Results were family-wise error (FWE) cluster-corrected ($p_{FWE} < .05$), with a primary voxel-wise threshold of $p < .001$. However, to not miss any possible relevant activation, we re-ran the analysis using a more liberal primary voxel-wise threshold of 0.005 instead of 0.001 (still with $p_{FWE} < .05$). We call these latter results exploratory. Furthermore, to check the robustness of any modulatory effects, we carried out Iteratively Reweighted Least Square (IRLS) robust regression analyses that reduce the influence of potential outliers (Wager et al., 2005).

3. Results

3.1. Behavior

First, we tested whether the presence versus absence of time-ambiguity on SS or LL options had an effect on choice. The dependent variable was choice (0 = SS; 1 = LL), and the predictors were time-ambiguity on the SS (yes (collapsed across 4 and 8 weeks)/no), time-ambiguity on the LL (yes (collapsed across 4 and 8 weeks)/no), reward magnitude (high/low; the 2 indifference pairs consisted of a fixed LL of €100 or €50, see also SM Appendix A), participants' mean *k*-value from the pre-scanner tasks (as indicator of participants' discounting steepness; continuous), all possible 2-way interactions with time-ambiguity on the SS or on the LL, as well as the 2-way interaction between time-ambiguity on the SS and on the LL. We added the *k*-value predictor (1) to control for individual differences in patience, and (2) to investigate whether more patient participants would be less affected by time-ambiguity. We added as control variables of no interest run number (continuous) and SS position on the screen (left/right).

Time-ambiguity on the LL was significant (χ (1) = 5.84, $p = .016$) and time-ambiguity on the SS showed a trend for significance (χ^2 (1) = 2.98, $p = .085$). As expected, presence of time-ambiguity on the LL decreased LL choice (i.e., the LL became less attractive; Fig. 2). Similarly, presence of time-ambiguity on the SS increased LL choice (i.e., the SS became less attractive) although only marginally significantly so. Both effects indicate that on average participants exhibited time-ambiguity aversion. The interaction between time-ambiguity on the SS and LL.was not significant ($p = .704$), thus the effect of ambiguity on one choice option did not differ dependent on whether the other choice option was ambiguous or not.

The effect of individuals' *k*-value was significant (χ^2 (1) = 4.86, $p = .028$): More impatient participants (higher *k*-values) chose the LL less often (confirming discount rates to be relevant, even in the context of using indifference pairs). Reward magnitude was not significant; neither were run number and SS-position (all *ps* > .37). None of the interactions were significant (all *ps* > .13)[2].

To test whether the level of time-ambiguity (4 or 8 weeks) mattered for choice, we constructed a separate model on a subset of the data (only ambiguous trials). We kept the same model structure in terms of factors and interactions, except that the two factors ambiguity on SS and on LL were replaced with (i) one factor coding whether ambiguity was on the SS, the LL, or both, and (ii) one factor coding for ambiguity level (4 weeks/8 weeks). These analyses revealed no main effect of ambiguity level ($p = .373$), but an interaction effect between time-ambiguity level and mean *k*-value (χ^2 (1) = 5.94, $p = .015$), indicating that more patient participants did not differentiate between 4 and 8 weeks of time-ambiguity, whereas impatient participants did. This seems consistent with the idea that more patient participants would be less affected by time-ambiguity, or in this case, the level of time-ambiguity. Furthermore, time-ambiguity effects on SS, LL, or both did not differ as a function of ambiguity level ($p = .634$). For a complete overview of these behavioral results, see SM Appendix G.

3.2. Neuroimaging results

The main goal of the neuroimaging analyses was to identify (1) common and (2) distinct neural substrates during trials with and without time-ambiguity. As the behavioral data provided almost identically good fits for two different computational value models, we ran and compared the results from two GLMs that were identical except that they differed in (a) how the parametric modulator $SV_{ChosenOption}$ was modeled (according to the time perception or additive model), and (b) the individually estimated time-ambiguity and discounting preferences per (time perception or additive) model, which were entered as covariates. This resulted in what we call the *time perception GLM* and the *additive GLM*, respectively. Both GLM results were mainly identical. Since the additive model provided a slightly better behavioral fit and showed more robust modulatory effects in our exploratory analyses, we report results of the additive model in the main text, while results of the time perception model are presented in SM Tables E, F I, and J.

