Discrete Adjustment with Multiple Changing Environments

Silvio Ravaioli

CD Lab Meeting

November 22, 2019

Motivation

- Lab experiment, tracking problem: estimate the probability of a binary event, which changes stochastically (as in Khaw, Stevens, and Woodford 2017 JME)
- Multiple simultaneous choices
- Framework: price adjustments
- Empirical motivation: sticky prices over time (Bils and Klenow 2004 JPE), but also uniform prices across stores (Della Vigna and Gentzkow 2019 QJE)
- **Main Hypothesis** (+ correlation): Changes occur more often together than in isolation
- **Opposite Hypothesis** (- correlation): Changes occur more often in isolation than together

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Side result of the experiment

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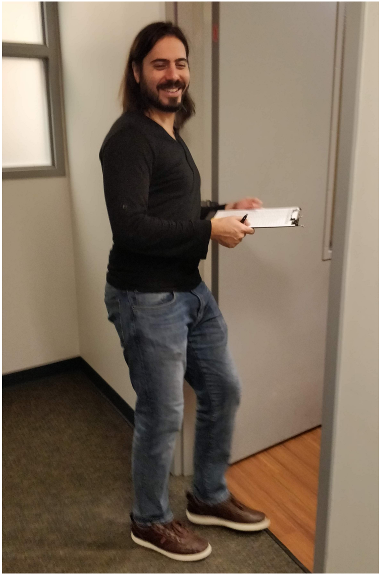
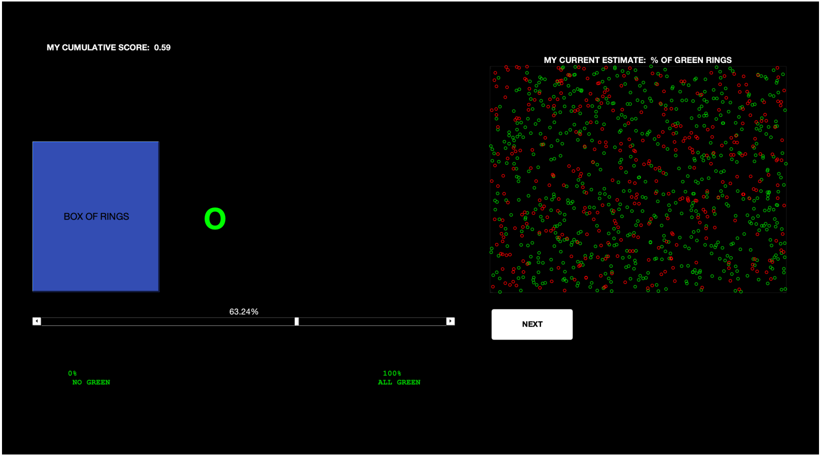
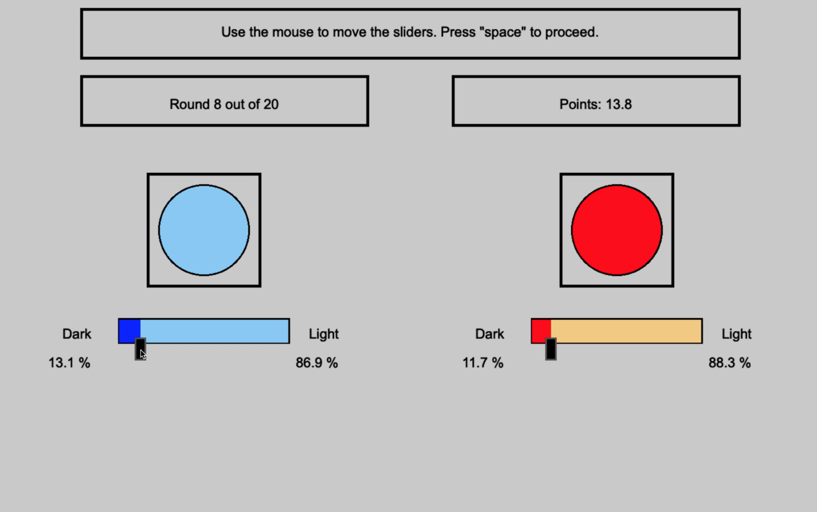


