Center for Adaptive Rationality
Max Planck Institute
for Human Development

Modeling choice and search in decisions from experience: A sequential sampling approach

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Risky decisions from description

	A	B	
probability:	1	.8	.2
value:	$3	$4	$0

Decisions from experience (DFE)

A	B
$3	
	$4
$3	
$3	
	$0
	$4

samples:

final choice: **B**

Adaptive exploration

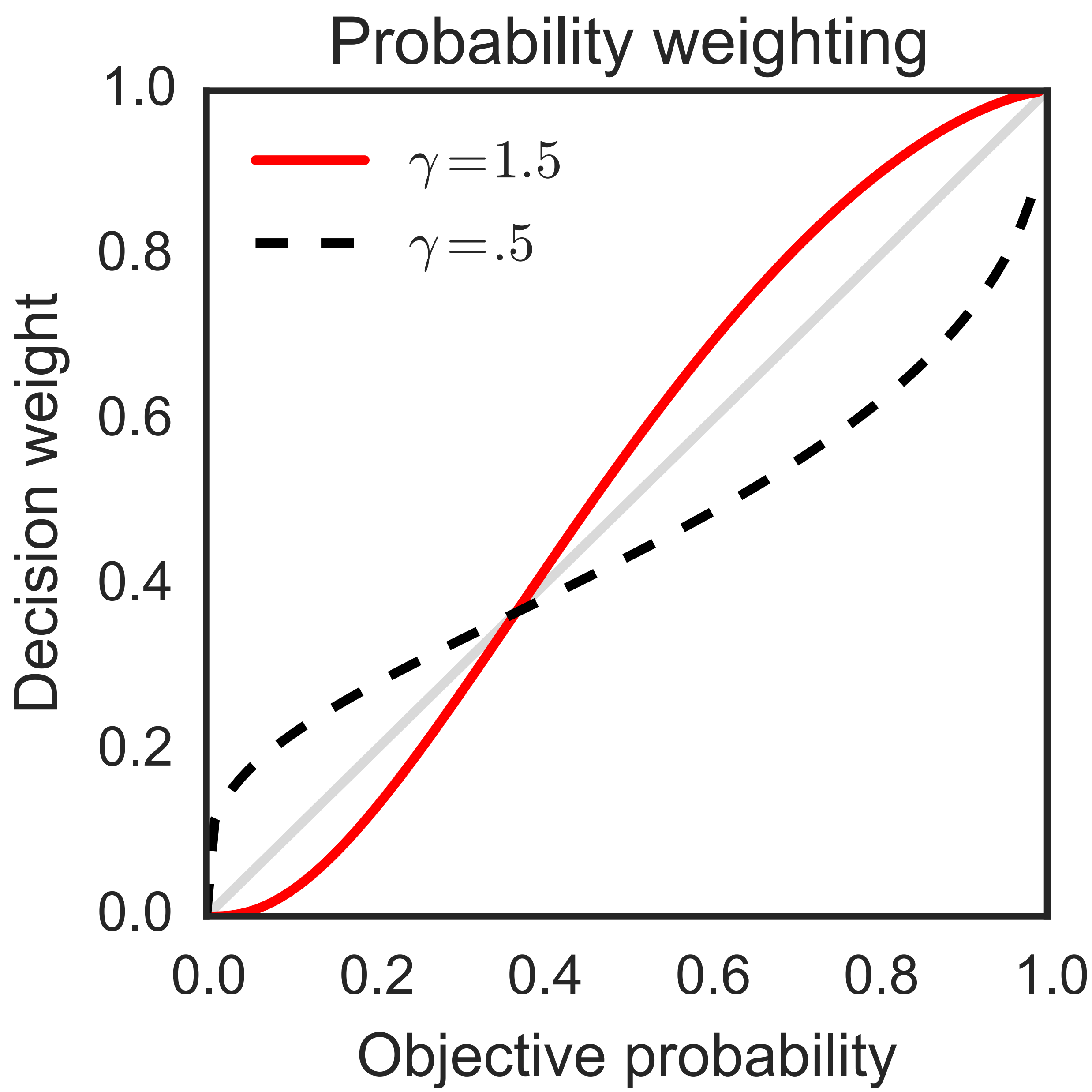
- **Do people adapt how they explore?**
  - Sample size sensitive to the cost of sampling (Busemeyer, 1985; Busemeyer & Rapoport, 1988; Rapoport & Tversky, 1970)
  - Increased sample sizes under higher stakes (Hau et al., 2008)
  - Increased sample sizes with high experienced variance in outcomes (Lejarraga et al., 2012; Spaniel & Wegier, 2012)

Existing models

- Prospect theory (Fox & Hadar, 2006; Ungemach et al., 2009; Camilleri & Newell, 2011)
- Heuristics (Hau et al., 2008; Hertwig & Pleskac, 2010; Erev et al., 2010)
- Learning/exemplar models
    - Value updating model (Hertwig et al., 2006; Frey et al., 2015)
    - Exemplar Confusion (ExCon; Hawkins et al., 2014)
    - Instance-based learning (Gonzalez & Dutt, 2011)

The uncertain impact of rare events

- **Sampling error** contributes to underweighting, but its impact depends on sample size and option structure
- Evidence of additional distortion after correcting or controlling for sampling error (Ungemach et al., 2009)