3.2.1. General intertemporal choice-related (de-)activations in dlPFC, PCC, and vmPFC

Given that intertemporal choices with and without time-ambiguity likely share common neural substrates, we first tested which regions show choice-related activity in trials with and without time-ambiguity (i.e., identifying common neural substrates). Thus, we performed a conjunction analysis under the conjunction null hypothesis, requiring that all comparisons in the conjunction are individually significant (Nichols et al., 2005). This analysis revealed largely overlapping activations for both types of trials in regions previously implicated in intertemporal choice (Bartra et al., 2013; Kable and Glimcher, 2007; McClure et al., 2004): Shared increased activation was found in a large cluster consisting of occipital and parietal cortex, as well as bilateral dlPFC and inferior frontal gyrus (IFG). Shared decreases in activation were found in PCC, left vmPFC, anterior cingulate cortex (ACC), and bilateral temporal regions (Fig. 3; Table 2; for results of the time perception GLM, see SM Table F). All these regions are commonly implicated in executive control, salience processing, and valuation.

3.2.2. Ambiguity-specific modulation of choice-related neural activity in IPS and vmPFC

Next, we tested which brain regions showed differential activations as a function of the presence versus absence of time-ambiguity (i.e., identifying distinct neural substrates). The right intraparietal sulcus (IPS) showed significantly increased activation during time-ambiguous compared to time-exact trials (Fig. 4; Table 3). The IPS is part of the PPC, where increased activation for probability-ambiguous versus risky

[2] There was one marginally significant interaction, namely between time-ambiguity on the LL and reward magnitude (χ^2 (1) = 3.21, $p = .073$), such that the effect of time-ambiguity on the LL was bigger for small than large magnitudes, possibly related to the *magnitude effect* in intertemporal choice (Prelec and Loewenstein, 1991).

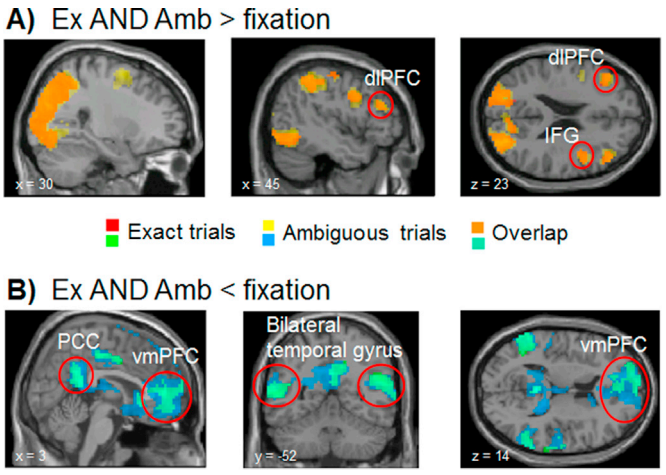

Fig. 3. (A) Activations and (B) deactivations common to intertemporal decisions involving time-exact and time-ambiguous choice options based on a conjunction analysis for the contrast [exact and ambiguous trials versus fixation]. Results were FWE cluster-corrected with a primary voxel-wise threshold of $p < .001$. Here neural responses for the additive GLM are shown; those of the time perception GLM were virtually identical.

Table 2
Results of the conjunction analysis, showing intertemporal choice-related activations and deactivations during time-exact and time-ambiguous trials for the additive GLM, thresholded at $p_{unc} < .001$. All these regions were also found in the time perception GLM.

Contrast / Brain region	$p_{FWE\text{-}cor.}$ cluster	MNI coordinates x	y	z	Peak *Z*-value	Cluster size
Ex AND Amb > fixation						
Occipital/parietal cortex	<.0001	15	−94	−1	7.42	4379
Cerebellum	.052	−3	−73	−25	5.45	47
SMA	.001	−3	8	53	5.21	109
R dlPFC	.01	48	38	17	5.12	70
L dlPFC	.038	−45	32	23	4.01	51
R IFG	.022	48	11	26	5.11	59
L IFG	.009	−45	5	35	4.76	72
Ex AND Amb < fixation						
L Middle/Superior TG	<.0001	−57	−61	8	5.40	212
R Middle/Superior TG	<.0001	51	−52	23	5.26	386
PCC	<.0001	3	−46	20	4.42	120
Dorsal PCC	.003	0	−25	47	4.74	88
L ACC/vmPFC/aPFC	<.0001	−24	44	35	4.60	523
L Superior TG	.001	−51	−34	20	5.06	103
R Somatosensory cortex	.014	21	−40	59	4.50	65
Posterior fronto-median cortex	.036	27	35	50	3.76	52

Abbreviations: Ex, exact trials; Amb, time-ambiguous trials; L, left; R, right; SMA, supplemental motor area; TG, temporal gyrus; aPFC, anterior prefrontal cortex.

choices (Krain et al., 2006) and uncertainty (Platt and Huettel, 2008) has been found. No significant deactivations were observed. To avoid missing any possible relevant (de)-activations we re-ran the model with a more liberal threshold (FWE-corrected clusters still at < 0.05, but a primary voxel-wise threshold of 0.005 instead of 0.001) and found significant decreased activation in the left vmPFC during time-ambiguous compared to time-exact trials (Fig. 4; Table 3). This exploratory result is consistent with the idea of reduced subjective value during time-ambiguous compared to time-exact trials.

