Hvidovre Hospital

DANISH RESEARCH CENTRE FOR MAGNETIC RESONANCE

UNIVERSITY OF COPENHAGEN
FACULTY OF HEALTH AND MEDICAL SCIENCES

Neural correlates of optimal risk-taking

Simon R. Steinkamp[1], Benjamin Skjold[1,2], Maria E.C. van der Weij[1], Colm Connaughton [2,3], Ole Peters[2,4] & Oliver J. Hulme[1,2,5]

simons@drcmr.dk

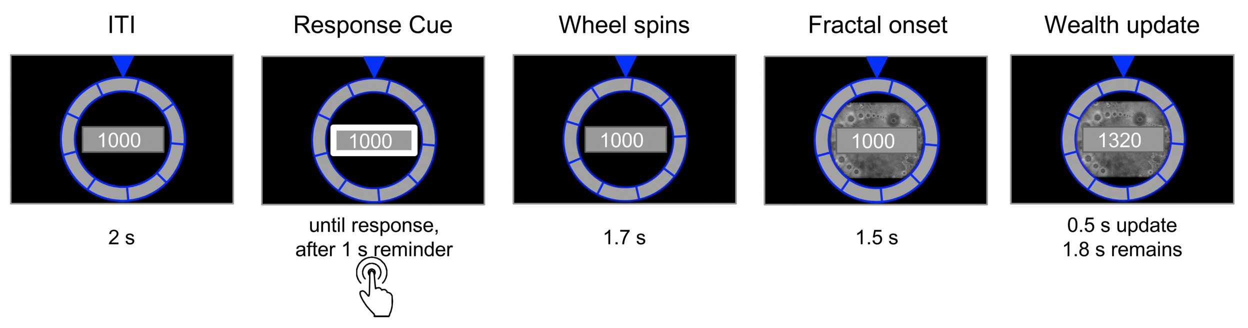
[1] Danish Research Centre for Magnetic Resonance, Copenhagen University Hospital - Amager and Hvidovre, Copenhagen, Denmark — [2] London Mathematical Laboratory, London, United Kingdom — [3] Warwick Mathematics Institute and Center for Complexity Science, University of Warwick, Coventry, United Kingdom —[4] Santa Fe Institute, Santa Fe, USA — [5] Department of Psychology, University of Copenhagen, Copenhagen, Denmark

Study

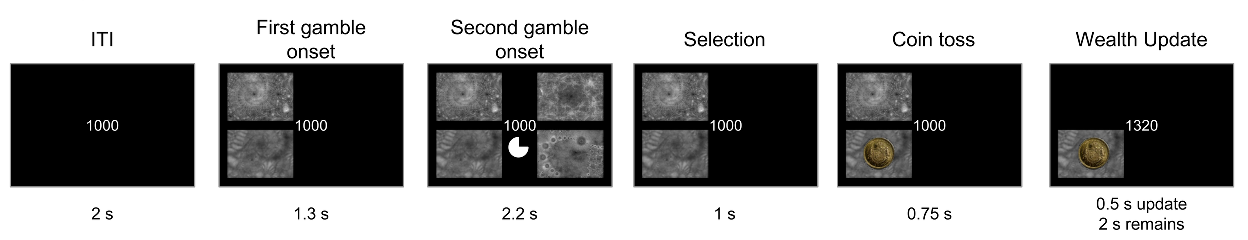
Do participants adapt their risk taking behavior to the environment?
Risk-taking behavior sometimes is seen as stable almost trait like within an individual. We here challenge that assumption showing — and replicating earlier results (Meder et al., 2021; Skjold et al., 2024) — that participants adopt their risk-preferences to the dynamics of the environment.
What drives participants' behavior?
With some individual variation, participants adopt their risk-taking behavior to the dynamics. Furthermore, they behave close to optimally maximizing the growth of their scores over time (Peters, 2019), by applying the appropriate transformation to (expected) changes in their scores.
How does the brain respond?
We can show that the brain encodes changes in the participant's score. The results indicate, that the encoding is in line with parameters of the correct transformation, mirroring the behavioral results.

