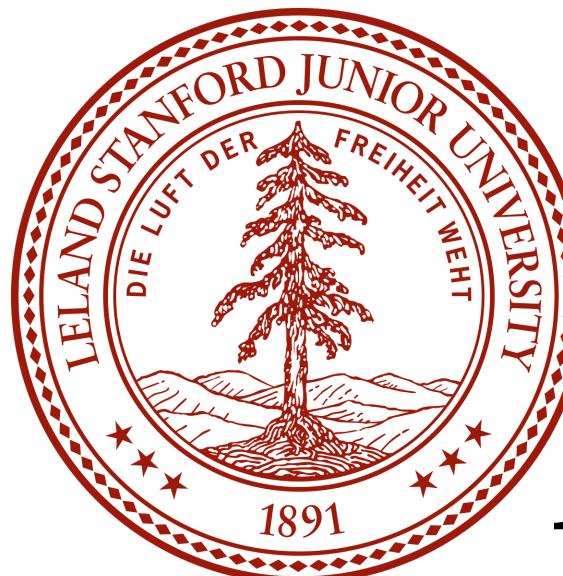


# Different forms of uncertainty differently affect the evolution of social learning

Matthew A. Turner<sup>1</sup>, Cristina Moya<sup>2,3</sup>, Paul E. Smaldino<sup>1,4,5</sup>, and James Holland Jones<sup>1</sup>

Cultural Evolution Society Conference 2022  
Aarhus University, Denmark  
September 23, 2022



1



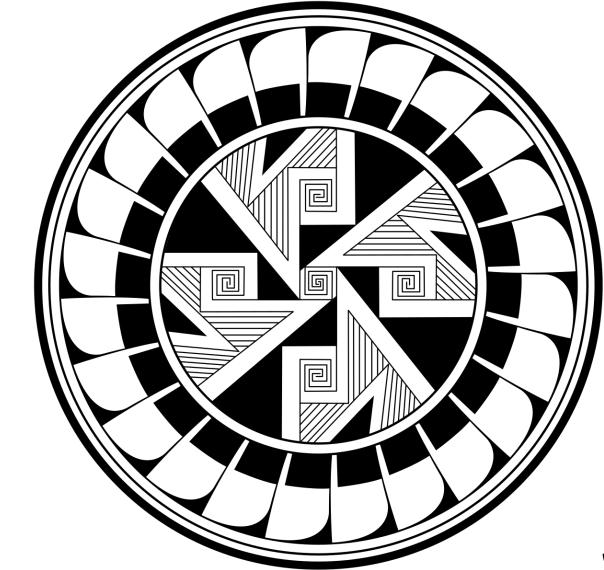
2



3



4



5

# Introduction: Uncertainty and learning



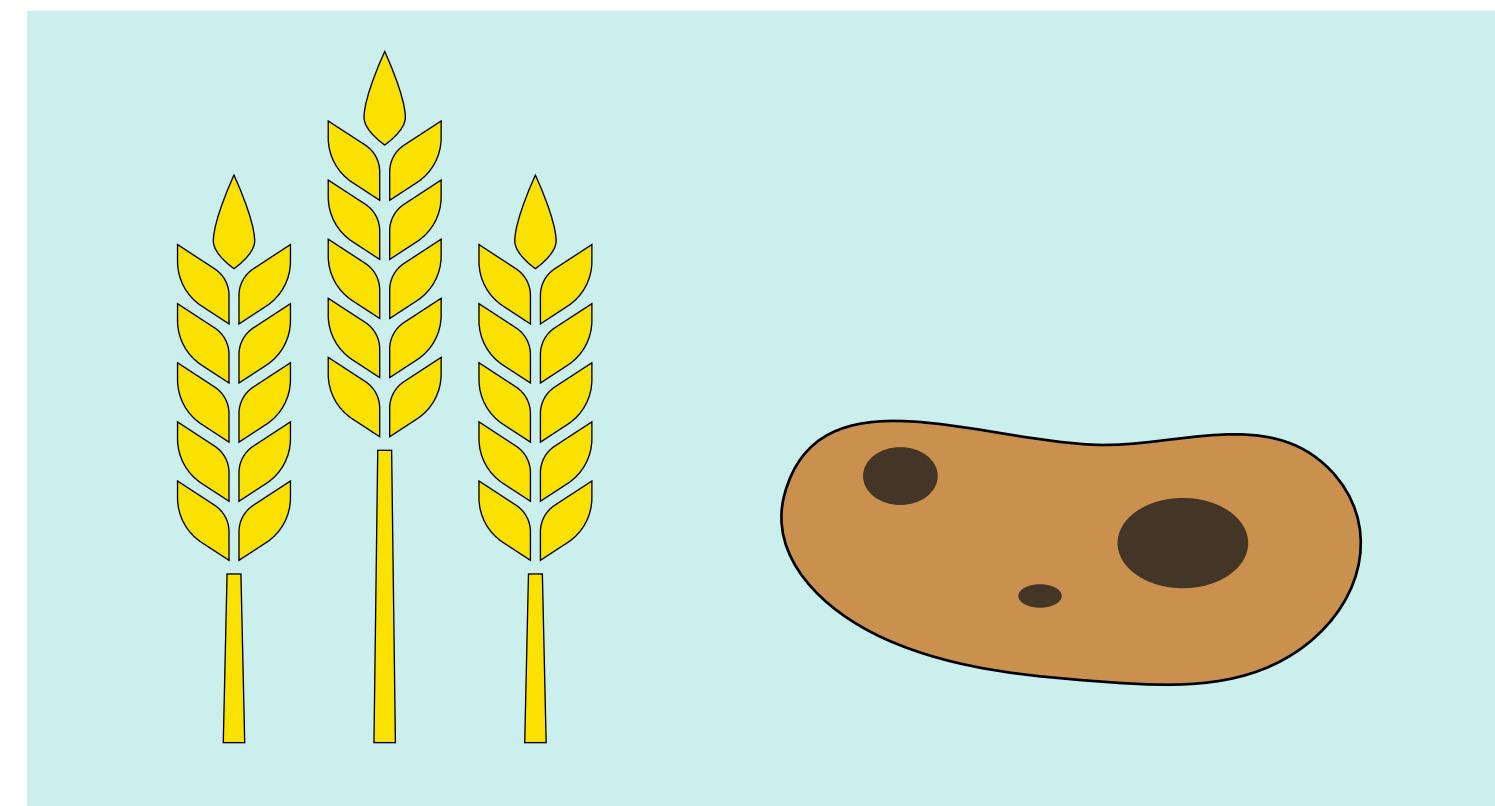
- We face unprecedented uncertainty: how does social learning evolve to address uncertainty?
- Social learning is beneficial when individuals are uncertain about which behavior is optimal.
- We know excessive environmental variability can deprecate and devalue social information.
- But which other forms of uncertainty are important, and how do they affect social learning?

# Varieties of uncertainty

1. **Environmental variability:** a measure of how frequently or in what way behavioral payoffs change over time.
2. **Payoff ambiguity:** a measure of how discernible expected payoffs are from performing different behaviors.
3. **Selection set size:** the number of behavioral options available.
4. **Effective lifespan:** number of opportunities for individual learning.