3.2.3. Associations between time-ambiguity preferences and subjective-value coding in dlPFC and insula

Lastly, we tested whether SV-encoding of the chosen option might differ between time-exact versus time-ambiguous trials. We did not observe any significant differences in any region (also not with our exploratory threshold). This is consistent with results from Levy et al. (2009), who found no SV-differences during exact and probability-ambiguous risky gambles. However, in our exploratory brain-behavior analyses, we found that more ambiguity averse participants showed (among other regions) more activity in the right dlPFC and left insula during SV-encoding of the chosen option in ambiguous compared to exact trials. These modulations were found in the additive GLM but not the time perception GLM, and can thus be seen as tentative evidence differentiating between the two GLMs (details in SM Appendix E; Figure C and Tables D and E).

4. Discussion

The current study investigated what we call *time-ambiguity*: uncertainty about when an outcome will be received. Using a novel task paradigm that incorporates time-exact and time-ambiguous intertemporal choice trials, we found converging evidence for time-ambiguity aversion, reflected at the behavioral, computational, and neural level. We showed that (1) participants on average display time-ambiguity aversion, as they chose options with ambiguous delays less often compared to options with exact delays, (2) accounting for time-ambiguity improves computational choice models, and the estimated mean ambiguity parameter β_{SV} confirms that the subjective value of choice options decreases as a function of time-ambiguity, and (3), in addition to a shared general network consisting of vmPFC, PCC and dlPFC, time-ambiguity has unique neural correlates as evidenced by increased IPS and decreased vmPFC activation, as well as modulatory effects in dlPFC and insula (but note: the modulatory results should be treated as tentative).

Disliking, and thus avoiding or trying to minimize time-ambiguity is consistent with the more general literature on uncertainty (see e.g., Clark, 2013; van den Bos and Hertwig, 2017; Blankenstein et al., 2017). Within this literature, it is particularly relevant to compare our findings to those in risky choice, where people typically show probability-ambiguity aversion (Ellsberg, 1961; Kahneman and Tversky, 1979; Tymula et al., 2012). Consistent with findings in that field, we establish the existence of ambiguity aversion in the time domain. Interestingly, the time-ambiguity level (4 versus 8 weeks) did not matter in our study – or more precisely, it mattered only to impatient participants – whereas in risky choice research ambiguity-level effects are typically reported (Hsu et al., 2005; Tymula et al., 2012; van den Bos and Hertwig, 2017). Possibly, in the time domain purely the presence or absence of ambiguity matters and less so the extent; alternatively, however, our ambiguity levels may have been too similar. Regarding possible underlying mechanisms, the additive model slightly outperformed the time perception model, even though the latter is conceptually more similar to the commonly used probability-ambiguity model by Gilboa and Schmeidler (1989). This suggests that in probability-ambiguity research, it might also be interesting to investigate an additive model. Lastly, similar to risk and probability-ambiguity preferences being uncorrelated (Cohen et al., 1985; Di Mauro and Maffioletti, 2004; van den Bos and Hertwig, 2017), individuals' discount rate and time-ambiguity preference were uncorrelated in our sample, suggesting that delay discounting and time-ambiguity aversion might be distinct phenomena, reflecting different psychological mechanisms.

Such a dissociation would be an important result, because real-life intertemporal choices often have time-ambiguity, yet existing task paradigms have not incorporated it, to the best of our knowledge. Including time-ambiguity in intertemporal choice paradigms promises to give us better insights into real-world impatient, impulsive, and shortsighted choices and behaviors, and might also increase the ecological and predictive validity of these tasks. Furthermore, research and interventions

