

# Does *efficient value synthesis* in the OFC explain how risk attitude adapts to the range of risk prospects?

(J. Brochard & J. Daunizeau, eLife, 2<sup>nd</sup> revision round)



Paris Brain Institute (ICM), Paris, France  
*Motivation, Brain & Behavior* lab

Jean Daunizeau

# What is *risk attitude*?



## Risk:

- is the possibility of something bad happening
- involves uncertainty about the consequences of an action

## Attitude toward risk:

- has many socio-economic implications (health, finance, etc)
- varies across people (risk-seeking vs risk-averse people):
  - ✓ genetic factors (e.g., 5HTTLPR, DRD4)
  - ✓ environmental factors (e.g., childhood harshness)
- determines how rewards are discounted by the prospect of losses:
  - ✓ affective factors (e.g. fear)
  - ✓ cognitive factors (e.g., “framing effect”)

# Risk attitude and value coding in OFC neurons

*Do you gamble?*



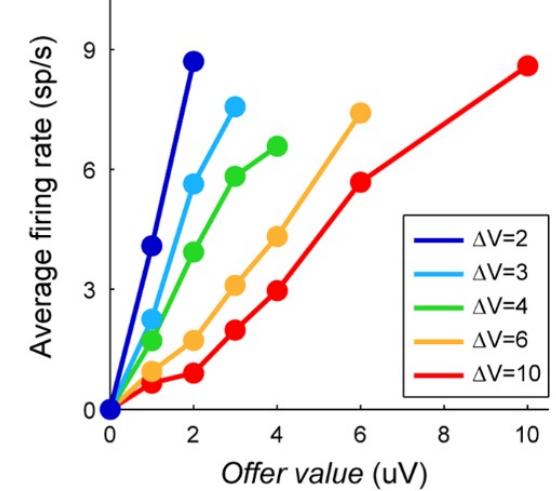
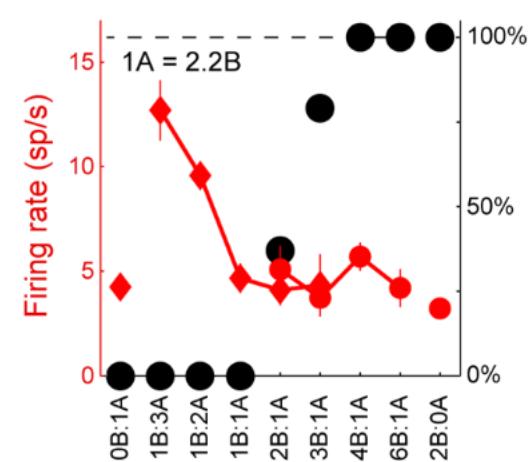
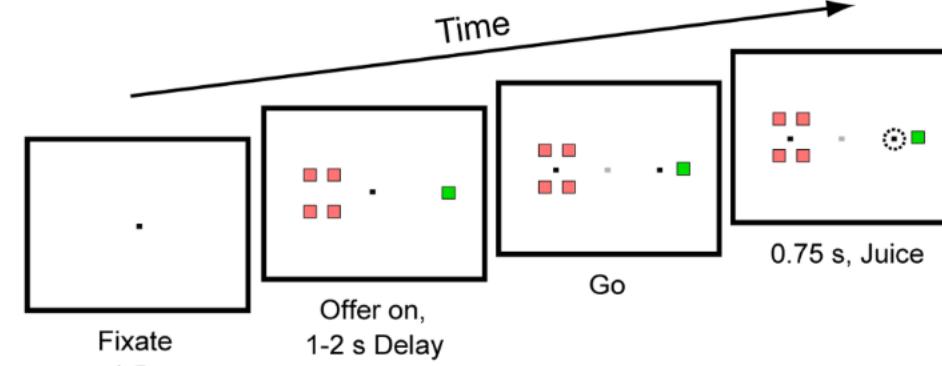
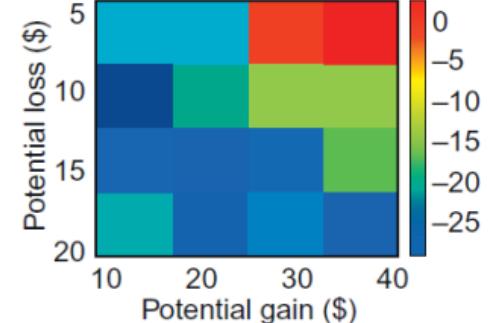
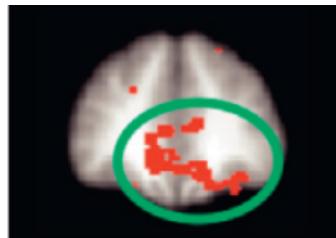
*Do you gamble?*



losses

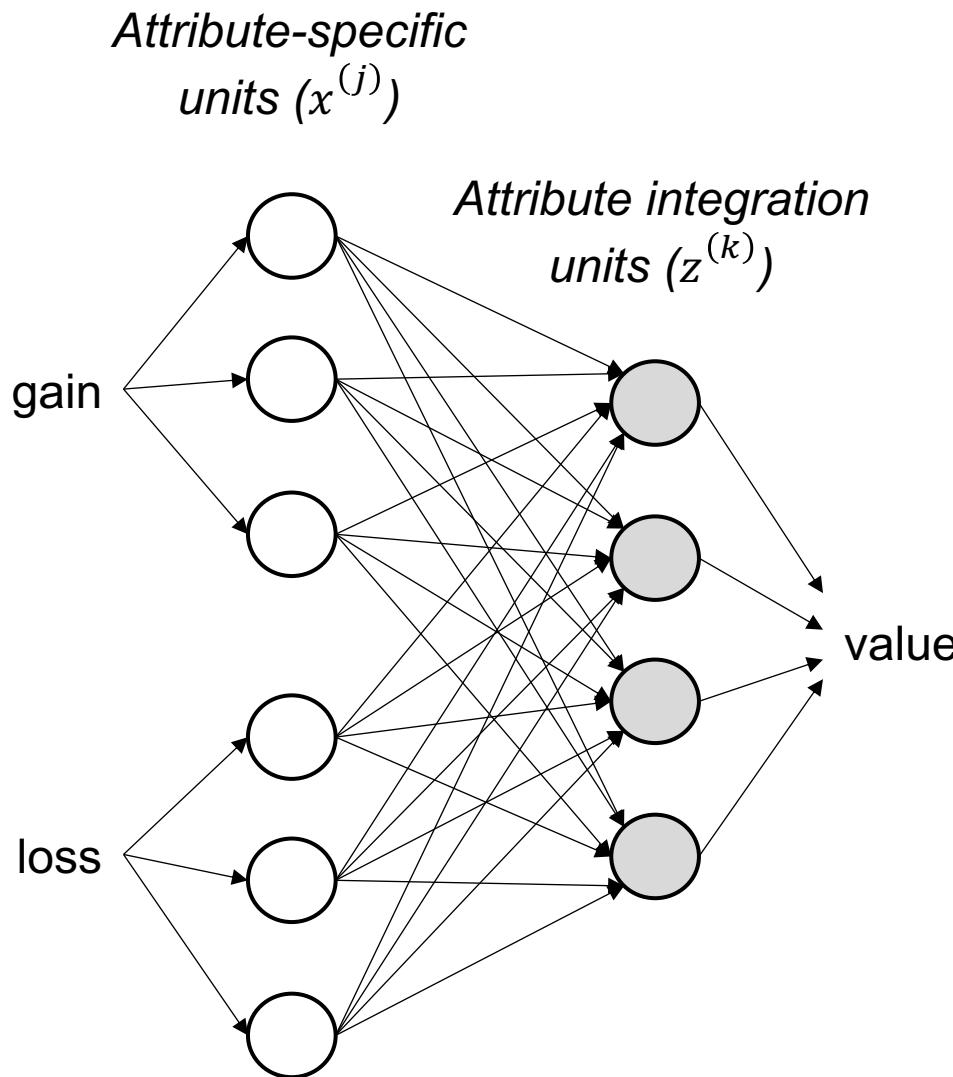
gains

OFC



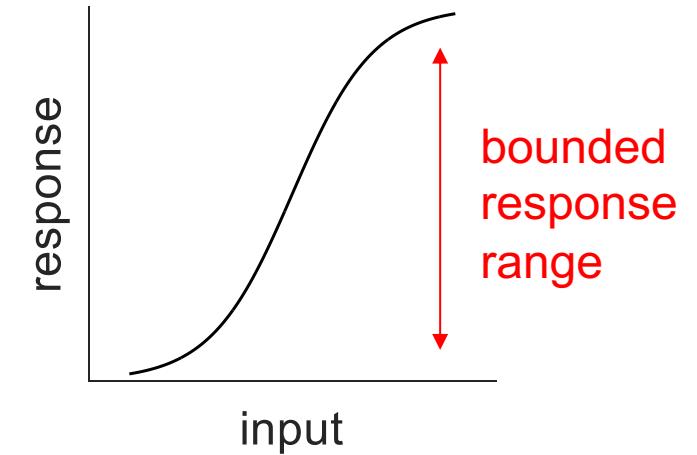
- Why/how do OFC neurons adapt to the value range?
- Can this modify peoples' risk attitude? If yes, how?

# Value synthesis in the OFC: biological constraints



- Neural noise in attribute-integration units:

$$\begin{cases} V_t = \sum_k w^{(k)} z_t^{(k)} \\ z_t^{(k)} = f^{(k)}(v_t^{(k)}) + \eta_t^{(k)} \\ v_t^{(k)} = \sum_j C^{(j,k)} x_t^{(j)} \end{cases}$$



- ... induces information loss:

$$IL = -MI(z, f_z(v)) \xrightarrow{\eta \rightarrow 0} K - H[f_z(v)] = K - H[v] - \sum_k E \left[ \ln \left| \frac{\partial f^{(k)}}{\partial v^{(k)}} \right| \right]$$

# *Efficient value synthesis (EVS)*

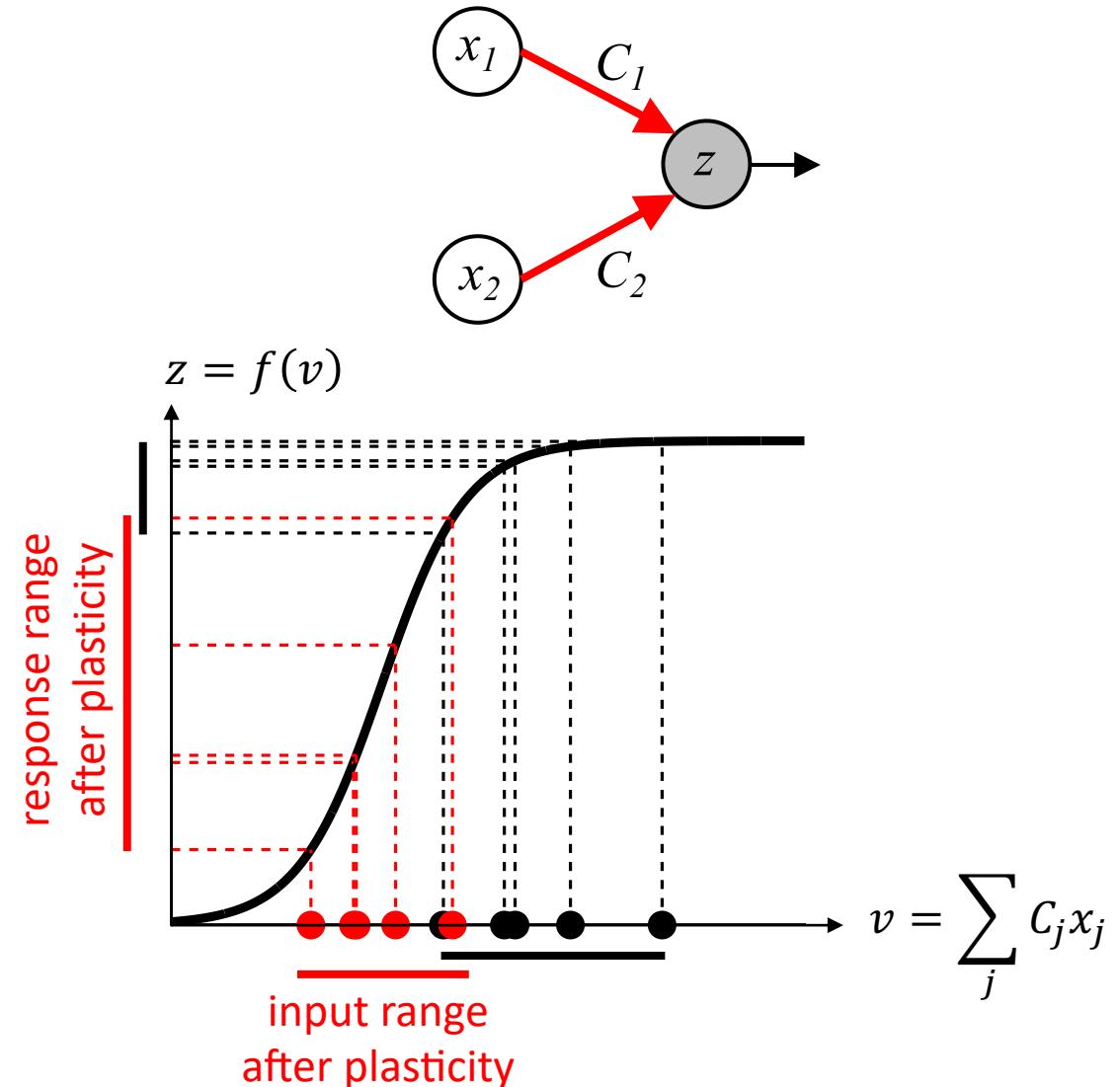
**Self-organized plasticity**  
upstream integration neurons

$$\dot{C}^{(j,k)} \propto -\frac{\partial IL}{\partial C^{(j,k)}} \approx \frac{\partial}{\partial C^{(j,k)}} \ln \left| \frac{\partial z^{(k)}}{\partial v^{(k)}} \right|$$

$$\Rightarrow \dot{C}^{(j,k)} \propto \lambda x^{(j)} (1 - 2z^{(k)})$$

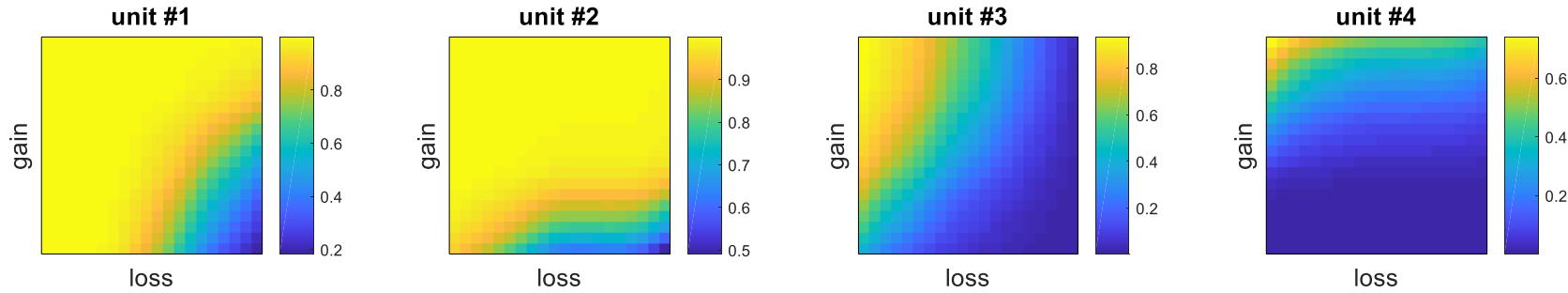
*anti-Hebbian rule*

(for sigmoidal integration units)