Task

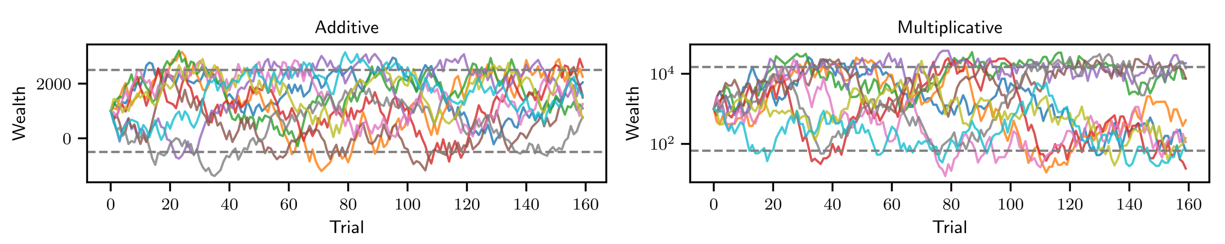
Participants (final $n = 32$) performed a consequential decision task in the scanner on two days. Each day was a different dynamic (i.e., additive or multiplicative changes to an endowed score). First, participants learned the value of nine fractal images in a learning task and then proceeded with the decision task.
Learning task: Participants learn the value of the images and are exposed to the dynamic in a conditioning task.



Decision task: Participants decide between two gambles. Each decision affects their score immediately afterward (160 trials).



Wealth dynamics: Example trajectories of scores experienced by ten participants during the experiment.



Rationale

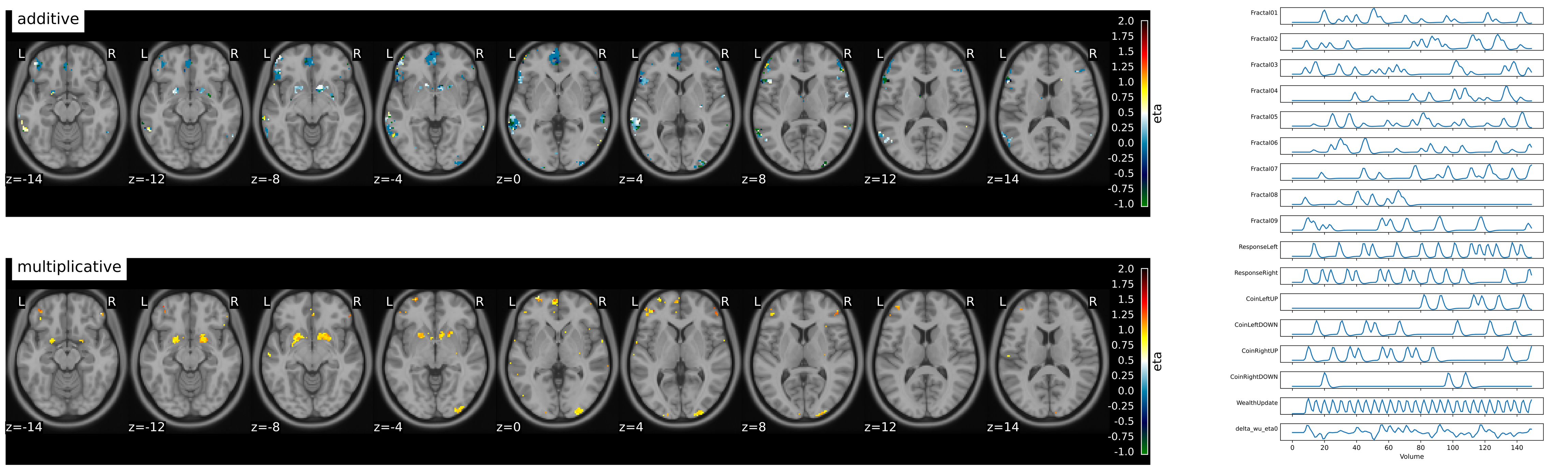
Optimal behavior in this task requires that participants apply a transformation to their expected wealth ($f_\eta(x_{t+1}) - f_\eta(x_t)$) changes. We can estimate the transformation used by the participant, by approximating the parameter η of the isoelastic utility function, that best describes behavior.

$$f_\eta(x) = \begin{cases} \frac{x^{1-\eta}-1}{1-\eta} & \text{for} \quad \eta \neq 1 \\ \ln x & \text{for} \quad \eta = 1. \end{cases}$$