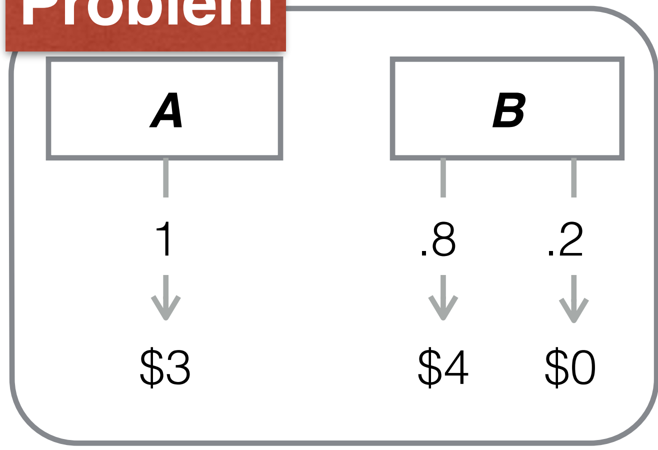


CHASE

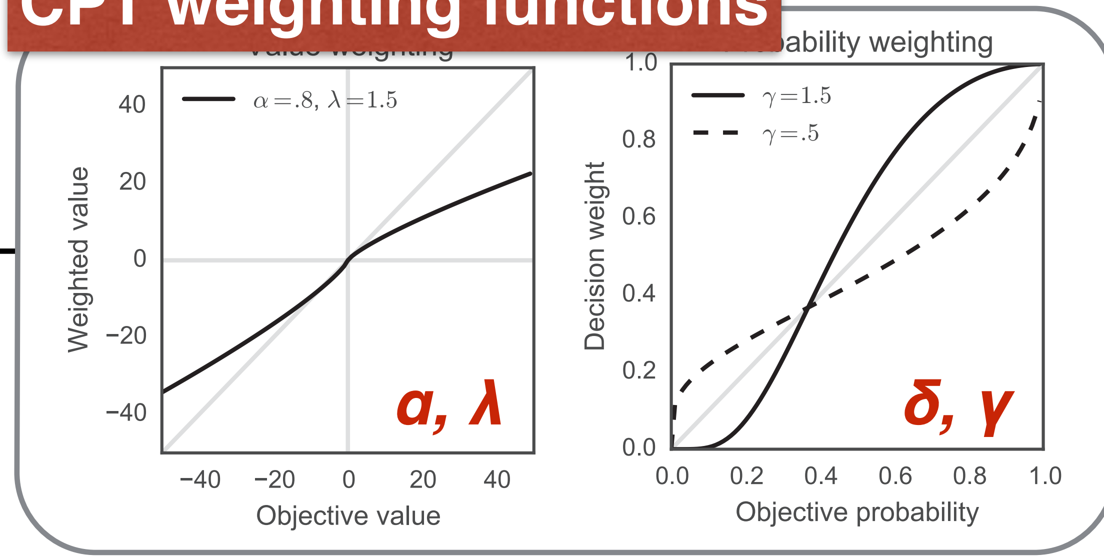
- **Choice from Accumulated Samples of Experience (CHASE)**
  - Sequential sampling model in which choice and sample size arise from interaction between decision threshold (controlled by decision maker) and the accumulation of relative preference
  - Accumulation is driven by relative evaluations of externally-generated, discrete outcomes
  - Drift is parameterized using value and decision weighting functions from cumulative prospect theory (CPT) to capture subjective evaluation of outcomes

CHASE

Problem



CPT weighting functions



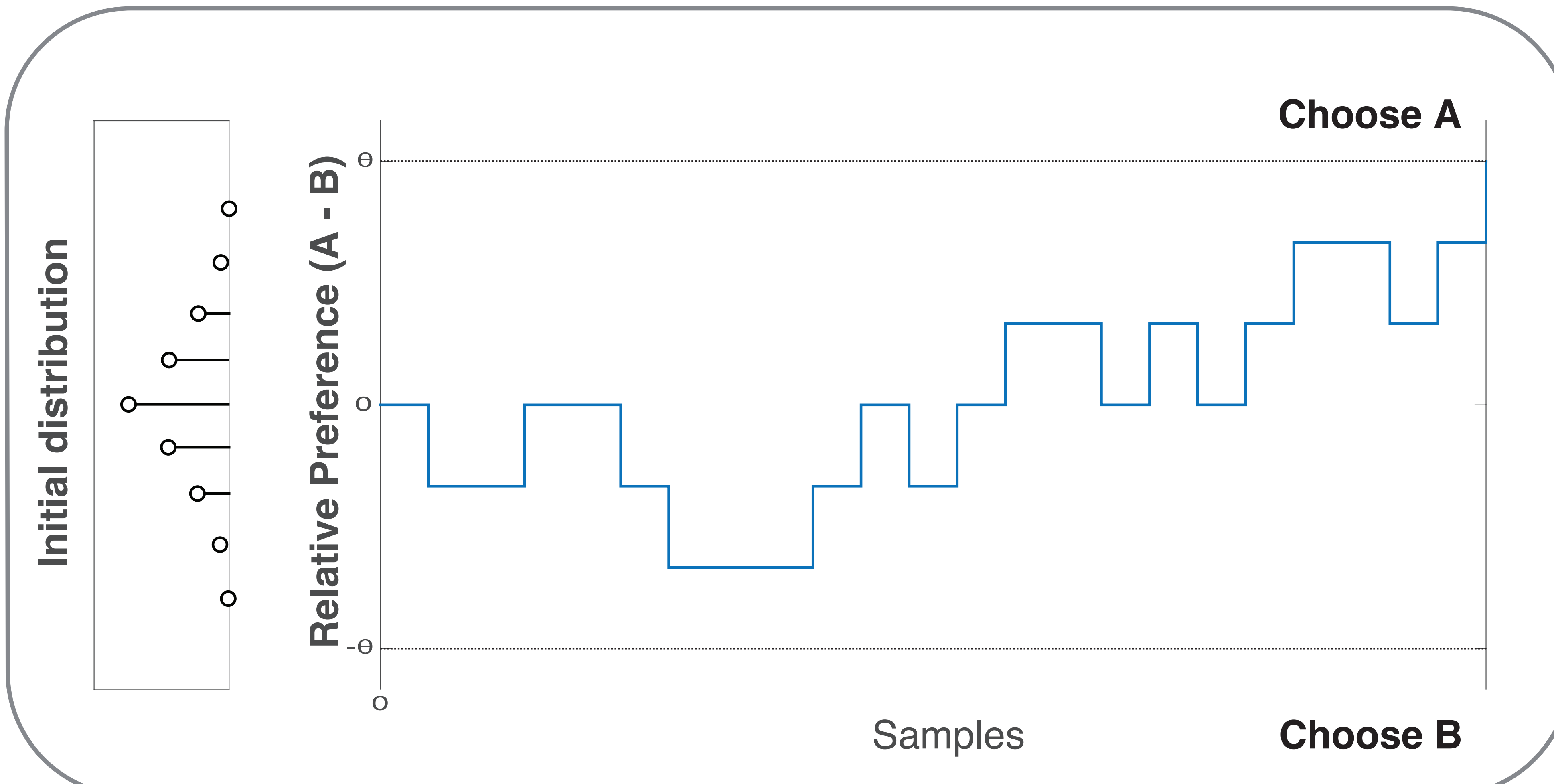
Drift

$$d = \frac{V_A - V_B}{\sqrt{\sigma^2}}$$

decision threshold ***θ***

start point variability **τ**

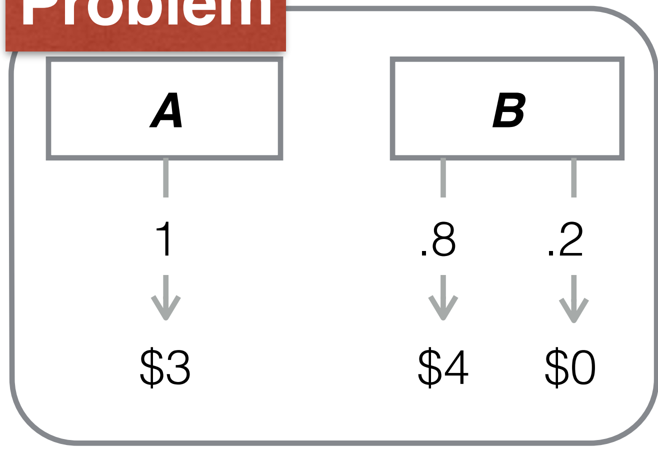
probability of staying in same state ***p(stay)***



cf. Busemeyer & Diederich (2003)