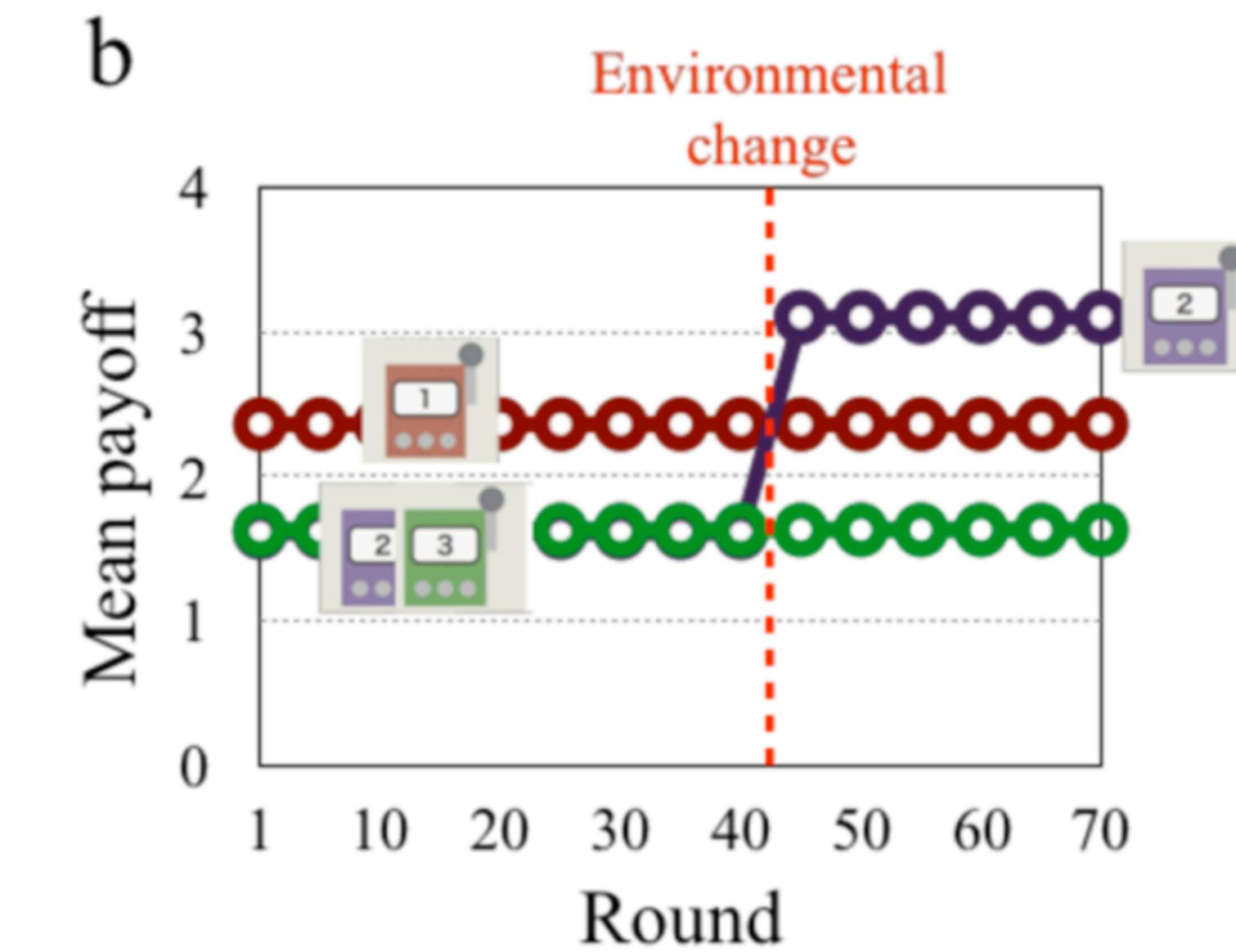
# Uncertainty parameter 1: environmental variability

Sub-variety A: Change occurs with some probability at each time step (i.e. change is Poisson-distributed).



McElreath, et al., (2005) prompt participants to choose between planting virtual wheat or potatoes in a computer-based experiment; which is more beneficial changes randomly with probability 1/20.

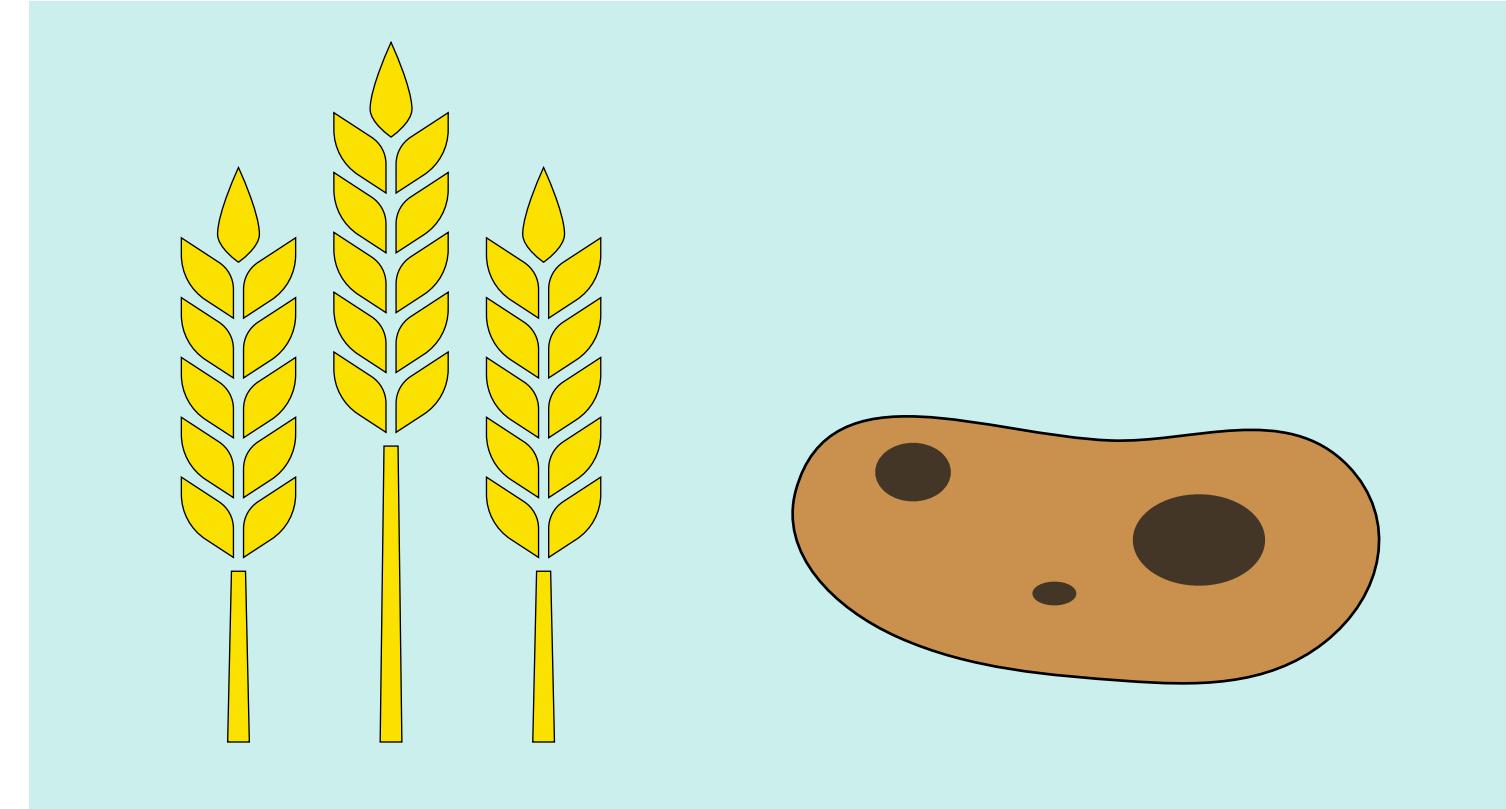
Sub-variety B: Change occurs once at some given time.



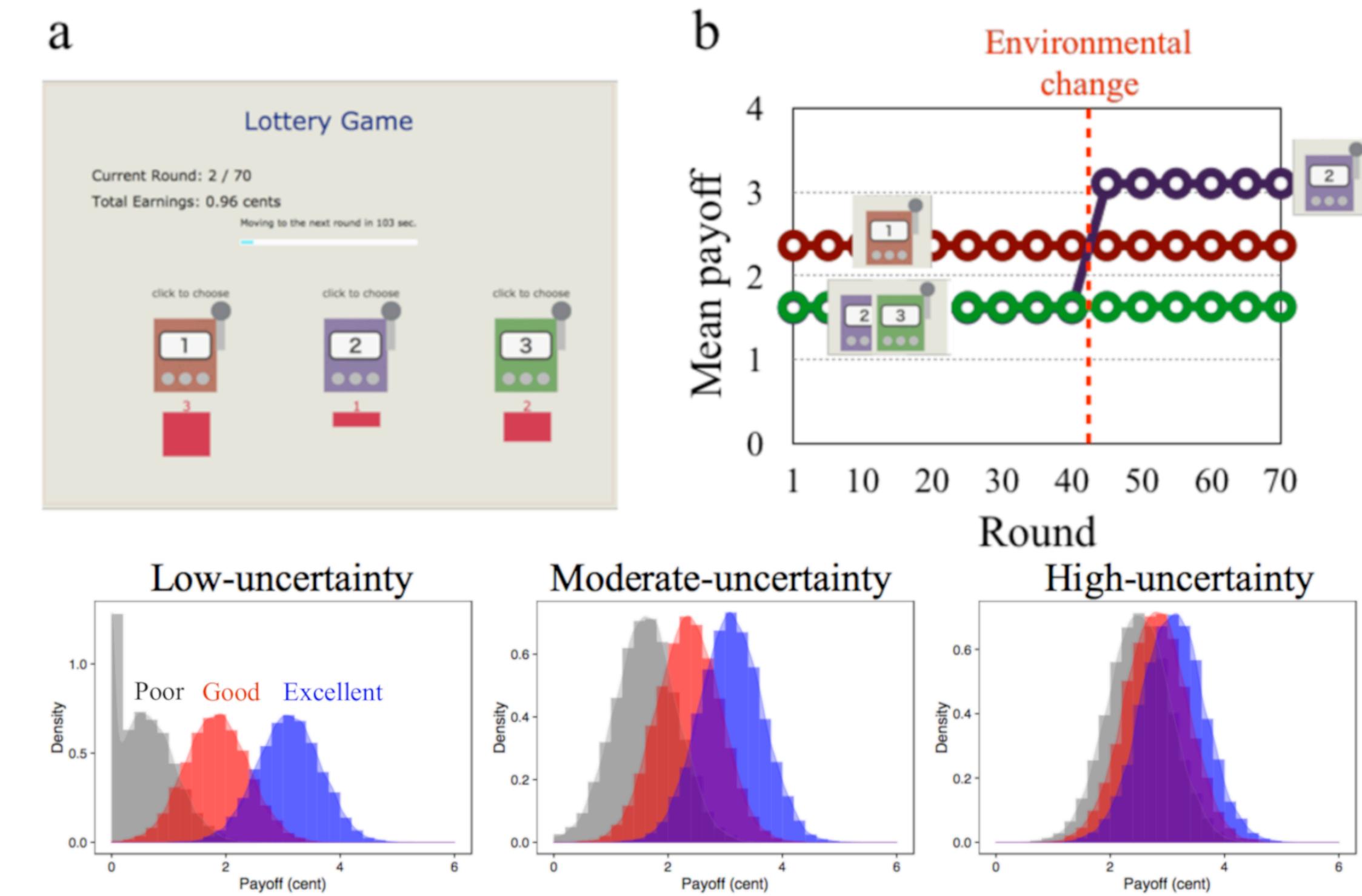
Toyokawa, et al., (2019) designed an experiment where one previously sub-optimal behavior became optimal at a certain round.