Lab experiment - Old vs New



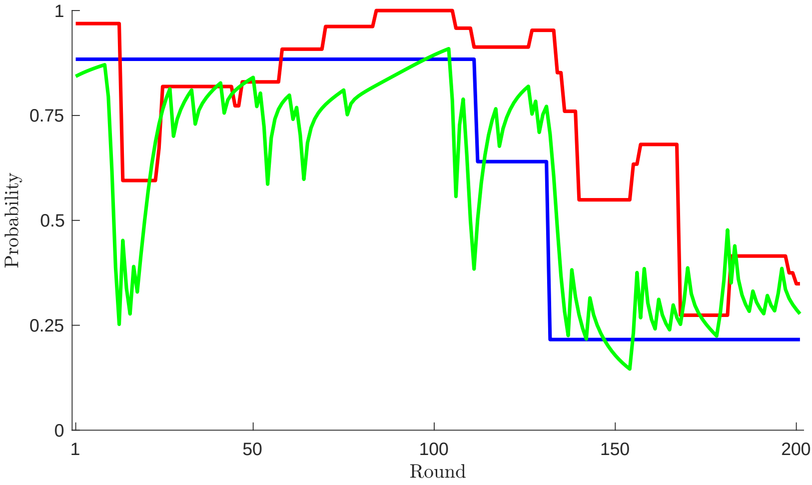
Khaw et al. 2017 - Discrete adjustment to a changing environment

Lab experiment - Old vs New

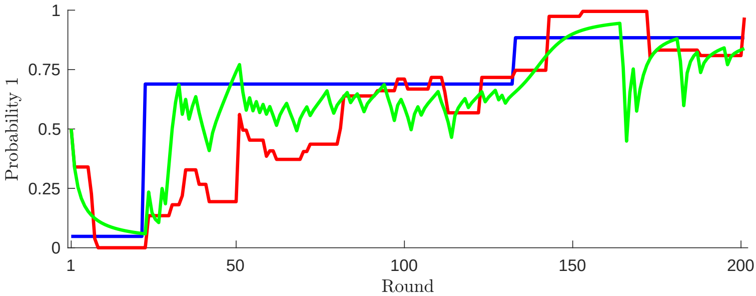


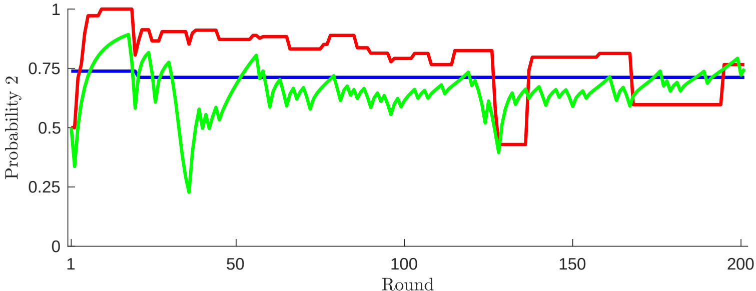
Adapted task with two independent states