CHASE

Problem



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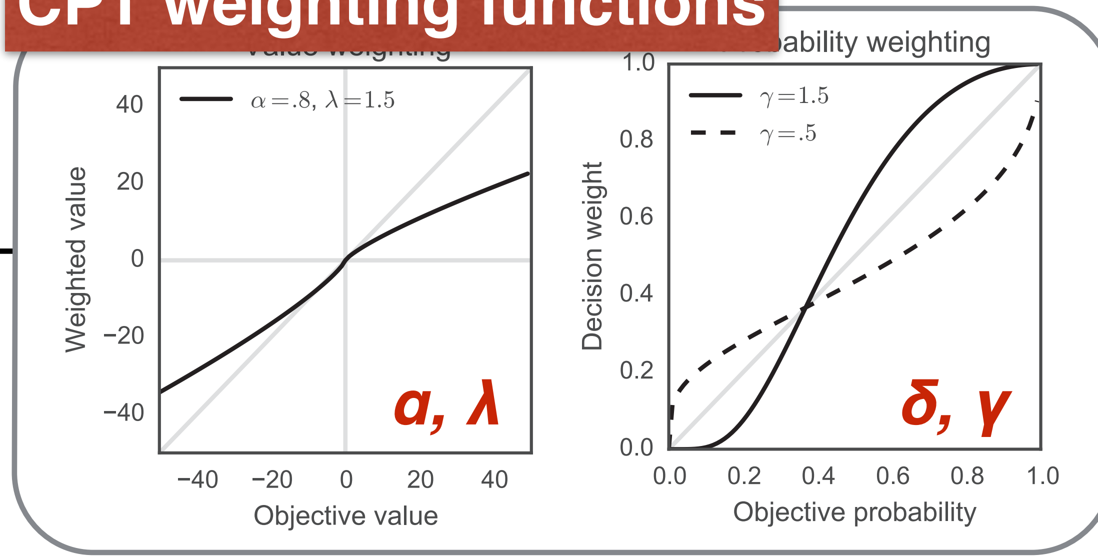

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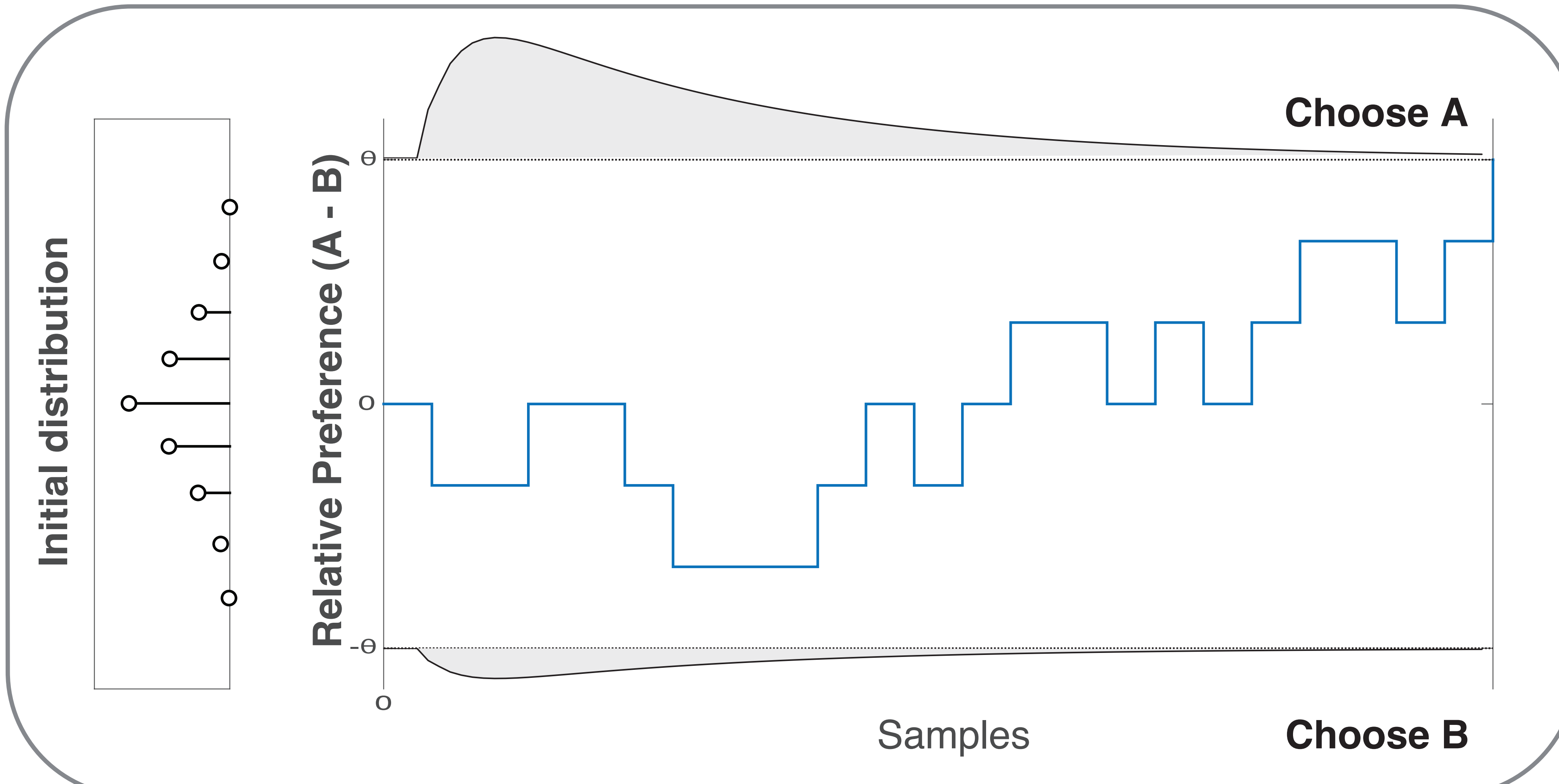