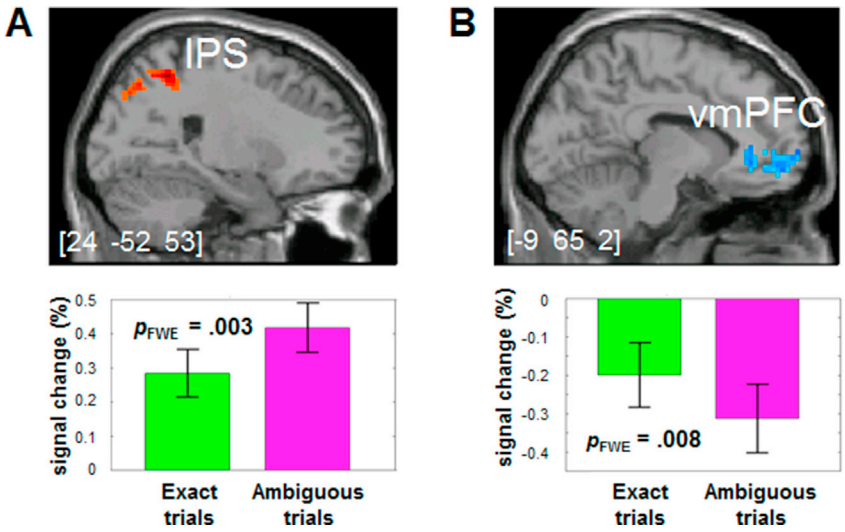

Fig. 4. Brain regions identified in the contrast [Amb versus Ex]. (A) Right IPS showed significantly increased activation during time-ambiguous compared to time-exact trials, while (B) left vmPFC showed significantly decreased activation. Both results were FWE cluster-corrected, but with a primary voxel-wise threshold of $p < .001$ for the IPS and $p < .005$ for the vmPFC. Neural responses for the additive GLM are shown; those of the time perception GLM were virtually identical.

Table 3
Significant results of the contrasts of interest for the additive GLM, thresholded at $p_{unc} < .005$. Both regions were also found in the time perception GLM.

Contrast / Brain region		$p_{FWE-cor.}$ cluster	MNI coordinates x	y	z	Peak Z-value	Cluster size
Amb > Ex							
R	Intraparietal sulcus*	<.0001	24	−52	53	4.48	341
Amb < Ex							
L	vmPFC	.008	−9	65	2	3.47	136

Note: * means this region was also significant with a primary voxel-wise threshold of $p < .001$. Abbreviations: Ex, exact trials; Amb, time-ambiguous trials; L, left; R, right.

on adolescent risk-taking and impulsivity, health behaviors, addictions, and disorders with an impulse-control component such as ADHD or gambling (van den Bos and Hertwig, 2017; Reynolds, 2006; Yoon et al., 2007; Mischel et al., 2011; Reimers et al., 2009; Scheres et al., 2010) might also benefit. Time-ambiguity is ubiquitous in real-life and likely contributes to shortsighted decisions beyond simple delay discounting. Thus, insight into alterations in time-ambiguity processing in addictions and impulsive disorders could provide starting points for better-tailored and more effective interventions.

Our approach to estimate and compare competing computational SV-models also led to several insights. First, including the level of time-ambiguity improved model-fit (compared to including only the presence/absence of ambiguity), even though time-ambiguity level did not show a significant main effect in the behavioral analysis. While future work should clarify this point, including ambiguity levels may have resulted in more variation in our (otherwise rather similar) SV-estimations and hence better model-fits. Second, time-ambiguity seems to influence the consistency of participants' choices, as both winning computational models include a time-ambiguity parameter that interacts with noise parameter θ (although the increased consistency may be related and/or specific to our use of indifference pairs). Finally, a single time-ambiguity parameter could capture time-ambiguity effects across different delay midpoints (models with separate ambiguity-parameters for SS and LL-rewards did not improve model-fit). This is similar to k being able to account for different delays, making β_{SV} a likewise generalizable parameter.

Although we could not clearly distinguish whether ambiguity influences SV via a simple penalty or via influencing time perception (though our exploratory neural results seem to suggest the former), one difference between the models is that in the additive model, the effect of time-ambiguity on SV is constant across all delays, whereas it is time-dependent in the time perception model (with less impact for longer delays). Thus, future research should try to differentiate the two models by creating trials for which the models generate differential predictions, e.g., by using a wider range of delay midpoints. Further, using trials with and without indifference pairs and more strongly varying time-ambiguity levels might clarify whether the increased consistency under ambiguous trials that we observed is due to our use of indifference pairs, and whether the sole presence versus absence or level of time-ambiguity influences choice, respectively.

