Biased or motivated? Starting point biases reflect early attention, not pre-choice biases

Hyuna Cho[1], Yi Yang Teoh[1], Cendri A. Hutcherson[1]

[1]Department of Psychology, University of Toronto

https://utoronto.zoom.us/j/87286386104
Pass: 521553

Background

Recent applications of the drift diffusion model (DDM) have suggested that people may have **intuitive choice defaults** that can be measured via a starting point bias parameter (e.g., a generosity bias or risk bias).[1,2]

Previous findings show that early biases to attend to specific attributes can influence early drift rates[3]. We hypothesized that early drift rates, if not modelled, could incorrectly influence estimated starting point biases.

Example Trial 1: High value for attribute 1   Example Trial 2: Lower value for attribute 1
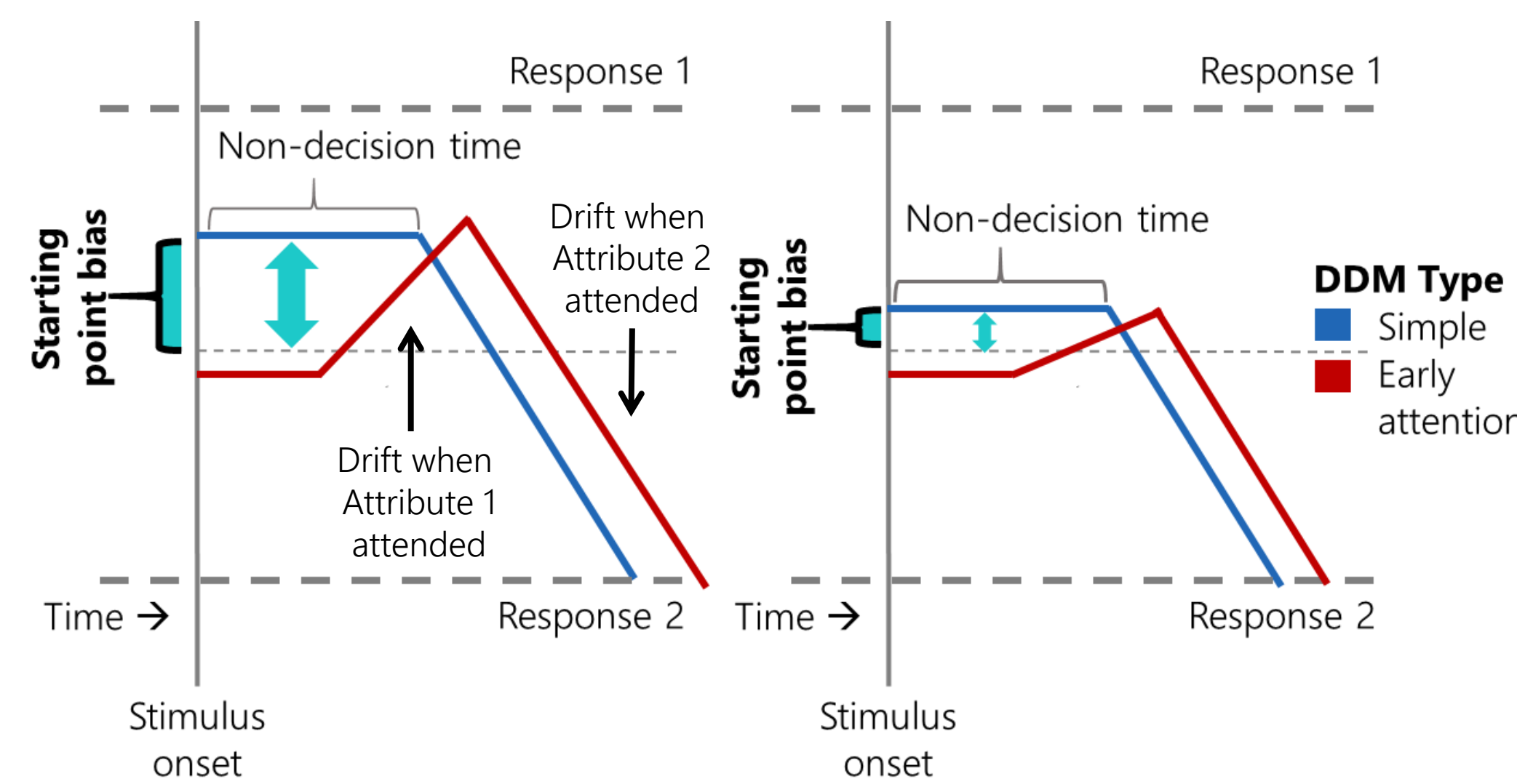
Predictions

1. Early attentional biases influence evidence accumulation, may be incorrectly attributed to the SPB.

2. SPB which is caused by early attention should be sensitive to trial-level attributes.

3. Biases in early eye gaze to focus on one attribute should predict "choice default" SPBs (e.g., generosity bias) toward that attribute.