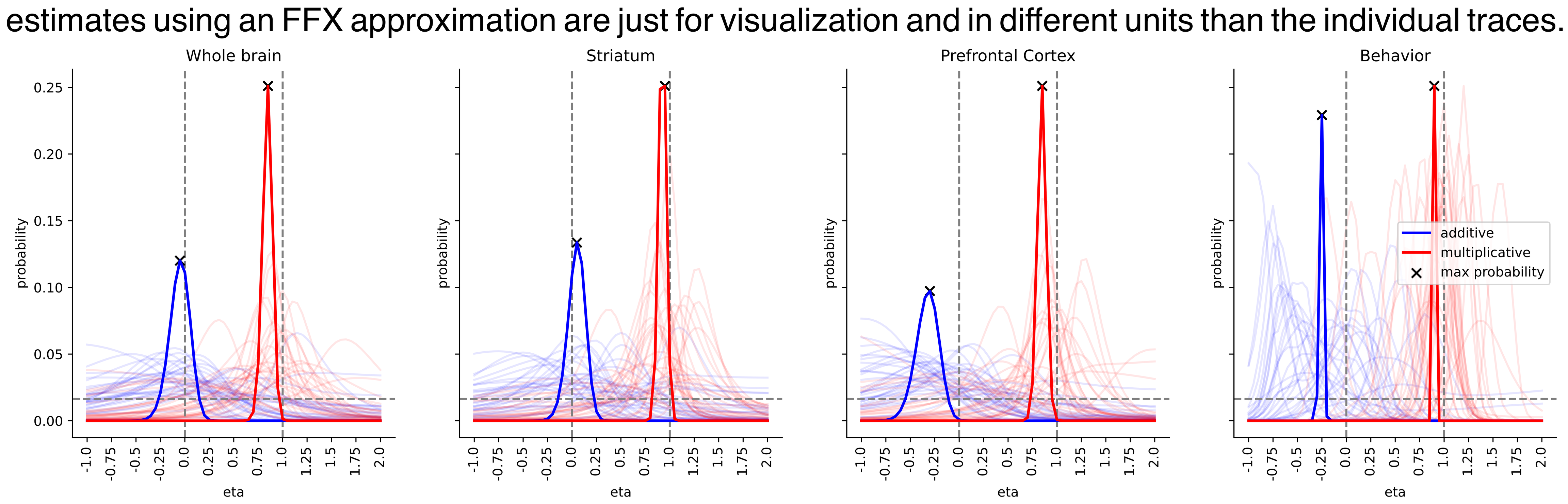
$\eta = 0$ indicates risk neutrality and is the optimal strategy in the additive setting. $\eta = 1$ indicates risk aversion and is the optimal strategy in the multiplicative setting.

Results

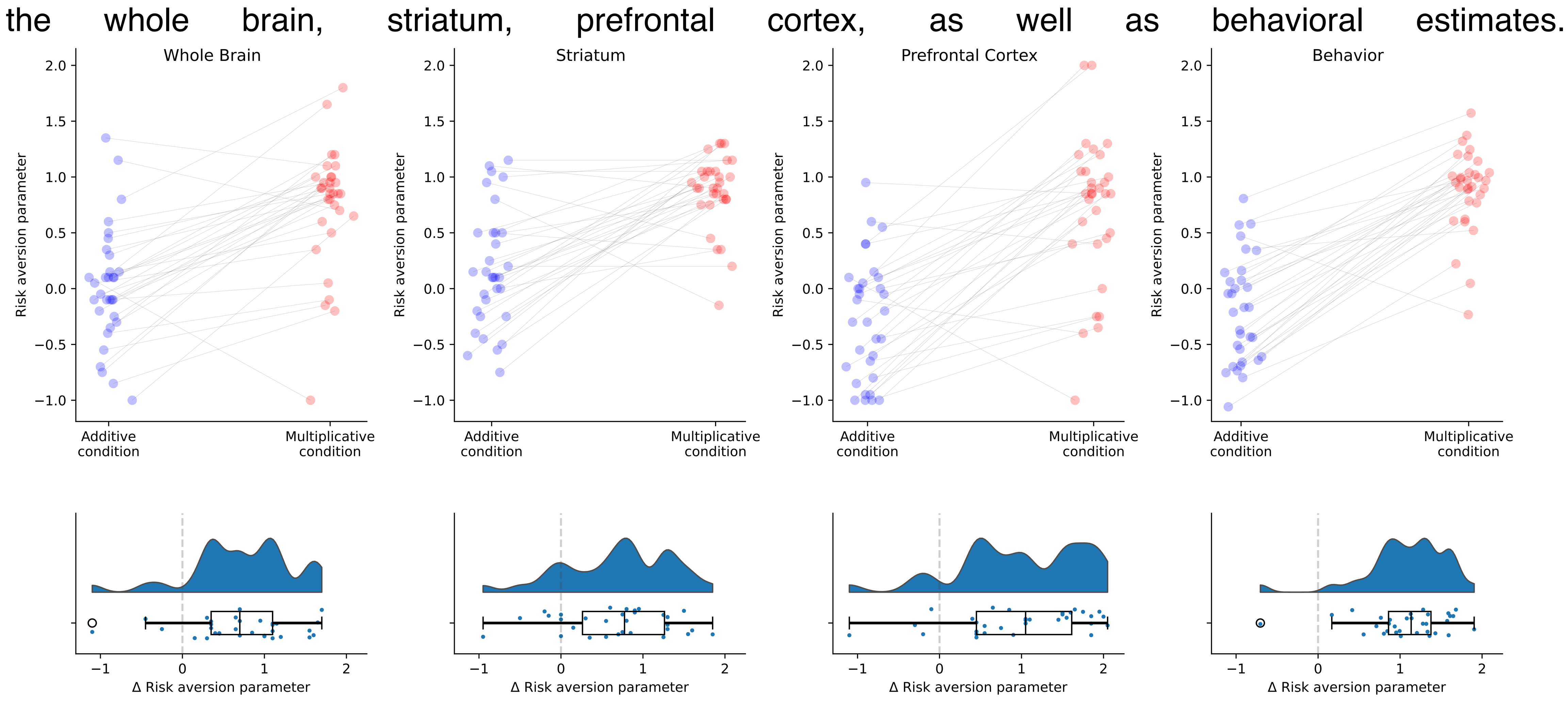
Neuroimaging group results: For the neuroimaging data of the decision task we created for each participant and session 61 design matrices (DM, right) spanning η values from $[-2.0, 1.0]$ in steps of 0.05, as well as a null model that did not include a modulated regressor. We used the MACS toolbox (Soch et al., 2016; Soch and Allefeld, 2018) to calculate the cvLME. Group results were thresholded using BMS comparing a family of modulated DMs against the null model and display η based on the highest group RFX exceedance probability.