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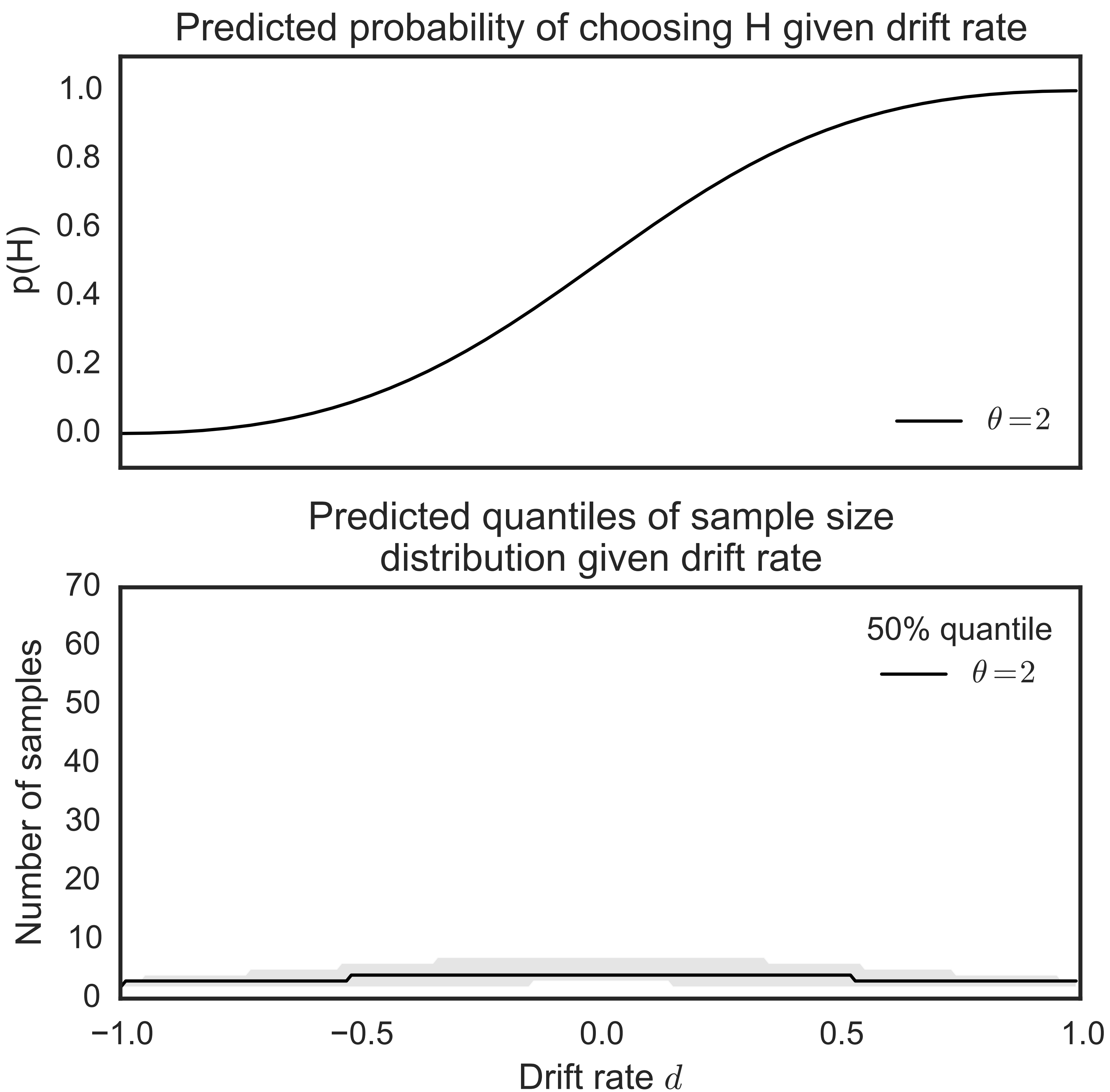
CHASE: Basic predictions



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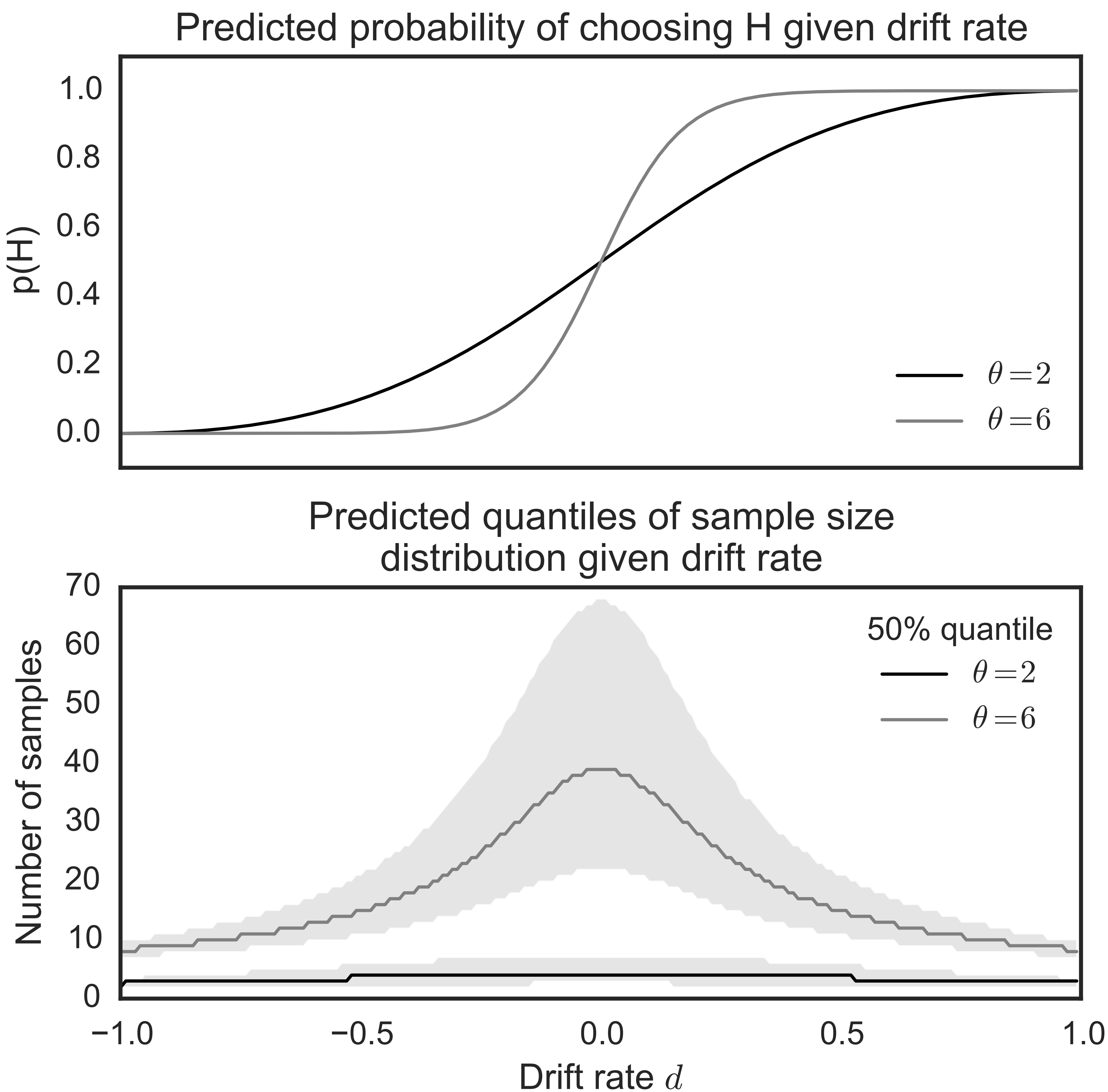
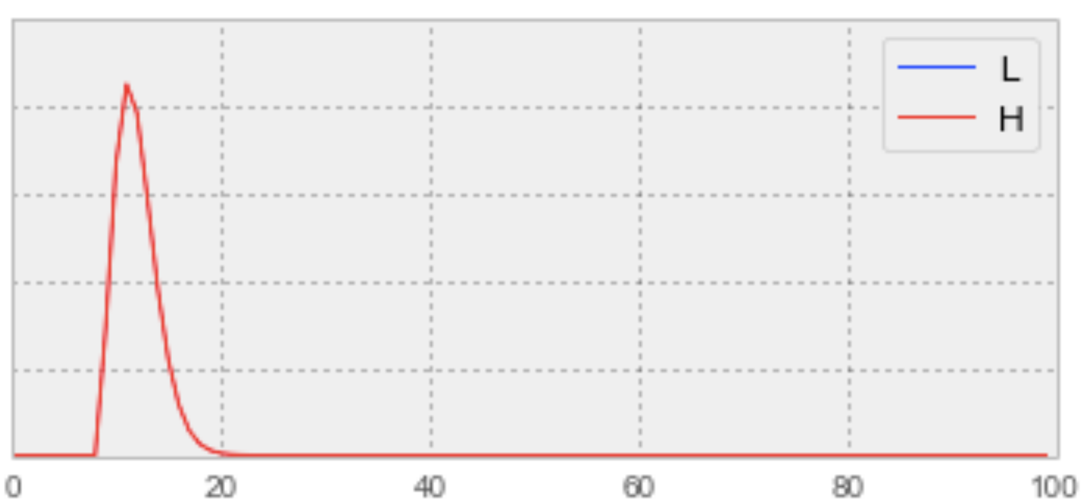


