



# Reward-based Decision Making

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## Approach

- Decision making involves strategies to obtain desired outcomes.
- When descriptions of the available options are at hand, these can be used to guide a decision.
- In the absence of such descriptions, people have to learn and base their decisions on experience.
- We investigate learning and decision making processes by:
  - Developing models and algorithms describing these processes.
  - Investigating the neural representation of (latent) learning and decision parameters.
  - Determining the relationship of model parameters and dopaminergic neuromodulation, as influenced e.g. by genetic polymorphisms like the COMT Val<sup>158</sup>Met polymorphism.

## The bright side of Val

### Background

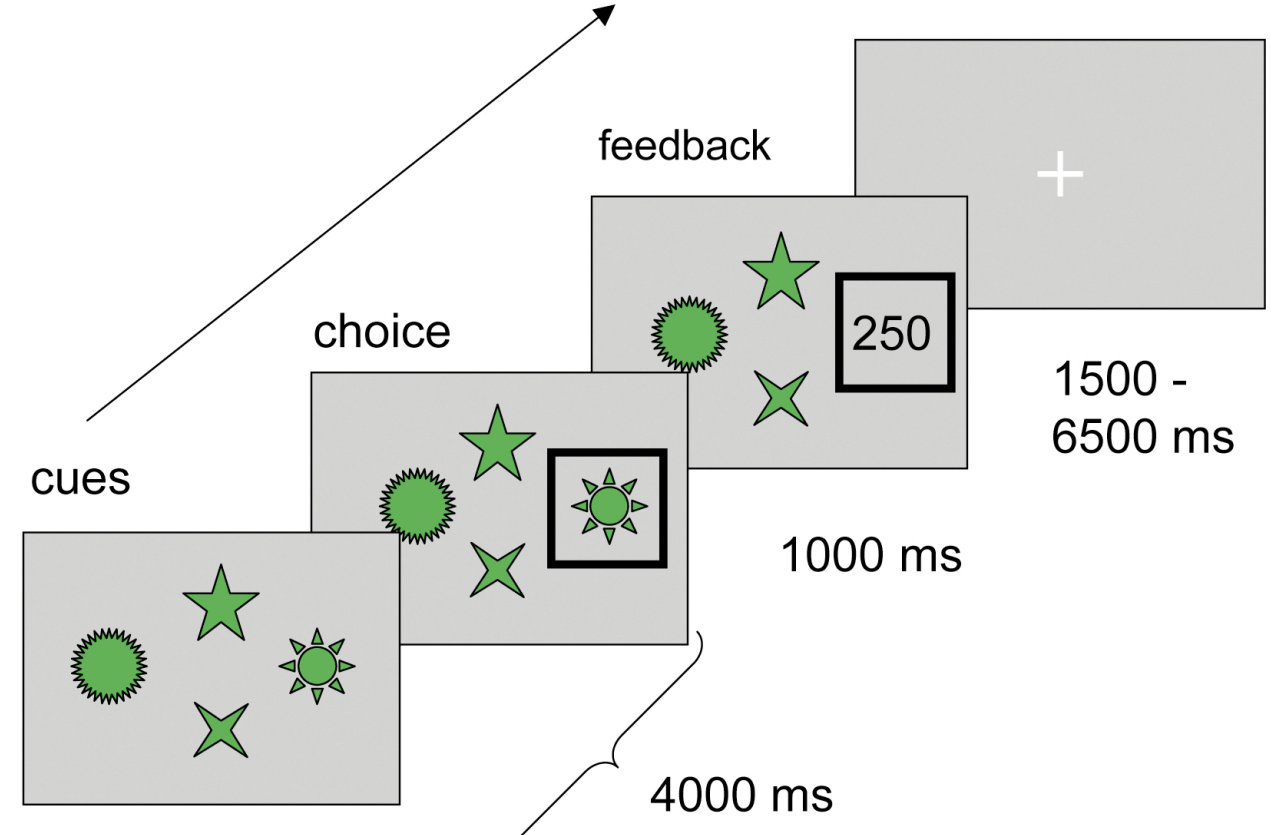
- Prominent models of reinforcement learning assume that learning is based on a deviation of expected reward from the actual outcome, the prediction error (*Rescorla Wagner, 1972; Sutton & Barto, 1998*).
- Neurophysiologic data suggest that the prediction error is encoded by dopamine (DA) release in the (ventral) striatum (*Schultz, 2000; Fiorillo, 2003*).
- The COMT polymorphism is known to influence both cortical and subcortical DA levels (*Lotta, 1995; Egan, 2001*), and there is evidence for a reciprocal cortico-striatal relationship in DA projections (*Carlsson, 2001; Akil, 2003; Bilder, 2004*).