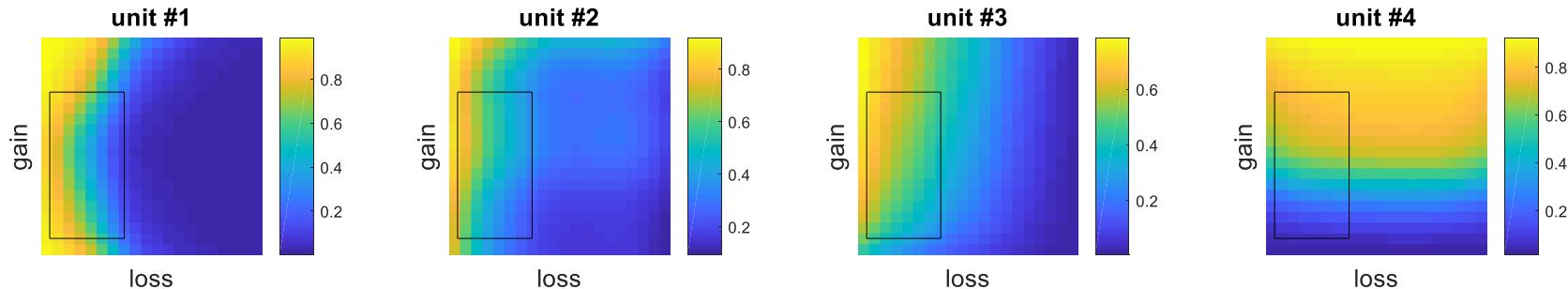


# What does self-organized plasticity do to the integration layer?

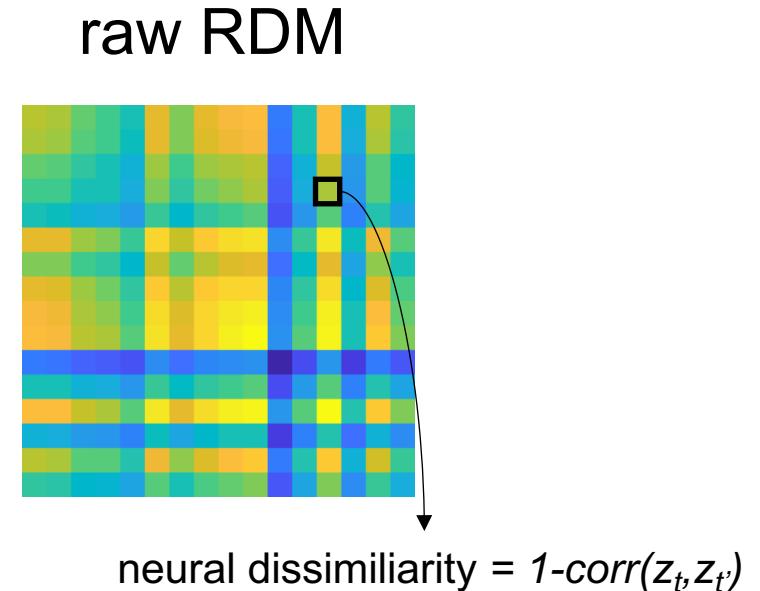
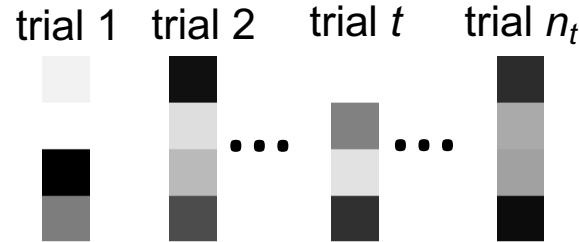
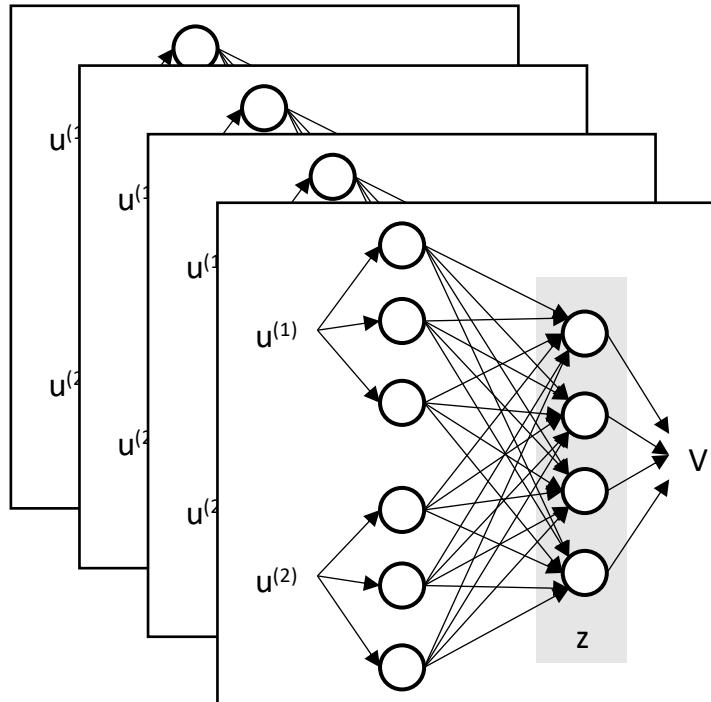
- Train the ANN to perform the synthesis of gambles' *expected value* :  $EV = 50\% \text{ gain} - 50\% \text{ loss}$



- Let the ANN self-organize while exposing it to a series of prospective gains and losses

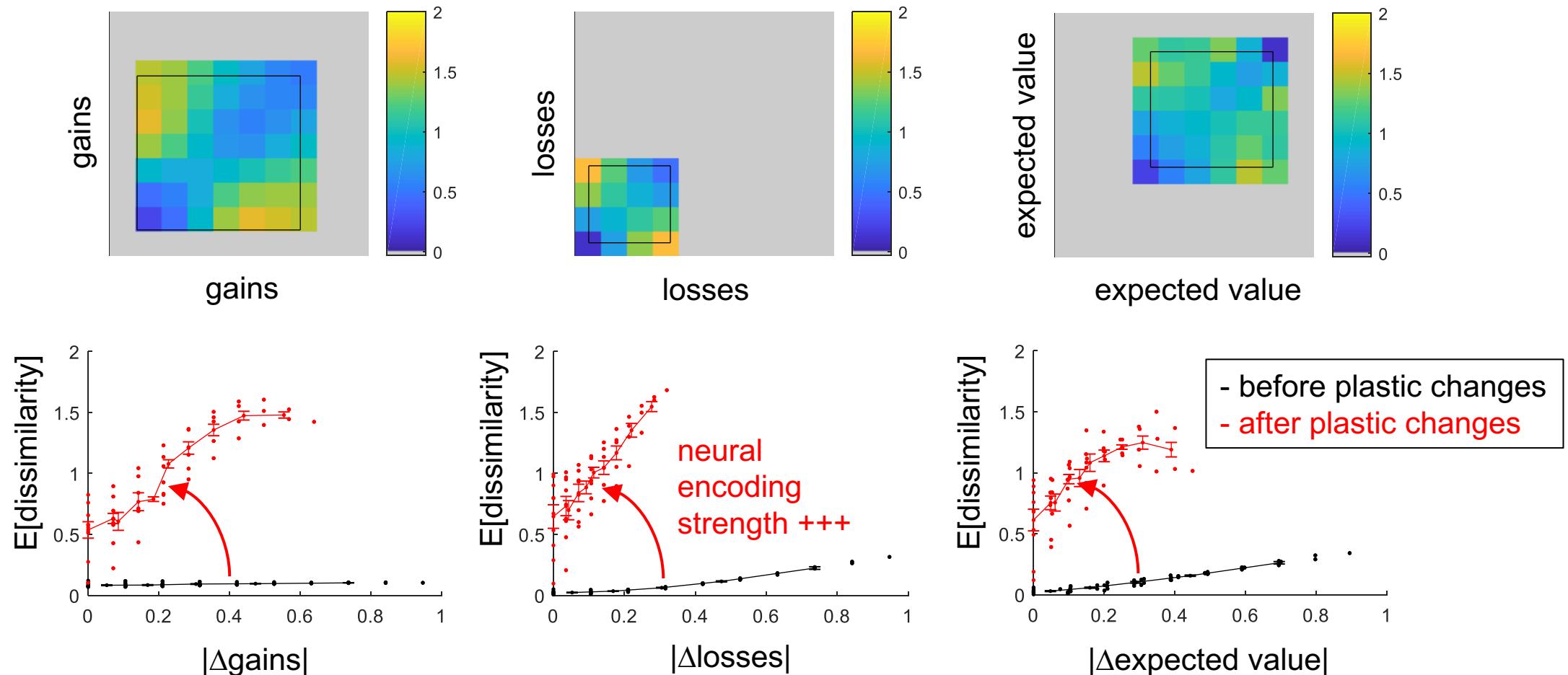


# Assessing the information content of the integration layer



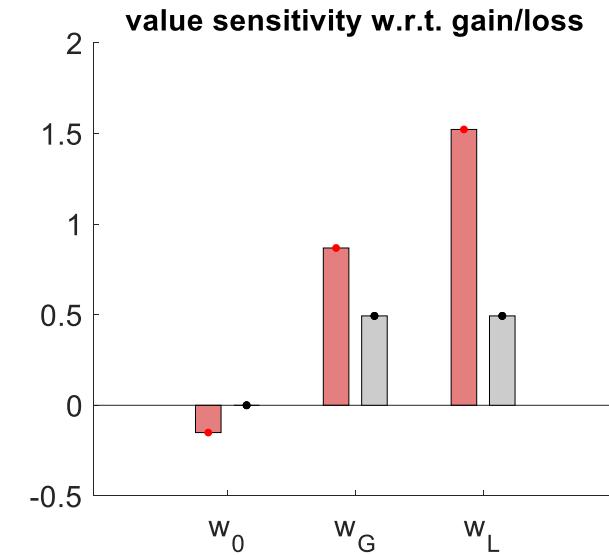
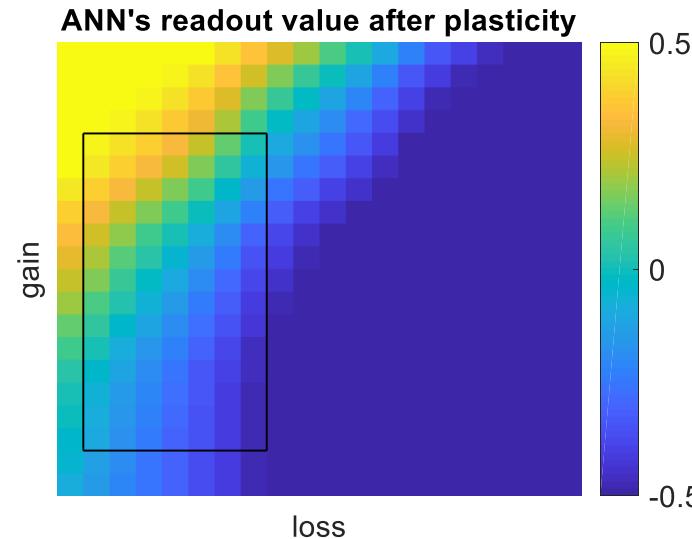
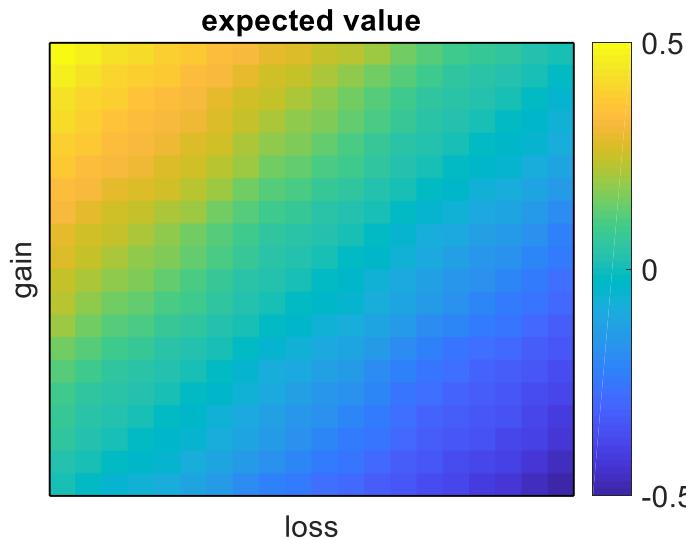
- bin trials according to variable of interest (VOI: gain, loss, EV)
- neural encoding strength =  $\partial$  neural dissimilarity /  $\partial$  VOI distance