Collected Data - Time Series

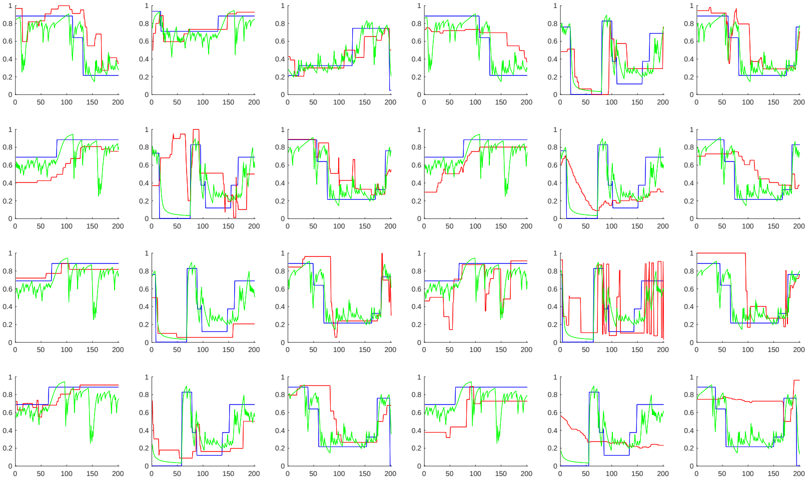


Collected Data - Time Series

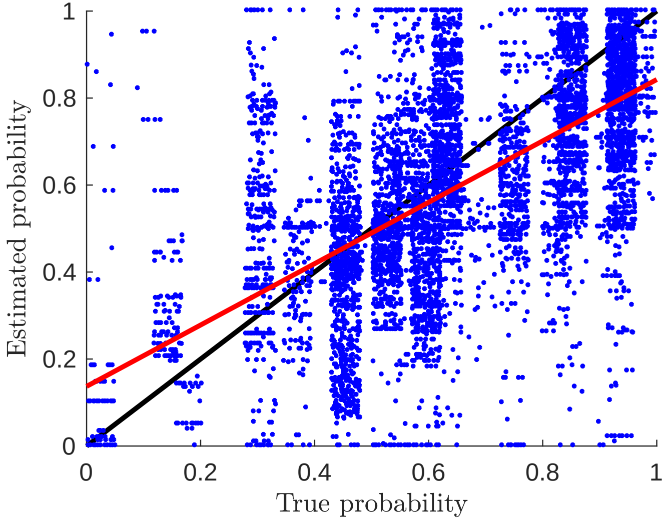




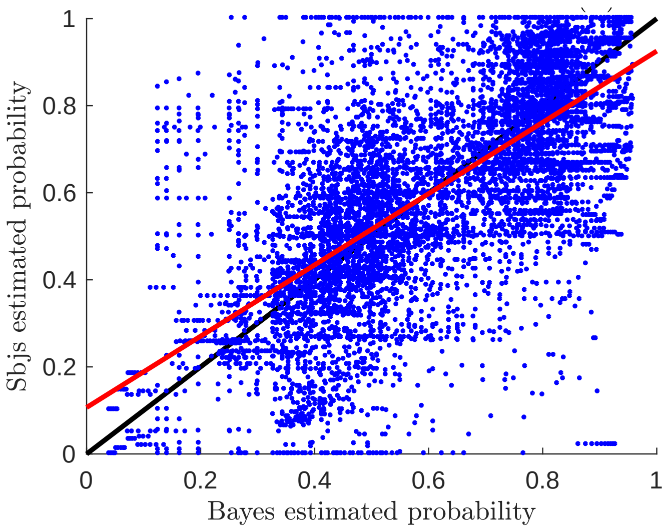
Collected Data - Time Series



Conservatism



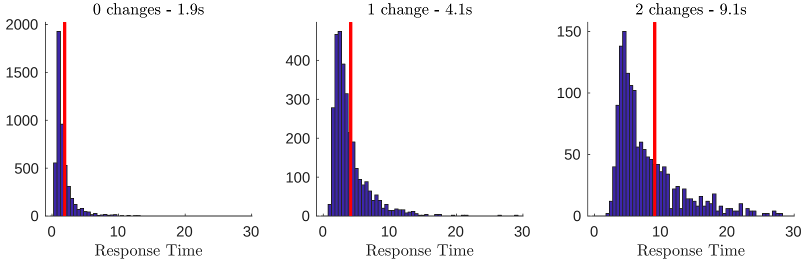
Participants vs optimal behavior



Inertia and correlated adjustment

- Inertia: no change in 51% of the rounds
- Correlated changes: a change in p1 increases the likelihood of changing p2 from 1/4 to 1/2