With regard to the neural correlates, choice-related activation during both the absence and presence of time-ambiguity was found in a network of brain regions commonly associated with intertemporal choices and decision-making (Bartra et al., 2013; Kable and Glimcher, 2007; McClure et al., 2004). Importantly, IPS and vmPFC activation was specifically modulated by the presence versus absence of ambiguous choice options. The right IPS showed increased activation during trials with (compared to without) time-ambiguity, consistent with probability-ambiguity results from a meta-analysis (Krain et al., 2006). The increased IPS activation might reflect an increased demand for executive control processes to evaluate or resolve the uncertainty present in time-ambiguous trials (Platt and Huettel, 2008). The increased complexity of our computational choice models seems to converge with this interpretation; however we did not find longer response times for ambiguous trials. Further, we observed reduced vmPFC activation during ambiguous compared to exact trials. Although this result was obtained at an exploratory threshold, it nonetheless informs the potential neural effects of time-ambiguous decision contexts. The reduction in choice-related activity in vmPFC during ambiguous compared to exact trials could indicate different processes. First, it could reflect the on average lower SV during trials with ambiguous choice-options, given the well-documented role of the vmPFC in SV-computations (Bartra et al., 2013; Peters and Büchel, 2010) and the time-ambiguity aversion that participants generally showed. Potentially inconsistent with this explanation, however, is that we did not find ambiguity-related modulation of SV-tracking in this region. This might be related to our use of indifference pairs, which may have resulted in few value differences and, accordingly, little opportunity to track variations in SV. Second, the reduced vmPFC activation may

reflect difficulties in properly estimating SV in the absence of sufficient information, thereby leading to a reduction in activity combined with no evidence of value tracking in vmPFC under conditions of ambiguity. Third, given that ambiguity has been shown to trigger aversive affect in risky choice paradigms (Hsu et al., 2005) and given that our result is reminiscent of a recent study showing suppressed vmPFC activity and reduced value tracking under conditions of incidental negative affect (Engelmann et al., 2015), the current results could reflect the effects of negative affect in the presence of ambiguous outcomes. While we cannot empirically decide between these possible explanations, we currently favor the first explanation (i.e., the decrease in vmPFC activation under ambiguity represents the reduced SV of ambiguous choice-options), based on the consistent implication of the vmPFC in SV-coding (Levy and Glimcher, 2012; Bartra et al., 2013; Peters and Büchel, 2010). However, future research is required to disentangle the relative contributions of SV-coding and other cognitive and emotional mechanisms in the context of decisions involving time-ambiguity.

The absence of differential SV-correlates for exact and time-ambiguous trials is consistent with Levy et al.'s (2009) results in probability-ambiguity, suggesting a common system to encode SV under time-exact and time-ambiguous trials. This seems in line with the idea of a 'common currency' of SV under different conditions: Across multiple reward types – including delayed and probabilistic monetary rewards, but also across primary and social rewards – SV has been found to be represented in the vmPFC, OFC, and (v)Str (Levy and Glimcher, 2012; Peters and Büchel, 2009; Bartra et al., 2013). Alternatively (and as already mentioned), the absence of differential SV-correlates may be related to be our use of indifference pairs. Interestingly, both the SV— and choice-related activations for time-ambiguity seem to show some overlap with findings in probability-ambiguity. Thus, future research could perhaps investigate the similarities and differences in underlying neural mechanisms by directly comparing exact and ambiguous risky choices to exact and ambiguous intertemporal choices.

Lastly, we observed SV-modulations of neural activity as a function of individual ambiguity preferences in the additive GLM but not the time perception GLM. Thus, at the neural level, the additive model seems to outperform the time perception model (but note that these results should be treated as tentative and interpreted with caution given our rather small sample size): More ambiguity-averse participants showed more activation in, e.g., the insula and dlPFC during SV-encoding of ambiguous compared to exact trials, as if SV-encoding during ambiguous trials became more salient (insula; Uddin, 2015) and required more executive control (dlPFC; Platt and Huettel, 2008; Niendam et al., 2012).

While future work needs to establish whether these results are reliable, it is tempting to point out that they are somewhat similar to findings in risky choice research, where activation in the dlPFC and amygdala, the latter another salience region, was modulated by risk and probability-ambiguity preferences (Hsu et al., 2005; Huettel et al., 2006; Blankenstein et al., 2017). Thus, one speculative interpretation of these results is that resolving ambiguity might occur at an executive control level and that the decision maker's ambiguity preference influences how much relevance and executive control processes are allocated to resolve the ambiguity. If so, this might explain why individual differences in ambiguity preferences are less apparent in valuation regions, as these regions might reflect the resulting computed SV more so than the actual computations (and individual differences therein) that lead to this value.