### Hypothesis

- Val homozygotes have higher striatal DA release than Met homozygotes, which leads to a stronger representation of positive prediction errors.
  - Val homozygotes perform better in an instrumental learning task.
  - Stronger correlation between prediction error and fMRI signal in the striatum in Val homozygotes than in Met homozygotes.

### Experiment

- 14 Met and 12 Val homozygotes performed a probabilistic object reversal task (pORT) in an fMRI experiment.
- Siemens Vision 1.5 T, EPI, 26 slices, TR=2.5 s, TE=40 ms, 4x4x4 mm voxel size



4 stimuli; 3 possible outcomes (250 points, 150 points, 50 points)  
good deck = 80 % probability of 250 points  
bad decks = 20 % probability of 250 points  
reversal after 6/7 choices for good deck

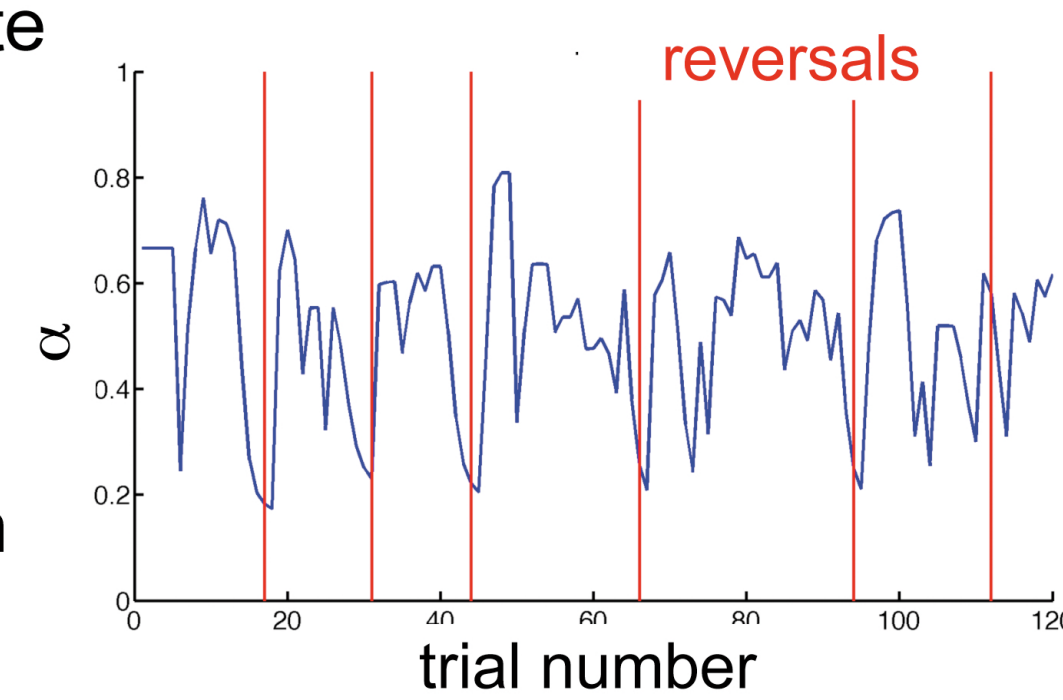
### Reversal learning with adaptive learning rates

- Reversal learning is a challenge for conventional learning models: constant learning rates either do not allow for fast adaptation, or do not allow for stabilization of behavior.
- A new learning model implements an adaptive learning rate in a temporal difference algorithm:

$$V_{t+1} = V_t + \alpha_t (r_t - V_t)$$

$$\alpha_t = \alpha_{t-1} + \Delta P E (1 - \alpha_{t-1})$$

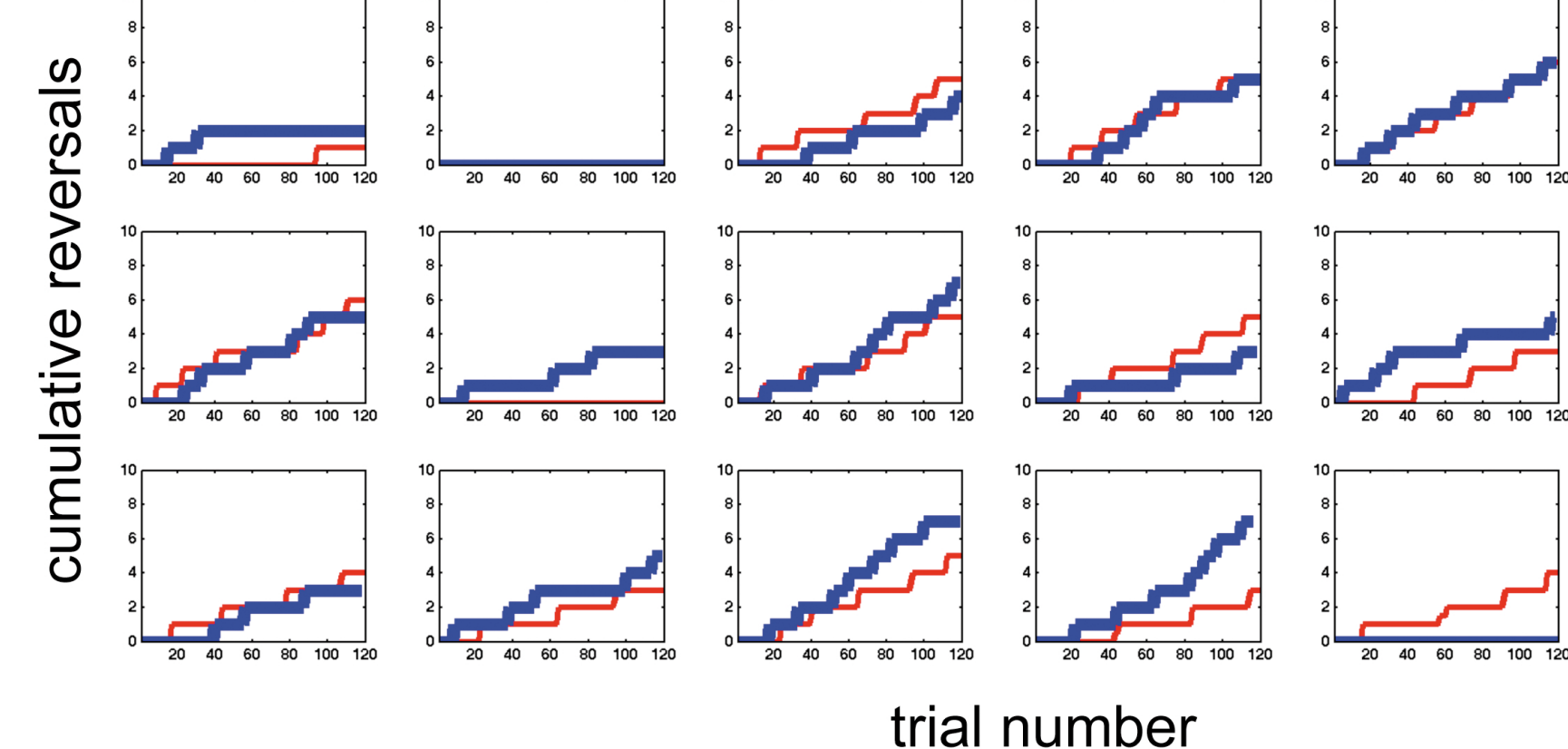
- Intuitively, the learning rate is modulated by the prediction error slope: positive slopes raise the learning rate.