	All	Conditional on p1 changed	Conditional on p1 unchanged
Pr(p2 change)	**32%**	**49%**	**24%**
Avg p2 c (cond.)	10.73%	8.68%	12.71%
Avg p2 change	3.44%	4.25%	3.05%



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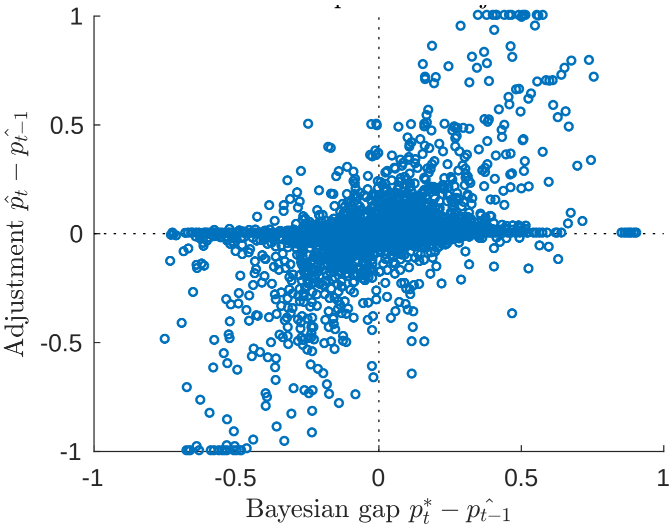
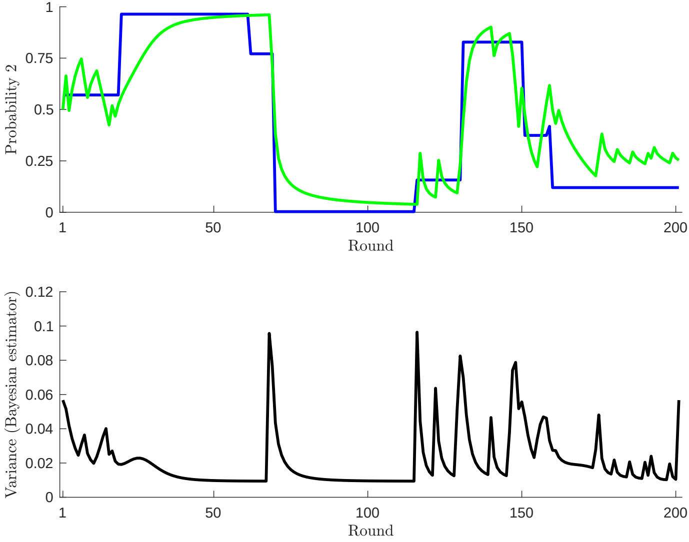
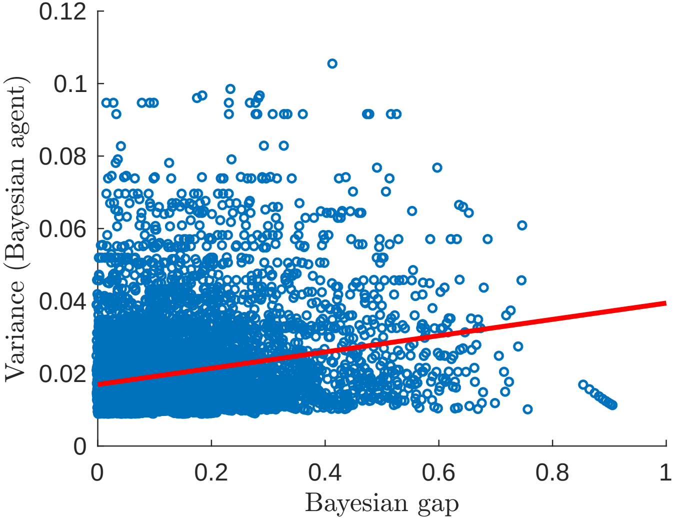