4. Changing motivation alters attention, which affects the SPB.
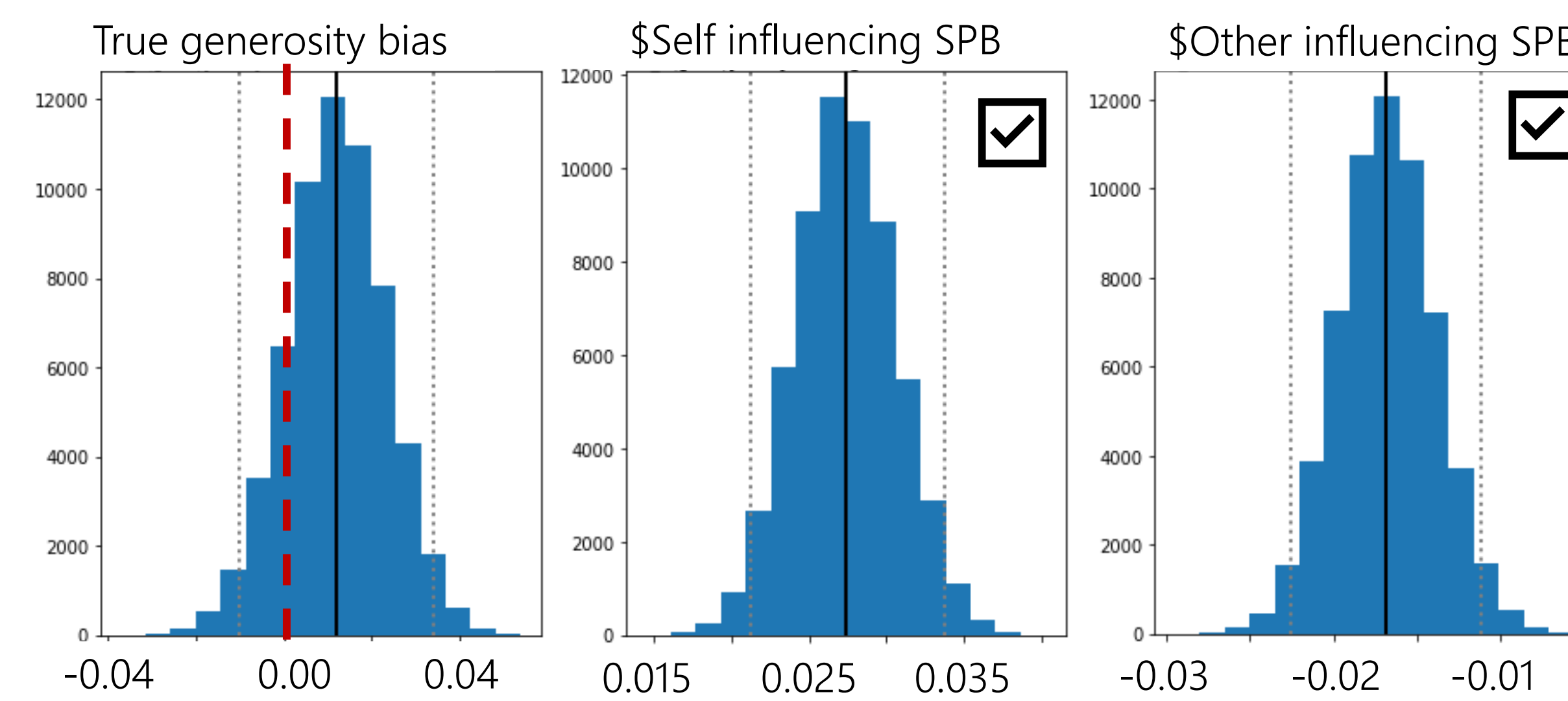