# Self-organized plasticity modifies neural encoding strengths



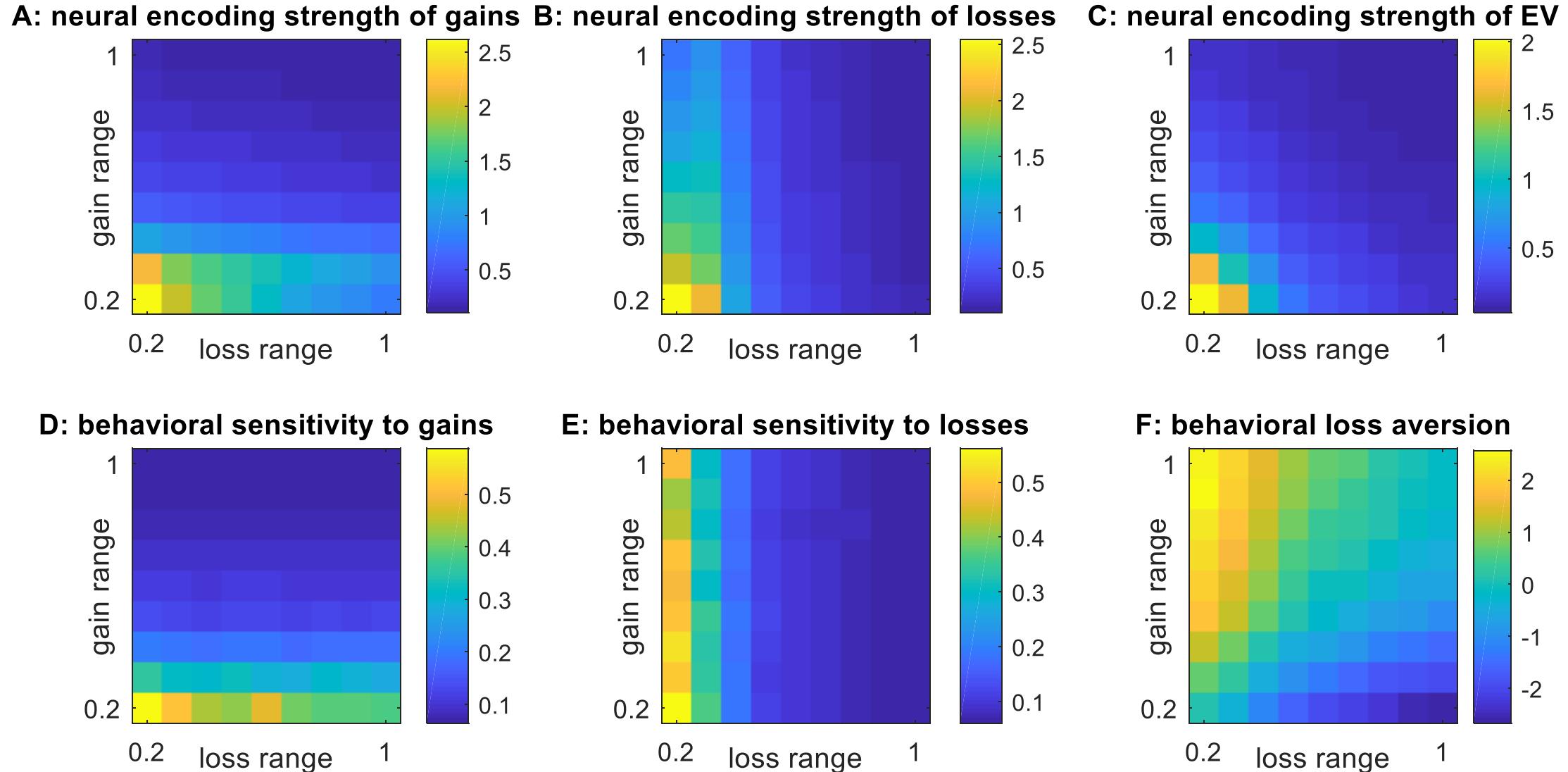
# Self-organized plasticity modifies behavioral sensitivity to gains and losses

- Risk attitude is determined by the relative impact of attributes (gain and loss) onto value
- behavioral sensitivity =  $\partial$  readout value /  $\partial$  value attribute

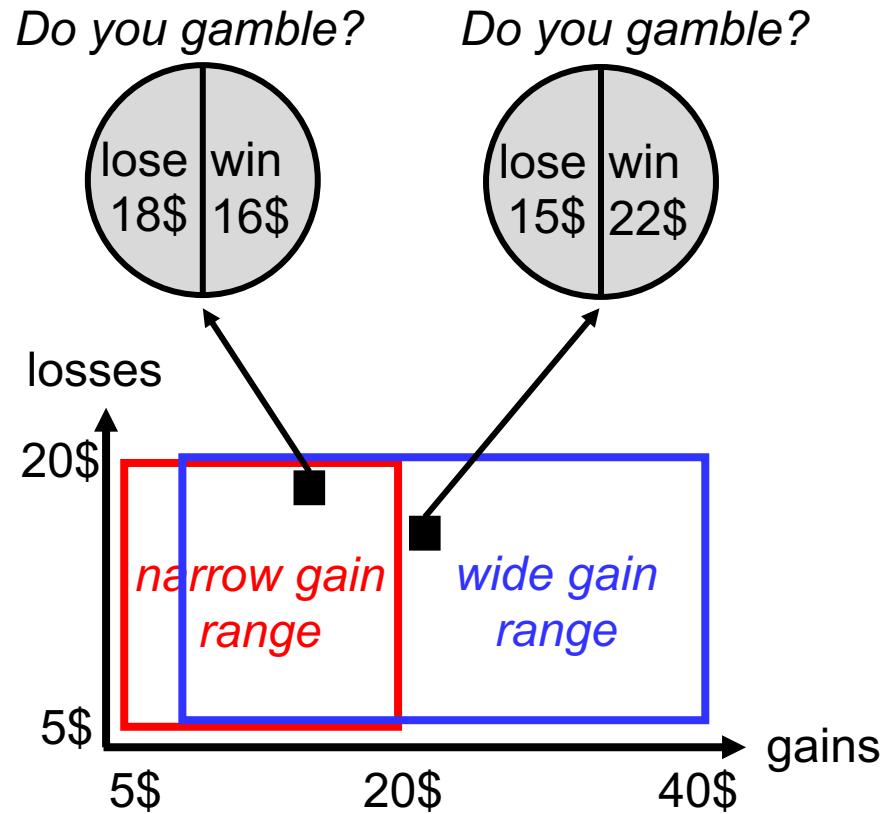


- before plastic changes  
- after plastic changes

# What is the impact of gain and loss ranges?



# The NARPS fMRI dataset (openneuro.org)



(Gamble outcomes are only revealed at the end of the experiment)

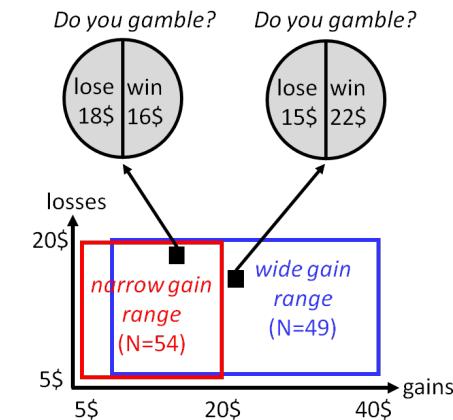
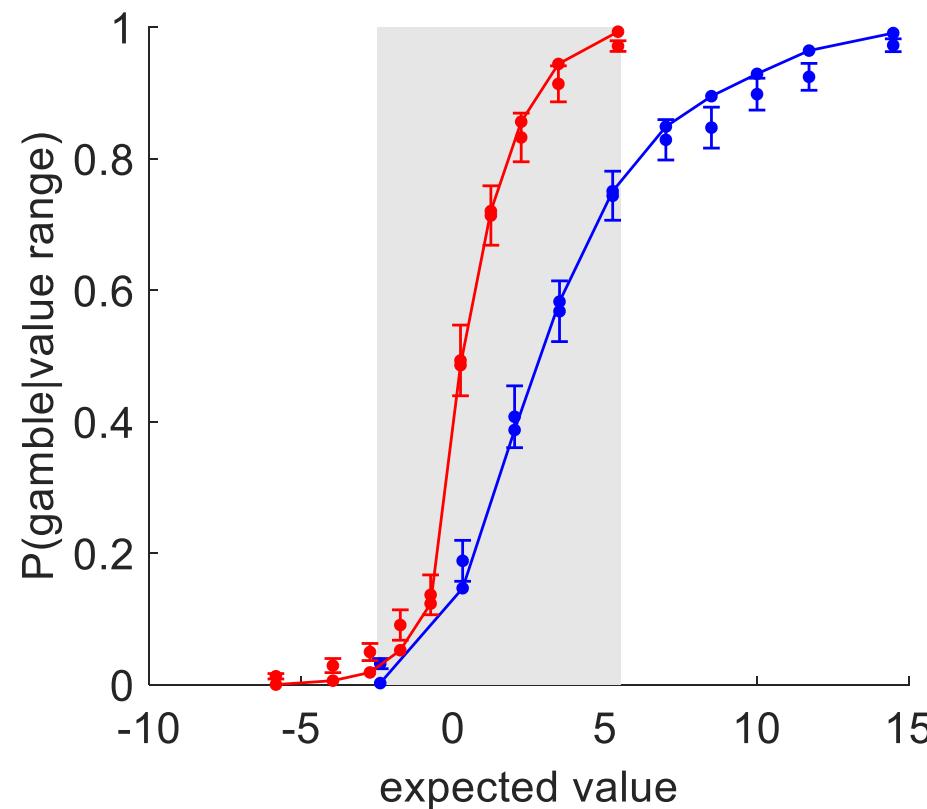
→ Two groups of participants:

- ✓ « narrow gain range » group (N=54):  $5 < \text{losses} < 20$ ,  $5 < \text{gains} < 20$
- ✓ « wide gain range » group (N=49):  $5 < \text{losses} < 20$ ,  $10 < \text{gains} < 40$

# Does risk attitude exhibit range adaption?

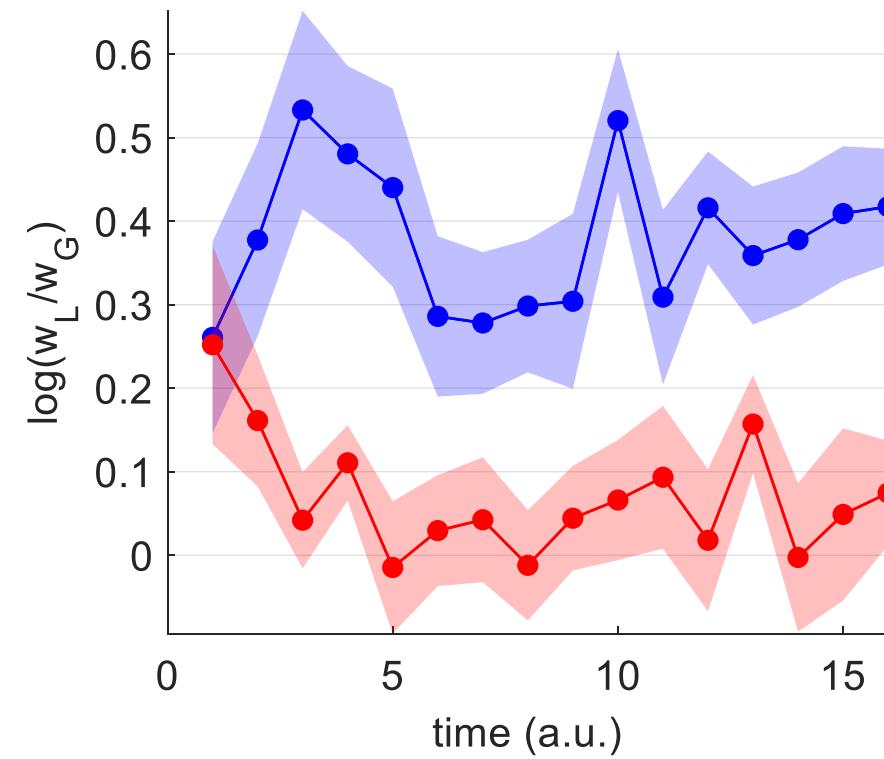
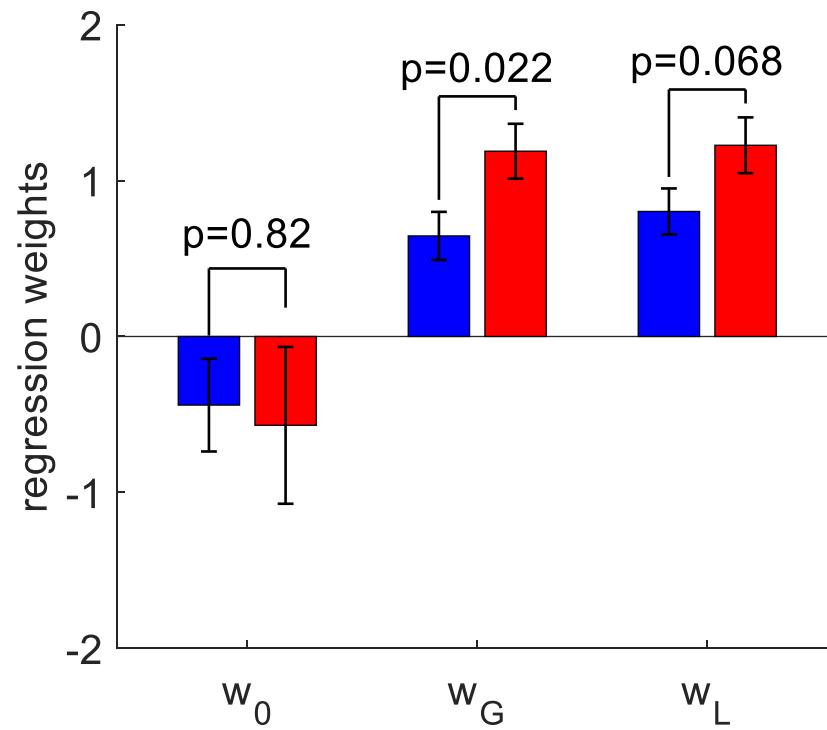
→ **Decision theory:**

- gamble's *expected value* = 50% gain – 50% loss
- $P(\text{gamble})$ : independent from the range of risk prospects

