

# Model-based fMRI

# Experiment

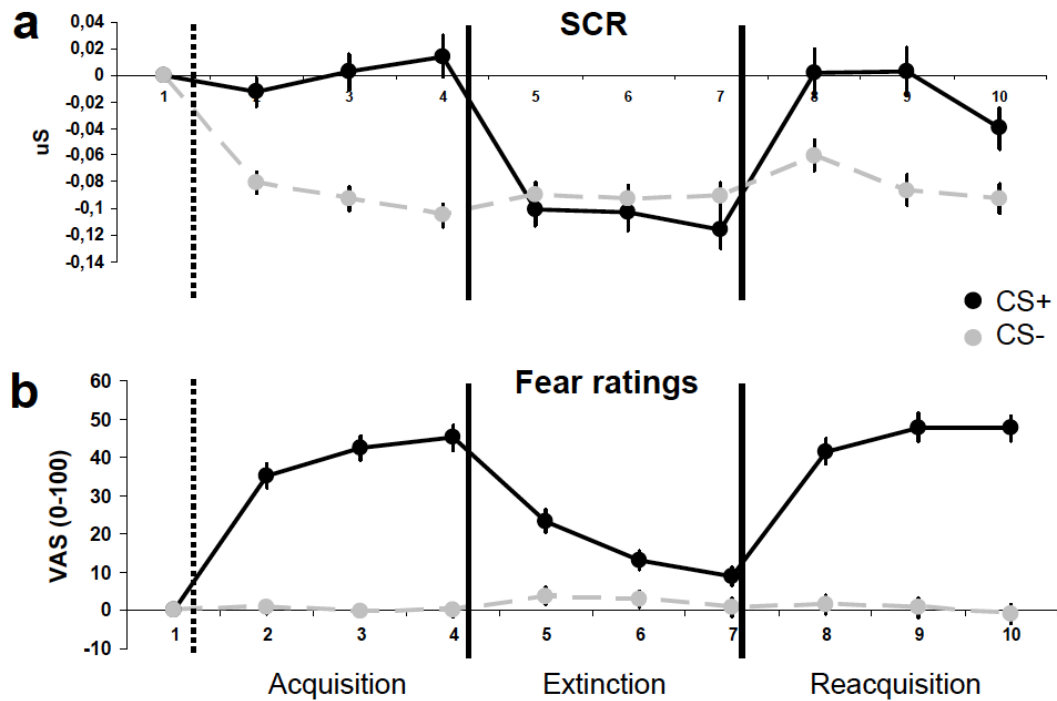
Raczka et al, *Transl Psychiatry* 2011:

Fear conditioning, extinction, re-conditioning

CS+/- = visual, UCS = shock (individual max. tolerable pain)

