# Numerocity Biases and the Perceived Chances of Getting a Job: Experimental Evidence and Implications for Directed Search

# Outline

- Background Idea
- Biases
- Experiment
- Equilibrium Model
- Conclusions

With the Internet:

- People apply to jobs faster.
- People apply to more jobs.
- The average person gets more rejections.
- More rejections, but more applications - chances of getting a job could be the same.
- How do job seekers handle this change?

## Research Question

Does an in the velocity of applications imply a corresponding increase in the bias of a job seeker's probability-of-success estimation?

**Ratio Bias**

- Cookie Jar experiment (Miller et al 1989).
- Numerocity of numerator <> numerocity of rejections!

## Numerocity Heuristic

- Chickens and then humans, specifically under cognitive load (Pelham et al 1994).
- Numerocity works as estimation tool for quantity.
- Probability of getting each job vs. chances of getting a job.

## Learning by Experience

- Opposite effect from "learning by description" ala Prospect Theory (Hertwig et al 2004)
- Hertwig points out undersampling in practice rounds.
- Does that imply a "snapping to zero" of low probability events?

# Turkeriment

MTurk:

- Task creators can specify the characteristics of those who perform their task.
- Turkers with similar qualifications have access to the same pool of jobs => same opportunity costs!
- They think about opportunity costs explicitly on a daily basis.
- Websites with hourly equivalents

J

jdzane

*An Experiment With Games of Chance. Up to $5 in bonuses!* - $0.50 +$2.00 bonus

| Unrated | Unrated | Pending | $120.00 / hour 00:01:15 / completion time |
|---|---|---|---|

**Pros**

-easy

**Cons**

Jun 19, 2018

Edit Review

A

AMindAtTurk

*An Experiment With Games of Chance ($5 Bonus)* - $0.50

| Generous | Unrated | Pending | $15.93 / hour 00:01:53 / completion time |
|---|---|---|---|

**Pros**

Potential bonus. Your completion time will vary based on your decisions.

**Cons**

Jun 14, 2018

Edit Review

B

BadPanda

*An Experiment With Games of Chance ($5 Bonus)* - $0.50

| Good | Unrated | Pending | $10.59 / hour 00:02:50 / completion time |
|---|---|---|---|

Jun 14, 2018

Edit Review

## Experimental Design

- Participants play a one-armed bandit.
- The game ends when they win or quit.
- 50% chance that their bandit pays out with probability 0.
- 50% chance that their bandit pays out with probability ???
- Group A: 3 seconds/play
- Group B: 12 seconds/play
- Participants who got lucky and won are excluded from the results.
- The question is: "how many losses do you experience before you quit trying?"

## Rational Response

True model:

$$k_{n+1} \sim Bernouli(p)$$

$$p \equiv P(\gamma|n, a_H)P(a_H|n)$$

Where $a_H$ denotes being in the "high skill" group, and $\gamma$ denotes the Bernouli payout probability of the bandit.

— True model requires concurrent estimation of two different probabilities, not identifiable without further assumptions.

Simplify to the estimation of the posterior mean of $p$ directly:

$$\hat{P}_n$$

Finite-horizon stopping time problem.

— No discounting.
— Think of it like the payment for one-days work.

$$V(n) = \max\{\mathbb{E}V_p(n), V_q(n)\}$$

## Rational Response

Where the value of quitting it given by:

$$V_q(n) = u\left(\sum_{n}^{T} ct\right)$$

With $c$ is the per-second wage of the outside option and $t$ is the number of seconds per round of play. The expected value of playing:

$$\mathbb{E}V_p(n) = \hat{P}_n u(W + \sum_{n+1}^{T} ct) + (1 - \hat{P}_n)\mathbb{E}V(n+1)$$

## Rational Response

Assume that in some $n+1$, $V(n+1) = V_q(n+1)$:

$$\mathbb{E}V_p(n) = \hat{P}_n u(W + \sum_{n+1}^{T} ct) + (1 - \hat{P}_n) u\left(\sum_{n+1}^{T} ct\right)$$

$$\hat{P}_n \left[ u(W + \sum_{n+1}^{T} ct) - u\left(\sum_{n+1}^{T} ct\right)\right] = u\left(\sum_{n}^{T} ct\right) - u\left(\sum_{n+1}^{T} ct\right)$$

## Rational Response

Letting $u_n^m$ denote the marginal utility of some consumption above and beyond $\sum_n^T ct$, we can write the stopping time conditions as follows:

$$\hat{P}_n u_{n+1}^m(W) = u_{n+1}^m(ct)$$

Use this for inference!