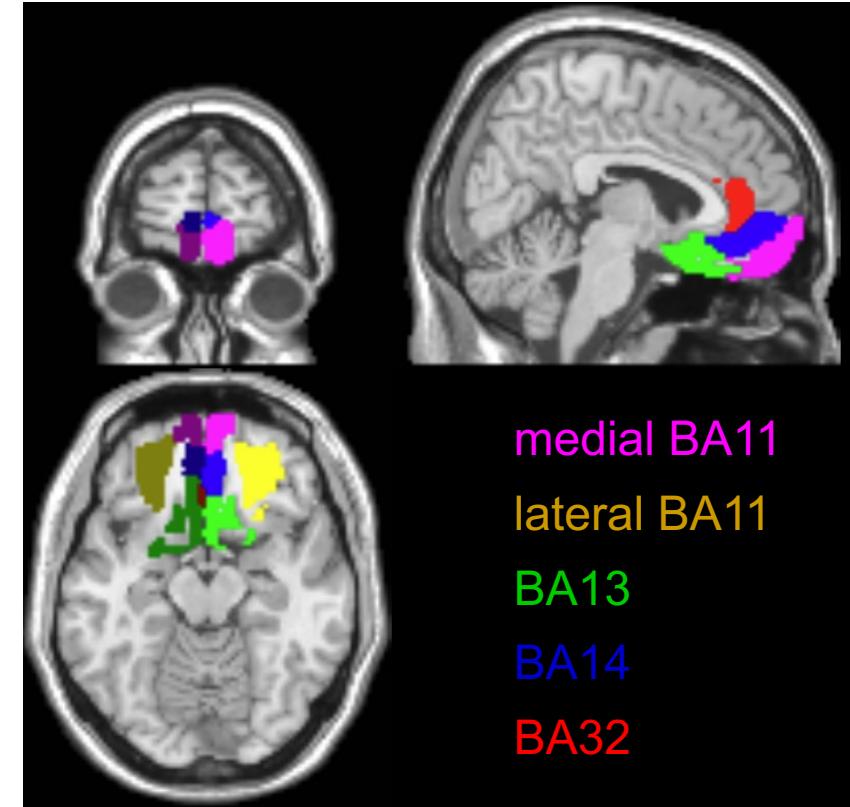
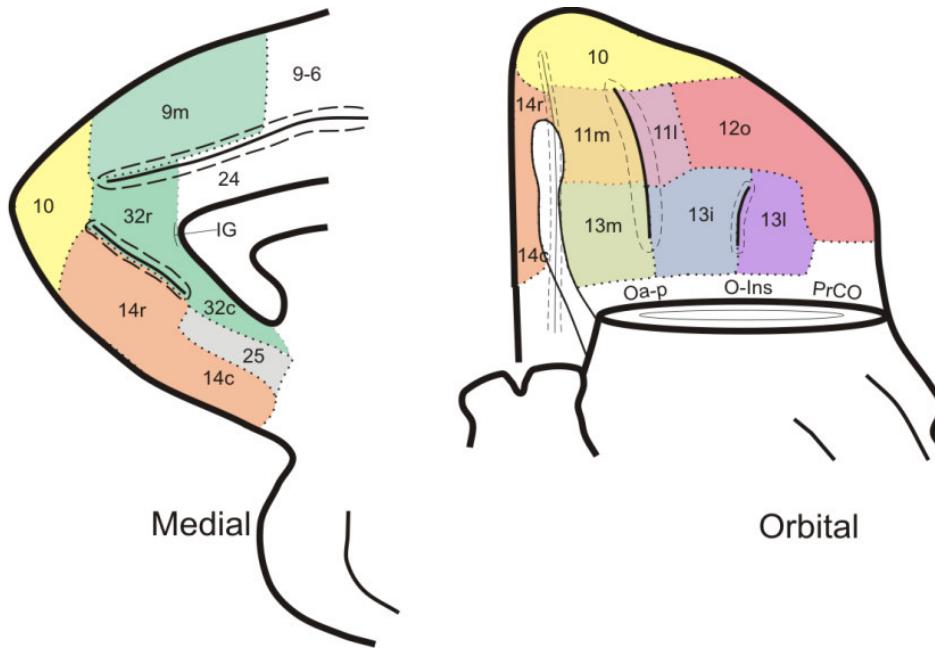


# Peoples' behavioral sensitivity to gains and losses

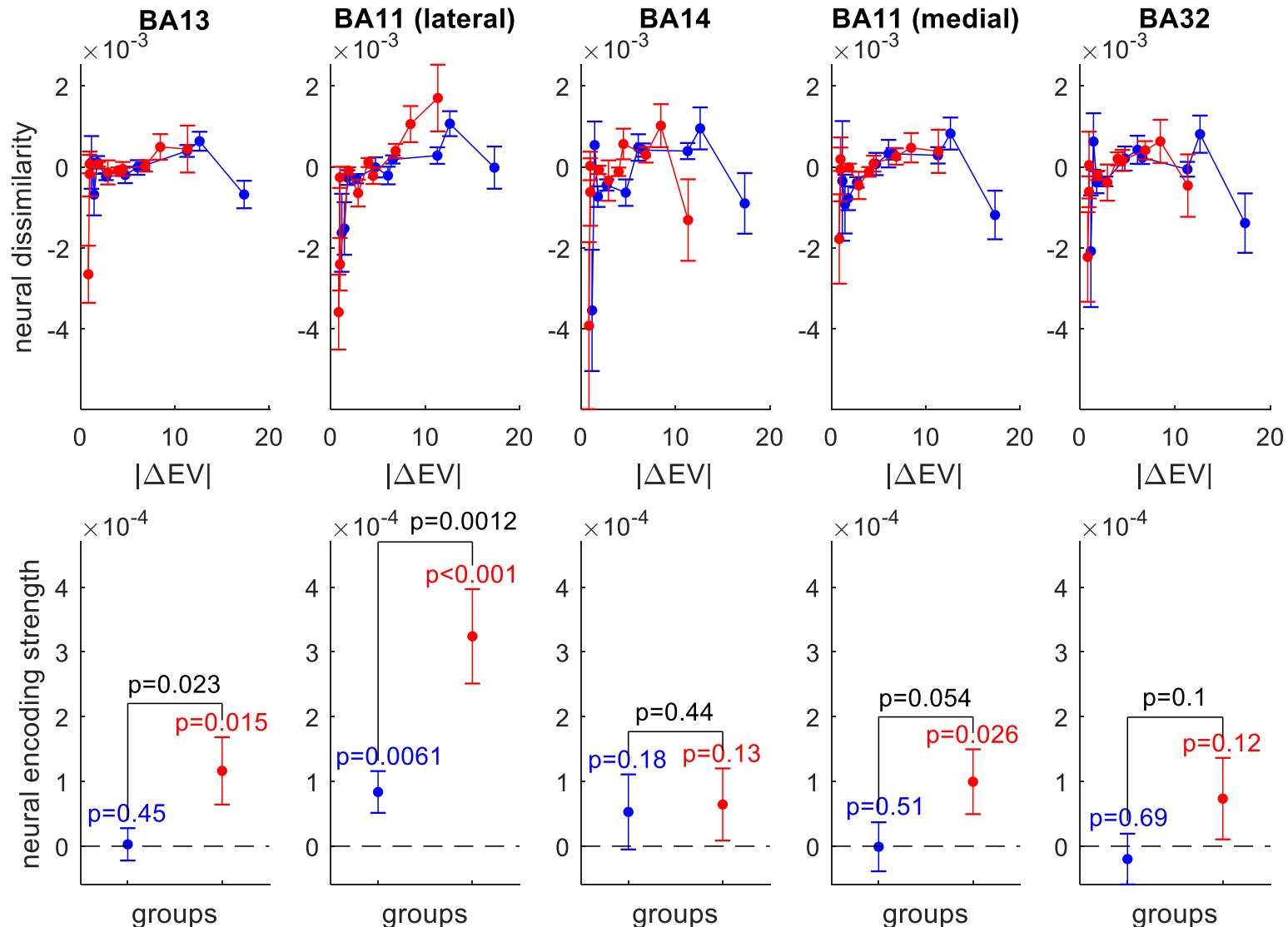
$$P(\text{gamble}) = \text{sigmoid}(\mathbf{w}_0 + \mathbf{w}_G \times \text{gain} - \mathbf{w}_L \times \text{loss})$$



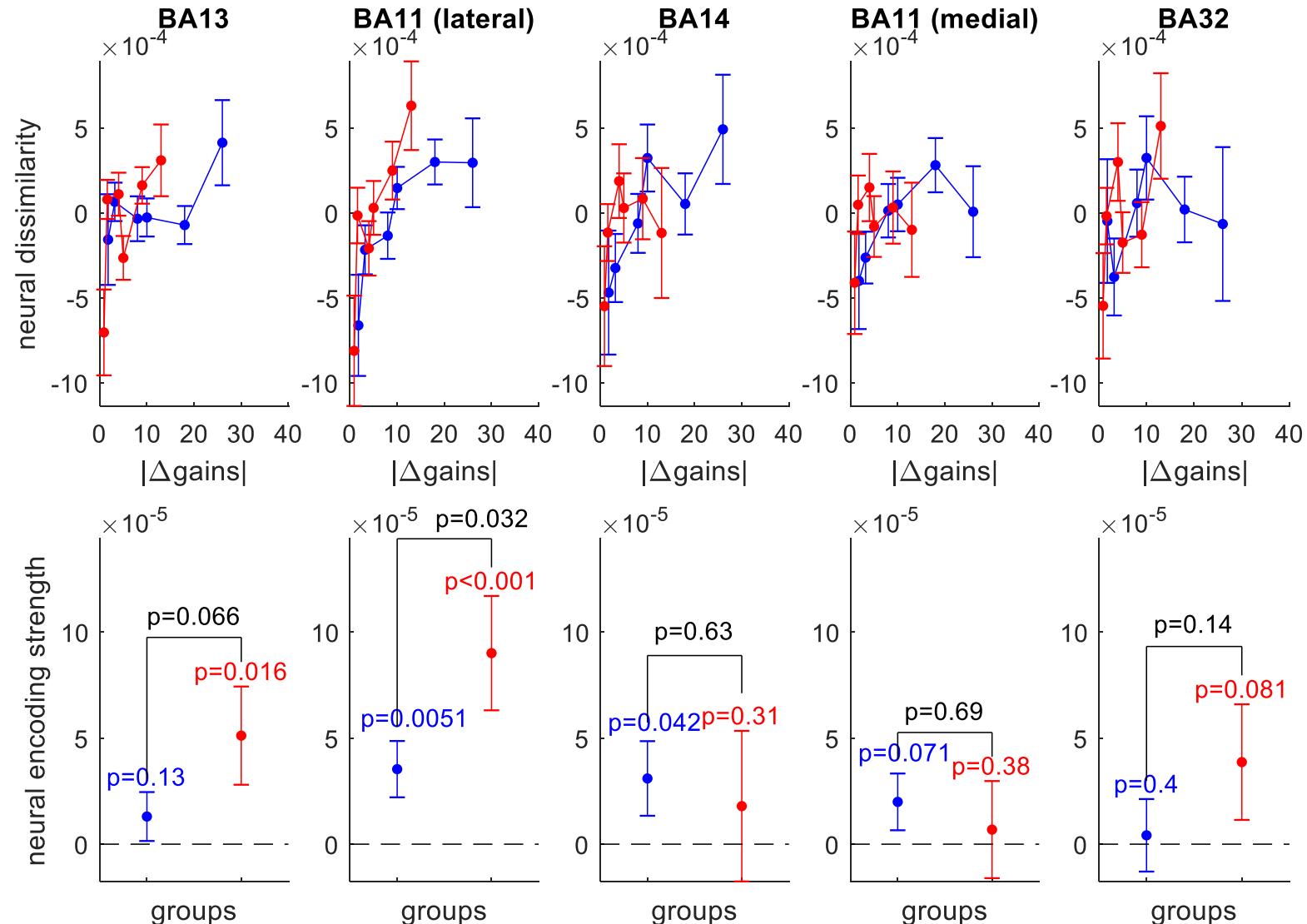
# fMRI data analysis: OFC subregions



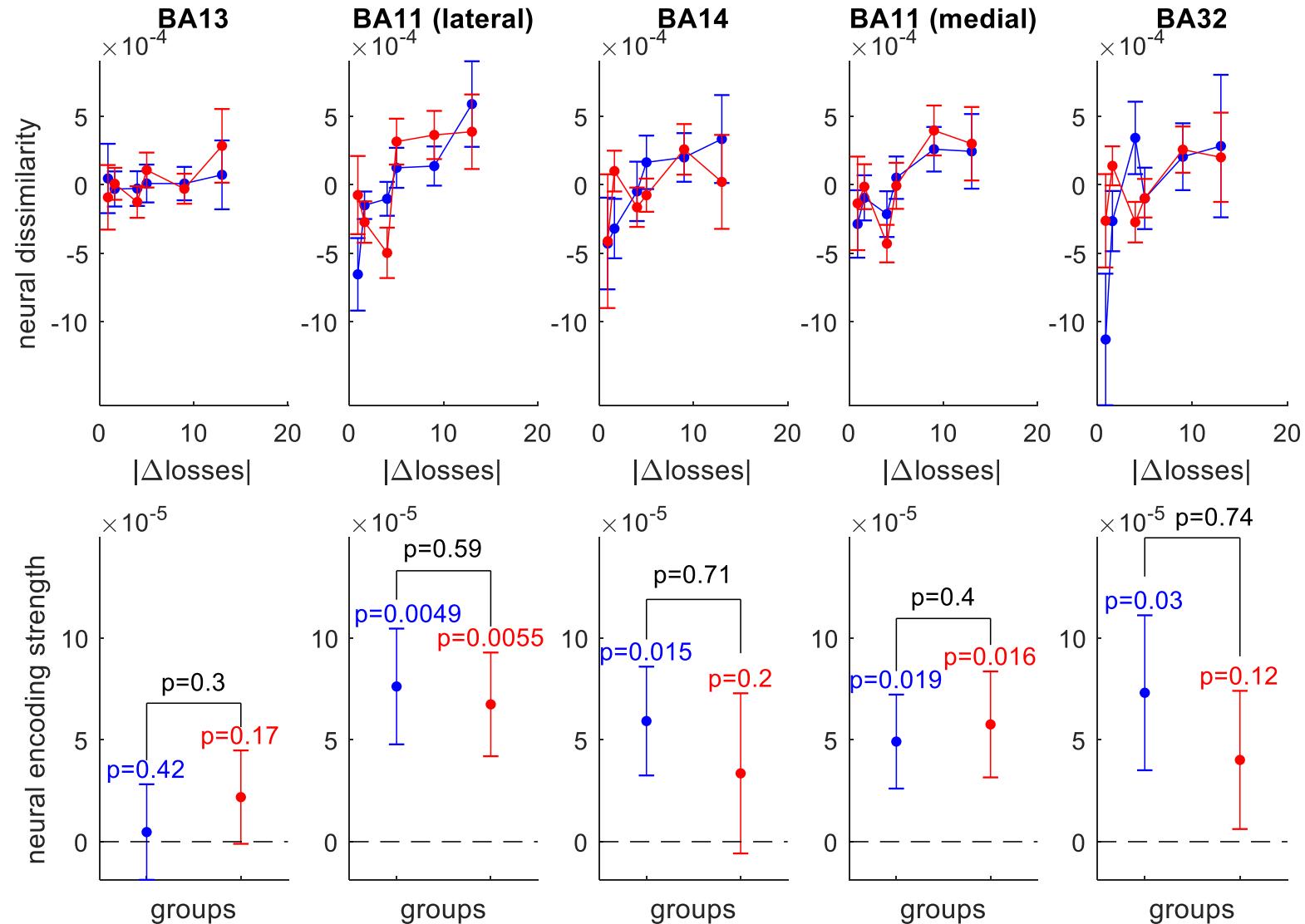
# Information content in the OFC: expected value