Some interpretational issues should be discussed. First, we used indifference pairs: While we deliberatively did this to maximize power to detect time-ambiguity effects, it also restricted SV-variation and thus complicated the computational modeling and SV-analysis. Future work might benefit from using a wider range of different stimuli to increase variation in SV. Second, future studies should increase the variation in time-ambiguity levels, to shed light on whether purely the presence/absence of time-ambiguity matters or whether there might be a more gradual dose-response relationship of time-ambiguity effects on SV and choice. Third, we had many more time-ambiguous than time-exact trials. Although this was on purpose (having more variation in both the amount of time-ambiguity and on which option, with the possibility to investigate each level separately), we ultimately decided to collapse across these ambiguity levels based on the behavioral results. Future studies should try to incorporate more similar numbers of trials, and perhaps rather use parametric modulators to systematically vary time-ambiguity. Finally, our most important constraint is our limited sample size. Future studies should increase sample size and attempt to replicate these findings, both at the behavioral and neural level. After all, the current study was essentially a first foray to reveal whether time-ambiguity aversion exists at all and how this might be implemented psychologically and in the brain. We hope that it inspires future research into what we think is a promising and relevant topic.

To conclude, the current study established the existence of ambiguity aversion in the time domain. To our knowledge, this is the first study to have demonstrated this phenomenon at a behavioral, computational, and neural level. We show that time-ambiguity has a neurobehavioral signature distinct from that of impatience and, until now, appears to have been overlooked.

Declarations of interest

None.

Authors' contributions

II, BF, and KR designed research. II performed research. II, BF, JBE, and WvdB analyzed data. II, BF, KR, JBE, and WvdB wrote the paper. All authors approved the final version of the manuscript for submission.

Funding

KR was supported by a starting grant from the European Research Council (grant agreement no. 313749) and a VICI grant (#453-12-001) from the Netherlands Organisation for Scientific Research. JBE gratefully acknowledges support from the Radboud Excellence Foundation.

Acknowledgements

We would particularly like to thank Shan Luo, John Monterosso, and Eustace Hsu for their support and the sharing of their scripts with us. Furthermore, we would like to thank our lab groups (D^2P^2, EPAN) for their valuable feedback on the first drafts of this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2018.10.008.

References

Barr, D.J., Levy, R., Scheepers, C., Tily, H.J., 2013. Random effects structure for confirmatory hypothesis testing: Keep it maximal. J. Mem. Lang. 68, 255–278. https://doi.org/10.1016/j.jml.2012.11.001.

Bartra, O., McGuire, J.T., Kable, J.W., 2013. The valuation system: a coordinate- based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. Neuroimage 76, 412–427. https://dx.doi.org/10.1016/j.neuroimage.2013.02.063.

Bates, D., Maechler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Software 67, 1–48. https://doi.org/10.18637/jss.v067.i01.

Blankenstein, N.E., Peper, J.S., Crone, E.A., van Duijvenvoorde, A.C.K., 2017. Neural mechanisms underlying risk and ambiguity attitudes. J. Cognit. Neurosci. 29, 1845–1859. https://doi.org/10.1162/jocn_a_01162.

Chakravarty, S., Roy, J., 2009. Recursive expected utility and the separation of attitudes towards risk and ambiguity: an experimental study. Theor. Decis. 66, 199–228. https://doi.org/10.1007/s11238-008-9112-4.

Charness, G., Gneezy, U., Halladay, B., 2016. Experimental methods: pay one or pay all. J. Econ. Behav. Organ. 131, 141–150. https://doi.org/10.1016/j.jebo.2016.08.010.