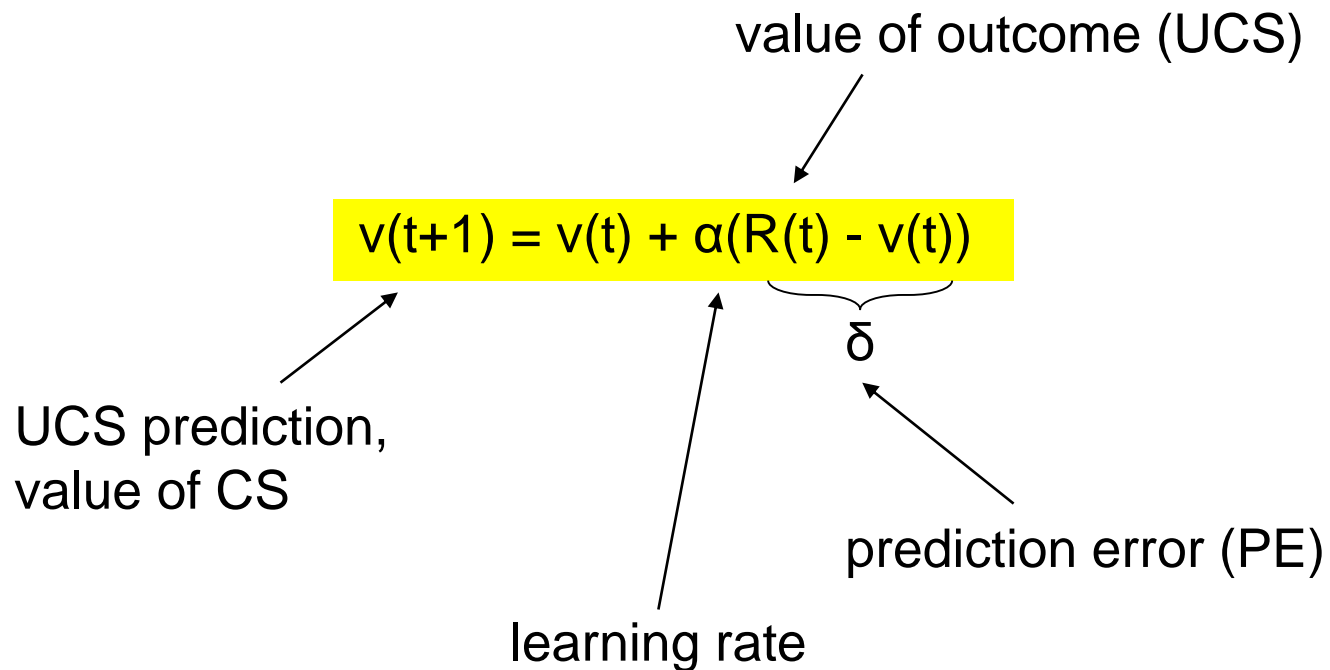
80% CS+ reinforcement

Measures: SCRs, fear ratings (every 12<sup>th</sup> trial)



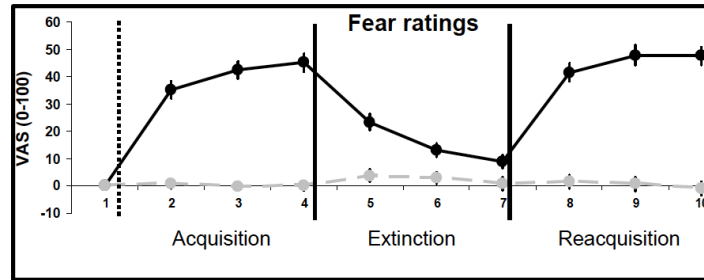
# A mathematically explicit model of associative learning

Rescorla-Wagner (1972):