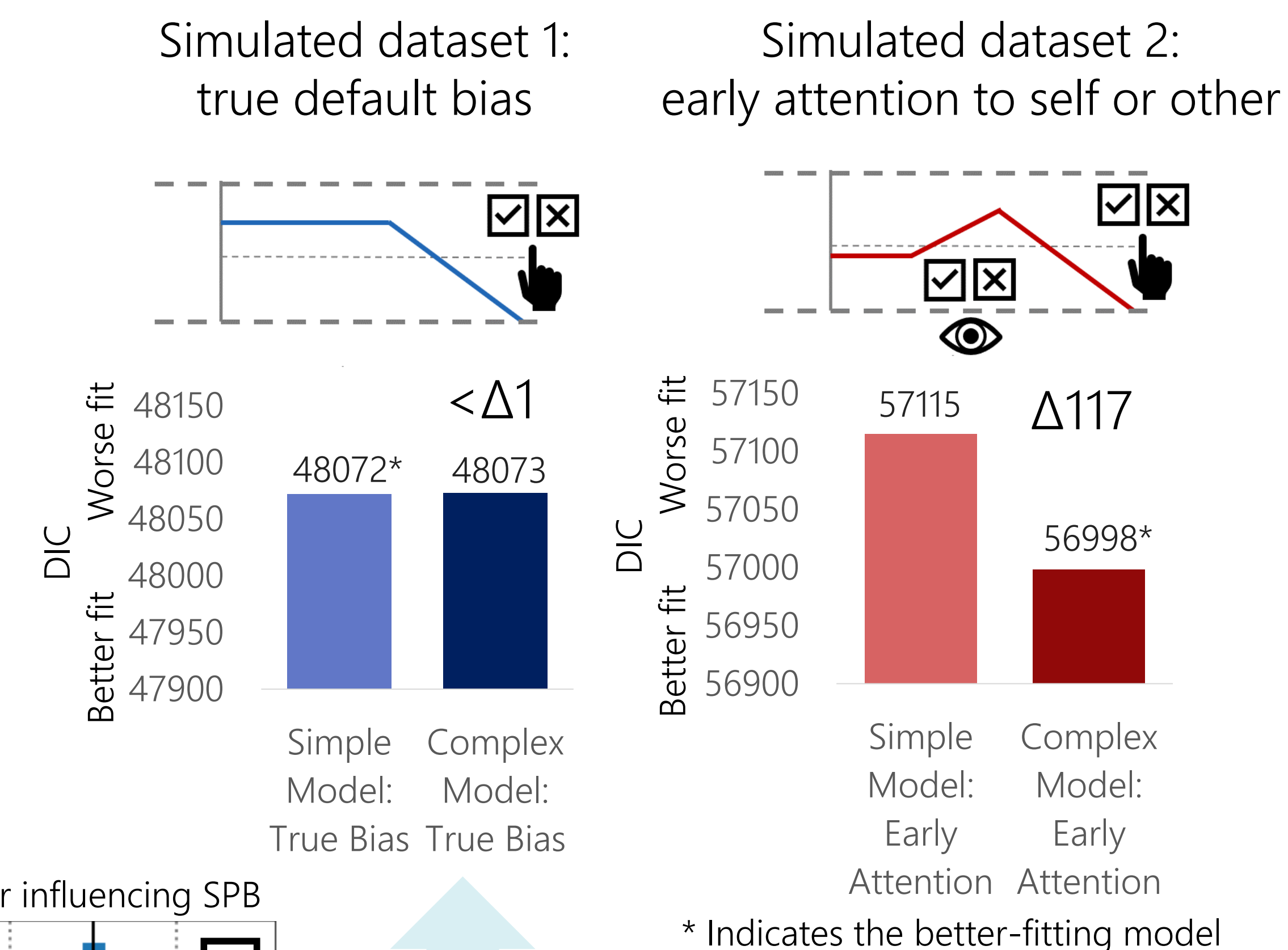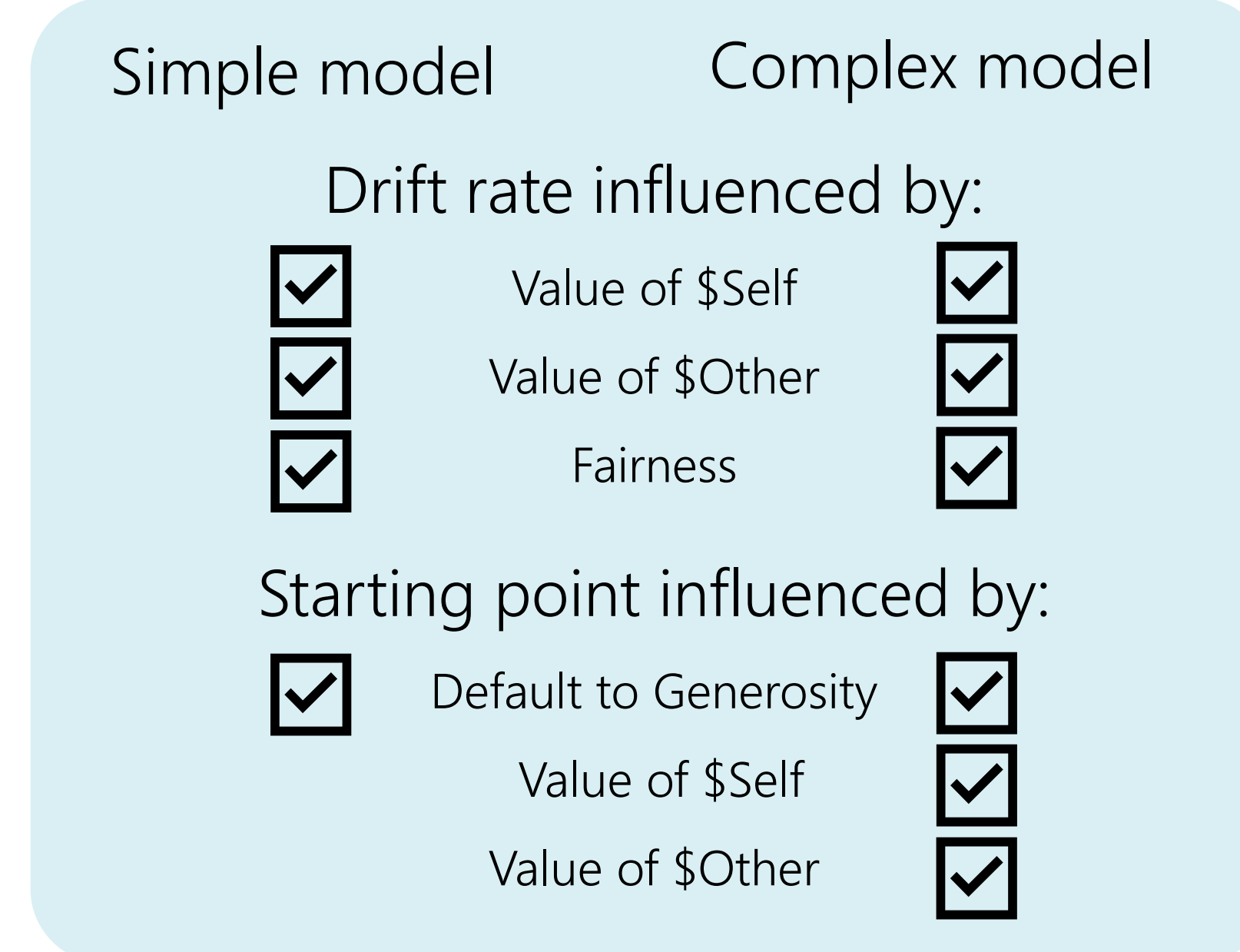
Methods
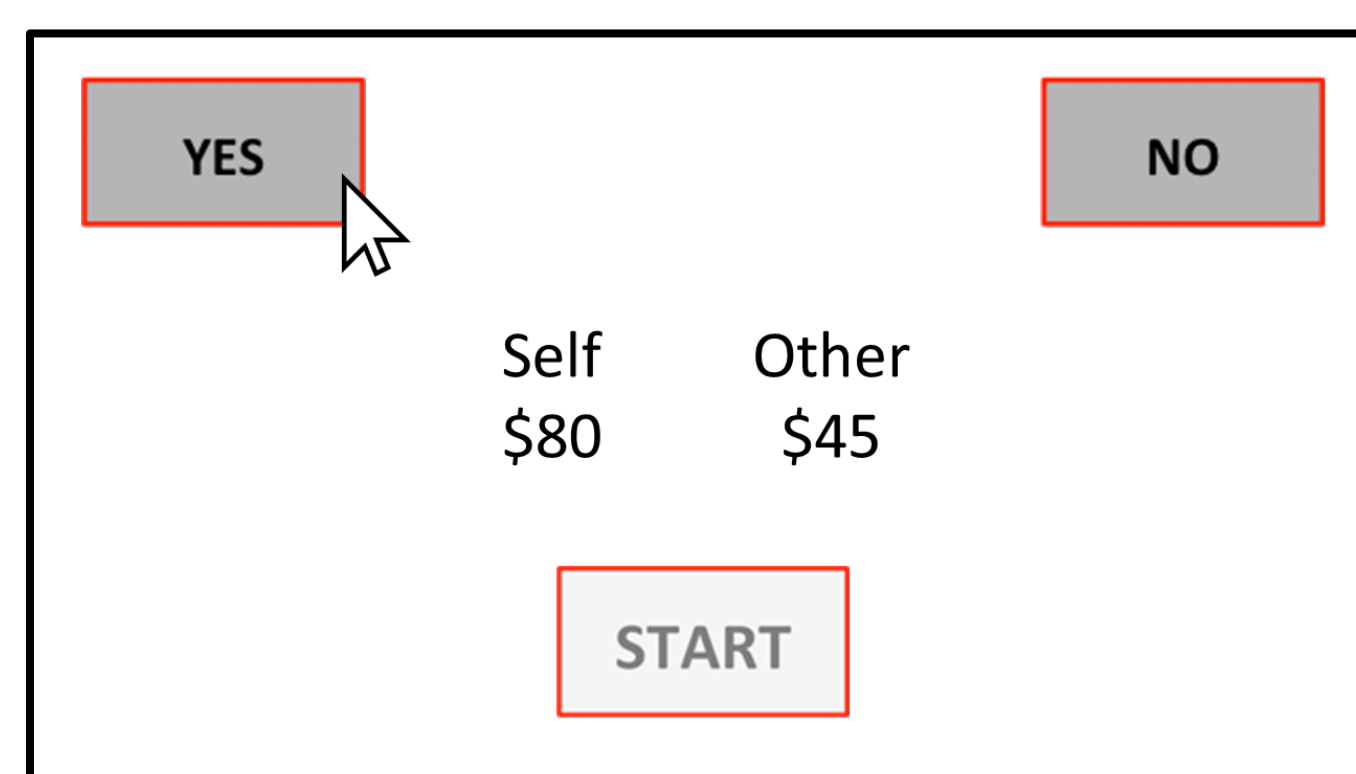
Study 1:
    simulated results
Study 2 (n=60):
    eyetracking
Study 3 (n=47):
    identity manipulation