Clark, A., 2013. Whatever next? Predictive brains, situated agents, and the future of cognitive science. Behav. Brain Sci. 36, 181–204. https://doi.org/10.1017/S0140525X12000477.
Cohen, M., Jaffray, J.Y., Said, T., 1985. Individual behavior under risk and under uncertainty: an experimental study. Theor. Decis. 18, 203–228. https://link.springer.com/content/pdf/10.1007/BF00134074.pdf.
Di Mauro, C., Maffioletti, A., 2004. Attitudes to risk and attitudes to uncertainty: experimental evidence. Appl. Econ. 36, 357–372. https://doi.org/10.1080/00036840410001674286.
Ellsberg, D., 1961. Risk, ambiguity, and the Savage axioms. Q. J. Econ. 75, 643–669. https://teaching.ust.hk/~bee/papers/Chew/1961-Ellsberg-Ambiguity.pdf.
Engelmann, J.B., Meyer, F., Fehr, E., Ruff, C.C., 2015. Anticipatory anxiety disrupts neural valuation during risky choice. J. Neurosci. 35, 3085–3099. https://doi.org/10.1523/JNEUROSCI.2880-14.2015.
Figner, B., Knoch, D., Johnson, E.J., Krosch, A.R., Lisanby, S.H., Fehr, E., Weber, E.U., 2010. Lateral prefrontal cortex and self-control in intertemporal choice. Nat. Neurosci. 13, 538–539. https://doi.org/10.1038/nn.2516.
Gilboa, I., Schmeidler, D., 1989. Maxmin expected utility with non-unique prior. J. Math. Econ. 18, 141–153. https://doi.org/10.1016/0304-4068(89)90018-9.
Grinband, J., Wager, T., Lindquist, M., Ferrera, V.P., Hirsch, J., 2006. Modelling reaction times in event-related fMRI designs. In: Organisation for Human Brain Mapping. http://www.stat.columbia.edu/~martin/Posters/grinband_HBM06.pdf.
Henson, R., Rugg, M.D., Friston, K.J., 2001. The choice of basis functions in event- related fMRI. Neuroimage 13, 149-149. https://www.fil.ion.ucl.ac.uk/spm/data/face_rfx/pdf/hbm-fir.pdf.
Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., Camerer, C.F., 2005. Neural systems responding to degrees of uncertainty in human decision-making. Science 310, 1680–1683. https://doi.org/10.1126/science.1115327.
Huettel, S.A., Stowe, C.J., Gordon, E.M., Warner, B.T., Platt, M.L., 2006. Neural signatures of economic preferences for risk and ambiguity. Neuron 49, 765–775. https://doi.org/10.1016/j.neuron.2006.01.024.
Kable, J.W., Glimcher, P.W., 2007. The neural correlates of subjective value during intertemporal choice. Nat. Neurosci. 10, 1625–1633. https://doi.org/10.1038/nn2007.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica: Journal of the Econometric Society 47, 263–291. https://doi.org/10.2307/1914185.
Kalenscher, T., Pennartz, C.M., 2008. Is a bird in the hand worth two in the future? The neuroeconomics of intertemporal decision-making. Prog. Neurobiol. 84, 284–315. https://doi.org/10.1016/j.pneurobio.2007.11.004.
Kirby, K.N., Petry, N.M., Bickel, W.K., 1999. Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. J. Exp. Psychol. Gen. 128, 78–87. https://doi.org/10.1037/0096-3445.128.1.78.
Knight, F.H., 1921. Risk, Uncertainty and Profit. Hart, Schaffner and Marx, New York.
Krain, A.L., Wilson, A.M., Arbuckle, R., Castellanos, F.X., Milham, M.P., 2006. Distinct neural mechanisms of risk and ambiguity: a meta-analysis of decisionmaking. Neuroimage 32, 477–484. https://doi.org/10.1016/j.neuroimage.2006.02.047.
Levy, D.J., Glimcher, P.W., 2012. The root of all value: a neural common currency for choice. Curr. Opin. Neurobiol. 22, 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001.
Levy, I., Snell, J., Nelson, A.J., Rustichini, A., Glimcher, P.W., 2009. Neural representation of subjective value under risk and ambiguity. J. Neurophysiol. 103, 1036–1047. https://doi.org/10.1152/jn.00853.2009.
Luo, S., Ainslie, G., Giragosian, L., Monterosso, J.R., 2009. Behavioral and neural evidence of incentive bias for immediate rewards relative to preference-matched delayed rewards. J. Neurosci. 29, 14820–14827. https://doi.org/10.1523/JNEUROSCI.4261-09.2009.
McClure, S.M., Laibson, D.I., Loewenstein, G., Cohen, J.D., 2004. Separate neural systems value immediate and delayed monetary rewards. Science 306, 503–507. https://doi.org/10.1126/science.1100907.
Mazur, J.E., 1987. An adjusting procedure for studying delayed reinforcement. In: Commons, M.L., Mazur, J.E., Nevin, J.A., Rachlin, H. (Eds.), Quantitative Analysis of Behavior: Vol. 5. The Effect of Delay and Intervening Events on Reinforcement Value. Erlbaum, Hillsdale, NJ, pp. 55–73.