### Behavioral and Modeling Results

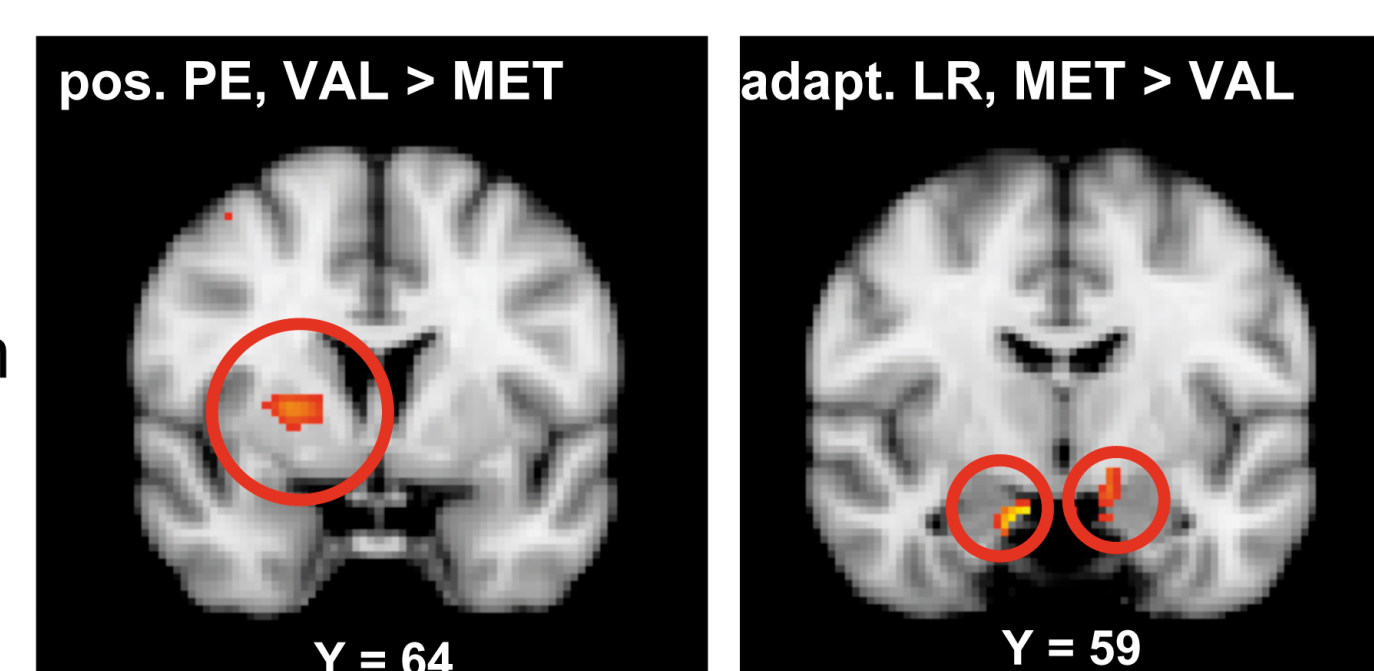
- Val homozygotes collect more winning points than Met homozygotes ( $p = 0.028$ ).
- The learning model successfully predicted participants' reversal learning.

observed and predicted reversals (exemplary participants)



### fMRI Results

- Representation of high rewards in the ventral striatum/ nucleus accumbens replicates previous studies.
- Greater ant. insula activation after low rewards: perceived as aversive events.
- Model based analysis shows:
  - Stronger correlation between positive prediction errors and brain activity in the ventral striatum/ putamen in the Val genotype.
  - Better covariation of hippocampal activity with the dynamic learning rate in the Met genotype.



### Conclusions

- Reinforcement learning model with adaptive learning rate related to behavioral & fMRI data.
- COMT homozygous genotypes differ in performance and BOLD response in reward-associated subcortical regions in an instrumental learning task.
- These effects may be explained by lower striatal DA release in the Met genotype, leading to a weaker prediction error signal.