All studies involved an altruistic choice task deciding between proposed amounts for self and other.

   Yes = receive $self and $other on screen.
    No = receive $50 each.

Study 1: Simulations show that sequential attention influences estimates of starting bias

Simple model   Complex model

Drift rate influenced by:
    Value of $Self
    Value of $Other
    Fairness

Starting point influenced by:
    Default to Generosity
    Value of $Self
    Value of $Other

Simulated dataset 1: true default bias

Simulated dataset 2: early attention to self or other

* Indicates the better-fitting model

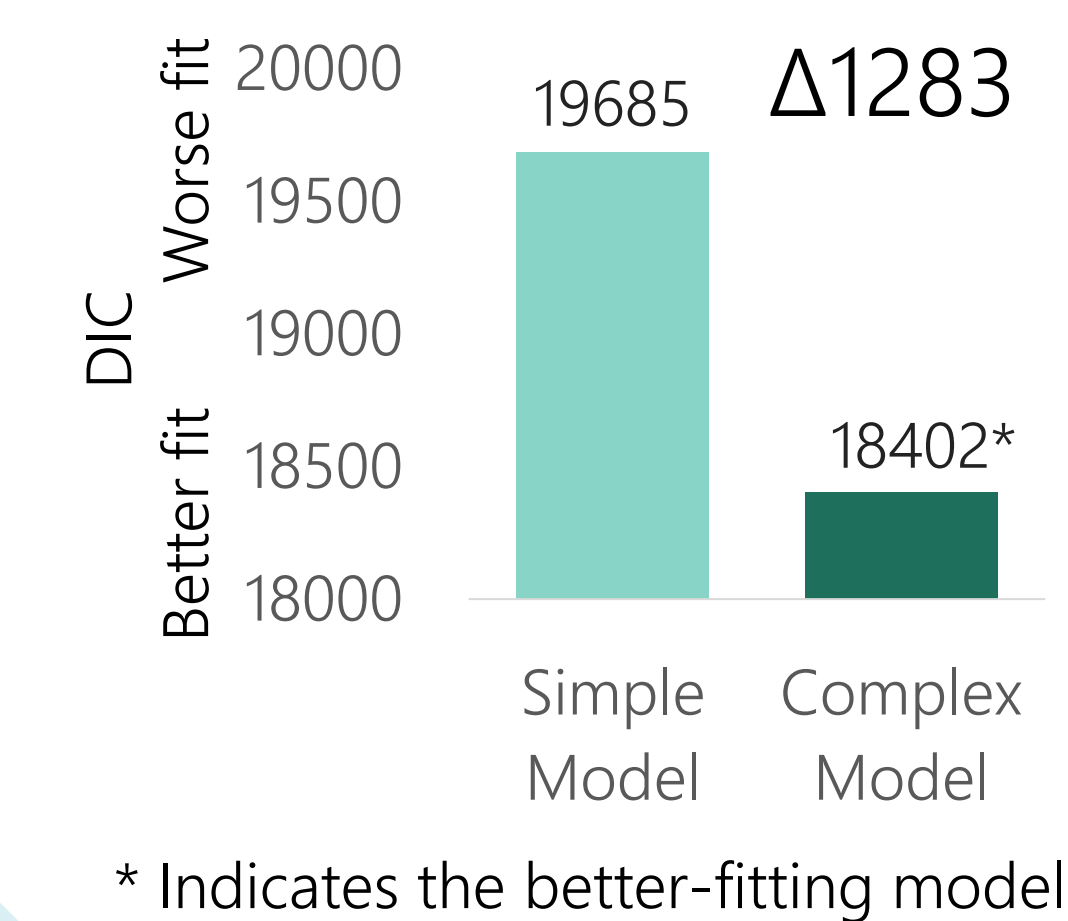True generosity bias $Self influencing SPB $Other influencing SPB

The complex model fits better only when there *are* early attentional processes.

When early attention influences the drift rate, it is captured in the model as the sensitivity of the SBP to trial-level attributes.