# Uncertainty parameter 2: payoff ambiguity

McElreath, et al., (2005) assume constant payoff ambiguity for participants deciding which virtual crop to plant: one crop has expected payoff 10 while the other has expected payoff 13, subject to environmental variability.

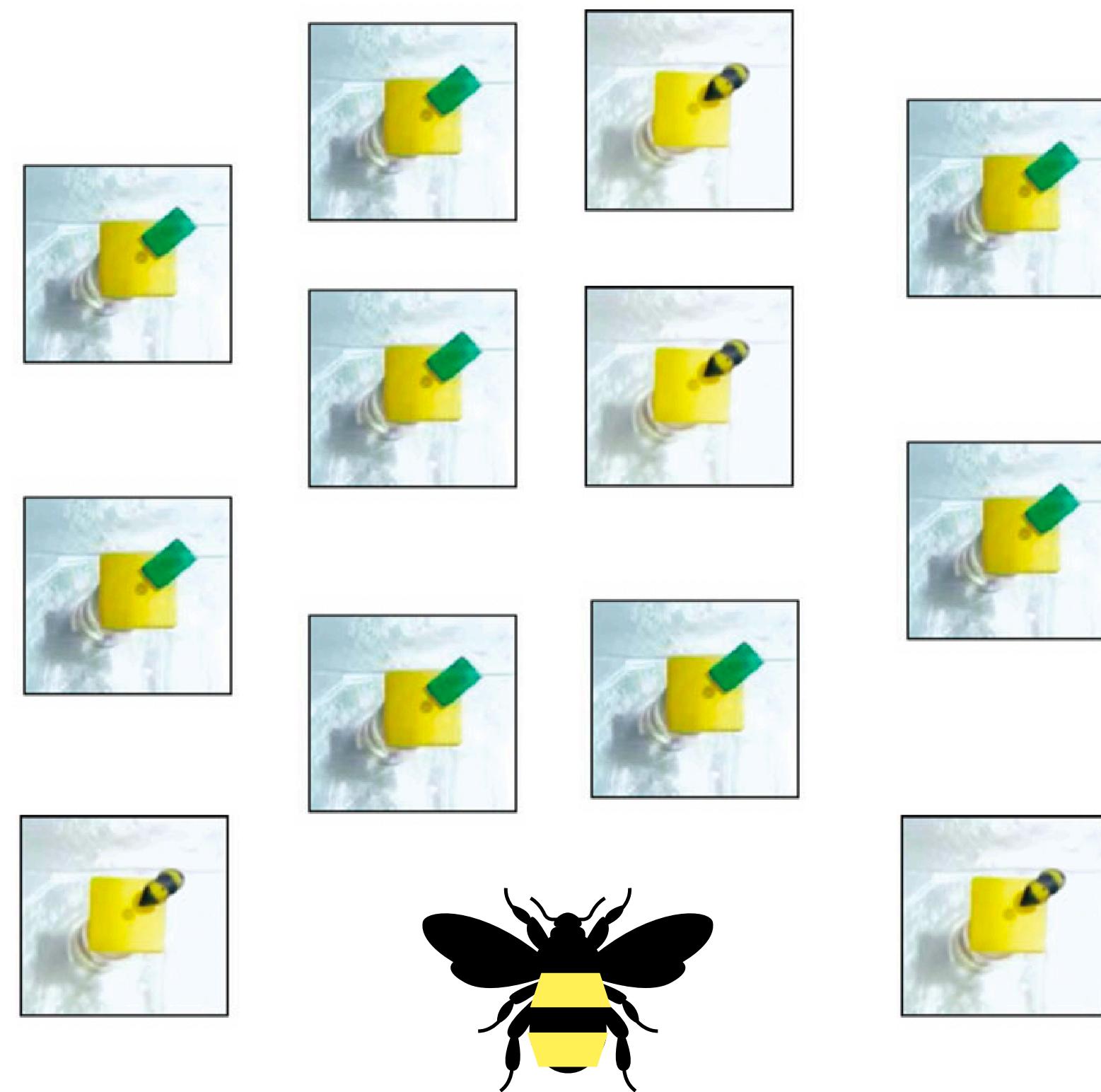


Toyokawa, et al., (2019) assume three different payoff distributions (bottom row). Closer means translates to greater uncertainty.



# Uncertainty parameter 3: selection set size

Smolla, et al., use insect model bumblebees (*bombus terrestris*) decide whether to use social cues (4 social cues spread among 12 in selection set).

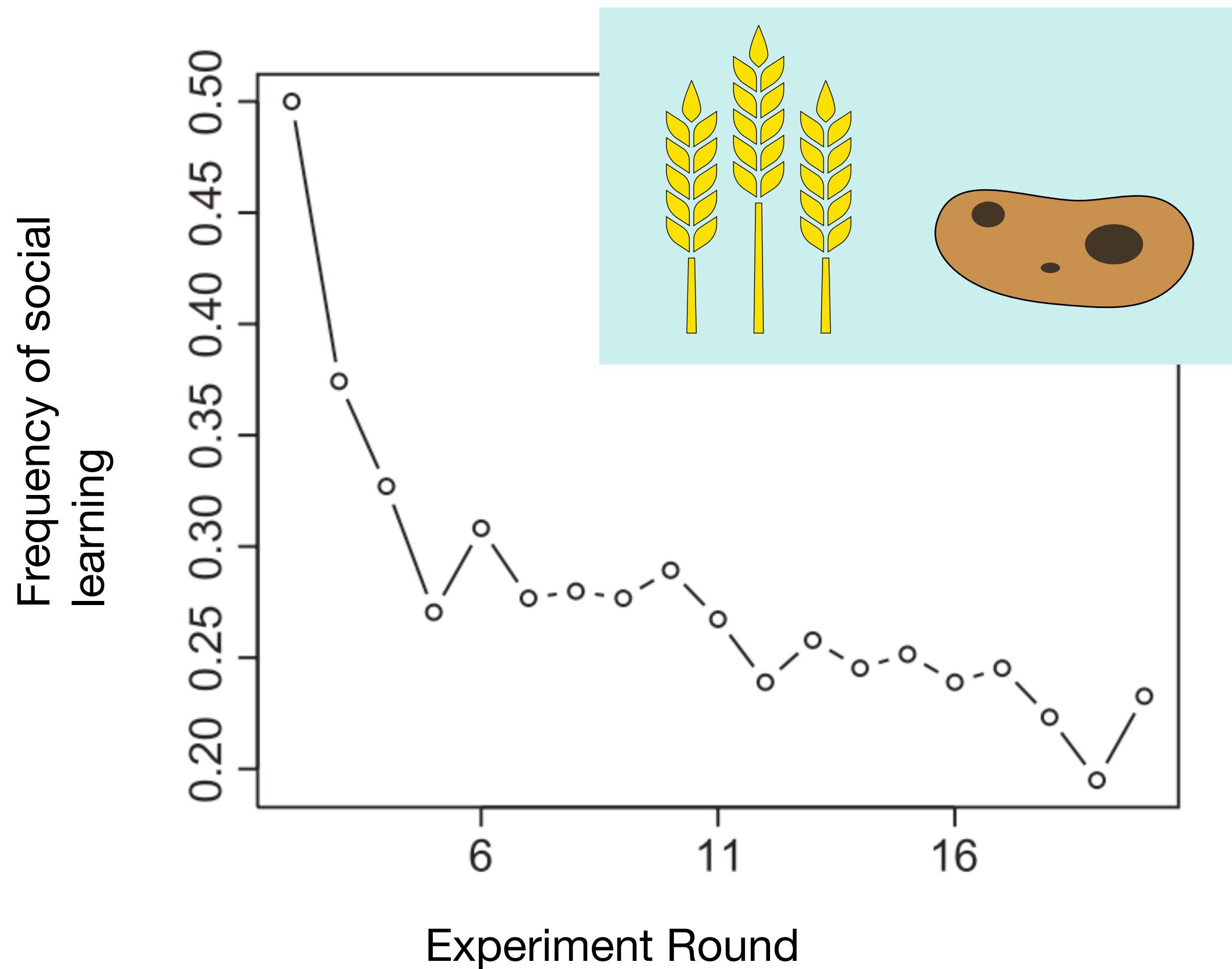


Aplin, et al., have animal model great tits (*parus major*) face a selection set size of 2: they can push a puzzle door on the blue side or red.