## Neurocognition of investment decisions

### Background

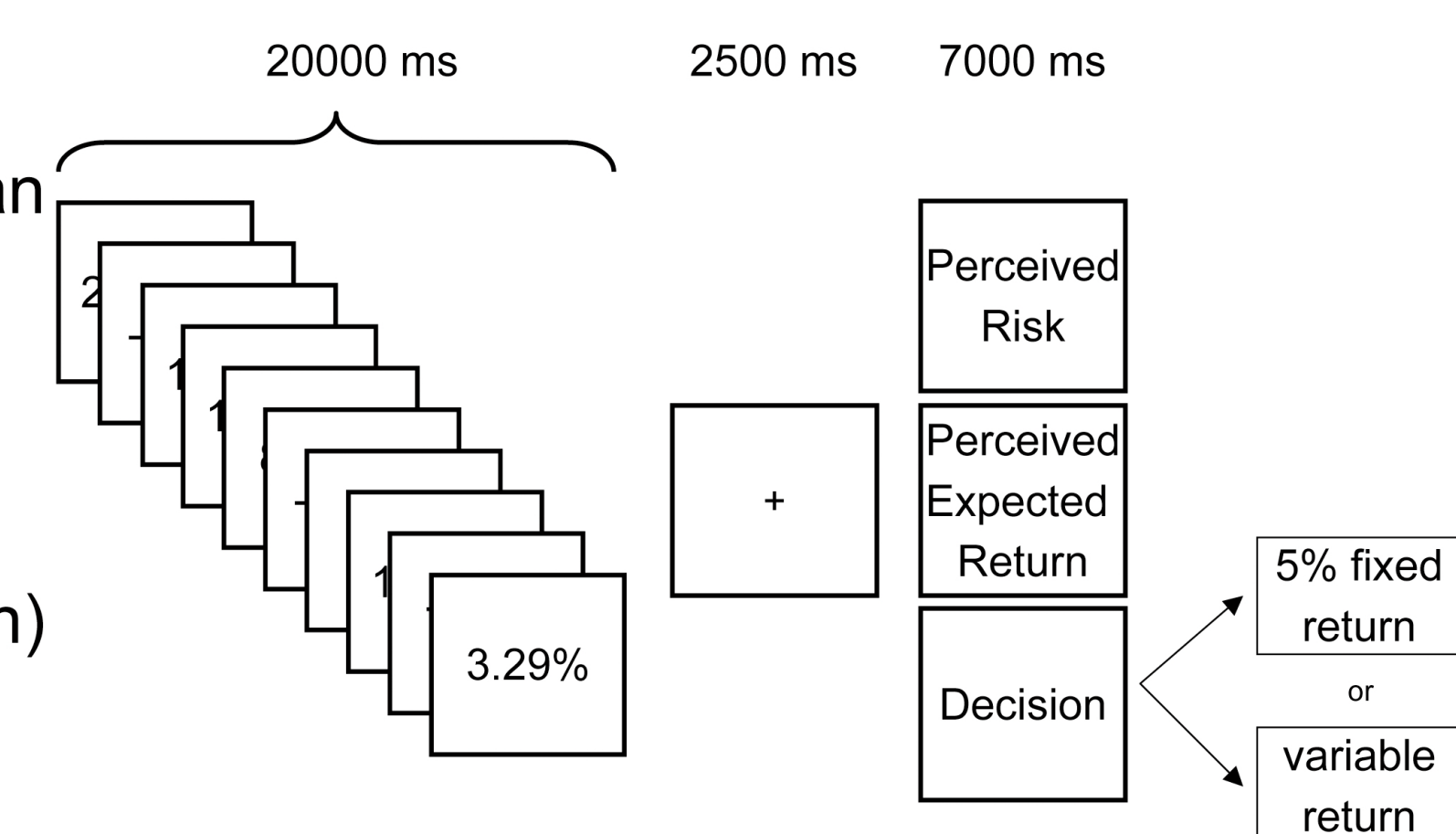
- Normative and descriptive theories of financial decision making suggest that decision makers evaluate investments by weighting their expected return and the associated risk (*e.g. Sarin & Weber, 1993*).
- Recent neuroeconomic experiments claim to have identified neural representations of decision variables like expected return, expected value, risk/uncertainty, outcome probability (*e.g. Knutson et al, 2005; Huettel et al., 2005*).
- Only few investigations of the representation of decision variables in the decision process.

### Hypothesis / Research questions

- Which models describe best how people:
  - Derive expected return of an investment, for which they saw a sample of returns?
  - Derive the risk of an investment, for which they saw a sample of possible returns?
  - Choose between a risky and a safe investment?
- Hypothesis: A common region represents the expected return / risk of an investment during presentation of return samples and during choice between a risky and risk free investment.