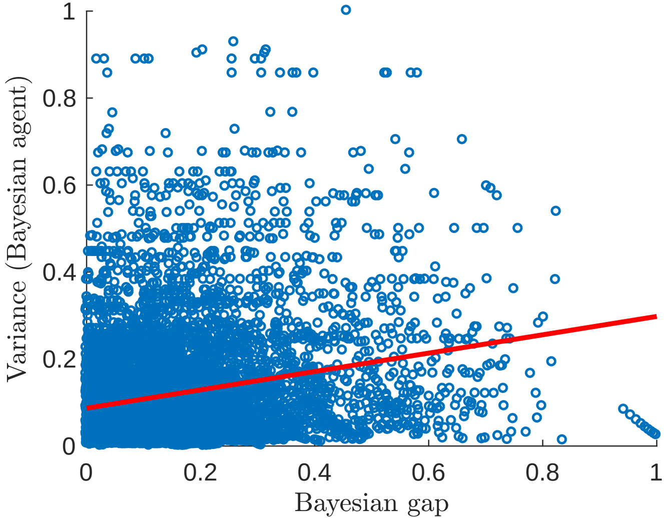
Predictors of change



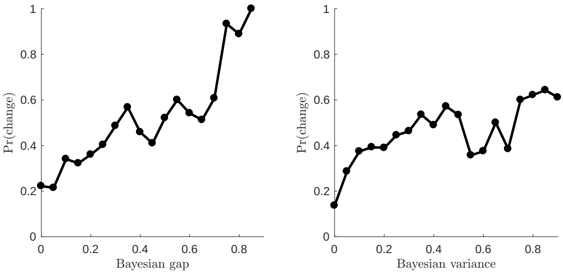
Predictors of change



Predictors of change

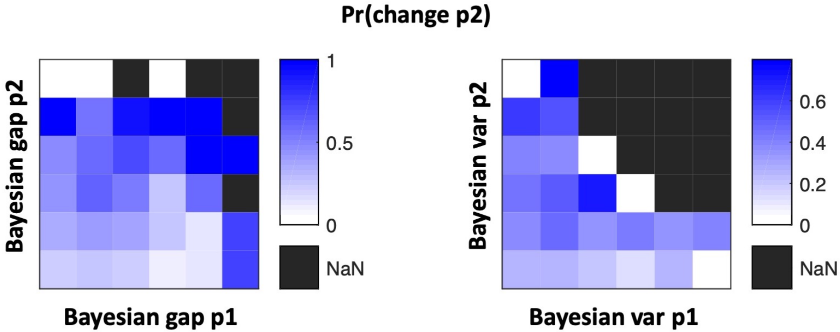


Logit Regression



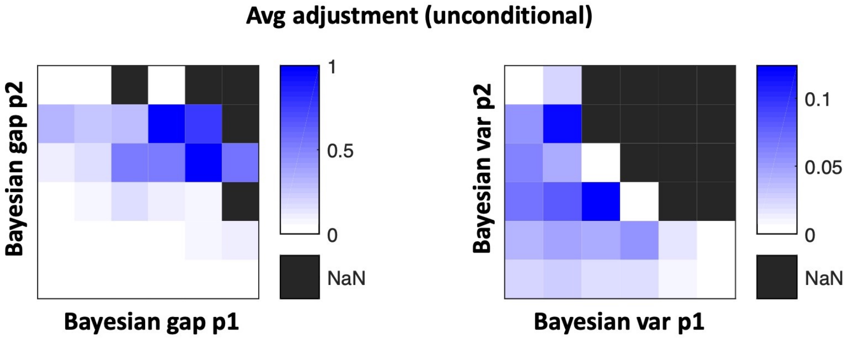
Logit(Change p2)	(1)	(2)	(3)	(4)
Constant	-1.26***	-1.16***	-1.55***	-1.93***
Bayesian gap p2	3.08***		2.64***	4.02***
Bayesian gap p1	0.222		0.265	1.18***
Bayesian var p2		3.01***	2.43***	4.28***
Bayesian var p1		0.334*	0.502***	1.69***
Bg p2 $\times$ Bv p2				-9.14***
Bg p1 $\times$ Bv p1				-6.18***