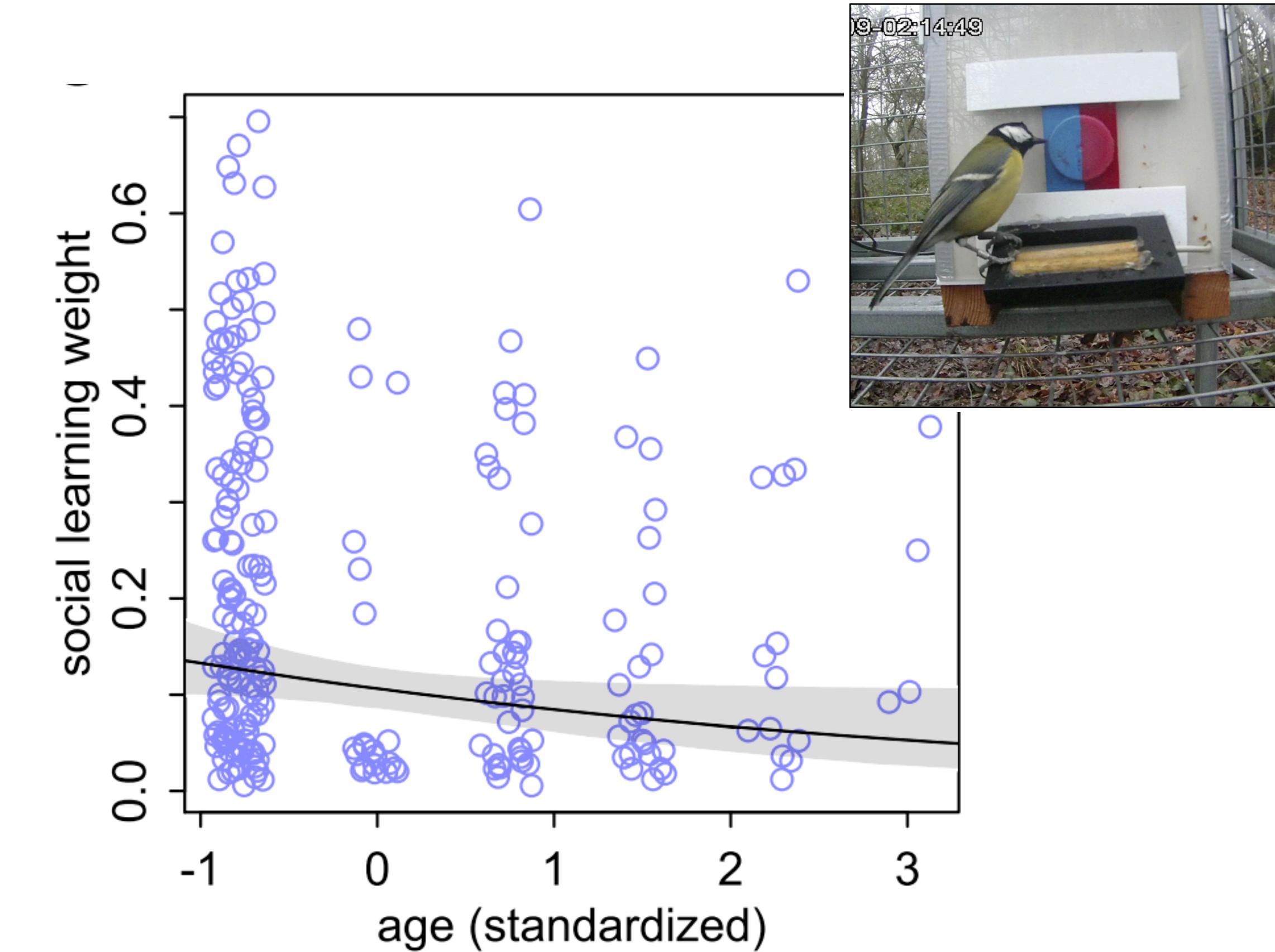


# Uncertainty parameter 4: effective lifespan

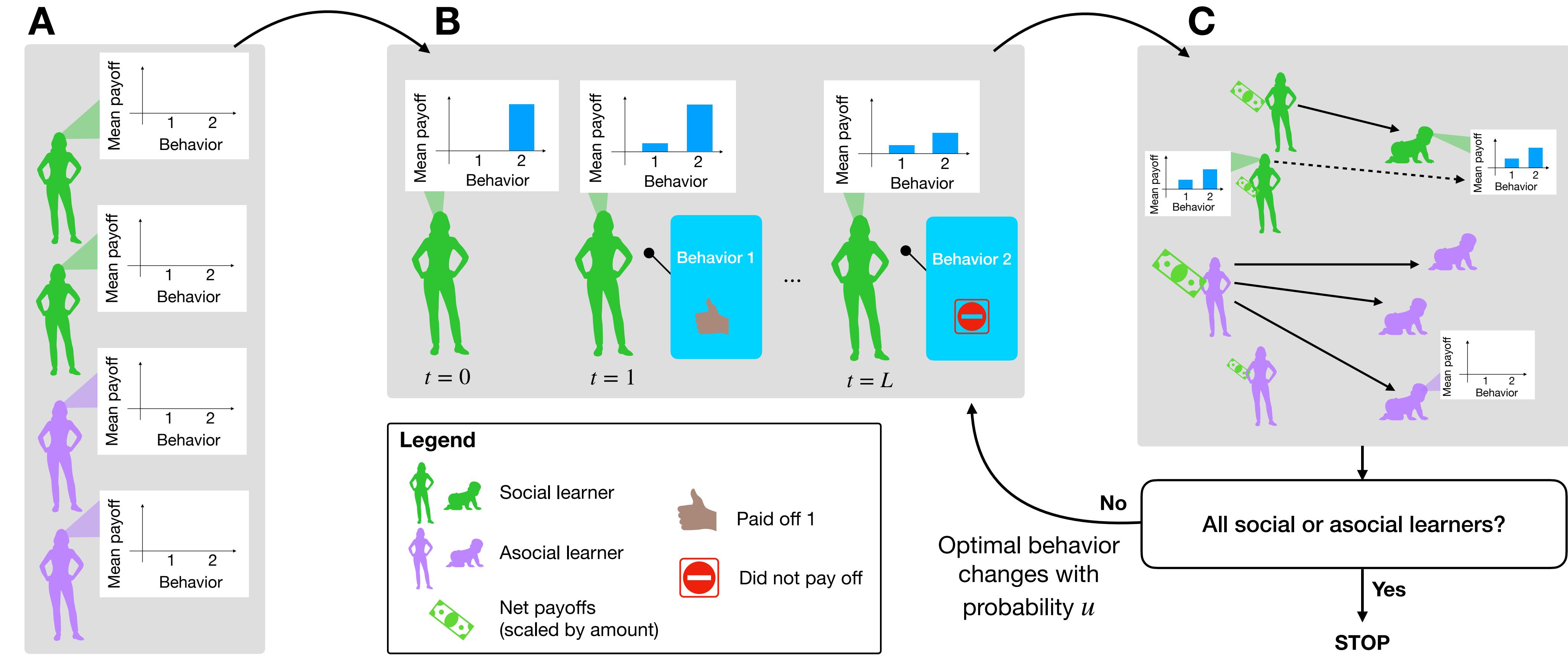
McElreath, *et al.*, observed social learning was utilized more in the first rounds of their multi-round experiment.



Aplin, *et al.*, found that younger great tits were more likely to rely on social information.