Study 2: Testing predictions with real gaze data

r = -0.319, t(48) = -2.334, p = 0.02
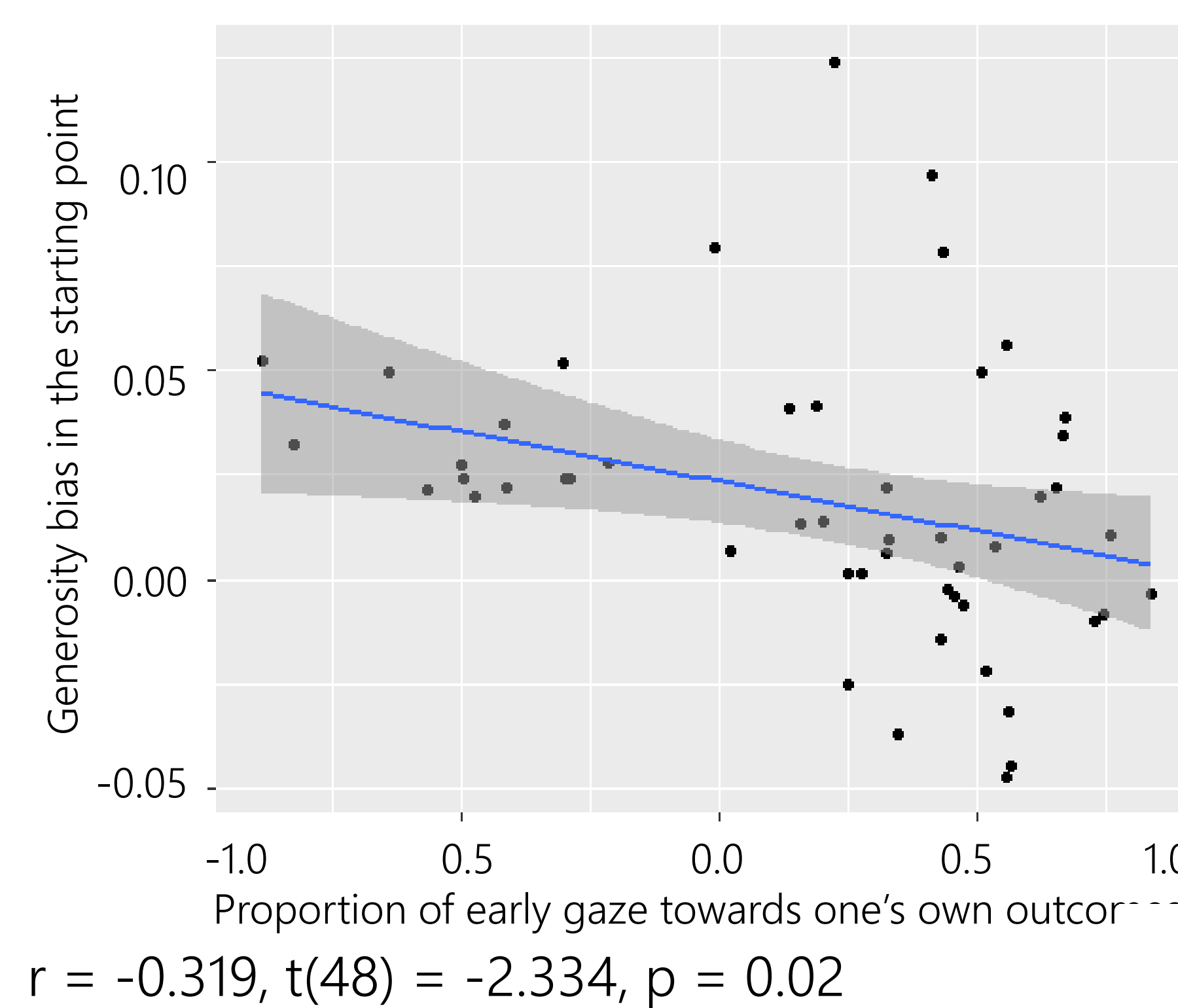
Looking biases correlate with fitted generosity biases in the simple model.

The complex model better accounts for behavioural data.

* Indicates the better-fitting model

Observed Data:
1. We observe an overall selfish default bias.
2. The generosity bias in the SPB is sensitive to value of $Self, suggesting bias to look first at self.