t = trial number

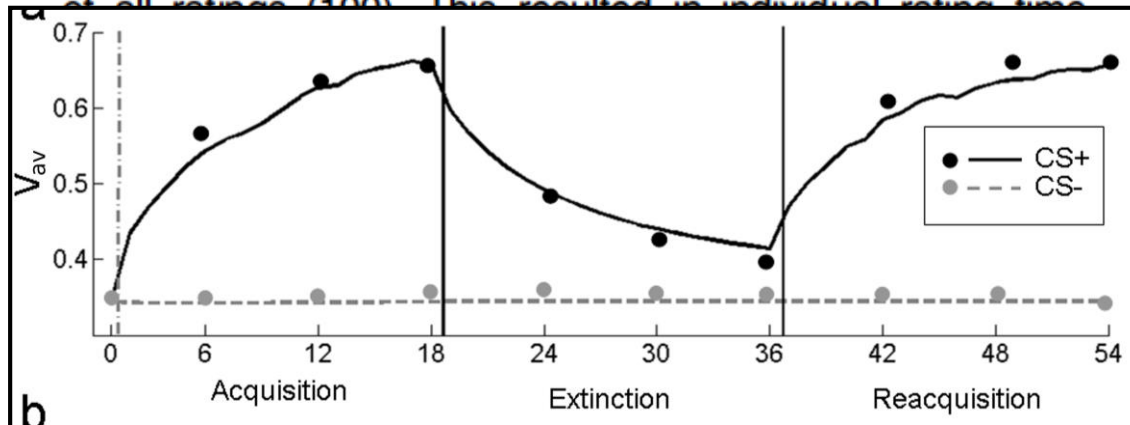
# Fitting behavioral data: step 1



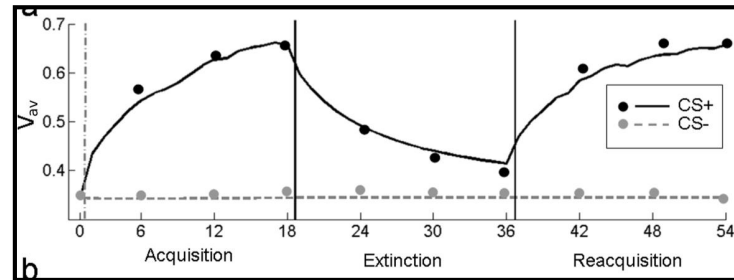
Methods. We first range corrected each participants' CS+ and CS- fear rating data (see Supplementary Figure 1a for sample average) according to

$$x_{i, \text{corr}, \text{CS+orCS-}} = (x_{i, \text{CS+orCS-}} - \text{min}) / (\text{max} - \text{min}),$$

with  $x_{i, \text{CS+orCS-}}$  ( $i=1, \dots, 10$ ) being the successive (CS+ or CS-) fear ratings, min being the sample-wide minimum of all ratings (-58) and max being the sample-wide maximum of all ratings (100). This resulted in individual rating time



## Fitting behavioral data: step 2



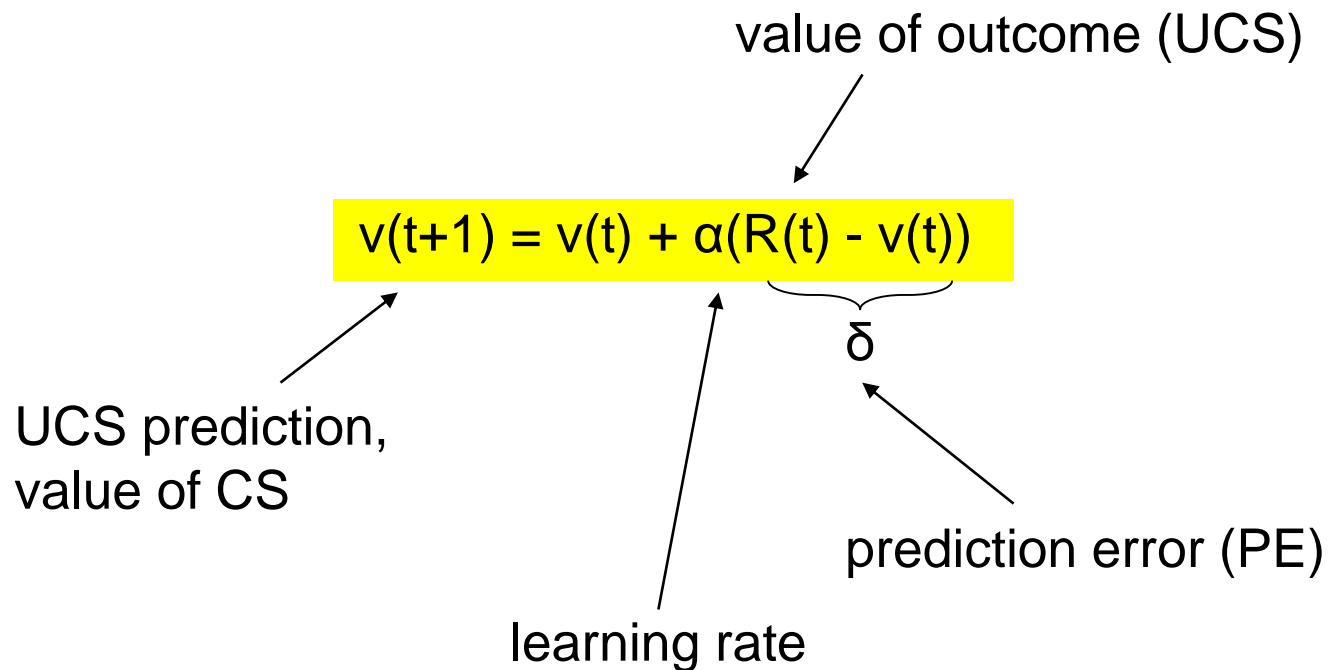
After complete learning, the aversiveness  $R$  of the UCS is reflected in the aversiveness of the CS + , that is, in the last CS + fear rating after acquisition ( $x_{4,corr,CS+}$ ). With a partial reinforcement schedule of 80%, a participant's  $R$  in paired CS + trials can thus be approximated as  $x_{4,corr,CS+}/0.8$ .<sup>40</sup>  $R$  in CS- trials (0% reinforcement) was set at each participant's  $x_{4,corr,CS-}$  rating. The same value of  $R$  was used for unpaired CS + trials. See the Supplementary Methods for a more