Parameter estimates - participant level: We applied the same voxel-wise thresholding on the participant level and estimated the FFX exceedance probability over voxels for each region of interest and session. For the behavior, data was estimated using a Gaussian KDE over the posterior trace samples of a Bayesian model as described in Skjold et al. (2024). For visualization, estimates were applied to a discretized grid. Group estimates using an FFX approximation are just for visualization and in different units than the individual traces.



Region-wise shifts η**:** Pairwise plots of participant level η estimates for the whole brain, striatum, prefrontal cortex, as well as behavioral estimates.



Take away

Estimates of risk-preferences independently modeled using neural behavioral data show the same directional shift: Becoming more risk-averse in the multiplicative session compared to the additive session.

Neural correlates of these estimates have the highest model evidence — compared against a null model — in regions classically associated with reward (vmPFC and striatum).

Participants learn stable wealth and time invariant representations of the fractals, allowing them to perform near optimally, maximizing the growth rate of their score over time.

Acknowledgements

The group's work was funded by a Novo Nordisk Foundation Exploratory Interdisciplinary Synergy grant (ref NNF20OC0064869) awarded to OH and OP. SRS was additionally funded by the Lundbeck Foundation postdoc grant (ref R402-2022-1411).

References

David Meder, Finn Rabe, Tobias Morville, Kristoffer H. Madsen, Magnus T. Koudahl, Ray J. Dolan, Hartwig R. Siebner, and Oliver J. Hulme. Ergodicity-breaking reveals time optimal decision making in humans. *PLOS Computational Biology*, 17(9): e1009217, September 2021. ISSN 1553-7358. doi: 10.1371/journal.pcbi.1009217.

Benjamin Skjold, Simon Steinkamp, Colm Connaughton, Oliver J. Hulme, and Ole Peters. Ergodicity transformations predict human decision-making under risk. May 2024. doi: 10.31219/osf.io/c96yd.

Ole Peters. The ergodicity problem in economics. *Nature Physics*, 15(12):1216–1221, December 2019. ISSN 1745-2473, 1745-2481. doi: 10.1038/s41567-019-0732-0.

Joram Soch, John-Dylan Haynes, and Carsten Allefeld. How to avoid mismodelling in GLM-based fMRI data analysis: Cross-validated Bayesian model selection. *NeuroImage*, 141:469–489, November 2016. ISSN 1053-8119. doi: 10.1016/j.neuroimage.2016.07.047.

Joram Soch and Carsten Allefeld. MACS – a new SPM toolbox for model assessment, comparison and selection. *Journal of Neuroscience Methods*, 306:19–31, August 2018. ISSN 01650270. doi: 10.1016/j.jneumeth.2018.05.017.