# Information content in the OFC: gains

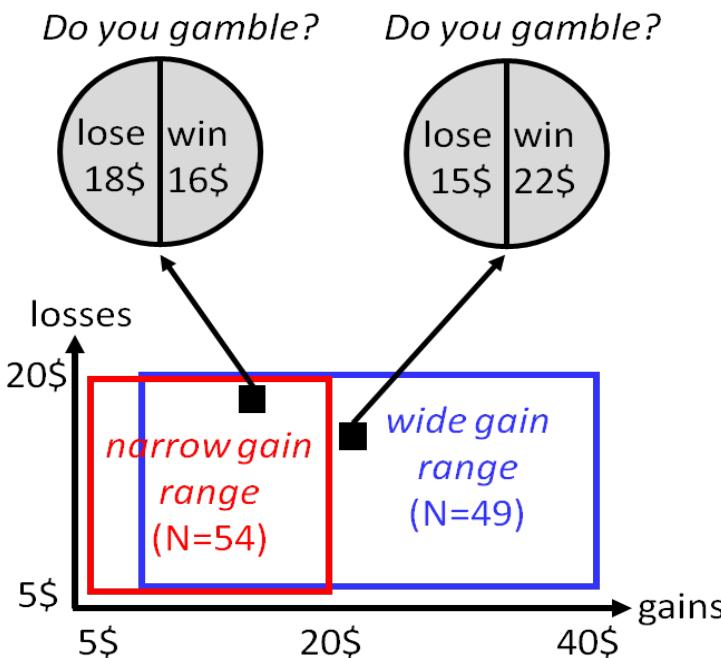


# Information content in the OFC: losses



# Model generalizability across risk range contexts

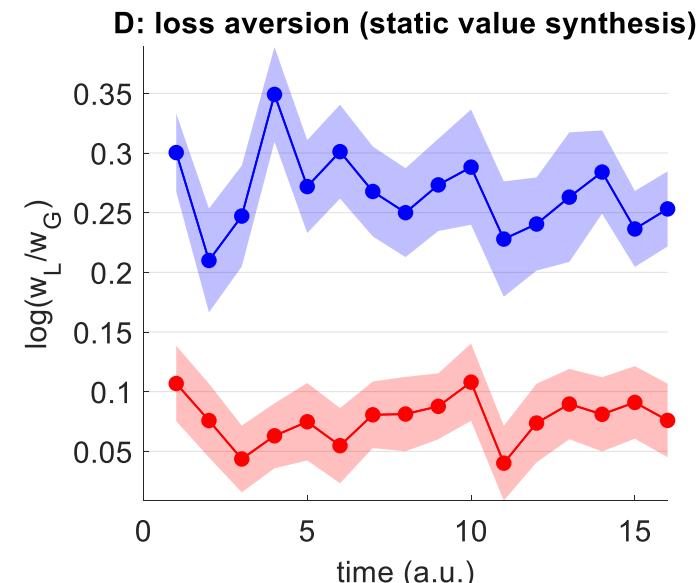
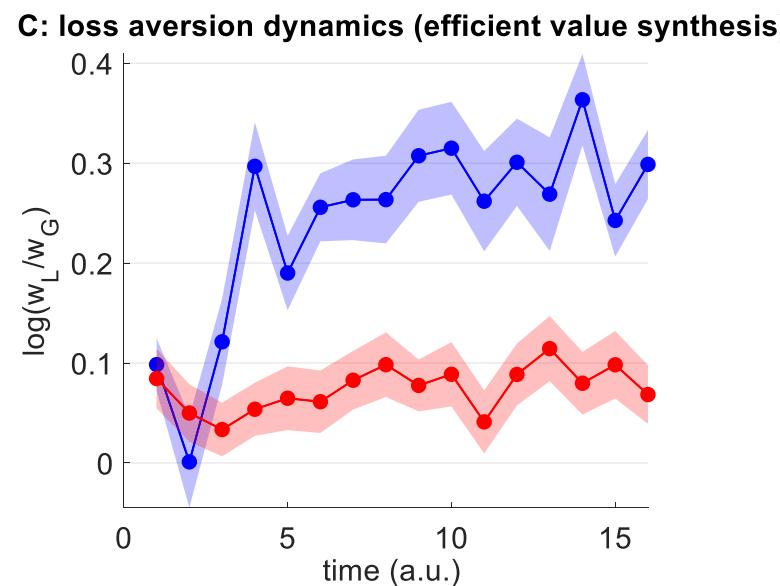
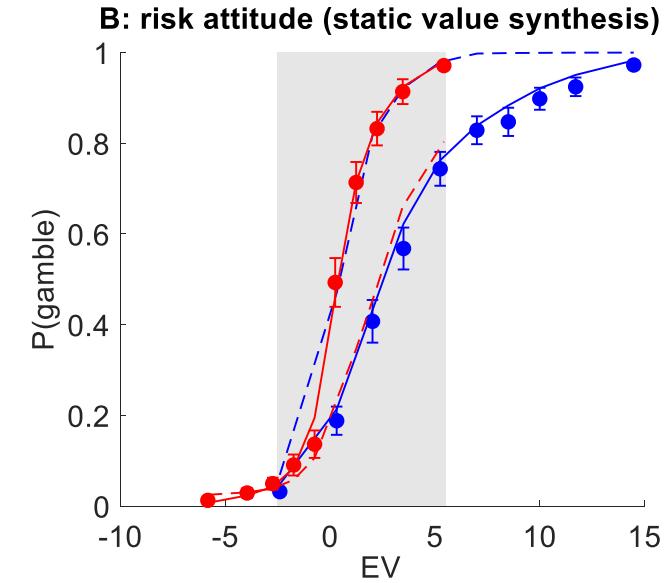
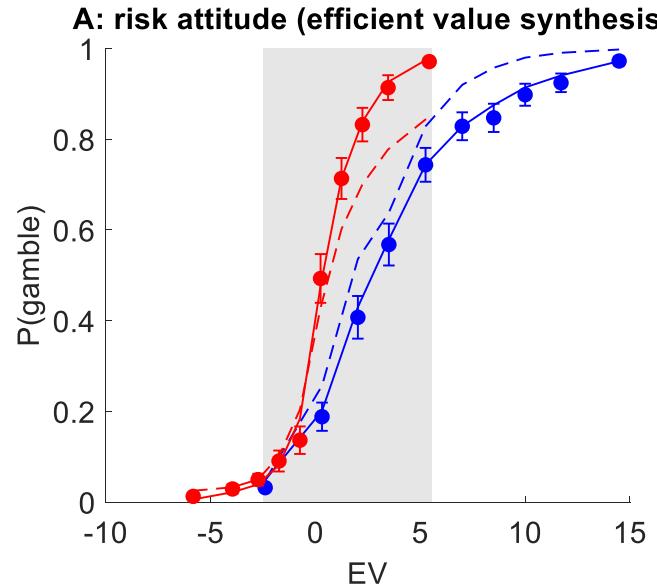
Can we predict (out-of-sample) what the other group would have done, from ANN models of value synthesis?



For each subject:

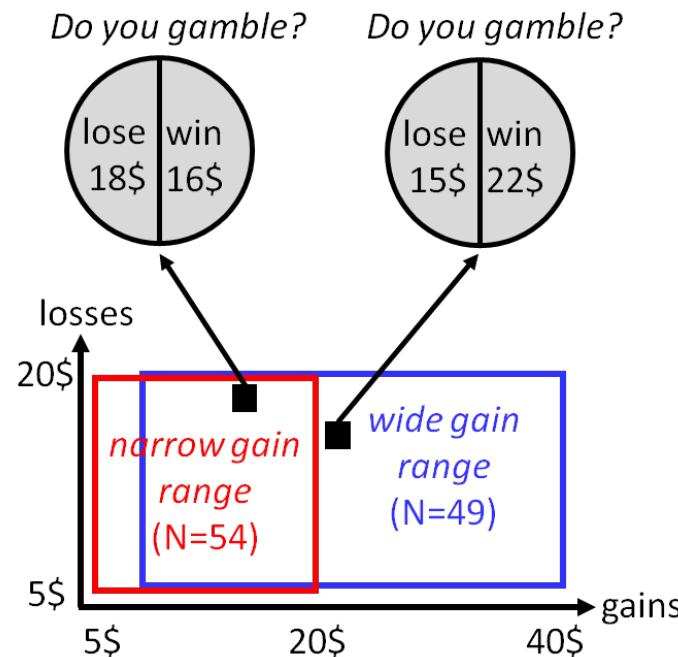
1. Fit ANN model to his/her trial-by-trial gamble decisions
2. Extract fitted ANN parameters and simulate trial-by-trial gambles of each subject *in the other group*
3. Bin trials according to EV and estimate  $P(\text{gamble}|\text{EV})$

# EVS generalizes over risk range contexts



# Model accuracy for OFC's information content

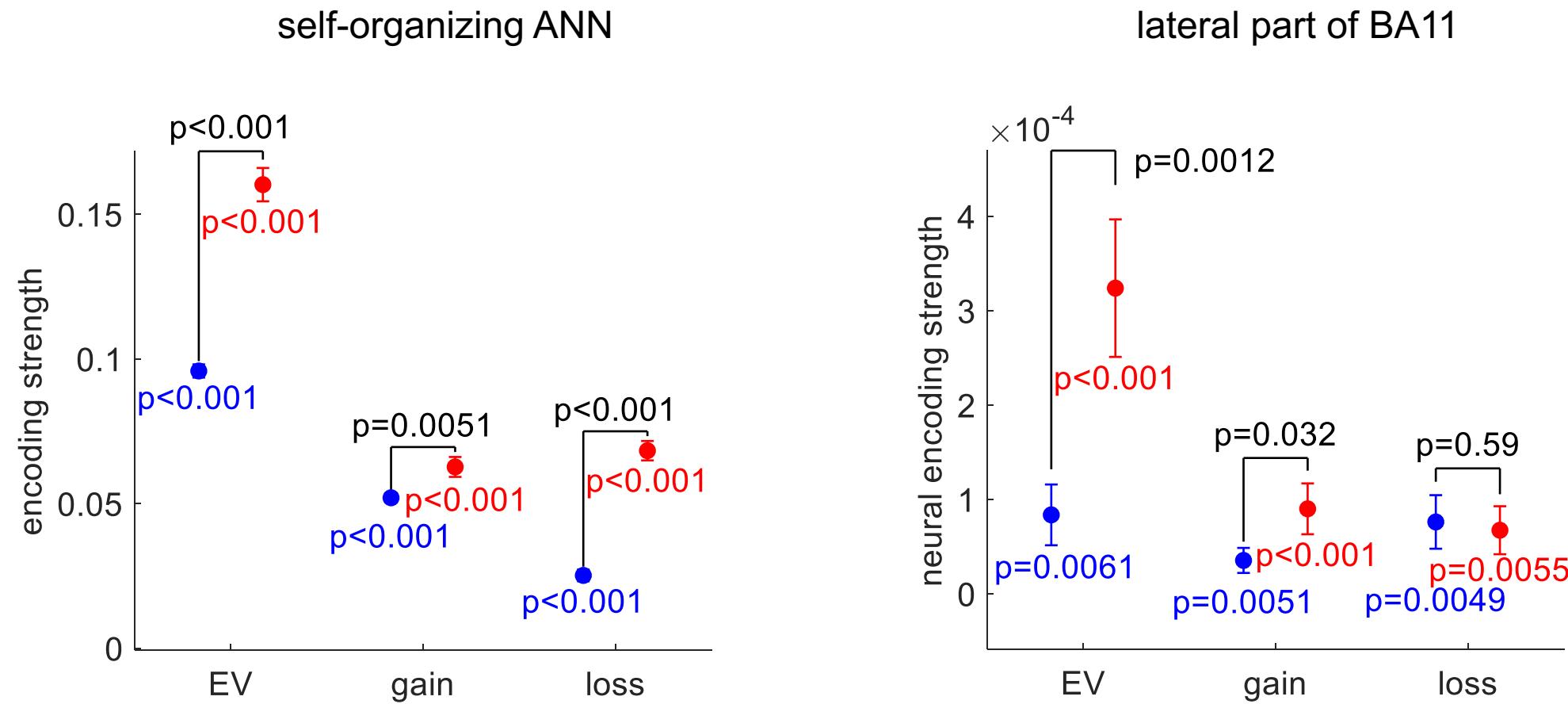
Can we predict (out-of-sample) multivariate fMRI patterns of activity in the OFC, from ANN models of value synthesis?