→ individual fixed  $R$  values

(requires individual calibration of UCS intensity to similar values)

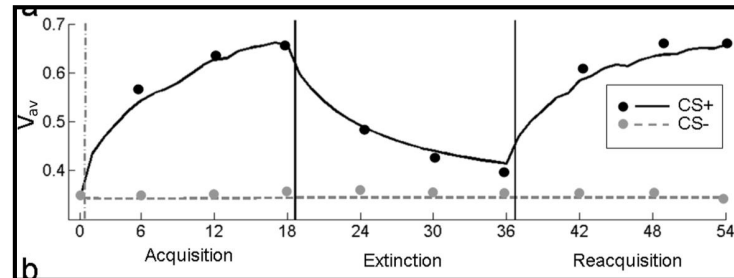
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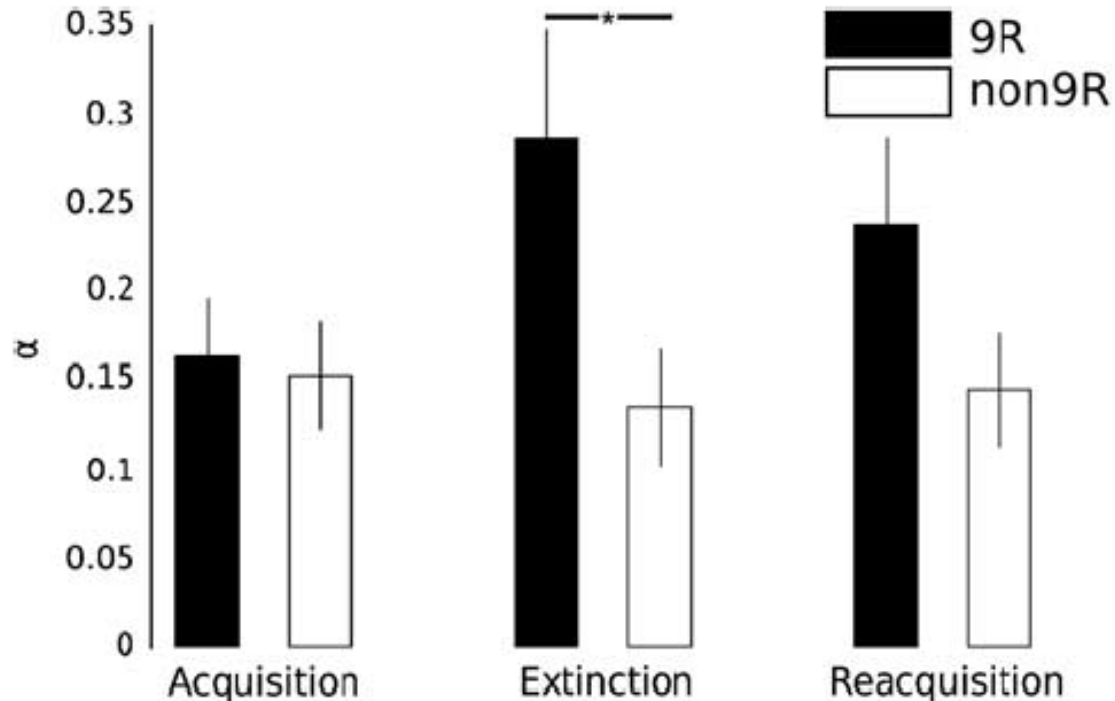
## Fitting behavioral data: step 3