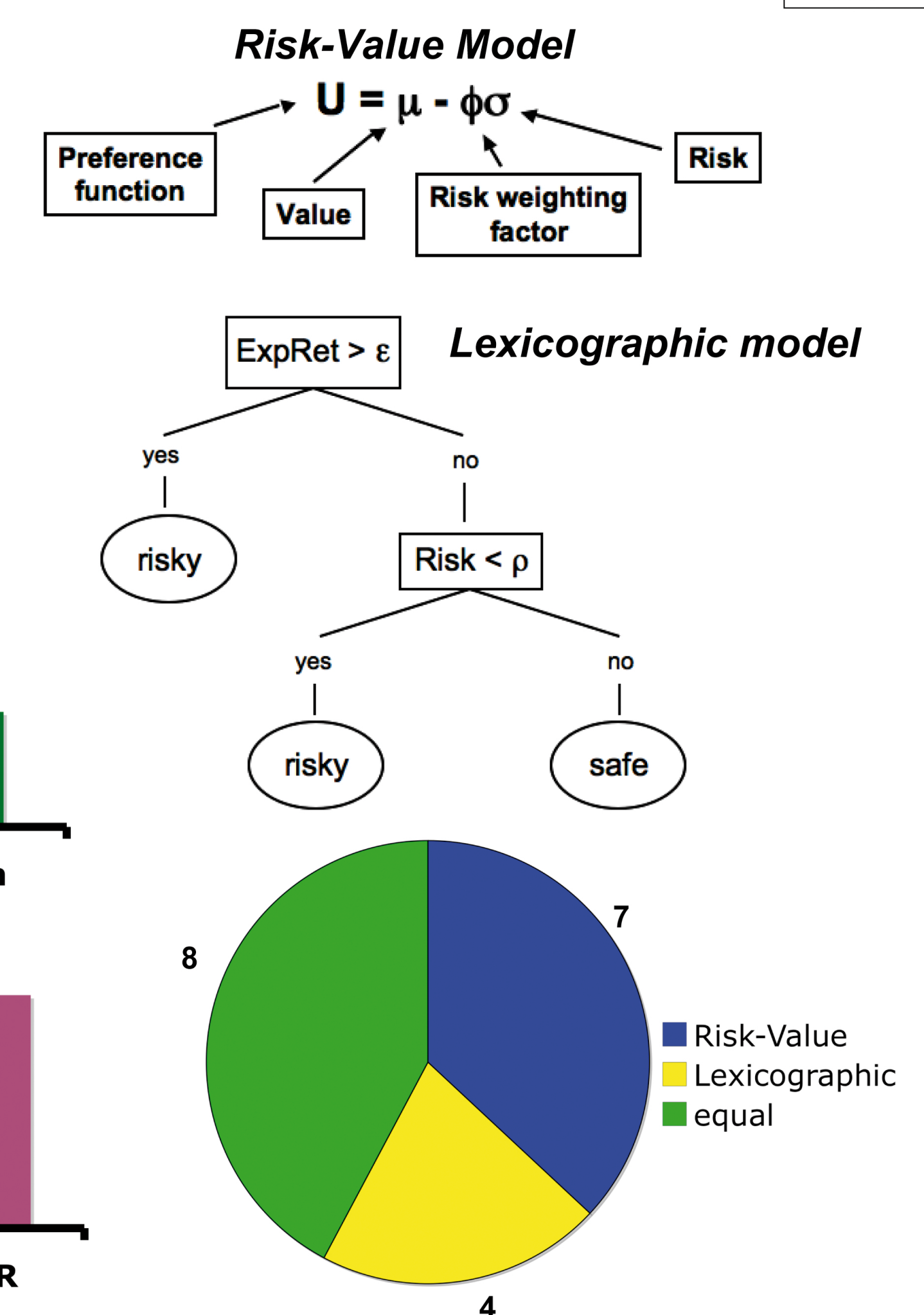