Heatmaps



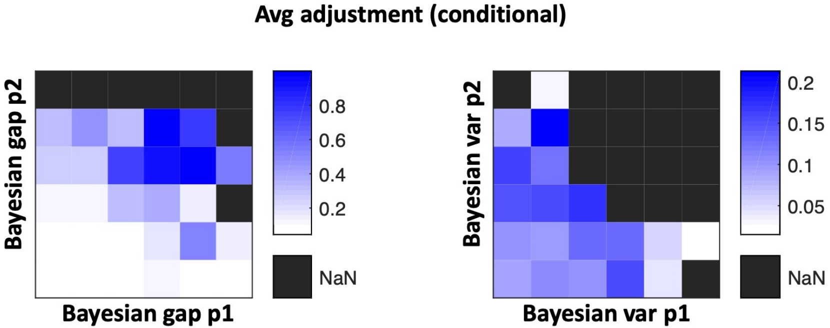
Pr(change p2)
Bayesian gap p2
Bayesian gap p1
1
0.5
0
NaN
Bayesian var p2
Bayesian var p1
0.6
0.4
0.2
0
NaN

Heatmaps

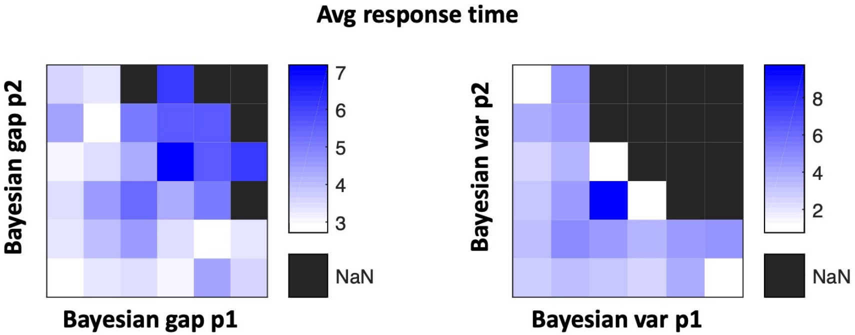


Avg adjustment (unconditional)
Bayesian gap p2
Bayesian gap p1
1
0.5
0
NaN
Bayesian var p2
Bayesian var p1
0.1
0.05
0
NaN

Heatmaps


Avg adjustment (conditional)
Bayesian gap p2
Bayesian gap p1
0.8
0.6
0.4
0.2
NaN
Bayesian var p2
Bayesian var p1
0.2
0.15
0.1
0.05
NaN

Heatmaps


Avg response time
Bayesian gap p2
Bayesian gap p1
7
6
5
4
3
NaN
Bayesian var p2
Bayesian var p1
8
6
4
2
NaN

