NeuroImage 81 (2013) 431–440

Contents lists available at SciVerse ScienceDirect

NeuroImage

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

Distinct encoding of risk and value in economic choice between multiple risky options☆

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ARTICLE INFO

Article history:
Accepted 3 May 2013
Available online 16 May 2013

Keywords:
Risk
Loss
fMRI
Approach–avoidance

ABSTRACT

Neural encoding of value-based stimuli is suggested to involve representations of summary statistics, including risk and expected value (EV). A more complex, but ecologically more common, context is when multiple risky options are evaluated together. However, it is unknown whether encoding related to option evaluation in these situations involves similar principles. Here we employed fMRI during a task that parametrically manipulated EV and risk in two simultaneously presented lotteries, both of which contained either gains or losses. We found representations of EV in medial prefrontal cortex and anterior insula, an encoding that was dependent on which option was chosen (i.e. chosen and unchosen EV) and whether the choice was over gains or losses. Parietal activity reflected whether the riskier or surer option was selected, whilst activity in a network of regions that also included parietal cortex reflected both combined risk and difference in risk for the two options. Our findings provide support for the idea that summary statistics underpin a representation of value-based stimuli, and further that these summary statistics undergo distinct forms of encoding.

Introduction

Decision-makers frequently have to choose between multiple risky options. For example, animals have to choose between foraging in higher or lower risk patches, or humans whether to invest in higher or lower risk stocks. Such value-based decision-making can be considered within a biologically-grounded, process-based account where a choice evolves from option-evaluation through to action-selection (Corrado et al., 2009). Regarding option-evaluation, recent studies examining the neural basis of risky economic choice have suggested two competing accounts, one that involves a neural representation of outcome distributions by "summary statistics", such as expected value (EV) and risk (Bossaerts, 2010; Preuschoff et al., 2006; Wright et al., 2012), and another in which subjective value (SV) is determined by the shape of a utility function, with risk-preference emerging as a by-product of that shape (Rangel et al., 2008). Here we seek new evidence for encoding of "summary statistics", specifically investigating the unknown question of how the summary statistics of multiple, simultaneously evaluated, risky options may be encoded.

We used a task where each trial subject was simultaneously presented with two risky options, one of which had to be selected. Risk is defined here as outcome variance (Bossaerts, 2010). Unlike in a single option, with multiple options there are different ways in which EV and risk may be represented. For both risk and EV we ask whether encoding depends on which option is chosen (i.e. chosen and unchosen EVs; chosen and unchosen risks) or alternatively whether encoding is determined directly by the presented stimuli (e.g. sum or difference in EV or risks). Furthermore, as choices are influenced by whether potential outcomes entail gains or losses (i.e. their valence) (Kahneman and Tversky, 1979) we also asked whether outcome valence differentially affects encoding of EV and risk.

However, even if option-evaluation involved such summary statistics, this does not address how risk, EV or valence influence action-selection. Thus, as a second aim we investigated the choice process from the perspective of a choice architecture in which multiple interacting systems influence action-selection (Dayan, 2008). In model-based systems, stimulus features such as EV, risk or valence may be incorporated within a unified subjective value (SV; utility) computed for each option and where action-selection involves choosing the option with the highest SV. Neurally, we test for encoding of SV. In contrast, in model-free systems that invoke approach–avoidance processes, a key feature is a contingency between stimulus properties and responsive action (i.e. to approach appetitive and to avoid aversive stimulus properties). For both risk and valence we previously found neural and reaction time (RT) data reflecting such contingencies in a task where choices involved a single risky option (Wright et al., 2012), and here asked whether these would be similarly expressed with multiple risky options. A further possibility, in line with choice resulting from multiple interacting systems, would be evidence relating to both: with model-based summary

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http://dx.doi.org/10.1016/j.neuroimage.2013.05.023

statistic encoding that may influence action-selection through comparator processes and/or approach–avoidance; as well as approach–avoidance to stimulus properties such as valence not requiring model-based processing.

Here we examined the neural basis of risky choice in a task where each trial subjects had to select between two simultaneously presented risky options. Regarding option-evaluation, we hypothesised that there would be encoding of summary statistics representing these options; and were agnostic as to whether these would depend on which option is chosen, or alternatively whether encoding is determined directly by the presented stimuli. Regarding action-selection, we tested for evidence of unified SVs in addition to summary statistics, and for contingencies consistent with approach–avoidance processes.

Methods

Participants

All participants, recruited through institutional mailing lists, were healthy and provided informed consent. 25 right-handed participants took part (age mean 24 years, range 19–36; 15 male), with one further participant excluded due to artefacts during fMRI data acquisition. None had taken part in our previous experiments with related tasks (Wright et al., 2012). The University College London Ethics Committee approved the study.