True generosity bias $Self influencing SPB $Other influencing SPB
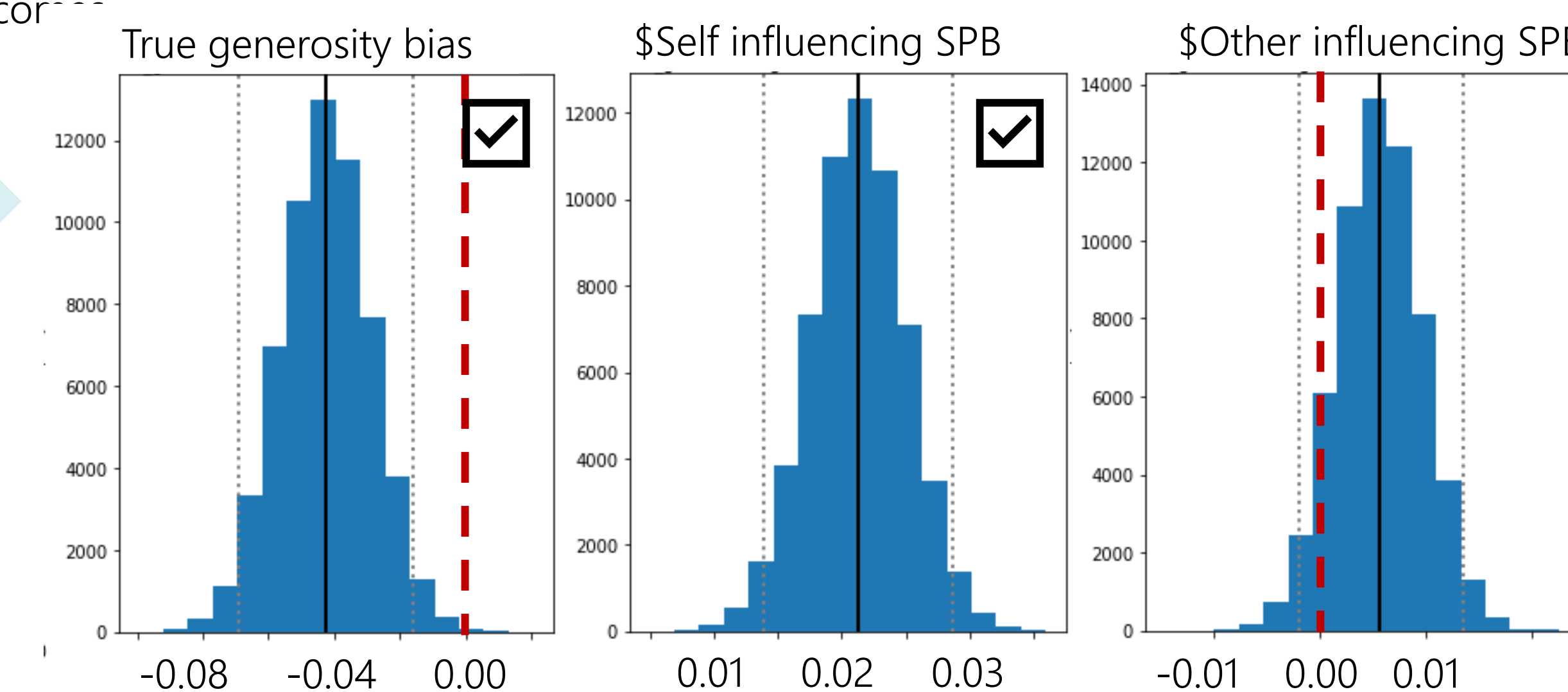
Study 3: Manipulating bias with identity

The complex model better accounts for behavioural data.