## Results

| | Group | N | t | Time played | c | c | c |
|---|---|---|---|---|---|---|---|
| | | | | | $\rho = 2$ | $\rho = 1$ | $\rho = 0$ |
| Median | a | 29 | 4 | 240 | 0.0204 | 0.0209 | 2.1368 |
| | b | 28 | 15 | 311 | 0.0138 | 0.0141 | 1.4448 |
| Mean | a | 29 | 5 | 374 | 0.0348 | 0.0356 | 3.6450 |
| | b | 28 | 17 | 400 | 0.0200 | 0.0204 | 2.0875 |
| MW p | | | | | 0.084 | 0.084 | 0.078 |

Where t is roll time and c is opportunity cost in cents per second

# Equilibrium Model

How can biases of probability judgement affect the labor force on an aggregate level?

What effects can they have on unemployment and wage distributions across the labor market?

Searching for a model with:

- Agent(s) that direct their search towards specific "submarkets" of jobs with different wage characteristics.
- Agent(s) that do not know the objective probabilities of getting a job in any particular submarket, and must estimate these probabilities through a process of learning by experience.
- Agent(s) that can experience both rejection and success in searching for jobs, and update their beliefs accordingly.

## Equilibrium Model

"An equilibrium theory of learning, search, and wages" Gonzalez, Francisco M and Shi, Shouyong. Econometric 2010.

## Equilibrium Model

Ax-ante heterogeneity in skill:

$$a_i \in \{a_L, a_H\}$$

Ax-ante homogeneity in beliefs about skill:

$$\mu_0 = pa_H + (1 - p)a_L$$

Apply to submarket, $x$, by maximizing continuation value given beliefs:

$$g(\mu)$$

## Equilibrium Model

Posterior Updates:

$$\phi(\mu) \equiv a_H + a_L - a_H a_L/\mu$$

$$H(x, \mu) \equiv a_H - (a_H - \mu)(1 - x a_L)/(1 - x\mu)$$

Yields posterior mean after $n = 2$ failures:

$$\hat{P}_2 \equiv H(g(H(g(\mu_0), \mu_0)), H(g(\mu_0), \mu_o))$$

# Equilibrium Model

# Calibration

## Calibration

Opportunity cost of worker i is estimated with a prior:

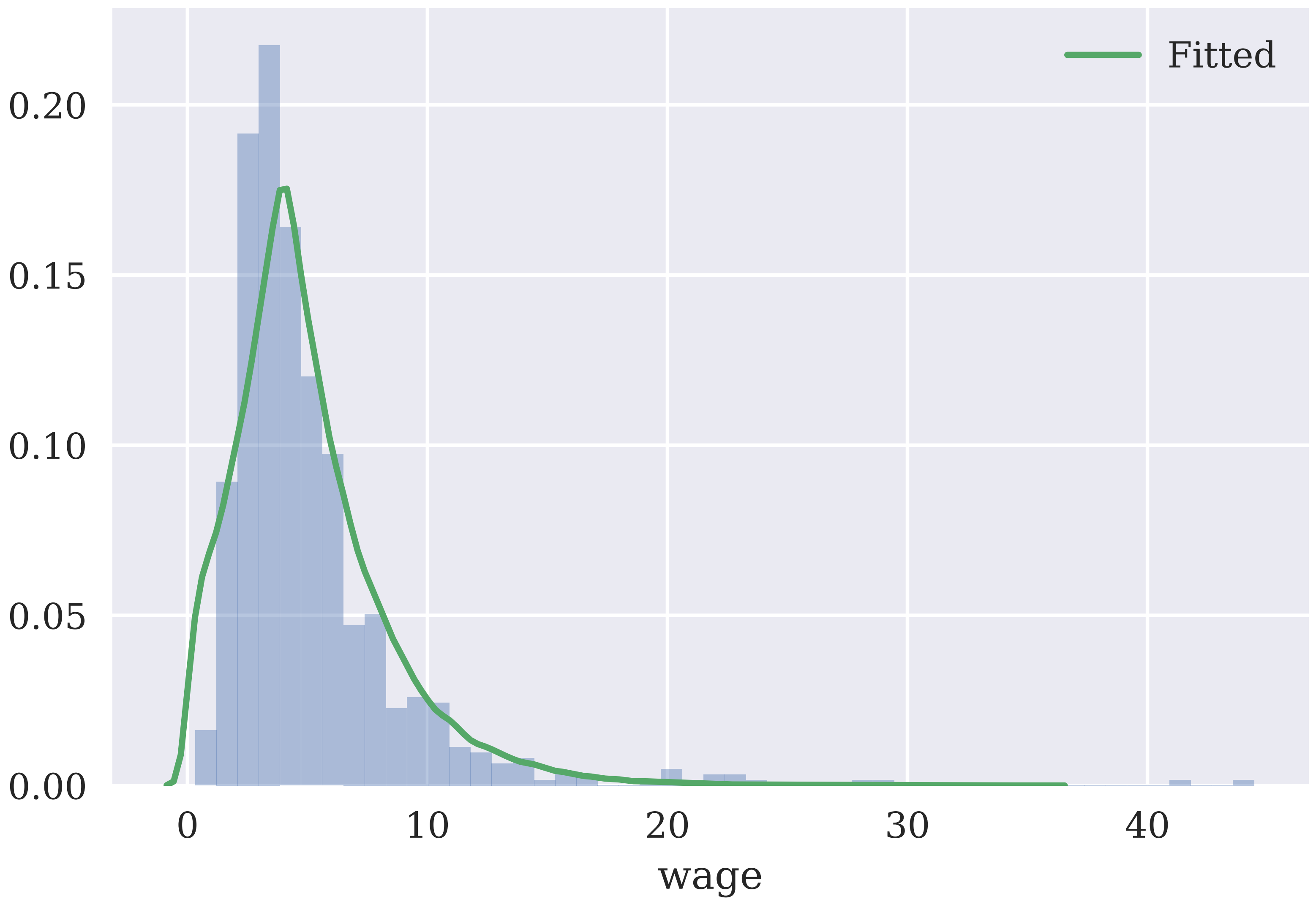
$$c_i \sim \mathrm{DoubleExponential}(\mu^c, \sigma^c)$$

Where $\mu^c$ and $\sigma^c$ are estimated by:

— Scraping the wages from the top 50 reviews of each worker who reviewed these experiments on Turkerview.

— Estimating the parameters by minimizing KL-divergence.

# Calibration



Updating is assumed to take the form:

$$p_i = \frac{1}{1 + N_i(1 + \epsilon_i)}$$

The bias of worker i in treatment group g is assumed to come from a treatment-group specific distribution:

$$\epsilon_i \sim \mathrm{Normal}(\mu_g^\epsilon, \sigma_g^\epsilon)$$

The condition:

$$u\left(\frac{p_{i,g}}{c_i}\right) = u\left(\frac{t_i}{W}\right)$$

Is enforced via log difference equation with penalty $\delta$:

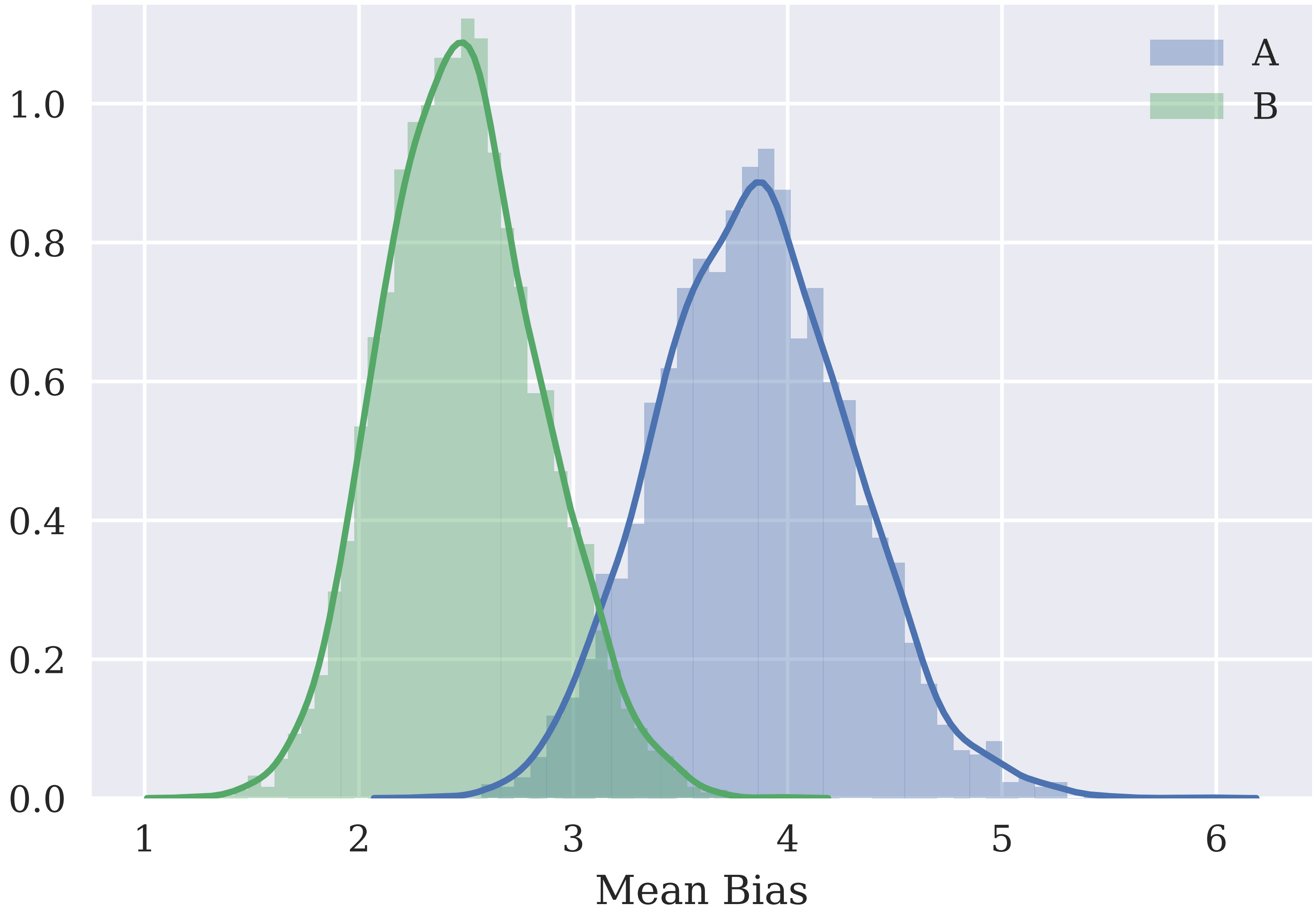
$$log\left(u\left(\frac{p_{i,g}}{c_i}\right)\right) - log\left(u\left(\frac{t_i}{W}\right)\right) \sim \mathrm{Normal}(0, \frac{1}{\delta})$$

## Calibration

Utility is assumed to be linear

— TODO: estimate per-person risk aversion!

# Estimated Posterior of Mean Bias



Model outputs an "equilibrium belief tree".