Task

The Selection task (Fig. 1) was identical to that used behaviourally in Wright et al. (2012) except that all amounts were doubled for fMRI scanning. There were 200 trials presented in a random order, of which 100 were "gain trials" (all possible outcomes ≥ 0) and 100 were "loss trials" (all outcomes ≤ 0). In each trial, individuals evaluated two lotteries and selected between them. Each trial began with a fixation cross presented for 1–2 s (mean 1.5 s), followed by viewing the options for 4020 ms; and finally a black square appeared to indicate participants had 1500 ms to input their choice by button press (the black square turned white when they chose). If participants did not respond, they received £0 on a "gain trial" and the maximum loss possible on a "loss trial" (£-24).

Our decision-variables of interest were EV, risk and valence. We generated a set of 100 "gain trials" (Fig. 1b and see below), in which we parametrically and orthogonally manipulated the difference in risk (10 levels of variance) and EV (10 levels) between two lotteries (each with two possible outcomes, all ≥ 0), giving five levels of absolute difference for risk and EV (these absolute differences henceforth denoted by ΔVar and ΔEV). To manipulate valence, we simply multiplied all amounts by -1 to give 100 "loss trials". This created a set of "gain trials" and a set of "loss trials" that were perfectly matched in their parametric modulations of risk and EV.

Participants began the day with an endowment of £24. After the experiment, one "gain trial" and one "loss trial" were picked at random and their outcomes were added to the endowment to determine final participant payment. Participants could receive between £0–48. There was a low proportion of non-responses (4% ± s.d. 3% of trials). The mean payment received was £23 (range £4–£42).

Stimulus set

We used the same set of 100 "gain trials" as in Wright et al. (2012) but with all amounts doubled (Fig. 1b). We created this stimulus set in two stages. First, we generated a list of every possible trial within the following constraints: each trial consisted of two pie charts each with two segments; outcomes were between £0 and £24; the smallest allowable probability was 0.1; and the smallest allowable probability increment was 0.05. Second, from within this very large number of potential trials, we selected our set of 100 trials that were the closest match to our desired levels of difference in Var and EV between stimuli. The difference in EV and variance between the options was up to a maximum ΔEV of 3.8 and maximum ΔVar of 73.

For a given lottery with N potential outcomes ($m_1, m_2, \ldots m_N$), with probabilities $p = p_1, p_2, \ldots p_N$, we define the EV and variance (Var) of the outcome distribution as follows:

$$\mathrm{EV} = \sum_{n=1}^{N} m_n p_n \tag{1}$$

$$\mathrm{Var} = \sum_{n=1}^{N} (m_n - \mathrm{EV})^2 p_n. \tag{2}$$

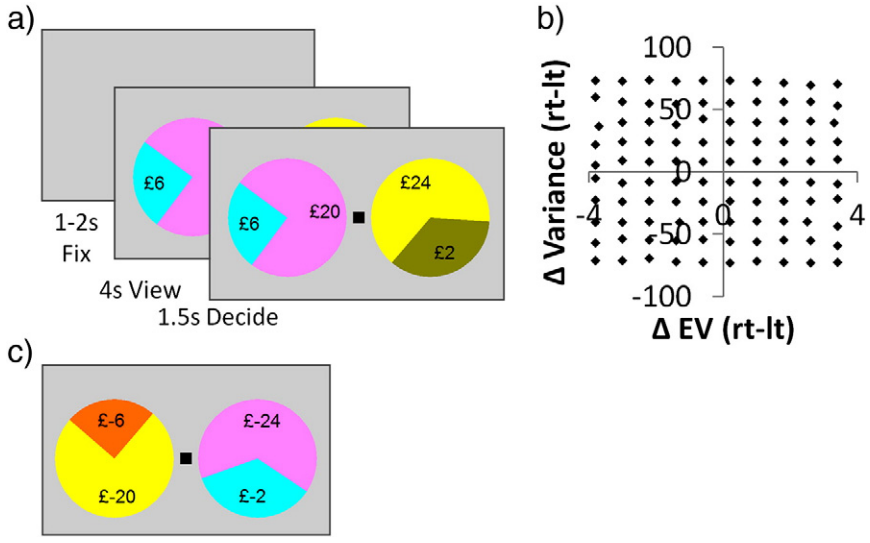

Fig. 1. Manipulating risk, expected value and valence. a) In each "gain trial" individuals were presented with two lotteries (each with 2 possible outcomes, both ≥ 0) to consider and select between. They viewed the options for 4 s, after which a black square appeared centrally and they had 1.5 s to input their choice by left or right button press. b) We created set of 100 "gain trials" in which we parametrically and orthogonally manipulated the difference in risk (defined as outcome variance; 10 levels) and EV (10 levels) between the lotteries (i.e. five levels of absolute difference for risk and EV, with these absolute differences used in our analyses). For illustration here we plot each metric for the right minus the left lottery (rt–lt). c) Multiplying all "gain trial" amounts by -1 gave 100 "loss trials" with identical parametric manipulations. All 200 trials were presented in random order.