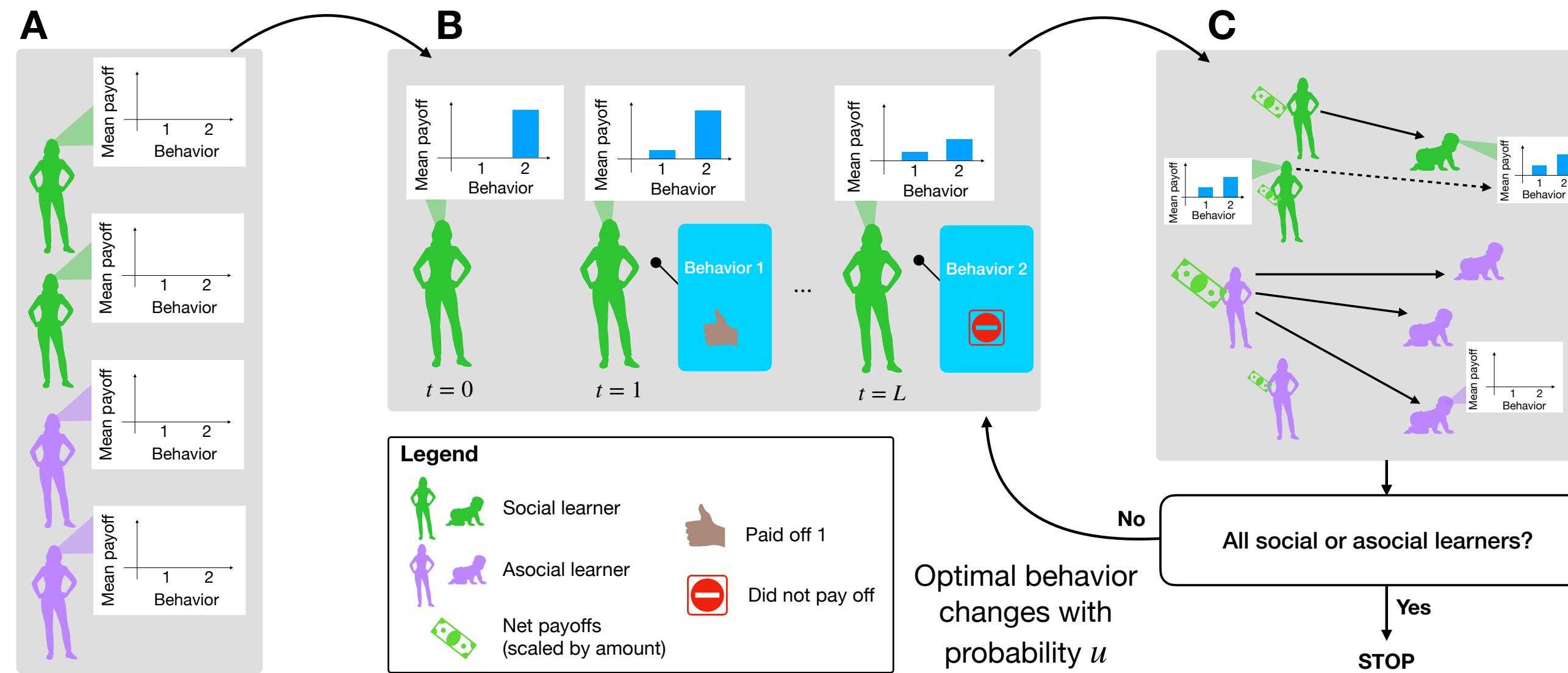


# Model



- Simulated individuals (agents) are initialized as social or asocial learners.
- All agents learn individually through trial-and-error greedy learning, with behavior selection weighted by softmax normalization. One behavior is optimal, pays off with probability  $\pi_{\text{high}} = 0.9$ ; the rest are suboptimal and pay off 1 with probability  $\pi_{\text{low}} \in \{0.1, 0.45, 0.8\}$ .
- A new population is generated by reproducers chosen at random with replacement, weighted by their relative net payoffs.

# Computational analysis



**Outcome measure:**  
Frequency of social learning fixation  $\langle s \rangle$

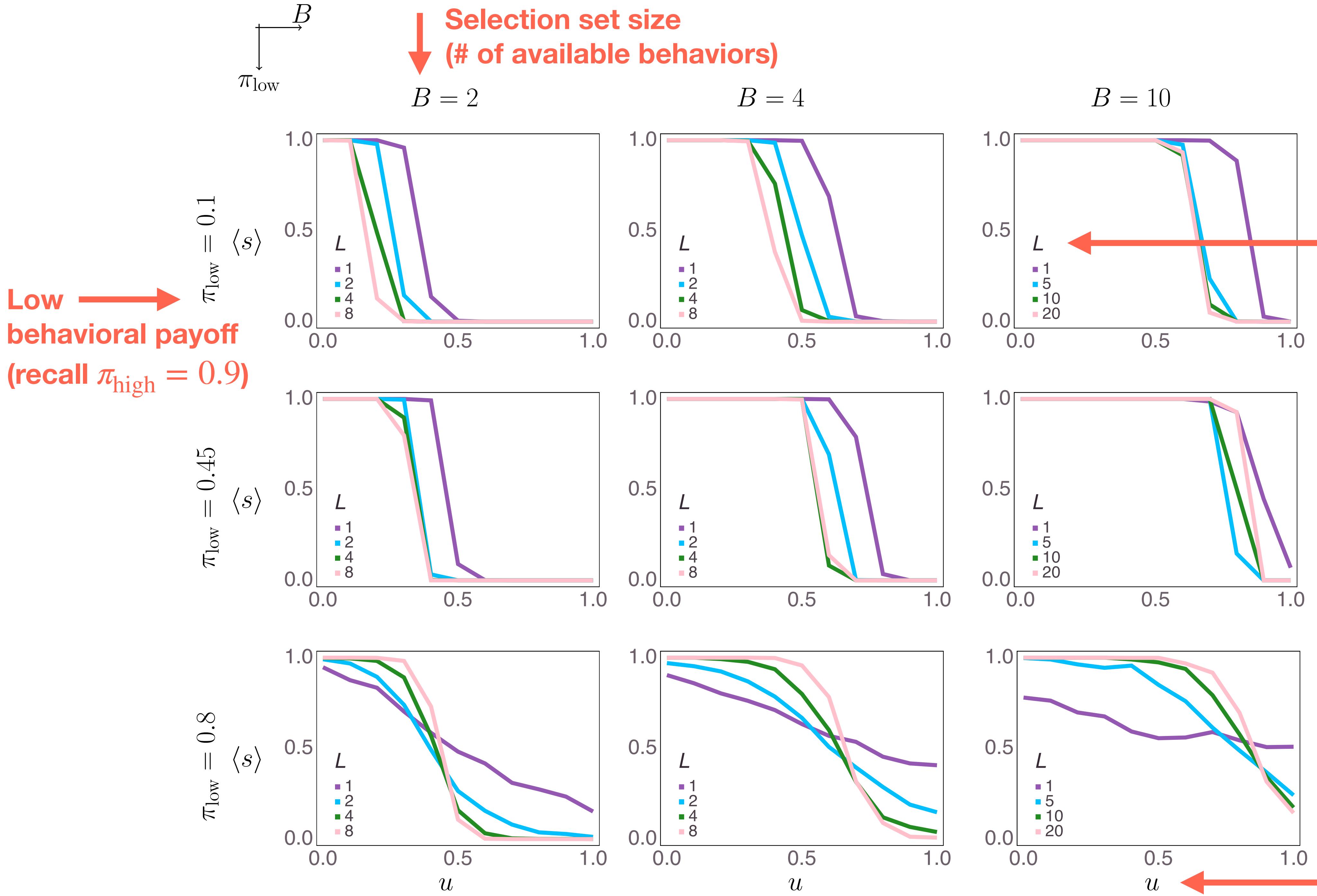
- Average over 1000 trials per uncertainty parameter combination.
- Each trial ends after one generation with fixated population.
- $11 u \times 3 \pi_{\text{low}} \times 3 B \times 4 L$   
 $= 396$  total uncertainty parameter combinations tested.