CHASE: Basic predictions

$$d = \frac{V_A - V_B}{\boxed{\sqrt{\sigma^2}}}$$

Low variance options

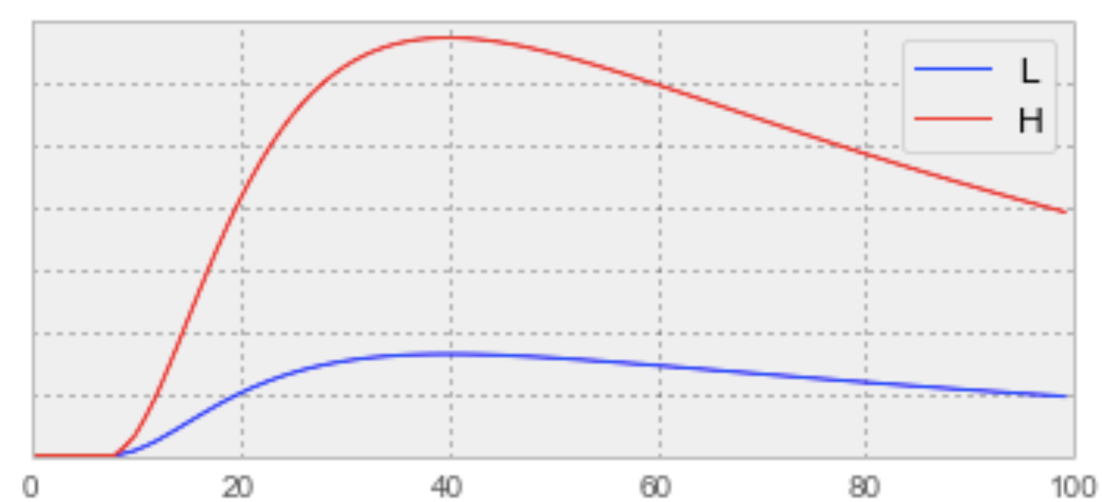
(H)igh: 2 with 100% chance
(L)ow: 1 with 100% chance