$V_{av,CS+}$  and  $V_{av,CS-}$  were modeled separately and set at 0.36 ( $= x_{1,corr,CS+}$  or  $CS-$ ; see above) before learning. On the basis of the idea of dissociable neural systems for fear acquisition and extinction (and possibly reacquisition as well), we used three free parameters  $\alpha_{Acq}$ ,  $\alpha_{Ext}$  and  $\alpha_{RAcq}$  (one for each of the three experimental phases), which were adjusted to minimize the distance between the change in  $V_{av,CS+}$  and  $V_{av,CS-}$  and the change in fear ratings  $x_{corr,CS+}$  and  $x_{corr,CS-}$  using a least-square approach. We did not use  $CS+ > CS-$  difference scores, and  $V_{av,CS+}$  and  $V_{av,CS-}$  were estimated at the same time within the same model.  $V_{av,CS+}$  and  $V_{av,CS-}$

(worse fits with only one alpha)

## Fitting behavioral data: results



**Figure 2** *DAT1* genotype affects learning rates during extinction. Formal modeling of fear rating data showed that 9-repeat (9R) carriers have significantly higher learning rates during extinction than non-9R carriers. Error bars: s.e.m. \* $P < 0.05$  (F test).



# Fitting behavioral data: background

## Theory:

Extinction mediated by a different learning system than conditioning  
Extinction mediated by dopamine-dependent reward system

## Assumptions:

DAT 9R: higher phasic extrasynaptic DA concentrations upon DA release

## Experimental hypotheses (behavior):

DAT 9R carriers: higher learning rates spec. in extinction

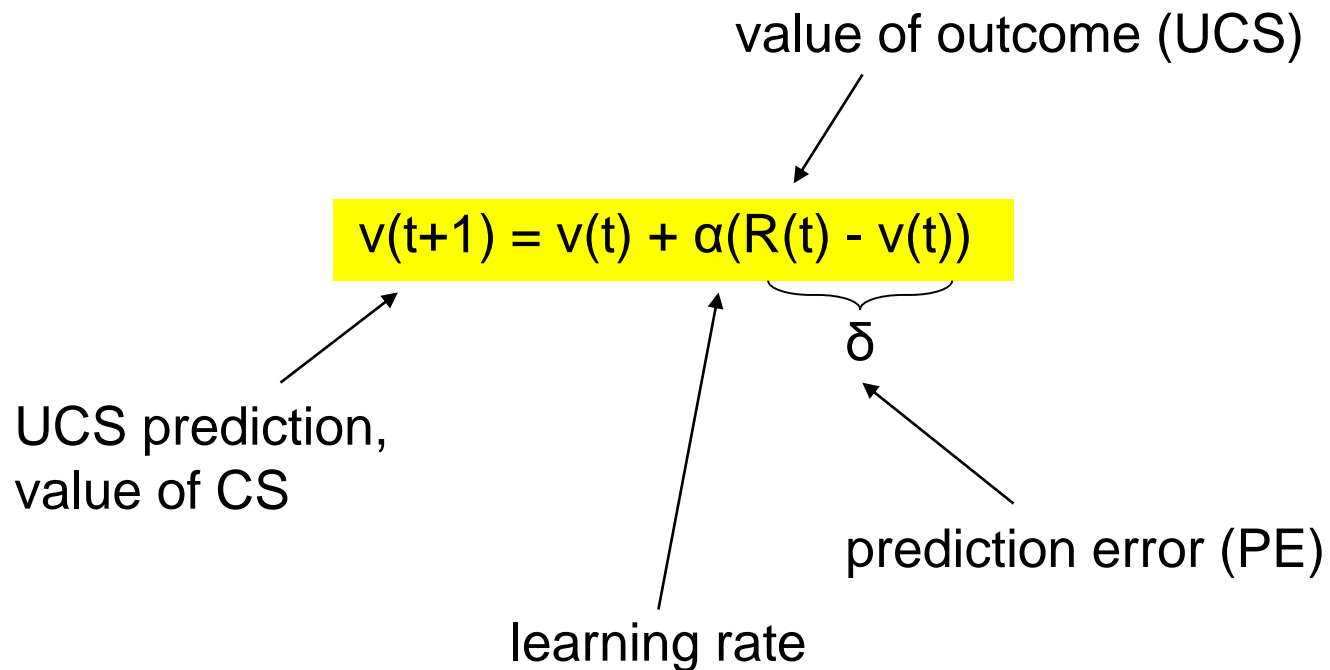
## Experimental hypotheses (imaging):