## Uncertainty parameters

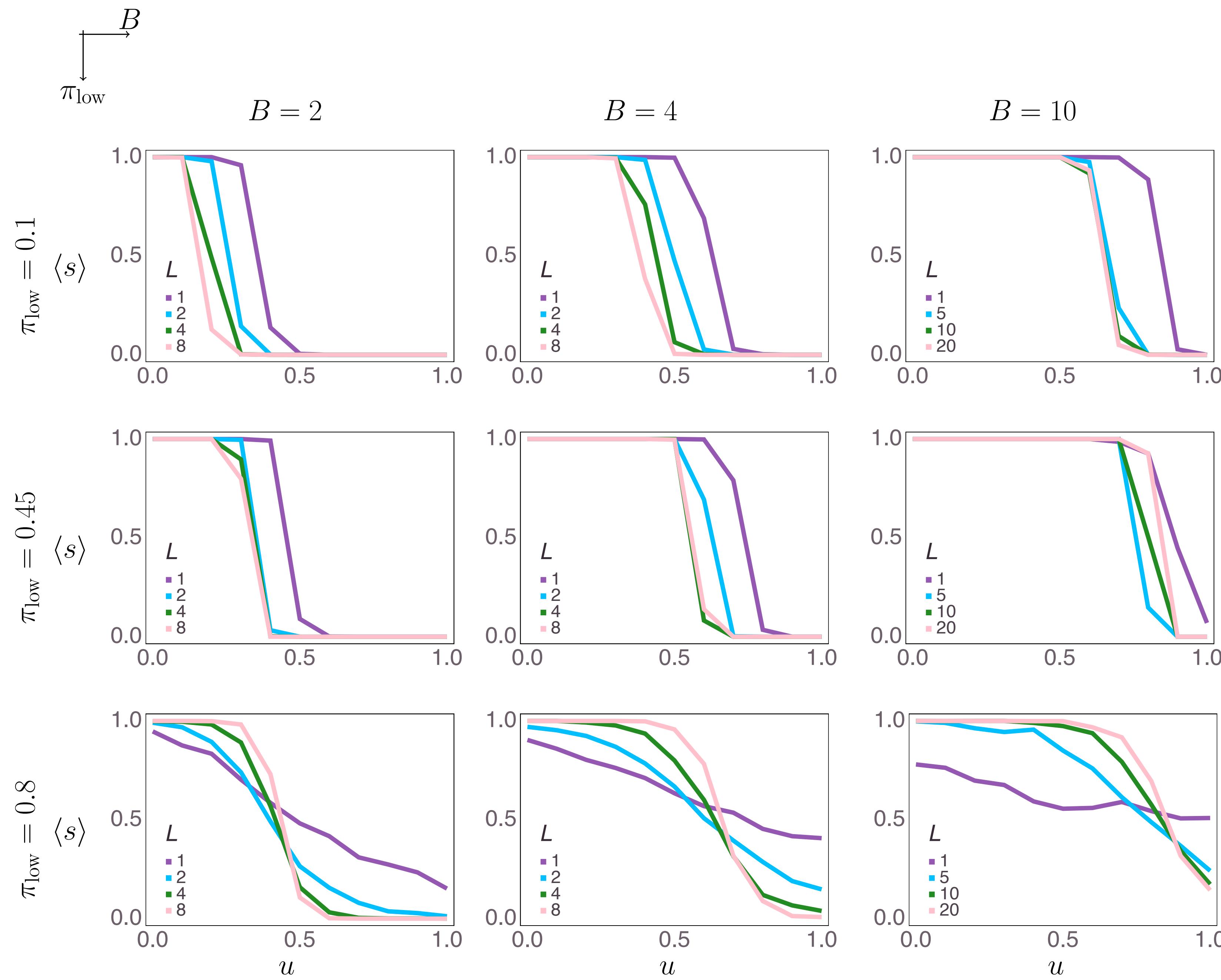
Symbol	Description	Values tested
$u$	Probability optimal behavior changes between generations	0.0, 0.1, ..., 1.0
$B$	Number of behavior options	2, 4, 10
$\pi_{\text{high}}$	Probability that the unique optimal behavior pays off 1	0.9
$\pi_{\text{low}}$	Probability one of $B - 1$ non-optimal behaviors pays off 1	0.1, 0.45, 0.8
$L$	Time steps per generation	1, $B/2$ , $B$ , $2B$ , $4B$
$N$	Population size	50, 100, 200, 1000

[https://github.com/mt-digital/UncMod/tree/CES2022\\_Pres](https://github.com/mt-digital/UncMod/tree/CES2022_Pres)