For each subject:

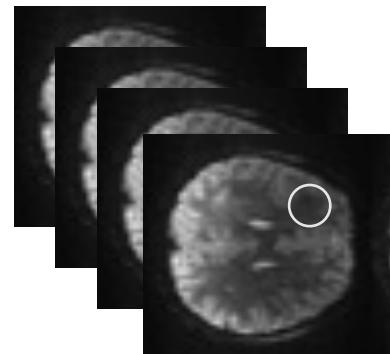
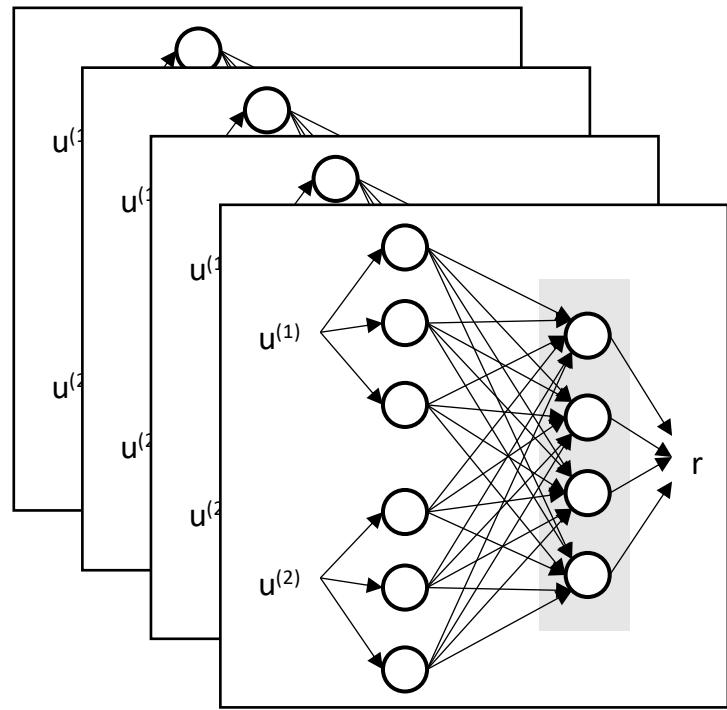
1. (Fit ANN model to his/her trial-by-trial gamble decisions)
2. Extract trial-by-trial activity profiles in the ANNs' integration layer
3. Compare those activity profiles to trial-by-trial fMRI activity patterns in the OFC

# Predicted information content of integration units



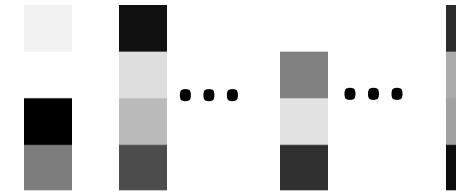
- Self-organizing ANN models reproduce the qualitative pattern of information content in BA11

# Representational Similarity Analysis

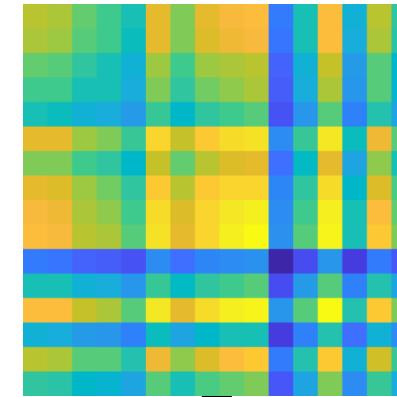


fMRI multi-voxel time series

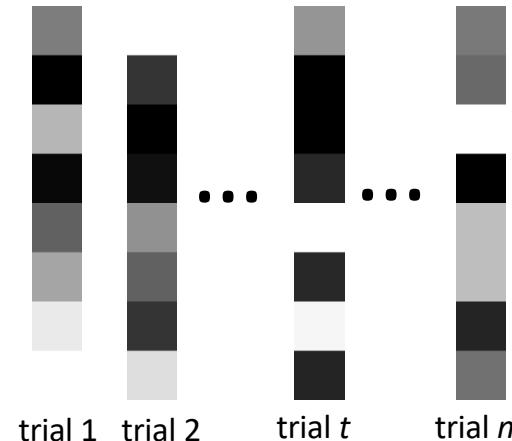
trial 1 trial 2 trial  $t$  trial  $n_t$



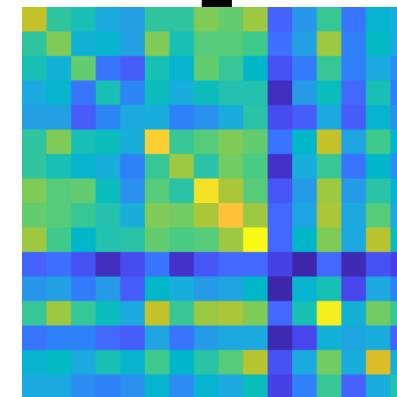
$RDM_{ANN}$



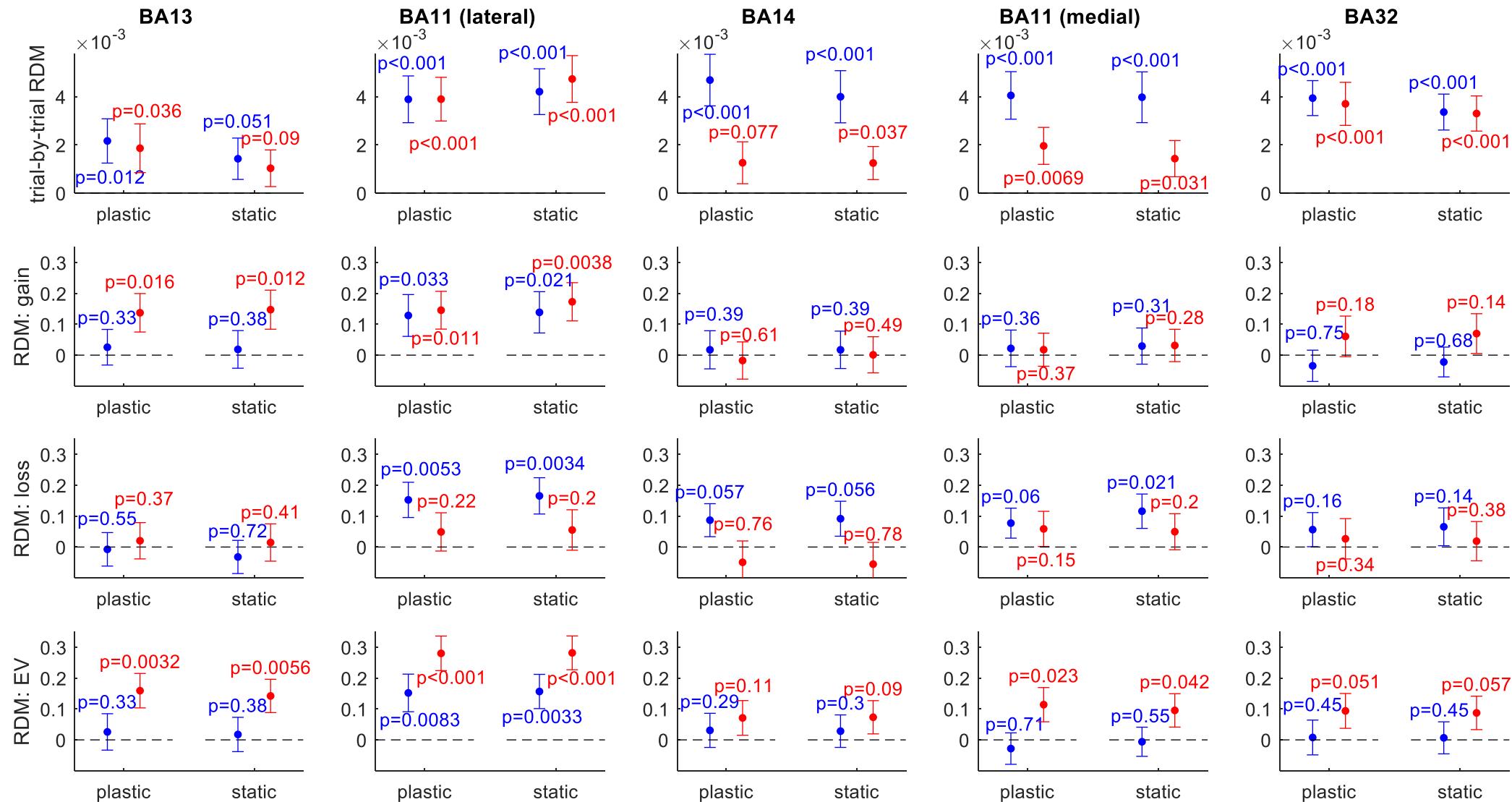
$$\rho = \text{corr}(RDM_{ANN}, RDM_{fMRI})$$



$RDM_{fMRI}$



# RSA results in the OFC (fMRI)



2/8

7/8

1/8

3/8

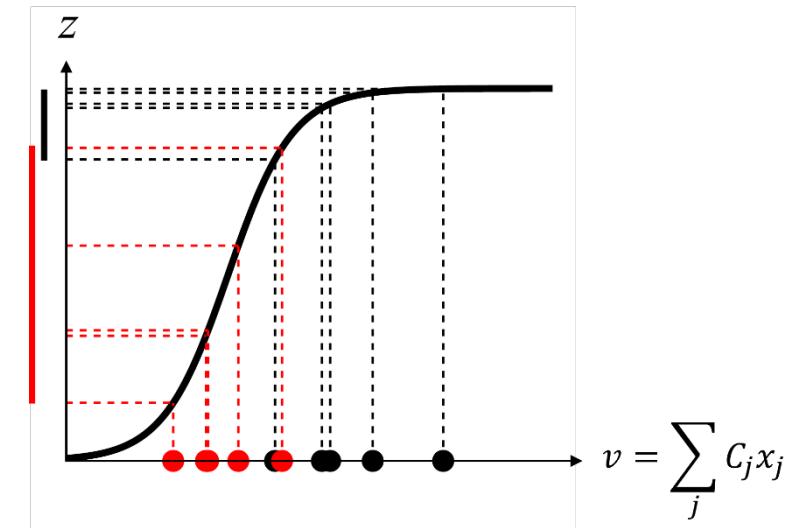
2/8

# Discussion

- Value range adaptation mechanistically follows from assuming that (i) neurons have a limited firing range and (ii) neural networks that operate value synthesis self-organize to minimize information loss.

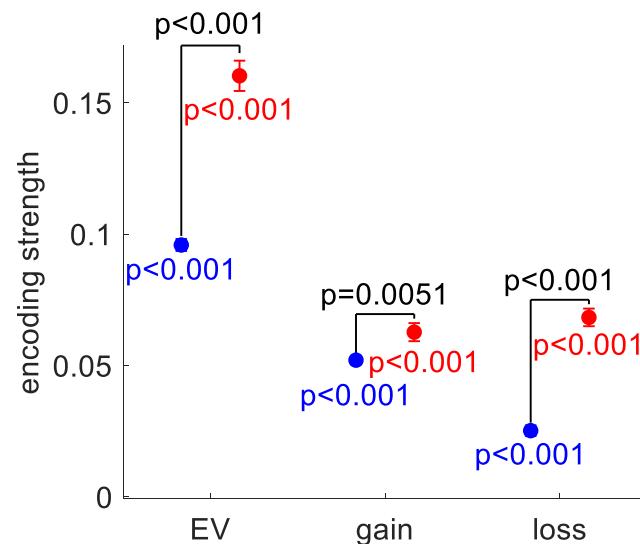
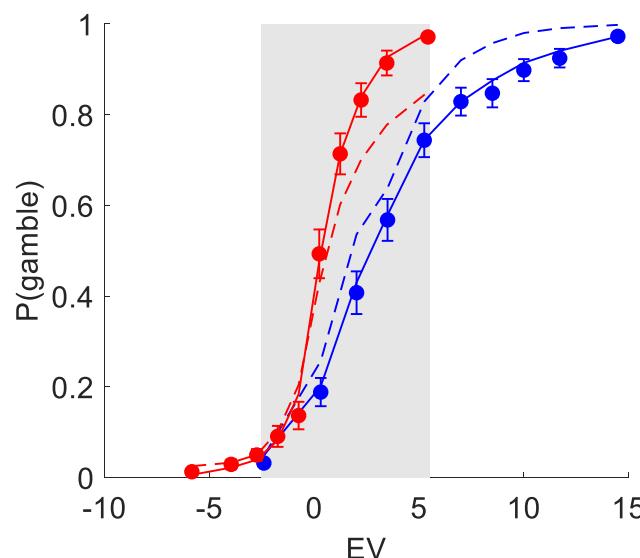
$$\dot{C}^{(j,k)} \propto -\frac{\partial IL}{\partial C^{(j,k)}} \approx \lambda x^{(j)}(1 - 2z^{(k)})$$

*anti-Hebbian rule*



# Discussion

- Value range adaptation mechanistically follows from assuming that (i) neurons have a limited firing range and (ii) neural networks that operate value synthesis self-organize to mitigate information loss.
- The ensuing *efficient value synthesis* most likely lies within lateral BA11 and eventually makes risk attitude context-dependent (i.e. irrational ).

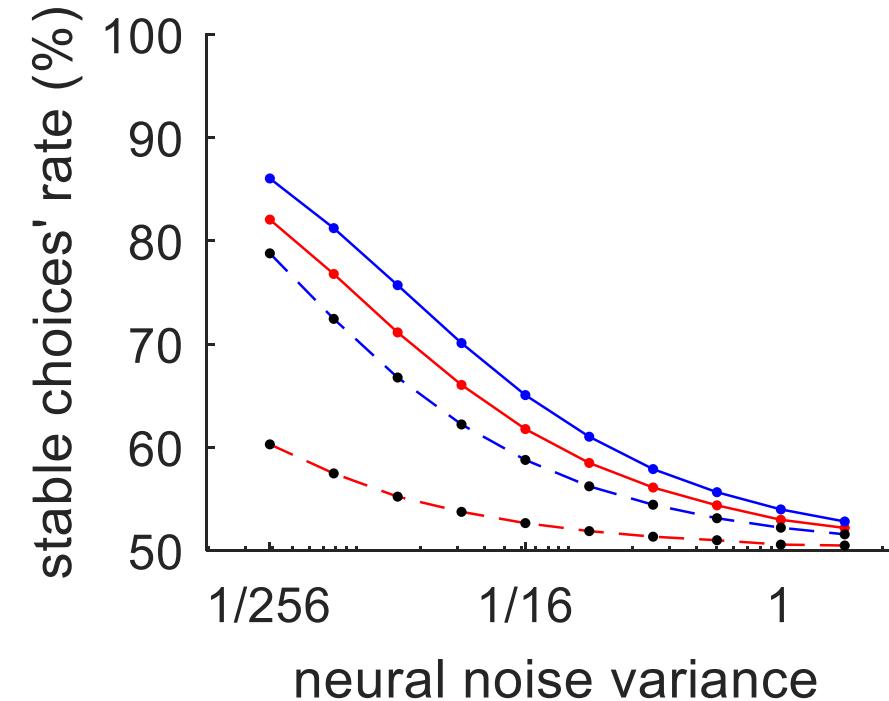
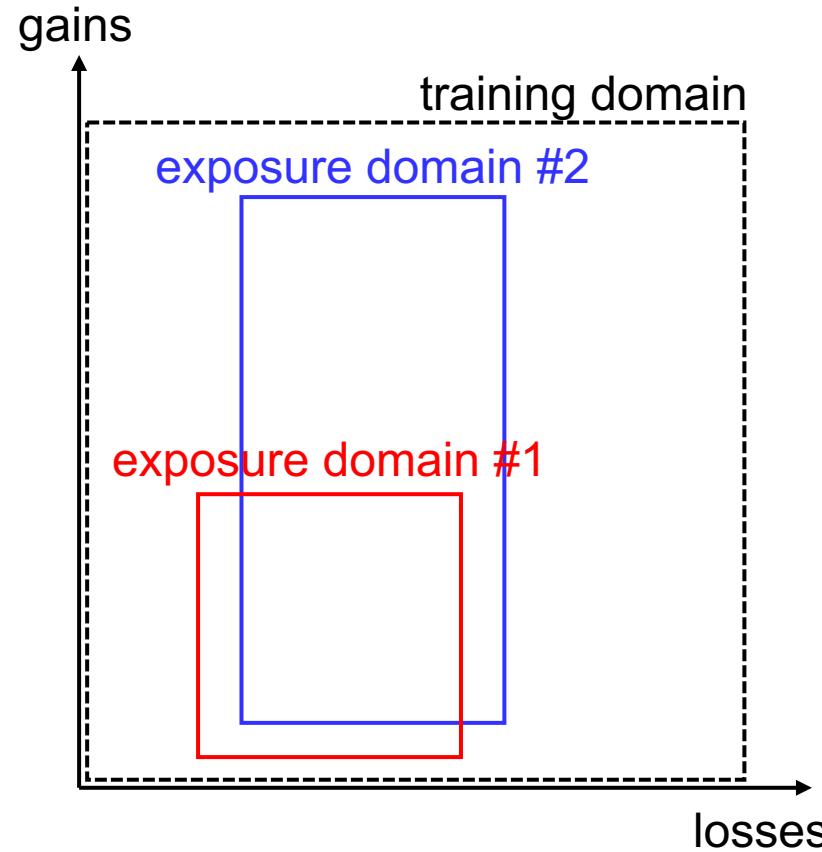