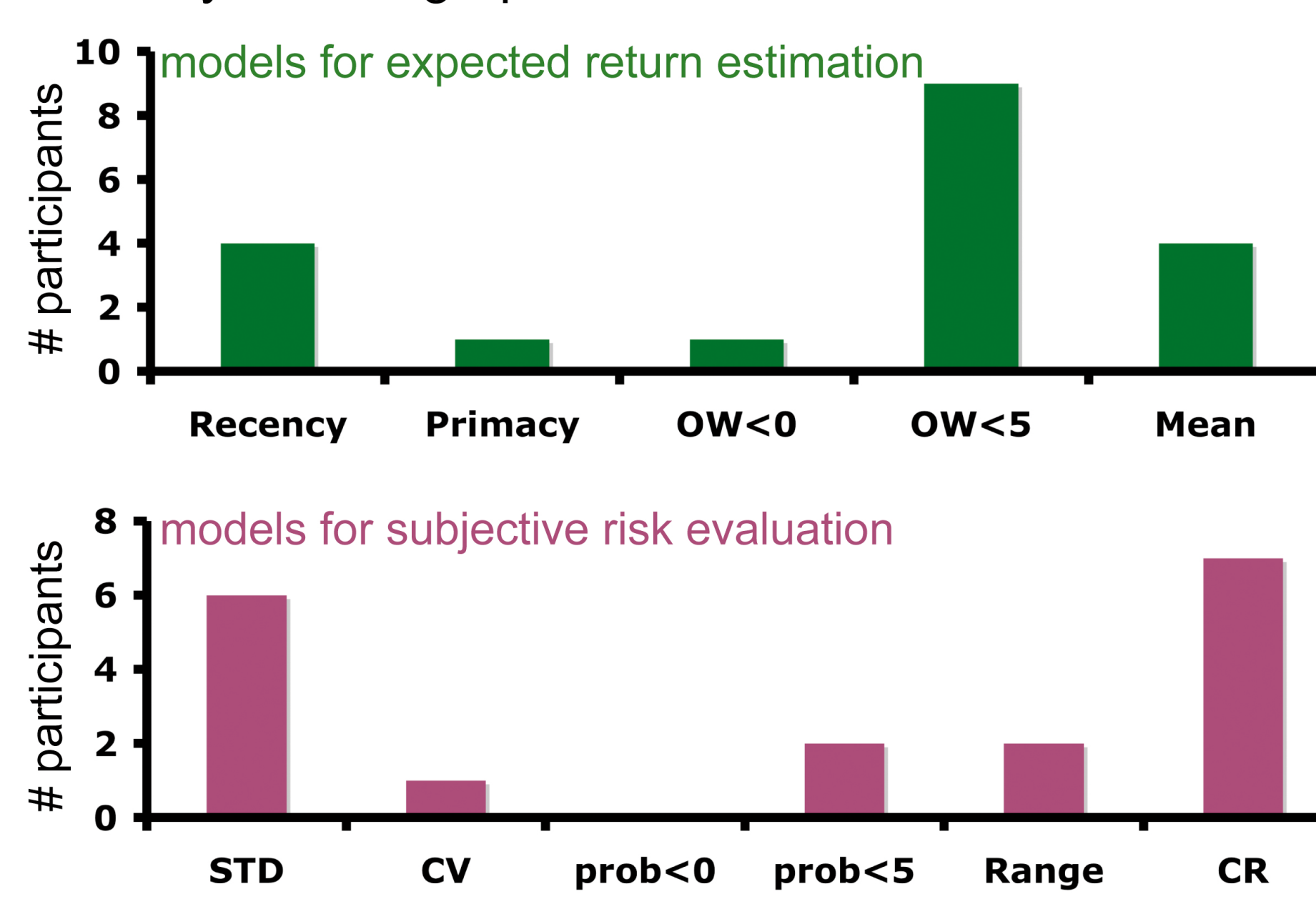
### Experiment