# Analysis Overview

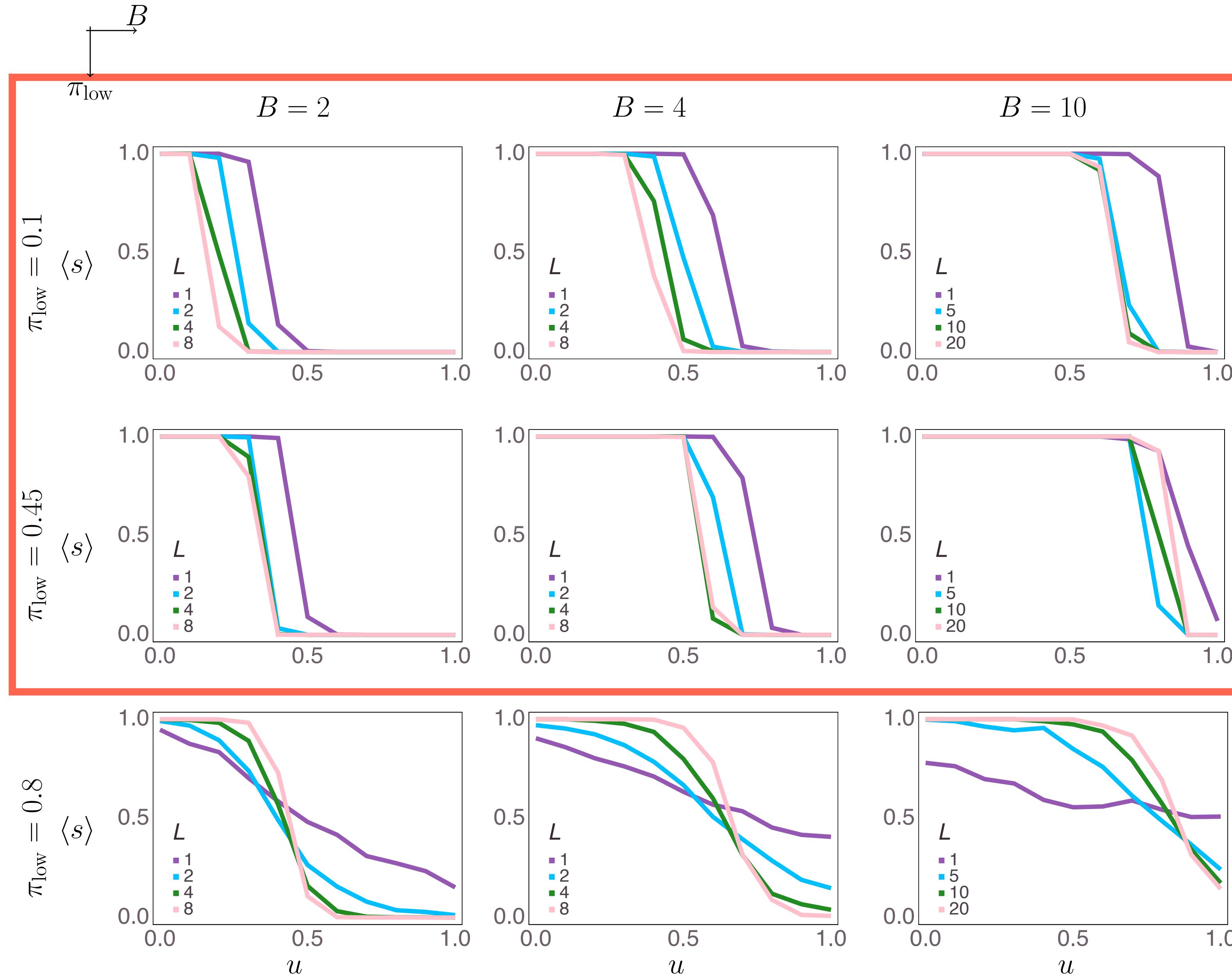


# Analysis Overview



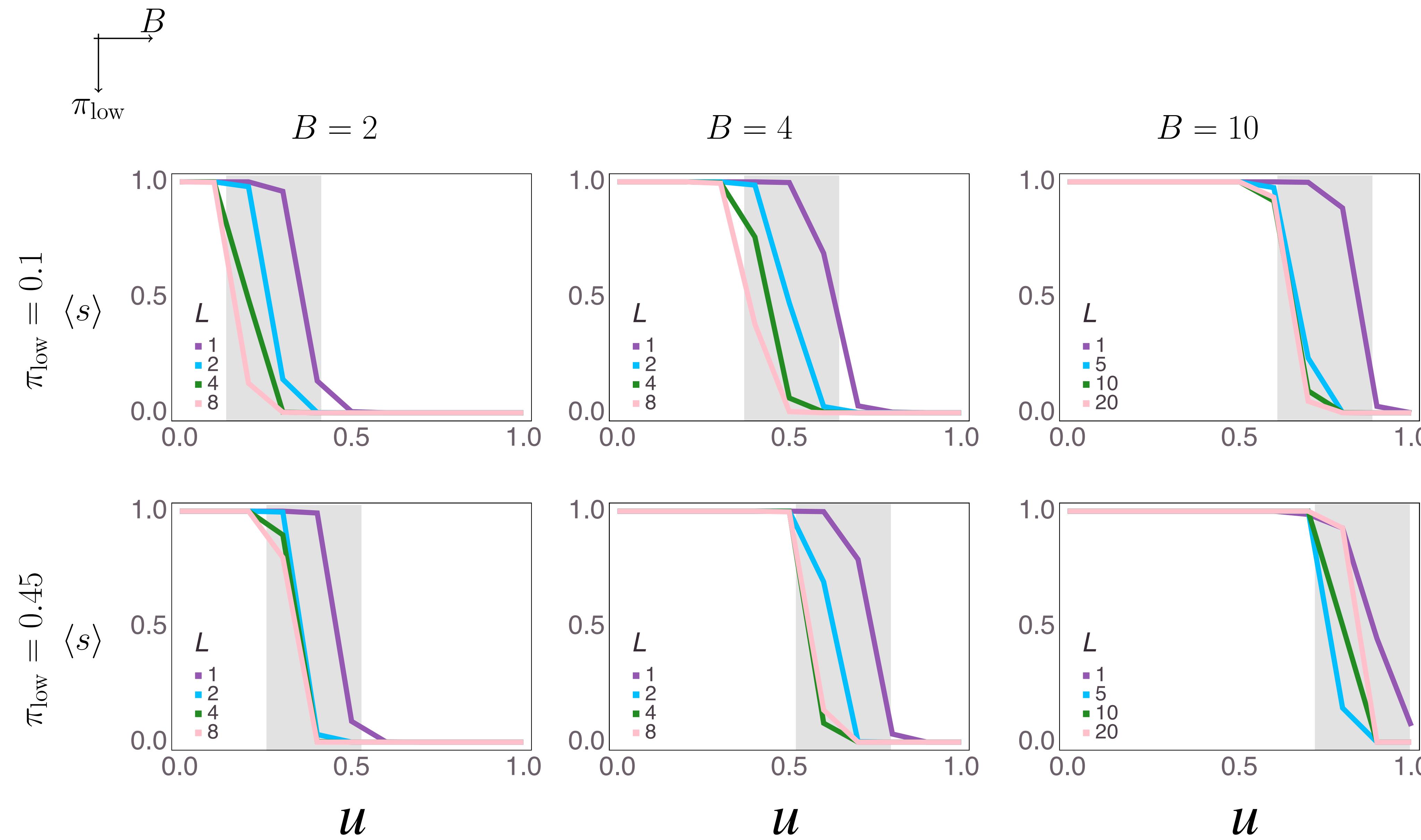
- The frequency of social learning fixation,  $\langle s \rangle$ , decreases as environmental variability,  $u$ , increases in all cases.
- Different uncertainty parameter settings change the **location** and **steepness** of the point where  $\langle s \rangle$  goes from 1 to 0.

# Large payoff ambiguity decreases selection strength, increases drift

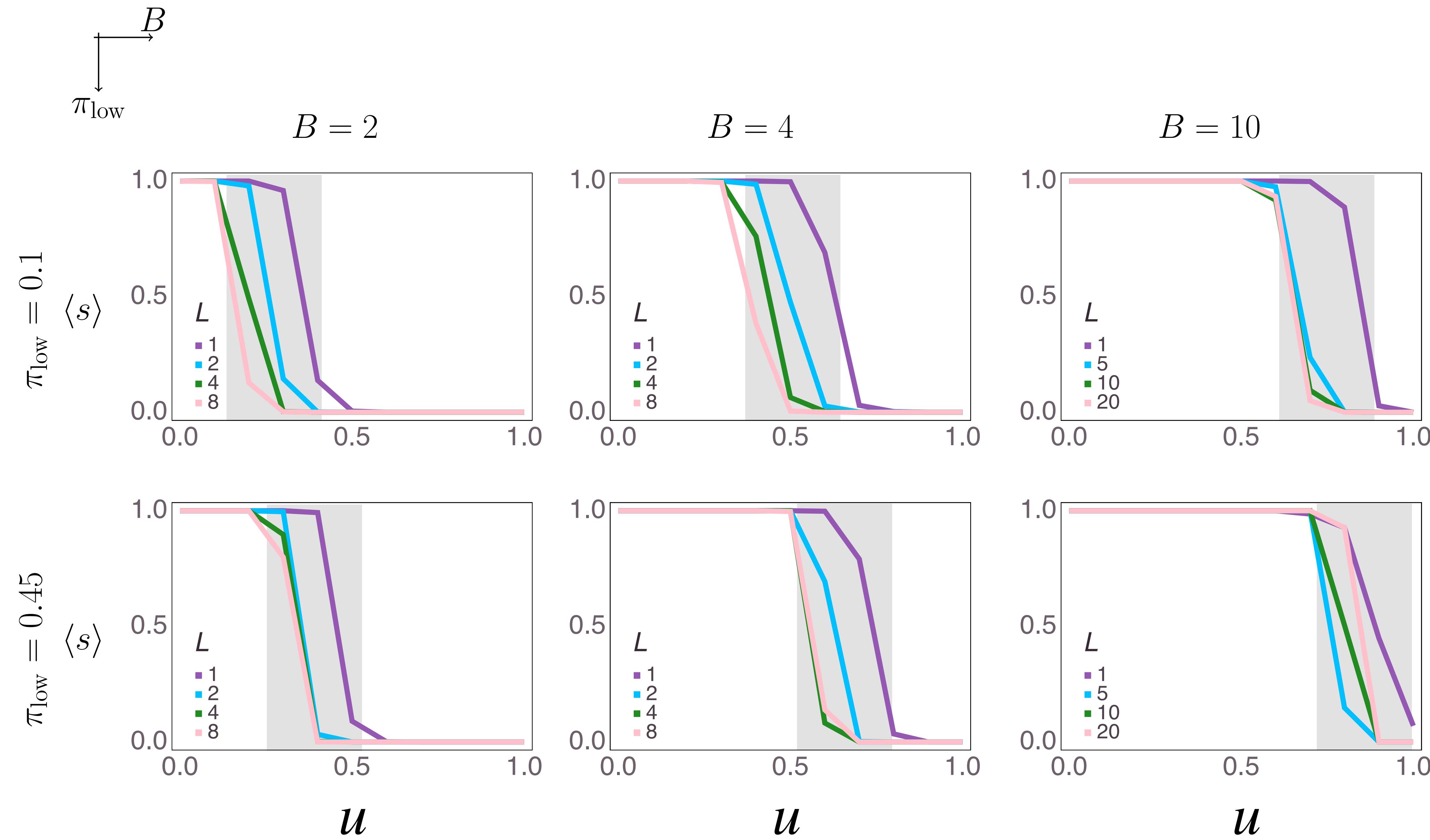


Less drift when  $\pi_{\text{low}} \leq 0.45$   
(recall  $\pi_{\text{high}} = 0.9$ )

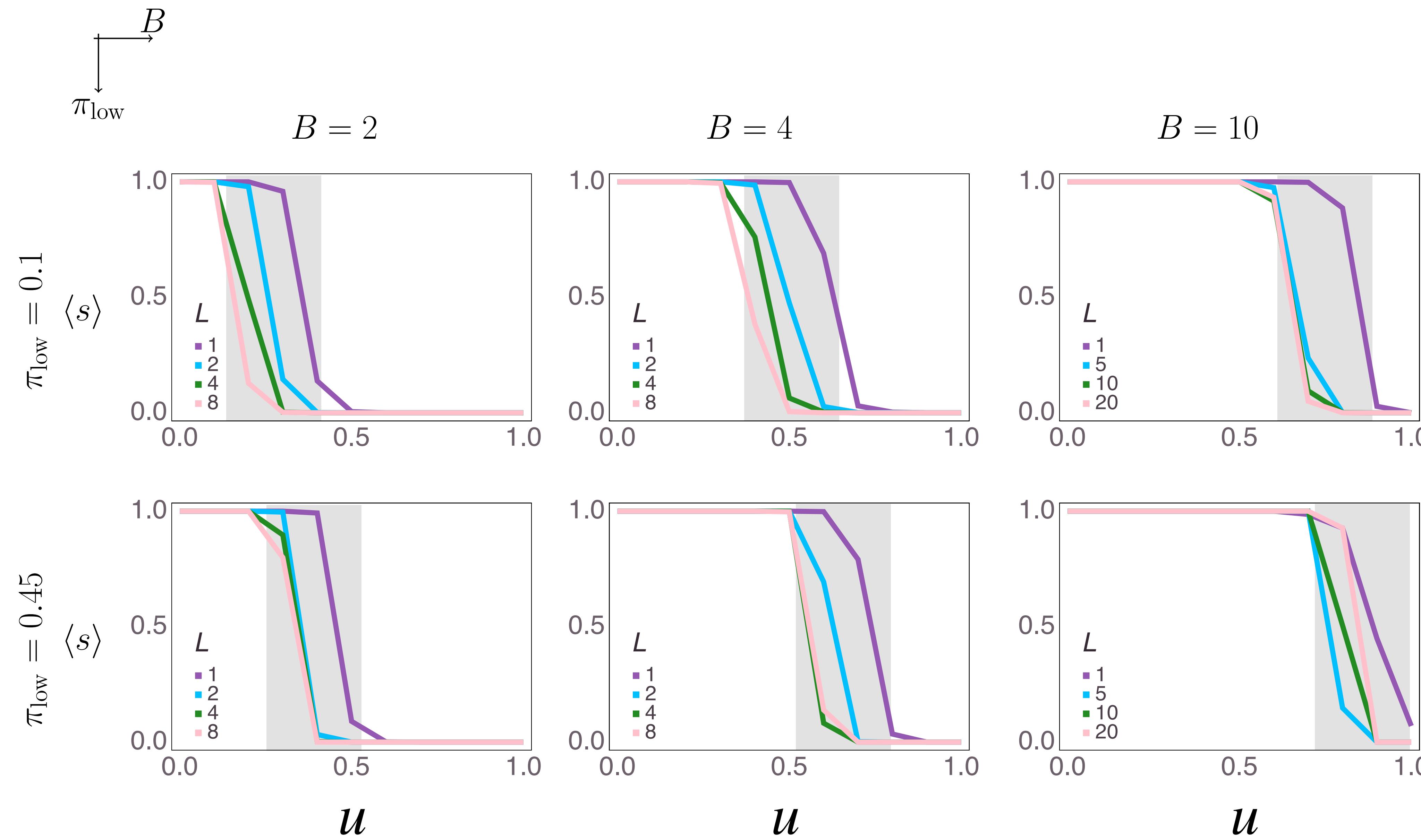
# Increased payoff ambiguity supports social learning