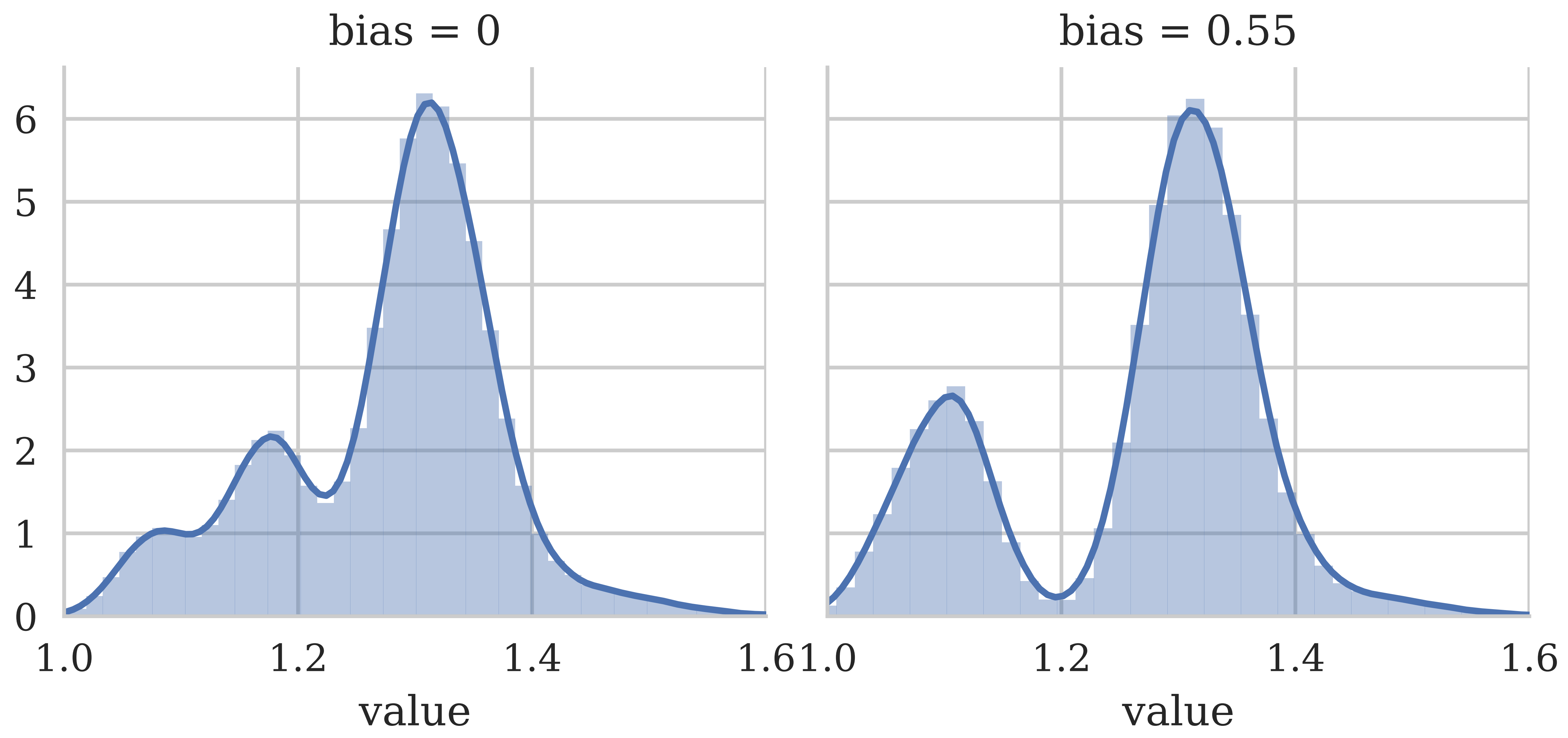
— Binary tree, every node contains a belief, every split a fail/success updating.

— Equilibrium flow maintained by exogenous exit from market (death?) and corresponding newborns.

## Results

```
|--m: 0.53, u: 0.1000, e: 0.0000
   |--m: 0.24, u: 0.0541, e: 0.0000
      |--m: 0.09, u: 0.0388, e: 0.0000
      |--m: 0.84, u: 0.0006, e: 0.0933
   |--m: 0.95, u: 0.0021, e: 0.3378
      |--m: 0.88, u: 0.0007, e: 0.0000
      |--m: 1.00, u: 0.0001, e: 0.0117
```

# Wage Results



## Future Research

One of the best established findings in social psychology is that people perceive themselves readily as the origin of good effects and reluctantly as the origin of ill effects…
— Anthony Greenwald (1980)

## Future Research

- Role of the ego and self-worth.
- Role of prior formation vs learning-by-experience.
- Effects for collective bargaining.
- Empirical evidence via platform data.