Extinction PE signal in VS

Higher VS-PE in 9R carriers (bec. higher alpha, i.e., higher weights)

# A mathematically explicit model of associative learning

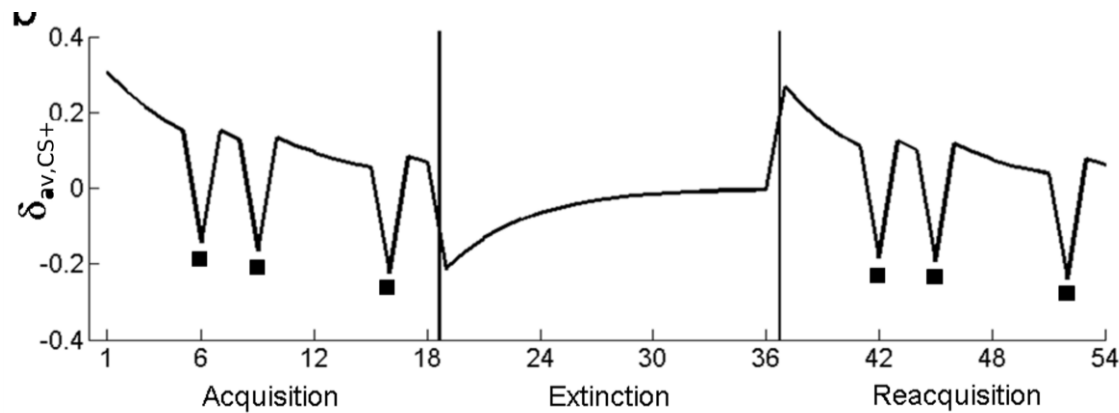
Rescorla-Wagner (1972):



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## Fitting imaging data: step 1

To prepare the analysis, we used the sample-averaged learning rates  $\alpha_{\text{Acq}}=0.16$ ,  $\alpha_{\text{Ext}}=0.21$  and  $\alpha_{\text{RAcq}}=0.19$  to derive individual trial-by-trial  $V_{\text{av}}$  and  $\delta_{\text{av}}$  estimates from the above modeling of the rating data, separately for acquisition, extinction and reacquisition. Averaging of learning rates was necessary to reduce noise in the data that resulted from a limited number of data points for fitting (10 ratings), and thus to obtain robust estimates. An exemplary individual  $\delta_{\text{av}}$  time course is shown in Figure 1b. We emphasize that our

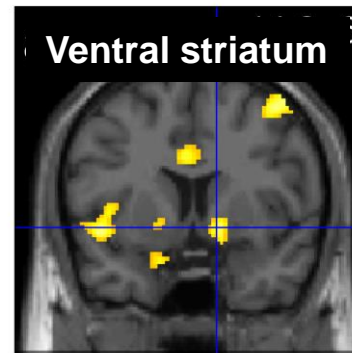
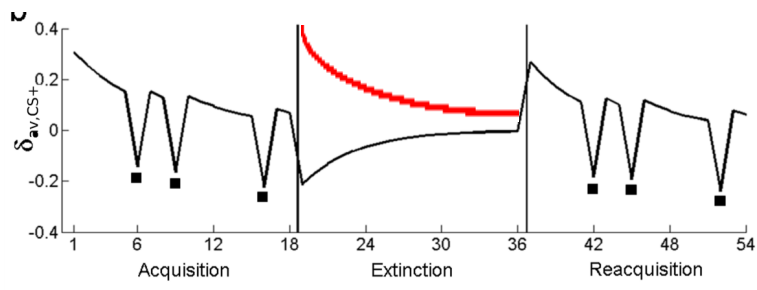