sample size

High variance options

(H)igh: 3 with 50% chance; otherwise 1
(L)ow: 2 with 50% chance; otherwise 0

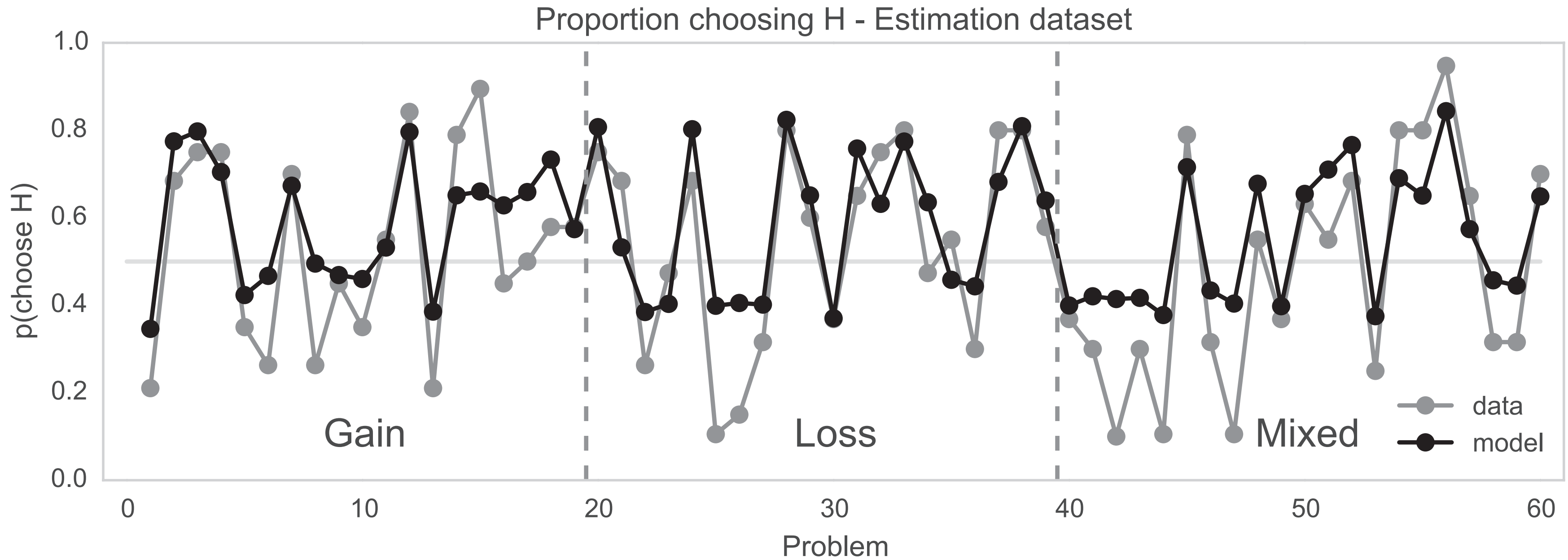


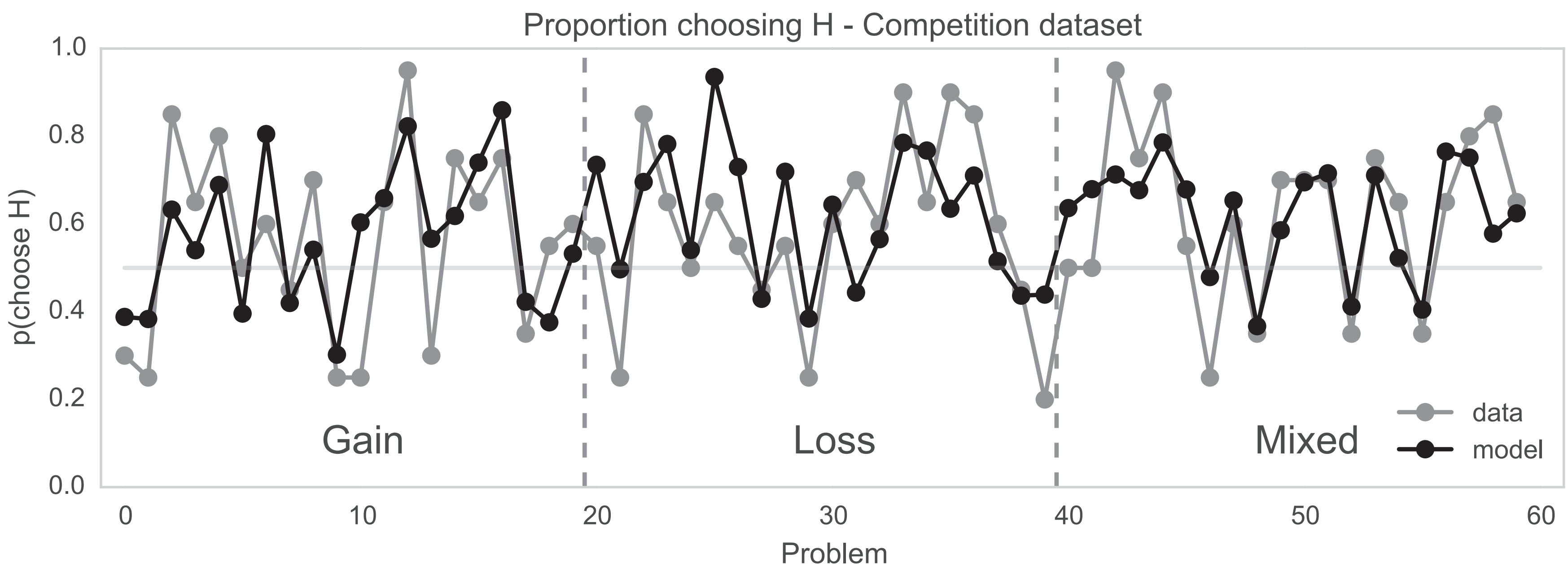
sample size

Example applications

- Fit the model with maximum likelihood to observed choice and sample size across all problems in a dataset
- Compared factorial combination of drift parameterizations (linear; value weighting only; <u>decision weighting only</u>; both value and decision weighting) using BIC
- Compared to competing model Instance-Based Learning (IBL) which assumes a fixed sample size distribution (fit to observed distribution)

Technion Prediction Tournament (TPT)





<u>CHASE (probability weighting only)</u>

estimation dataset
MSD: .019 (.009)
p(agree): .94 (.95)
r = .88 (.92)

competition dataset
MSD: .022 (.019)
p(agree): .90 (.83)
r = .68 (.80)

Erev et al. (2010)

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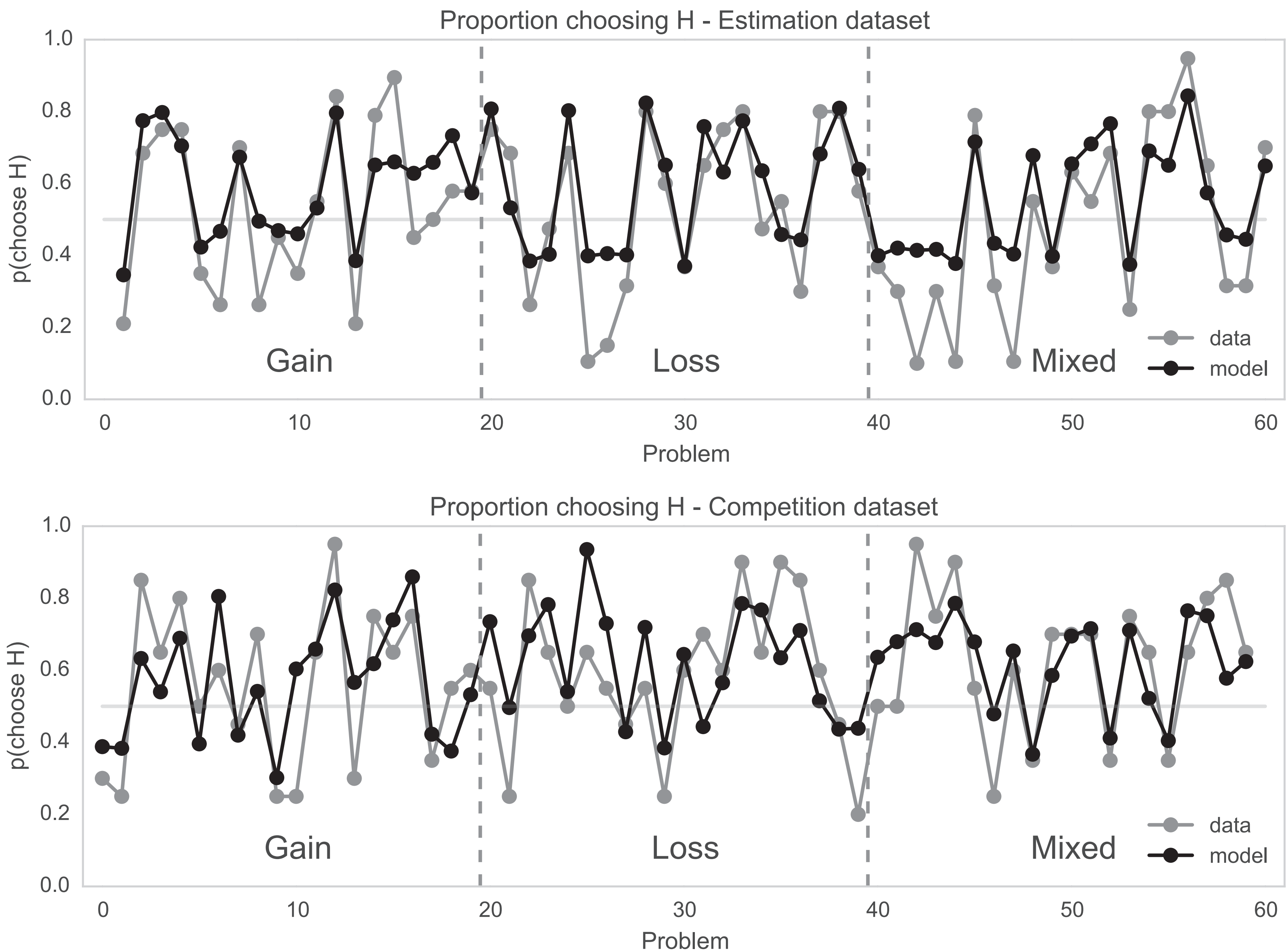