- New investment perception & choice task in an fMRI experiment, n=19
- Siemens Sonata 1.5 T, EPI, 26 slices, TR=2.5 s, TE=40 ms, 4x4x4 mm voxel size
- Independent variables: 3 tasks X 3 expected return levels X 3 risk levels (3 repetitions each)



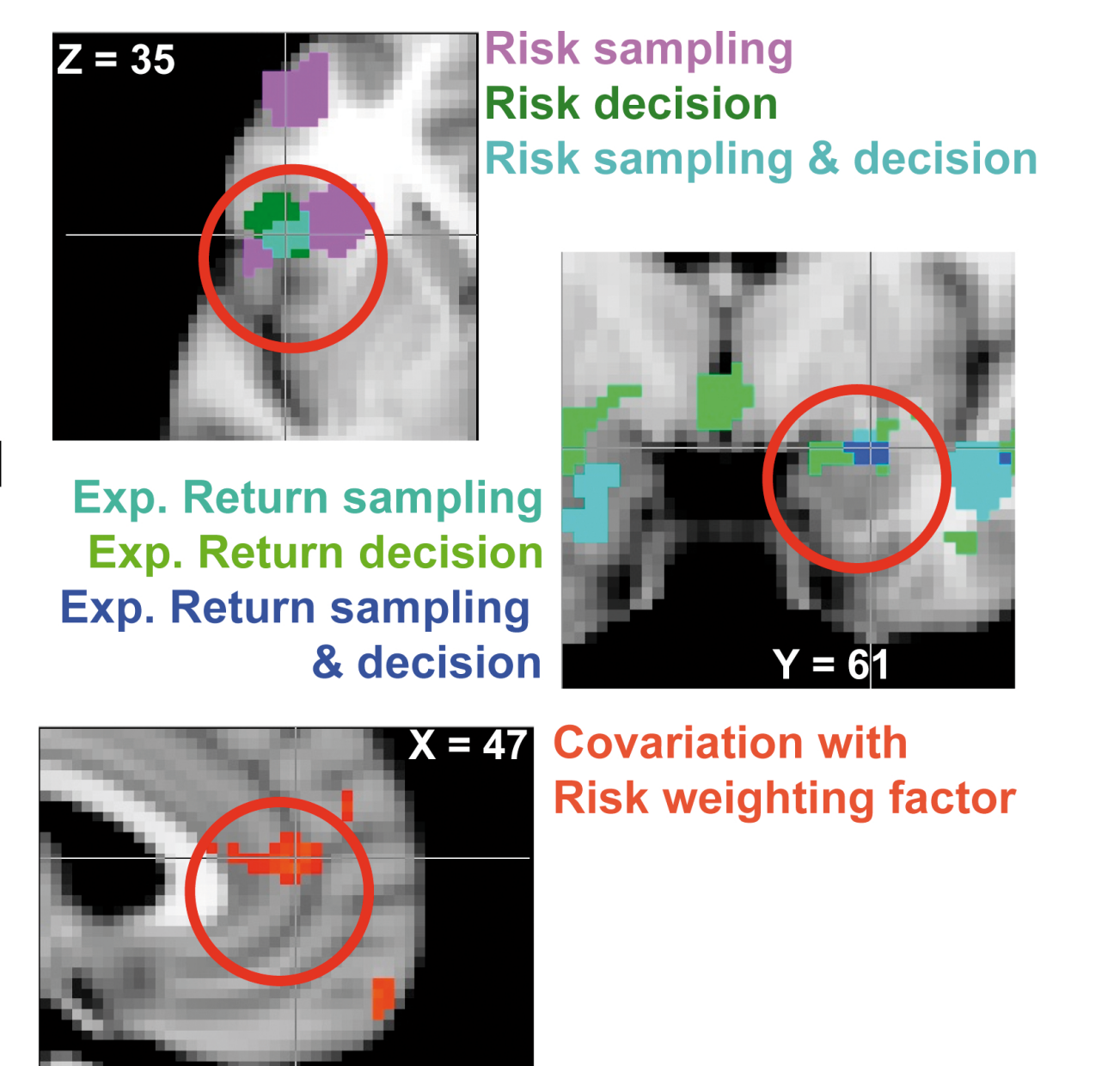
### Behavioral and Modeling Results

- Estimation of the expected return best modeled by a model giving higher weights to low outcomes.
- Subjective risk most frequently predicted by the standard deviation or the coefficient of range (range/mean).
- Decisions were similarly well predicted by a weighted additive model (Risk-Value Model) and by a lexicographic model.



### fMRI Results

- Risk and expected return estimates as predicted by models were used as regressors in the decision phase.
- Anterior insula activation correlates with risk of an investment during presentation of sample returns and during the decision task.
- Amygdala activation correlates with the expected return of investments during the presentation of sample returns and during task.
- Ant. cingulate cortex (ACC) activity during decision correlates with the individual Risk Weighting Factor.



### Conclusions

- Results suggest a common representation of risk and expected return during perception and decision related evaluation of risky prospects.
- Correlation of ACC activity with Risk Weighting Factor suggests that more risk averse participants experience more decision conflict.

## Other projects / Collaborations

- **Implementation of decision thresholds in perceptual decision making (with Nikos Green):**  
In this project the decision threshold (as assumed in sequential sampling models) is manipulated by varying payoff matrices. The goal is to identify how decision thresholds are implemented and adapted.
- **Instrumental learning of Parkinson patients on and off medication (with Susanne Gräf; F. Klostermann & F. Marzinzik, Dept. of Neurology, Charité Berlin):**  
Model based analysis of instrumental learning in Parkinson patients with high & low striatal dopamine release (on and off medication). Goals are to describe learning differences as a function of learning parameters and to relate latent learning variables to EEG signals.
- **Decision making in approach avoidance conflicts (with U. Basten & C. Fiebach, University of Heidelberg):**  
fMRI experiment investigating the representation of potential gains and losses in decision making.
- **Learning in restless bandits (with I. Erev & E. Ert; Technion Haifa):**  
This project examines pattern learning in variable environments and aims to shed light on (sequential) pattern learning by exposing participants to different Markov Decision Processes.