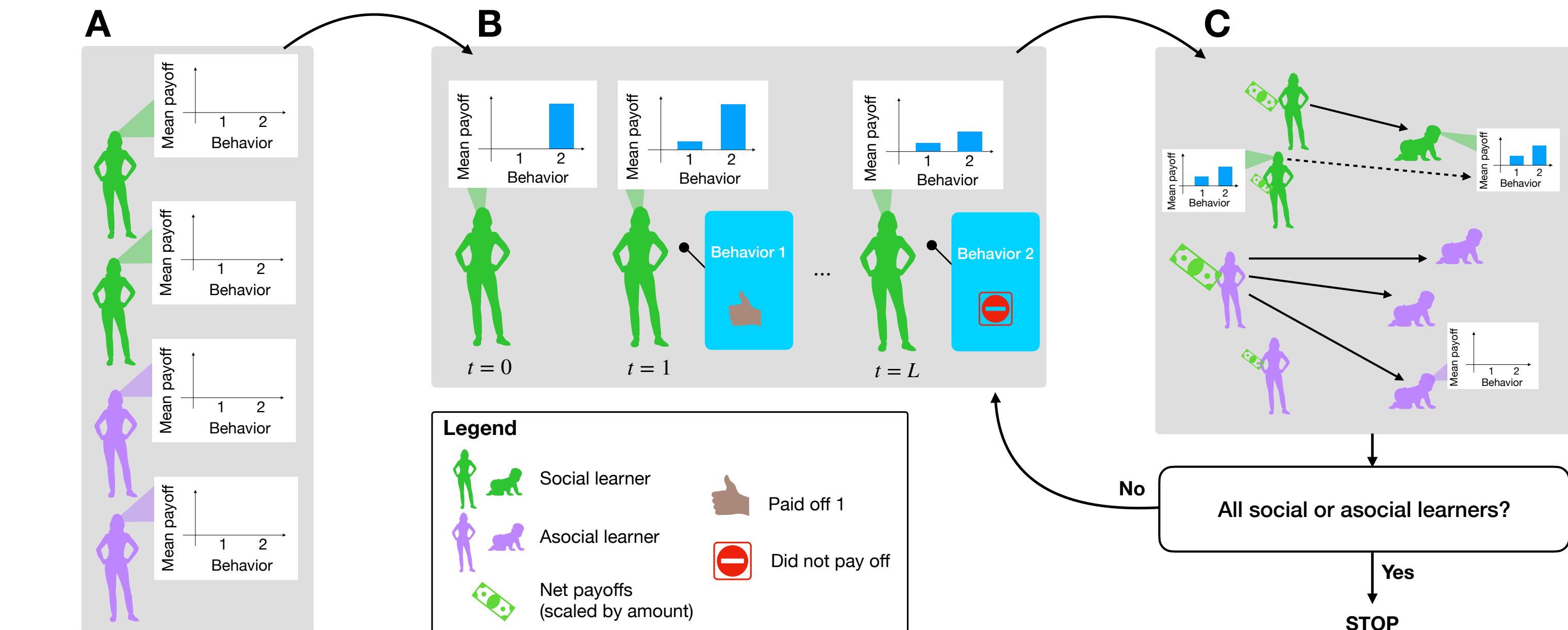
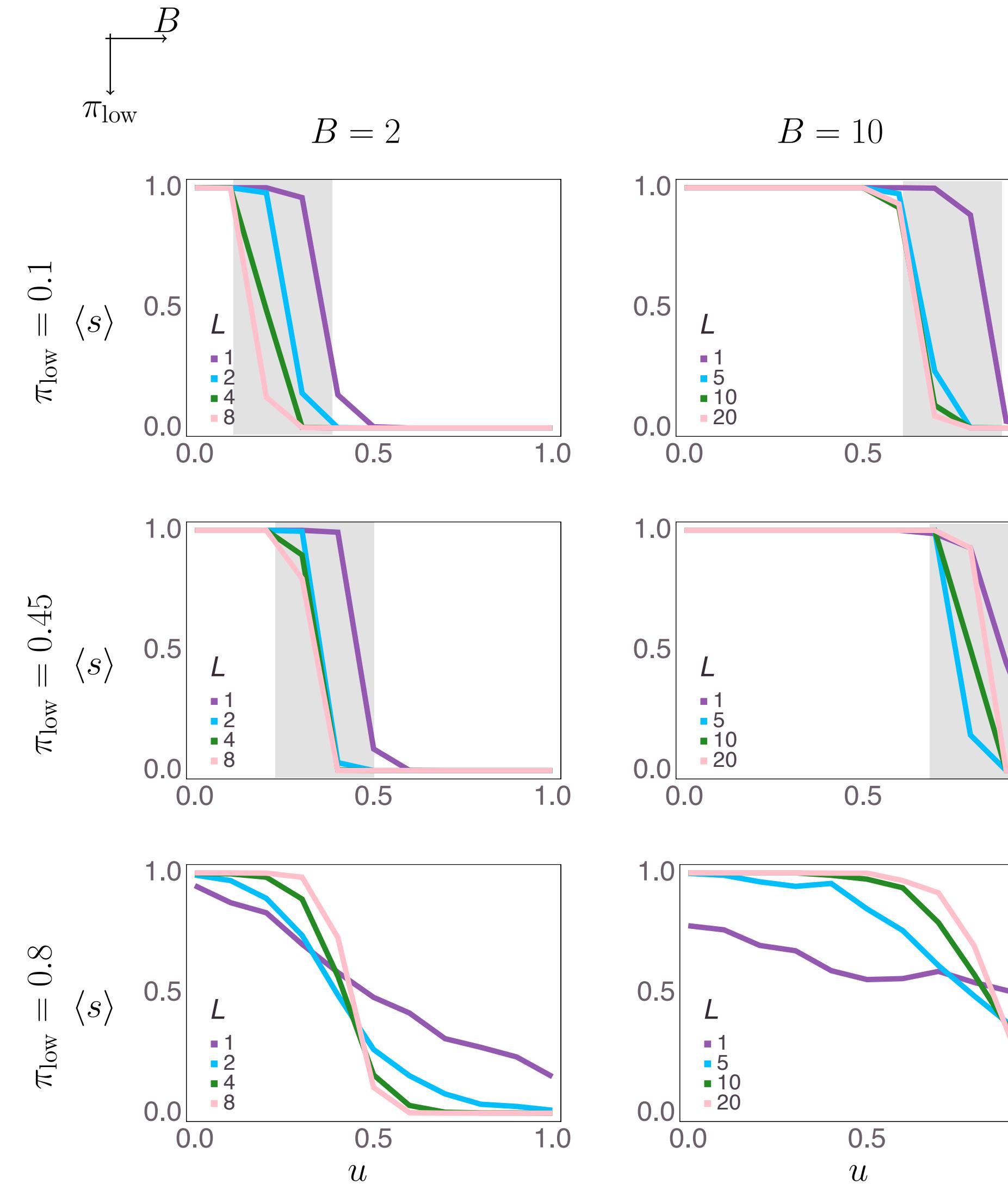
# Larger selection set size, $B$ , supports social learning



# Shorter life span, $L$ , supports social learning



# Conclusion



[https://github.com/mt-digital/UncMod/tree/CES2022\\_Pres](https://github.com/mt-digital/UncMod/tree/CES2022_Pres)

@MATurnerPhD

## ABM and analysis v1.0:

Turner MA, Moya C, Smaldino PE, & Jones JH (2022). Some forms of uncertainty may suppress the evolution of social learning. *Proceedings of the 44th Annual Conference of the Cognitive Science Society*. <https://psyarxiv.com/dzteh/>