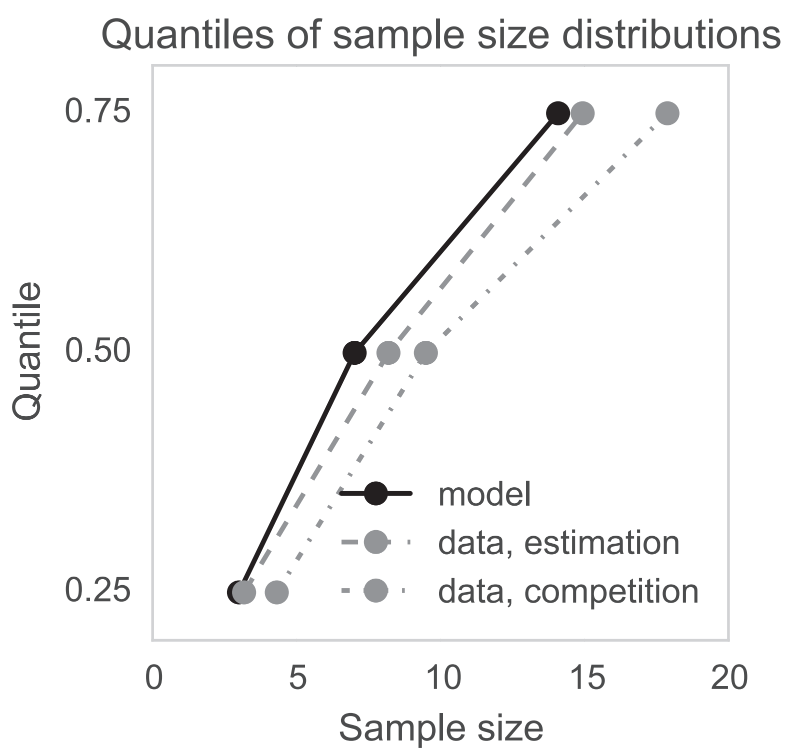

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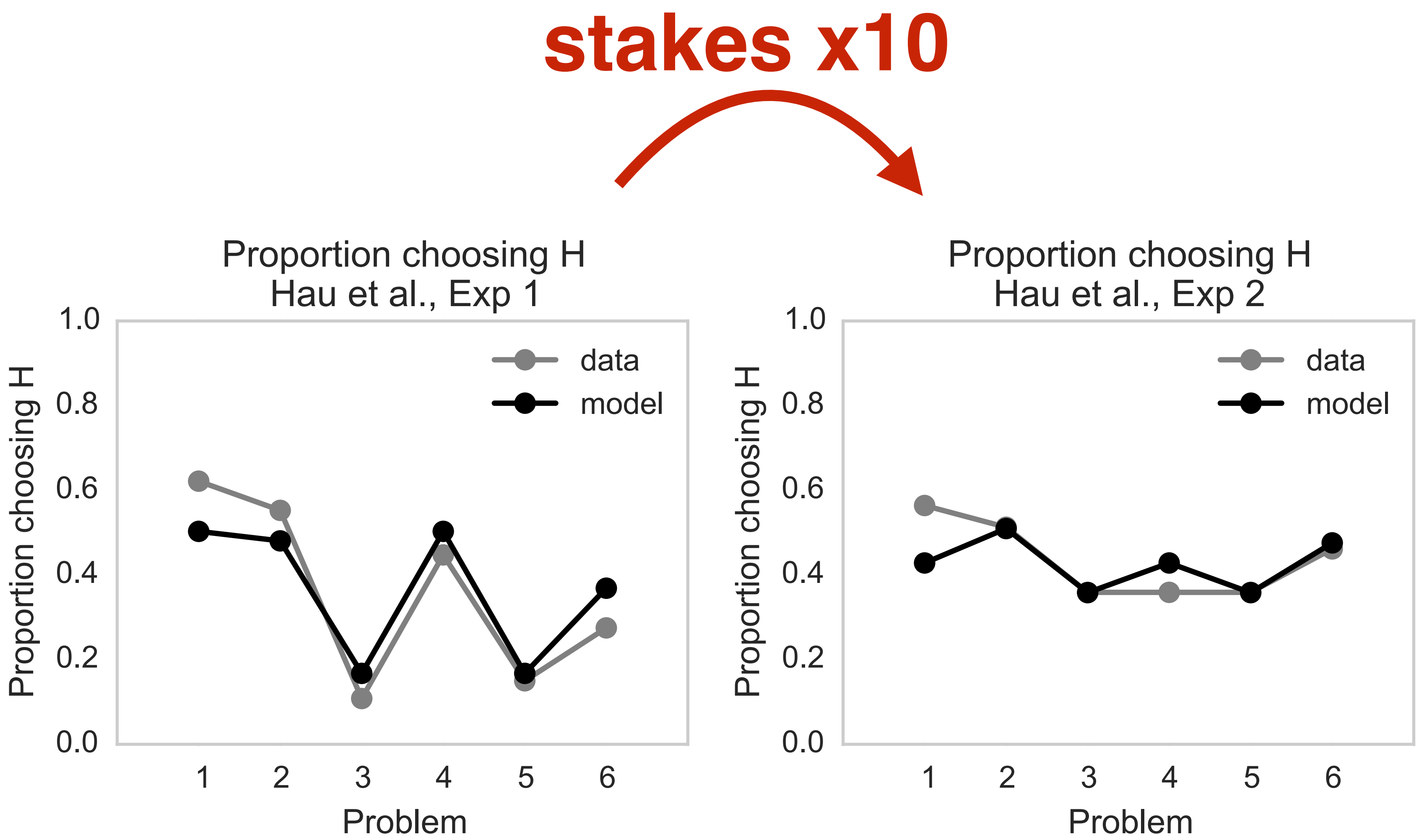
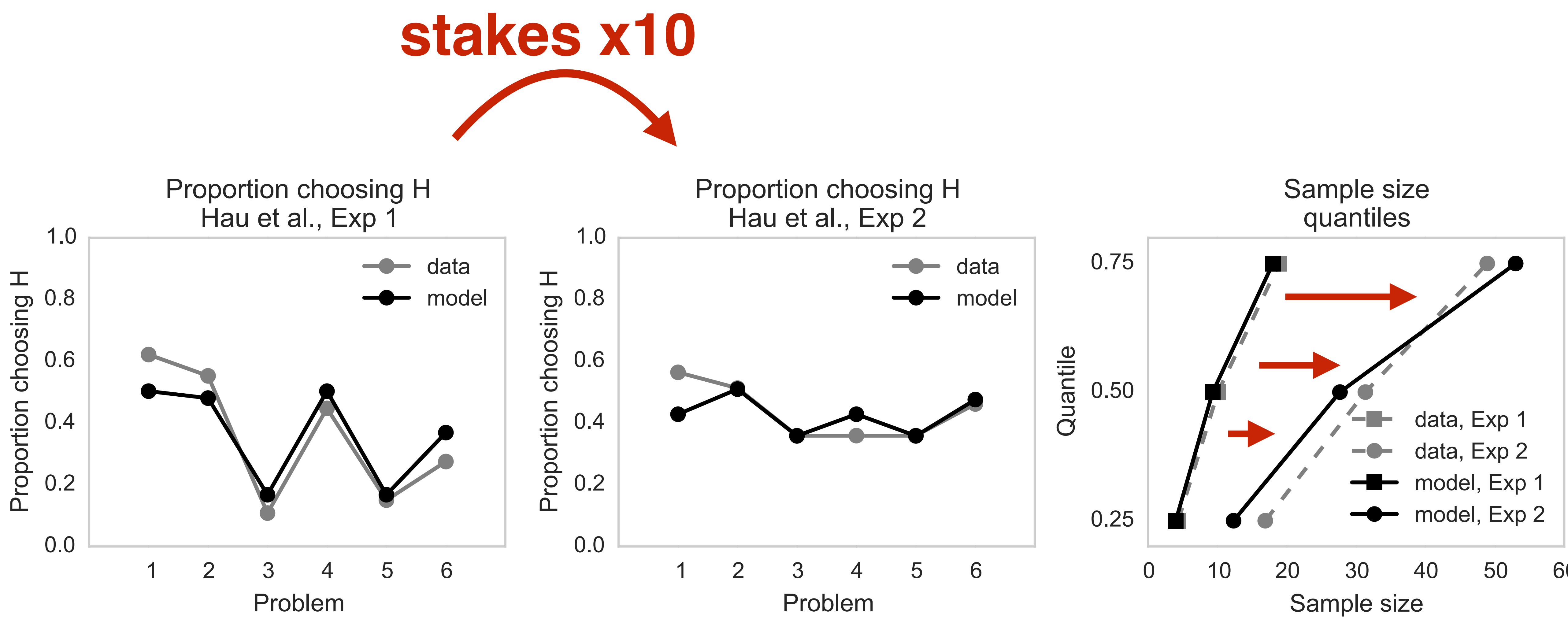
Manipulation of stakes (Hau et al., 2008)