# Discussion

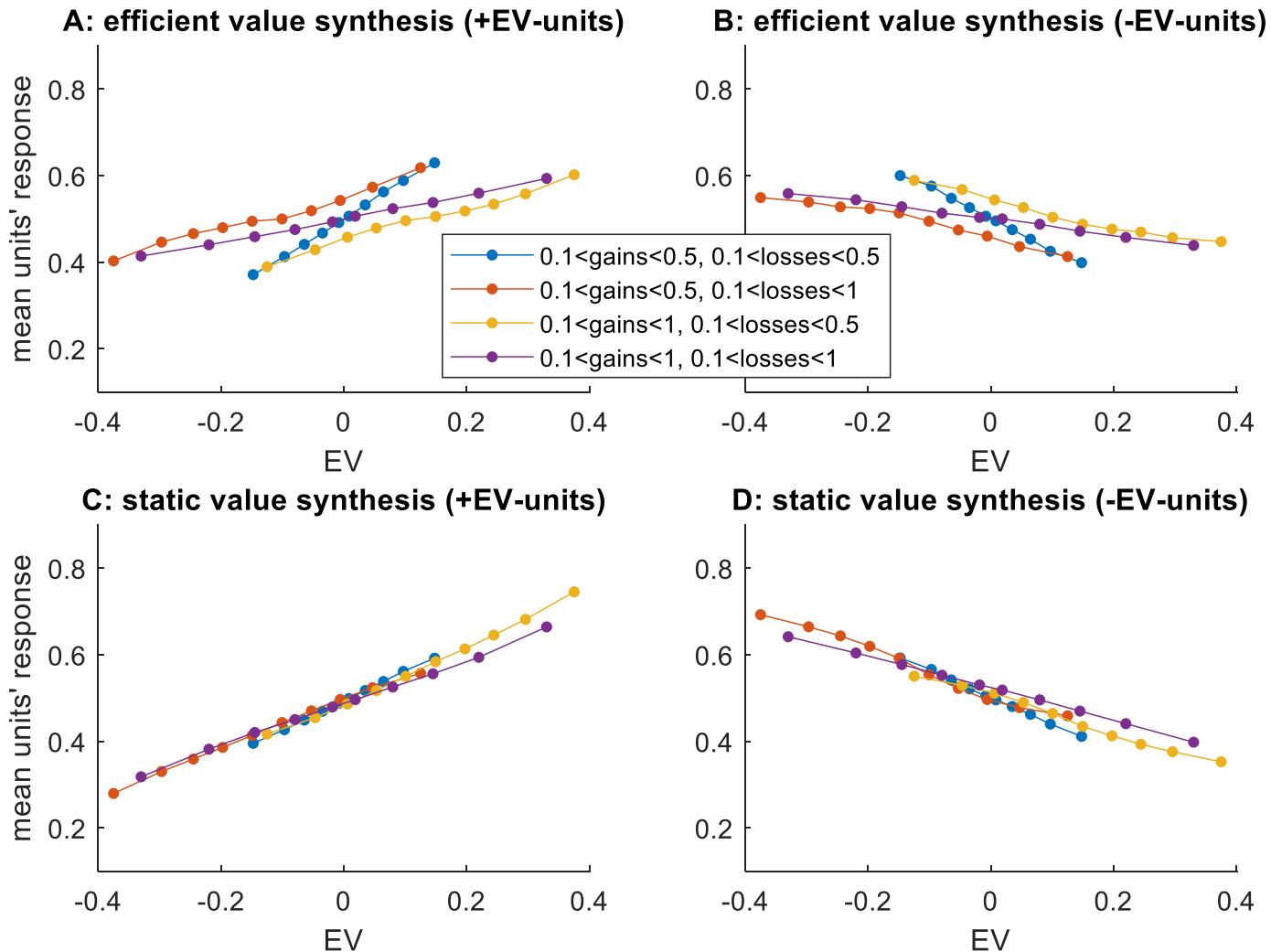
- Value range adaptation mechanistically follows from assuming that (i) neurons have a limited firing range and (ii) neural networks that operate value synthesis self-organize to minimize information loss.
- The ensuing *efficient value synthesis* most likely lies within lateral BA11 and eventually makes risk attitude context-dependent (i.e. irrational ).
- ANN models of decision-relevant computations enable the identification of hard-wired biological mechanisms and/or constraints that eventually shape and/or distort decisions.

# Is efficient value synthesis actually efficient?

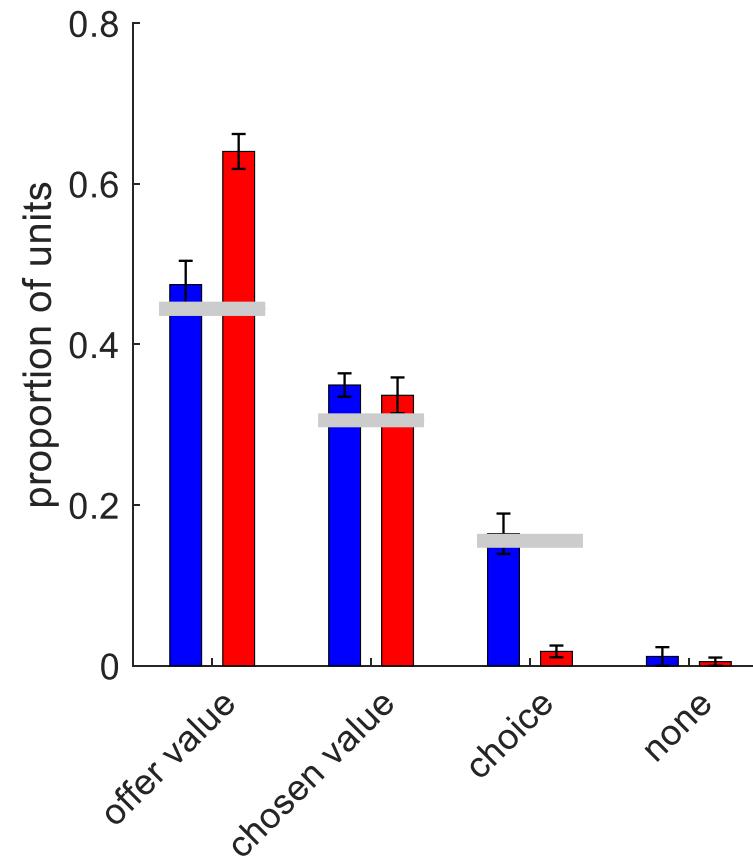
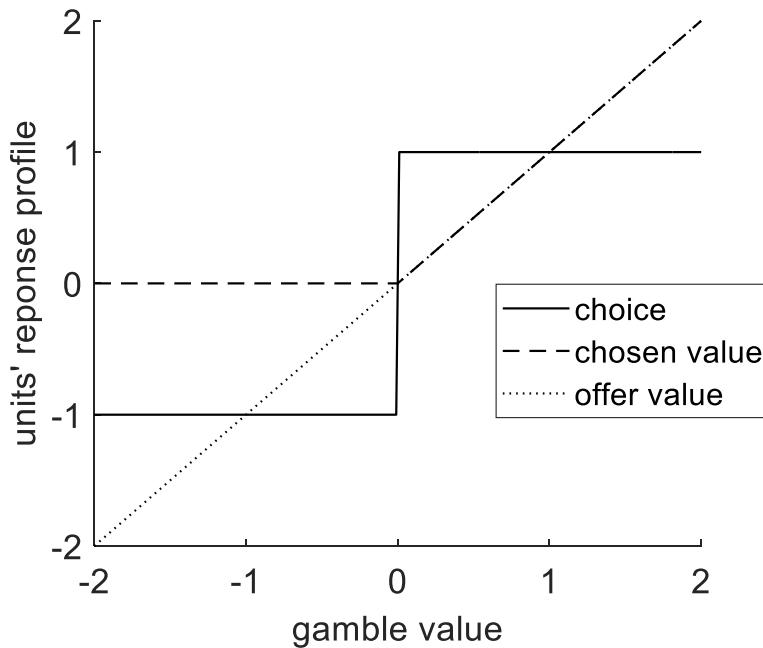
- Let the ANN self-organize while exposing it to a series of prospective gains and losses



# Integration units exhibit apparent value range adaptation

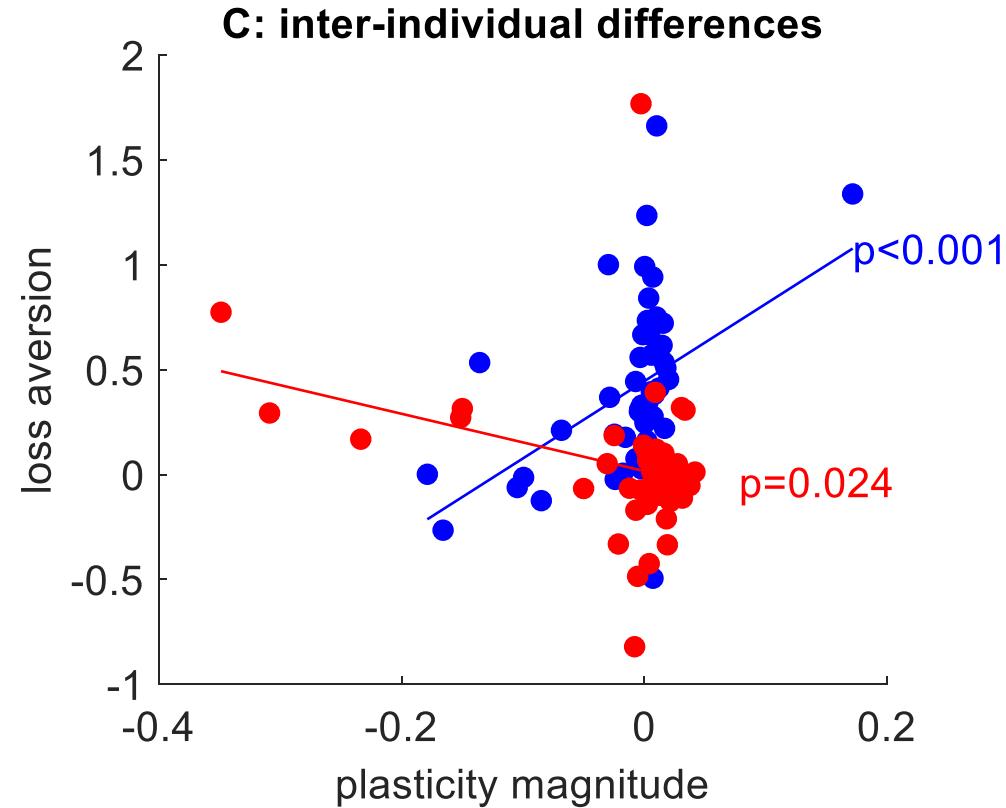


# Integration units' response profiles

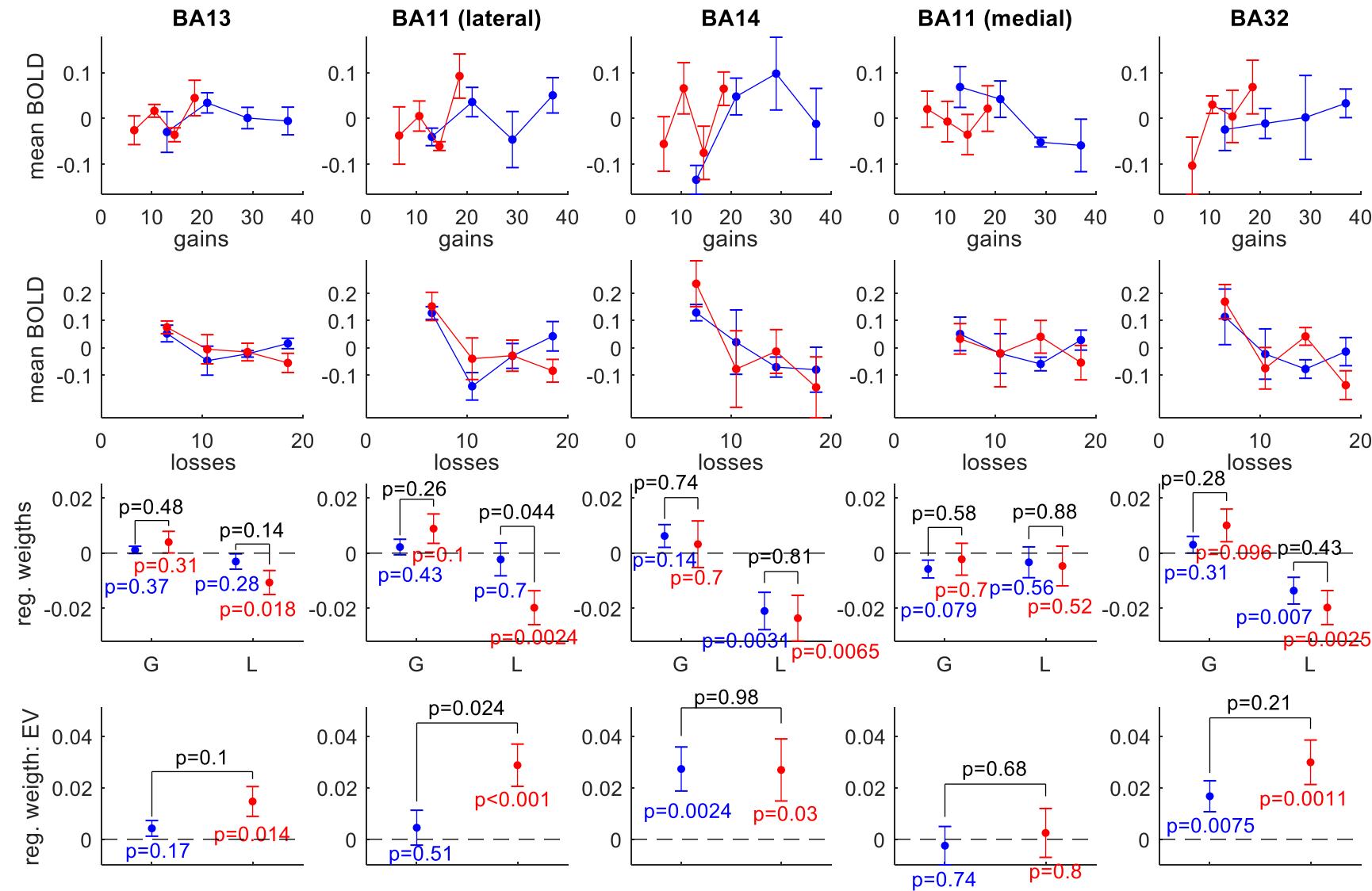


- ANN integration units exhibit known properties of OFC value-coding neurons  
(see Padoa-Schioppa & Assad, 2006)