Identity and $Other on the SPB

* Indicates the better-fitting model
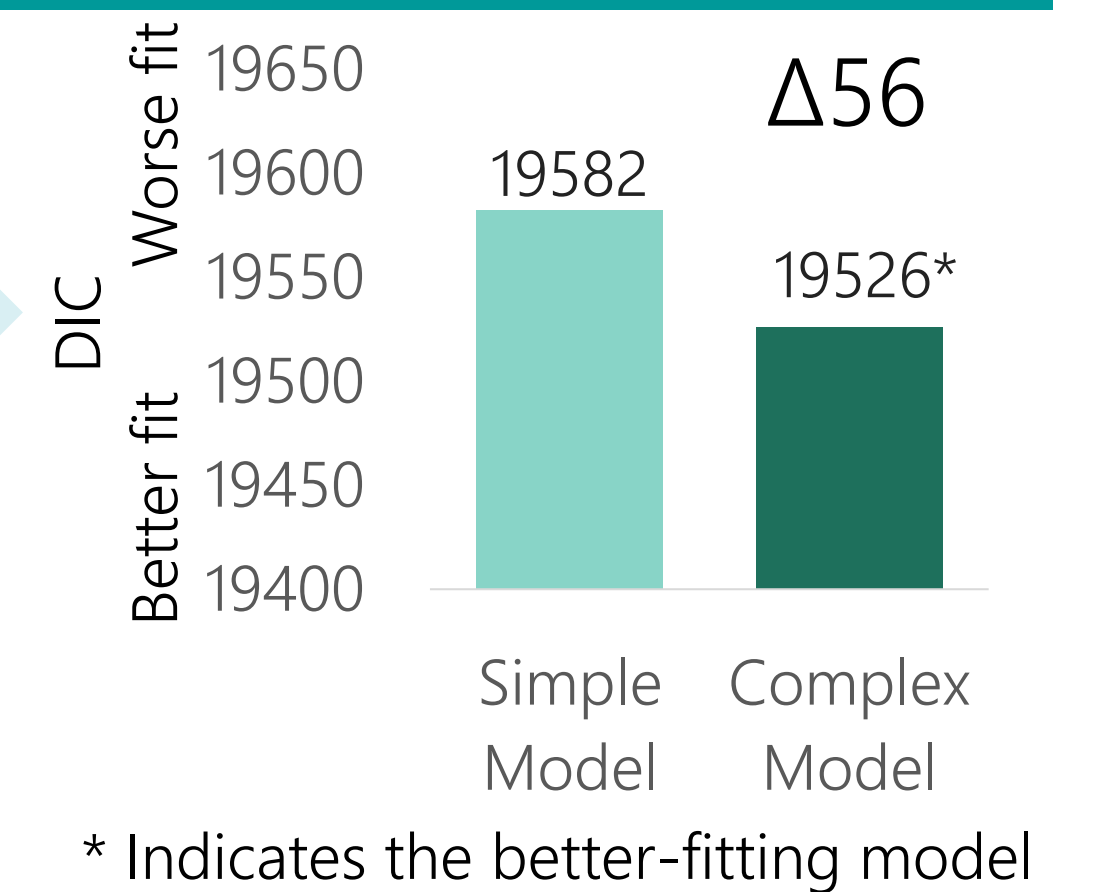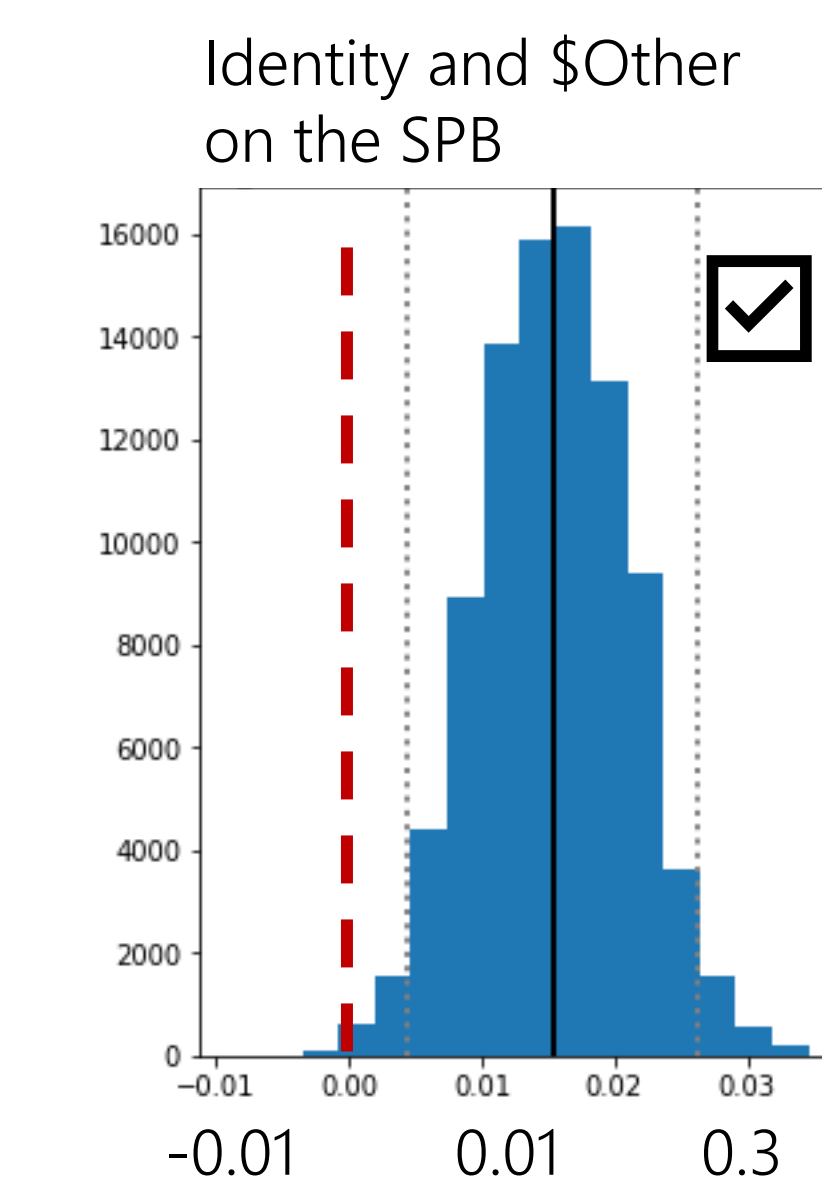
Changing the identity of the other from a random student to a child in need changes the influence of the other's value in the SPB.

Conclusions

Early evidence processing due to attention results in a change in the estimated starting point, even when there is no pre-choice bias.

SPBs in generous decision making may reflect early attention to choice attributes. This may mask the effects of pre-choice biases on the SPB.

Future work: Does this hold true in other choice domains, such as risky decision making and intertemporal choice?

Future work: Can we distinguish the effects of pre-choice biases and early attention using computational models?

References

1. Johnson, D. J., Cesario, J., & Pleskac, T. J. (2018). How prior information and police experience impact decisions to shoot. *Journal of personality and social psychology*, 115(4), 601.

2. Chen, F., & Krajbich, I. (2018). Biased sequential sampling underlies the effects of time pressure and delay in social decision making. Nature communications, 9(1), 1-10.

3. Teoh, Y. Y., Yao, Z., Cunningham, W. A., & Hutcherson, C. A. (2020). Attentional priorities drive effects of time pressure on altruistic choice. *Nature communications*, 11(1), 1-13.

4. Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the drift-diffusion model in Python. *Frontiers in neuroinformatics*, 7, 14.

Acknowledgements