Mischel, W., Ayduk, O., Berman, M.G., Casey, B.J., Gotlib, I.H., Jonides, J., Shoda, Y., 2011. 'Willpower' over the life span: decomposing self-regulation. Soc. Cognit. Affect Neurosci. 6, 252–256. https://doi.org/10.1093/scan/nsq081.
Nichols, T., Brett, M., Andersson, J., Wager, T., Poline, J., 2005. Valid conjunction Inference with the minimum statistic. Neuroimage 25, 653–660. https://doi.org/10.1016/j.neuroimage.2004.12.005.
Niendam, T.A., Laird, A.R., Ray, K.L., Dean, Y.M., Glahn, D.C., Carter, C., 2012. Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. Cognit. Affect Behav. Neurosci. 12, 241–268. https://doi.org/10.3758/s13415-011-0083-5.
Peters, J., Büchel, C., 2009. Overlapping and distinct neural systems code for subjective value during intertemporal and risky decision making. J. Neurosci. 29, 15727–15734. https://doi.org/10.1523/JNEUROSCI.3489-09.2009.
Peters, J., Büchel, C., 2010. Neural representations of subjective reward value. Behav. Brain Res. 213, 135–141. https://doi.org/10.1016/j.bbr.2010.04.031.
Platt, M.L., Huettel, S.A., 2008. Risky business: the neuroeconomics of decision making under uncertainty. Nat. Neurosci. 11, 398–403. https://doi.org/10.1038/nn2062.
Poser, B.A., Versluis, M.J., Hoogduin, J.M., Norris, D.G., 2006. BOLD contrast sensitivity enhancement and artifact reduction with multiecho EPI: parallel-acquired inhomogeneity-desensitized fMRI. Magn. Reson. Med. 55, 1227–1235. https://doi.org/10.1002/mrm.20900.
Prelec, D., Loewenstein, G., 1991. Decision making over time and under uncertainty: a common approach. Manag. Sci. 37, 770–786. https://doi.org/10.1287/mnsc.37.7.770.
R Core Team, 2013. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. 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. Pers. Indiv. Differ. 47, 973–978. https://doi.org/10.1016/j.paid.2009.07.026.
Reynolds, B., 2006. A review of delay discounting research with humans: relations to drug use and gambling. Behav. Pharmacol. 17, 651–667. https://doi.org/10.1097/FBP.0b013e3280115f99.
Scheres, A., de Water, E., Mies, G.W., 2013. The neural correlates of temporal reward discounting. Wiley Interdisciplinary Reviews: Cognit. Sci. 4, 523–545. https://doi.org/10.1002/wcs.1246.
Scheres, A., Tontsch, C., Thoeny, A.L., Kaczkurkin, A., 2010. Temporal reward discounting in attention-deficit/hyperactivity disorder: the contribution of symptom domains, reward magnitude, and session length. Biol. Psychiatry 67, 641–648. https://doi.org/10.1016/j.biopsych.2009.10.033.
Seeley, W.W., Menon, V., Schatzberg, A.F., Keller, J., Glover, G.H., Kenna, H., Greicius, M.D., 2007. Dissociable intrinsic connectivity networks for salience processing and executive control. J. Neurosci. 27, 2349–2356. https://doi.org/10.1523/JNEUROSCI.5587-06.2007.
Sescousse, G., Caldú, X., Segura, B., Dreher, J.C., 2013. Processing of primary and secondary rewards: a quantitative meta-analysis and review of human functional neuroimaging studies. Neurosci. Biobehav. Rev. 37, 681–696. https://doi.org/10.1016/j.neubiorev.2013.02.002.
Singmann, H., Bolker, B., Westfall, J., Aust, F., 2017. Afex: Analysis of Factorial Experiments. R Package Version 0.18-0. https://CRAN.R-project.org/package=afex.
Tymula, A., Belmaker, L.A.R., Roy, A.K., Ruderman, L., Manson, K., Glimcher, P.W., Levy, I., 2012. Adolescents' risk-taking behavior is driven by tolerance to ambiguity. Proc. Natl. Acad. Sci. Unit. States Am. 109, 17135–17140. https://doi.org/10.1073/pnas.1207144109.
Uddin, L.Q., 2015. Salience processing and insular cortical function and dysfunction. Nat. Rev. Neurosci. 16, 55–61. https://doi.org/10.1038/nrn3857.
van den Bos, W., Hertwig, R., 2017. Adolescents display distinctive tolerance to ambiguity and to uncertainty during risky decision making. Sci. Rep. 7, 40962. https://doi.org/10.1038/srep40962.
Wager, T.D., Keller, M.C., Lacey, S.C., Jonides, J., 2005. Increased sensitivity in neuroimaging analyses using robust regression. Neuroimage 26, 99–113. https://doi.org/10.1016/j.neuroimage.2005.01.011.
Yarkoni, T., Barch, D.M., Gray, J.R., Conturo, T.E., Braver, T.S., 2009. BOLD correlates of trial-by-trial reaction time variability in gray and white matter: a multi-study fMRI analysis. PloS One 4. https://doi.org/10.1371/journal.pone.0004257 e4257.
Yoon, J.H., Higgins, S.T., Heil, S.H., Sugarbaker, R.J., Thomas, C.S., Badger, G.J., 2007. Delay discounting predicts postpartum relapse to cigarette smoking among pregnant women. Exp. Clin. Psychopharmacol 15, 176–186. https://doi.org/10.1037/1064-1297.15.