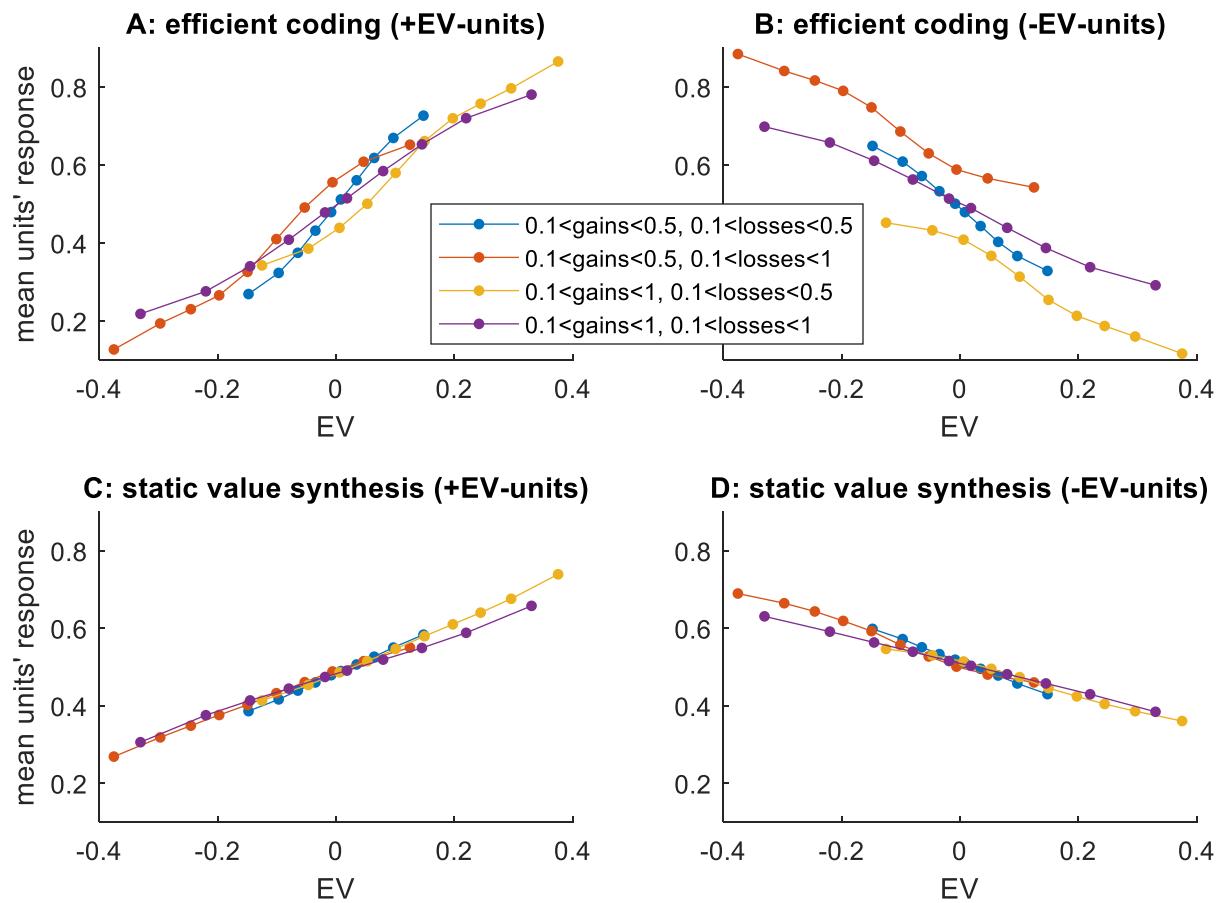
# Loss aversion: inter-individual differences



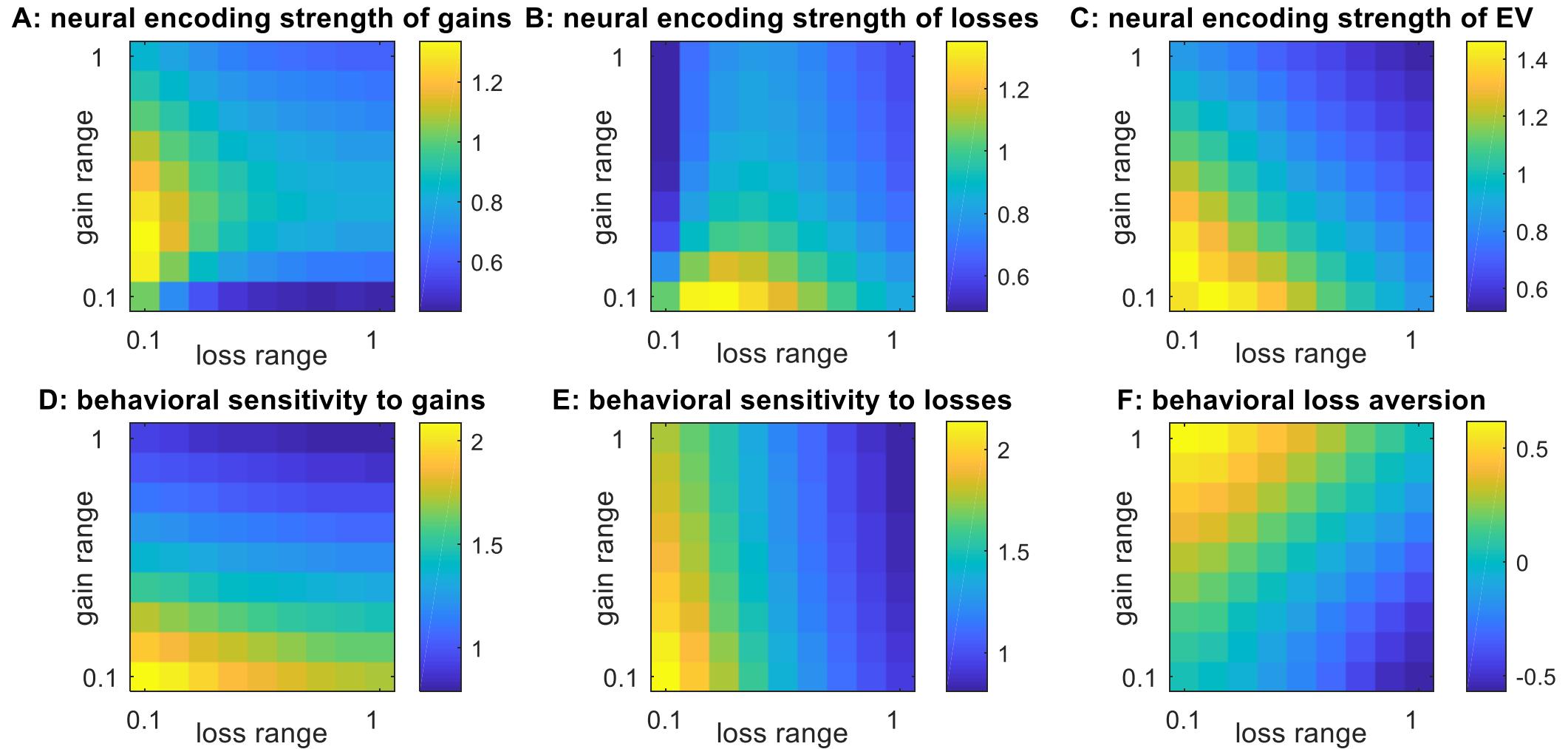
# Univariate responses in OFC subregions



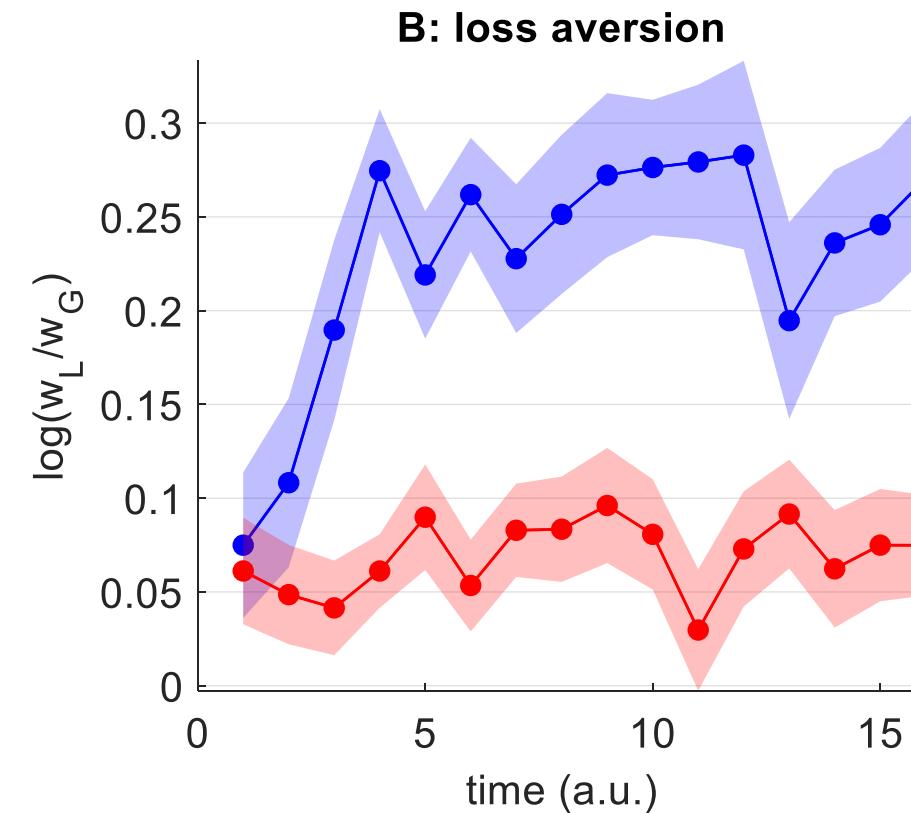
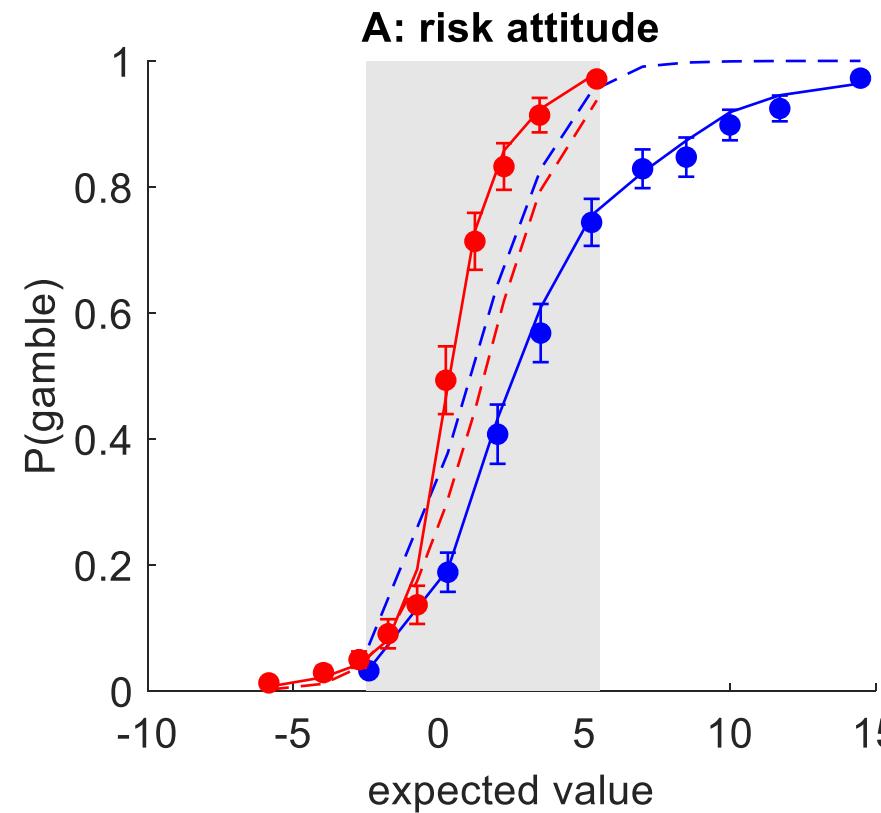
# Efficient coding of value attributes (1)



# Efficient coding of value attributes (2)



# Efficient coding of value attributes (3)



# Efficient coding of value attributes (4)