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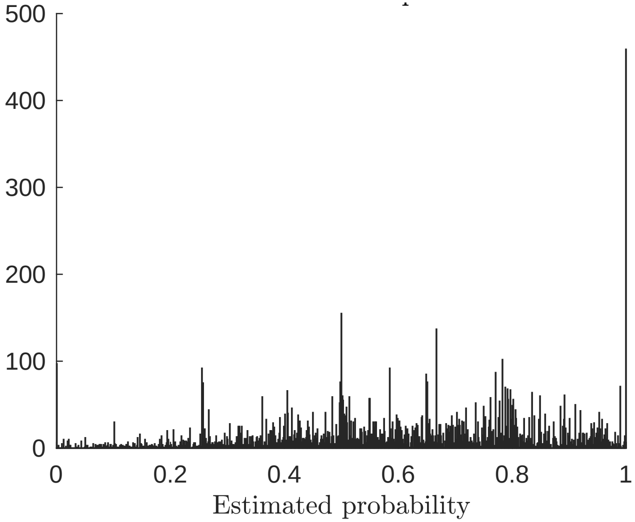
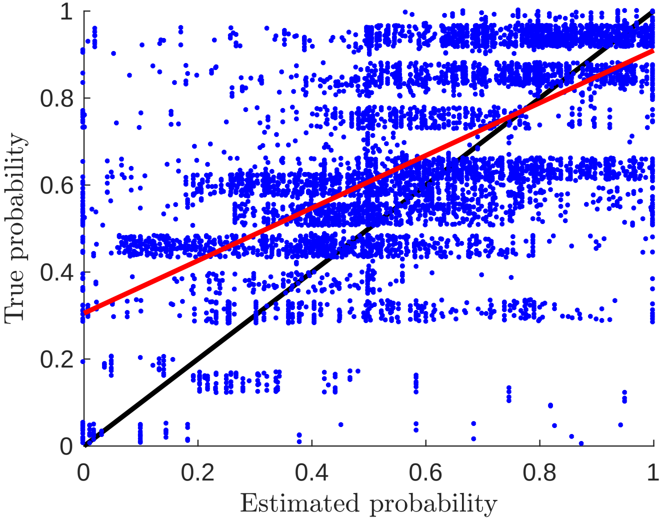
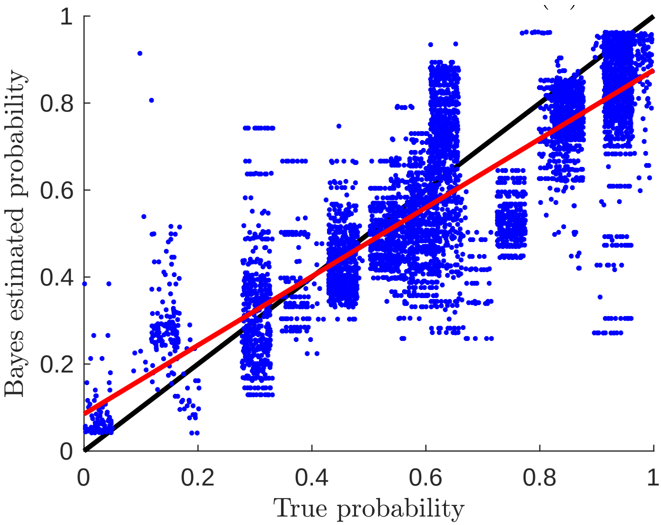
Preference for round numbers



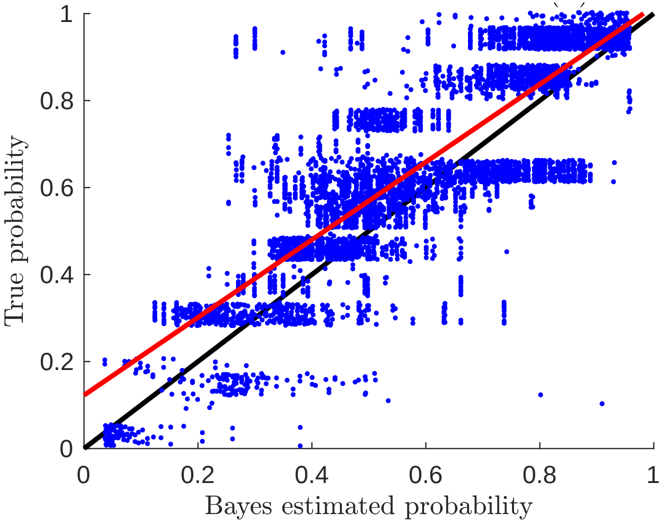
Overconfidence



Conservatism (Bayesian agent)



NO overconfidence (Bayesian agent)



Benchmark (Bayesian agent)