## Fitting imaging data: step 2

### Regressors (separately for 3 phases):

- CS onsets (CS+/- combined): event-type
- *parametric modulator: indiv. trial-by-trial V estimates*
- CS offsets (CS+/- combined): event-type
- *parametric modulator: indiv. trial-by-trial PE estimates*
- UCSs (events)
- Key presses (events)
- Rating periods (box cars)

→ Max. inter-correlation: PE in Cond. and UCS: -0.43

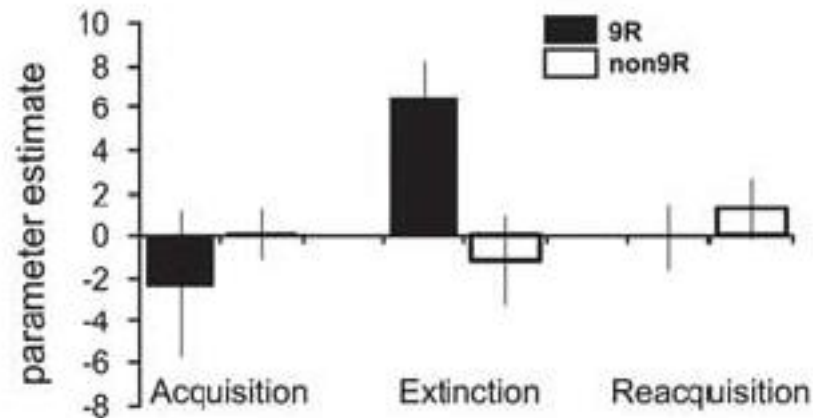
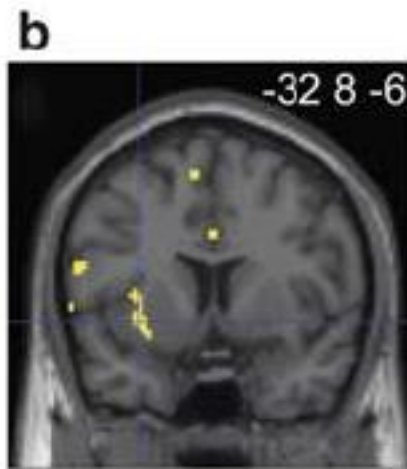


## Fitting imaging data: step 3

Comparison DAT 9R vs. non9R carriers:

2-sample t-test of PE in Ext.

Small volume correction in a priori VS-ROI from literature



## Fitting behavioral data: step 2 – addendum

### *Estimating R*

The logic of estimating R from fear ratings while taking into account a given reinforcement ratio (here, 80%) can be illustrated by comparing the present situation to a hypothetical experiment with half as much reinforcement (that is, 40%), the UCS magnitude staying the same. With half as much reinforcement, associative theory predicts that participants will rate half as much fear after full learning (that is, here, the  $x_{4,corr,CS+}$  rating). To this effect, dividing  $x_{4,corr,CS+}$  by the reinforcement ratio (0.8 and 0.4, respectively) will lead to an identical estimate for R in both scenarios. Assume that in the 80% scenario the  $x_{4,corr,CS+}$  rating is 1, then  $1/0.8$  makes  $R=1.25$ . If in the 40% scenario the  $x_{4,corr,CS+}$  rating is 0.5 (as associative theory would predict), then  $0.5/0.4$  also makes  $R=1.25$ . Hence, one obtains the same estimate of R, in accordance with an identical UCS magnitude employed in both scenarios. Note that, with partial reinforcement as used here, R must always be larger than  $x_{4,corr,CS+}$ , because the aversiveness of the CS scales not only with UCS magnitude but also with UCS probability, according to the RW model. Concerning the CS-, there is no need for scaling because reinforcement is absent in 100% of all CS- trials. This allows for using the  $x_{4,corr,CS-}$  rating as a direct estimate of the value of no-reinforcement.

# General take-home message

- Variant of task-based fMRI
- Objective: isolate cognitive processes/operations
- Exploits advantages of parametric designs
- More precise predictions

## Extension

- Model choice/model comparison: which is the best model?
- Best fit with simplest possible model (Occam's razor)
  - Penalize number of model parameters
  - E.g., Akaike Information Criterion (AIC), Bayes IC (BIC)