- Best-fitting model: CHASE with probability weighting only
- Increase in payoff magnitude from Exp 1 to Exp 2 (with identical choice problems) accounted for by increase in decision threshold.

Manipulation of stakes (Hau et al., 2008)



- Best-fitting model: CHASE with probability weighting only

- Increase in payoff magnitude from Exp 1 to Exp 2 (with identical choice problems) accounted for by increase in decision threshold.

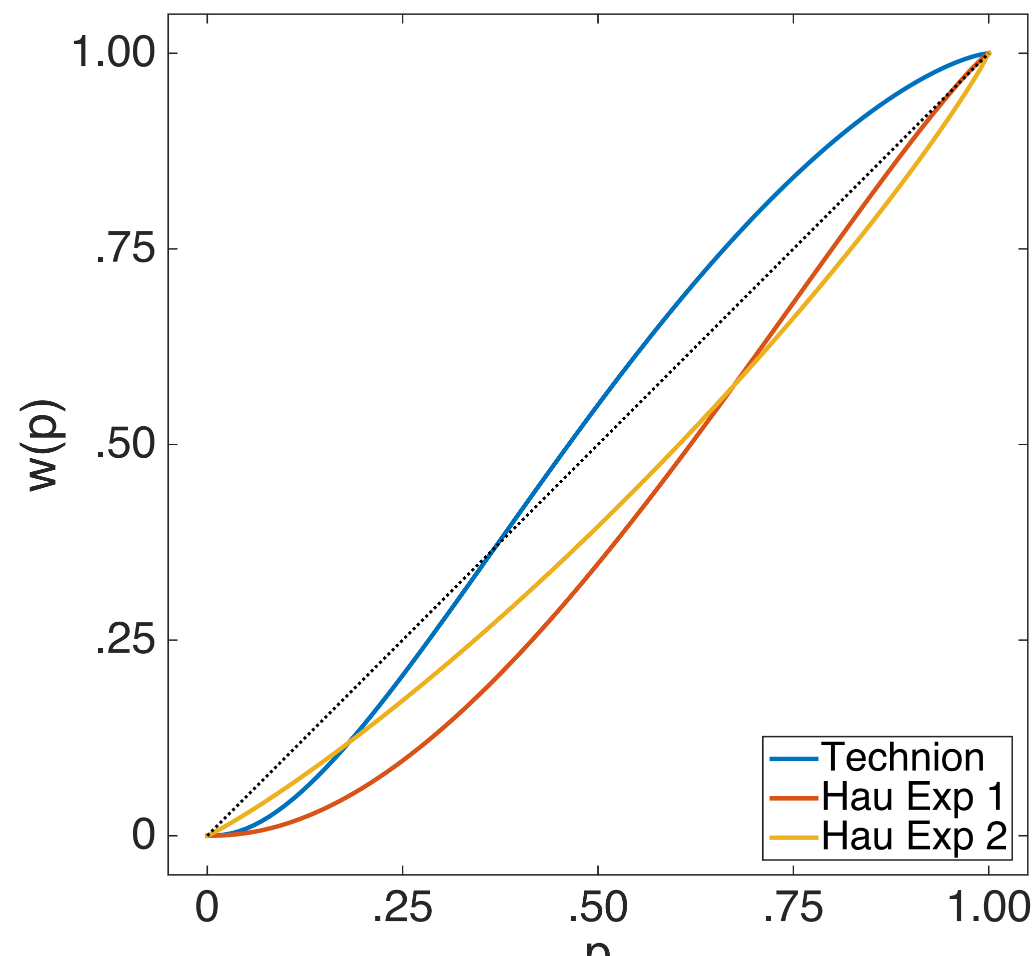
Measuring probability weighting

- Parameterizing the drift with CPT allows us to fit the probability weighting function to both choices and sample sizes
- Sampling error is modeled through the interaction between the drift and decision threshold
  - For example, if drift weakly favors option A (due to rare, high-magnitude outcome), the likelihood of reaching the B boundary is high at low thresholds
  - As decision threshold increases (leading to larger sample sizes), likelihood of such “fast errors” decreases

Measuring probability weighting

Best fitting parameter estimates

	TPT	Hau, Exp 1.	Hau, Exp 2.
Choice threshold θ	2	3	5
Start point variability τ	40	40	2.46
Probability of staying (p_{stay})	.68	.49	.46
Weighting function γ	1.41	1.15	.92
Weighting function δ	1	1.61	1.30



Summary

- CHASE combines sequential sampling framework with rank-dependent, subjective evaluation of CPT
- Demonstrates how both sample size and choice depend on interactions between the probabilistic structure of choice options and properties of the decision maker
- Moves beyond existing models of DFE with a mechanism for adaptive exploration under different goals, option structures, and properties of the individual decision maker

Thank you!

Slides available at www.dougmarkant.com