“Truth serum” mechanisms for survey research

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7th Workshop On Non-market Valuation

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“Truth serum” assumptions
Differences relative to other mechanisms

- Bayesian respondents, with private signals (opinions, intentions, preferences)
- Common knowledge of a prior over signals (or, more weakly, that different signals imply different posteriors over signals received by others)
- Analyst only knows the set of possible signals (types), which are 1:1 with answers to a multiple-choice question
- Honesty is unverifiable
- Respondents have no preferences apart from maximizing their score
- Solution goal: There exists a ‘unique’ strict Bayesian Nash equilibrium in which respondents honestly reveal their signal (type)

.

Three distinct applications of truth serums

- To provide incentives for honest, careful responding
- To make more accurate population estimates of e.g., future voting behavior, or willingness-to-pay for goods and services
- Crowd wisdom: To improve on simple democratic averaging of opinions

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The essential idea:
Convert the survey into a competitive game

Asking people for two judgments

1. A personal endorsement of one answer (opinion or forecast)
2. A prediction of the distribution of answers

Each person receives a score, which is a function of his answer and prediction.

The scoring algorithm does not select the most popular (majority) answer. Instead, it selects the answer that is most popular relative to predictions.

It handicaps (1) against (2)

Theorem 1* (Truth serum) Truthtelling in answers and predictions is the unique (modulo permutations) strict Bayesian Nash equilibrium in a countably infinite sample.

Theorem 2** (Crowd wisdom) Scores reveal which individuals place highest probability on the actual world (i.e., the correct hypothesis).

* Prelec, D. <u>Science, 2004.</u>
* *Prelec, D., Seung, H. S., & McCoy, J. <u>Nature</u>, 2017

Bayesian truth serum inputs

Ask each respondent r for <u>dual</u> reports:

(1) an endorsement of an answer to an m-multiple-choice question

$x_k^r \in \{0,1\}$

indicates whether respondent r has endorsed answer $k \in \{1,...,m\}$

(2) a prediction $(y_1^r,..,y_m^r)$ of the sample distribution of endorsements

Truth is person-dependent

(i) Would you vote in favor of referendum proposition X?

(Yes / No)

(ii). Have you had more than twenty sexual partners over the past year?

(Yes / No)

(iii) Is Philadelphia the capital of Pennsylvania?

(True / False)

(iv) The best current estimate of the temperature change by 2100 is (check one):

___ $< 2^\circ$ C ___ $2\text{-}5^\circ$ C ___ $5\text{-}8^\circ$ C ___ $> 8^\circ$ C

Truth is impersonal

(i) Would you vote in favor of referendum proposition X?

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Mechanisms of the ‘truth serum’ type
2004 BTS = infinite sample, common prior..

Prelec, D A Bayesian truth serum for subjective data. Science, 2004

Witkowski, J. and Parkes, D.C. A Robust Bayesian truth serum for small Populations. Proceedings AAAI, 2012

Radanovic, G. and Faltings, B. A robust Bayesian truth serum for non-binary signals. Proceedings AAAI, 2013.

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Baillon, A. Bayesian markets to elicit private information, PNAS 2018

Cvitanic, J,. Prelec, D., B. Riley, and B. Tereick., Honesty by choice matching. American Economic Review: Insights (Sept. 2019, forthcoming).

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... rewards 'information'

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How it works (BTS 2004) ...

Ask each respondent r for dual reports:

(1) an endorsement of an answer to an m-multiple-choice question

- $x_k^r \in \{0,1\}$

  indicates whether respondent r has endorsed answer $k \in \{1,\ldots,m\}$

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Then calculate BTS scores

The total BTS score for person r, for endorsement $(x_1^r,.., x_m^r)$ and prediction $(y_1^r,..,y_m^r)$ is based on two statistics:

$\bar{x}_k$ = fraction endorsing answer k

$\bar{y}_k$ = geometric average of endorsement predictions for answer k

BTS score = Information score + Prediction score

$$u^r = \sum_{k=1}^{m} x_k^r \log \frac{\bar{x}_k}{\bar{y}_k} + \sum_{k=1}^{m} \bar{x}_k \log \frac{y_k^r}{\bar{x}_k}$$

The prediction score measures prediction accuracy (and equals zero for a perfect prediction)

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The Information score measures whether an answer is "surprisingly common"

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The Information score measures whether an answer is "surprisingly common"

The total BTS score for person r, for endorsement $(0,0,1,0,..,0)$ and prediction $(y_1^r,..,y_m^r)$ is based on two statistics:

$x_j^r = 1$

$\bar{x}_k$ = fraction endorsing answer k

$\bar{y}_k$ = geometric average of endorsement predictions for answer k

BTS score = Information score + Prediction score

$$u^r = \log \frac{\bar{x}_j}{\bar{y}_j} + \sum_{k=1}^{m} \bar{x}_k \log \frac{y_k^r}{\bar{x}_k}$$

Mathematical assumptions and results

- Person r gets a signal $t^r \in \{1,..,m\}$ representing his opinion or type
- $\boldsymbol{\omega} = (\omega_1,..,\omega_m) =$ distribution of signals in the population
- Everyone has the same prior distribution $p(\omega_1,..,\omega_m)$ over $\boldsymbol{\omega}$
- a person r with signal j treats this as a sample of one, yielding a posterior distribution $p(\boldsymbol{\omega} \mid t^r=j)$ on $\boldsymbol{\omega}$.
- $E(\boldsymbol{\omega} \mid t^r=j) = E(\boldsymbol{\omega} \mid t^s=k) \Longleftrightarrow j=k$
- countably infinite sample

<u>Theorem 1</u> Truthtelling (both answers and predictions) is the unique strict Bayesian Nash equilibrium in a countably infinite sample.

<u>Theorem 2</u> A respondent's BTS score in the truthteling equilibrium equals the log probability she assigns to the actual distribution of signals, $\boldsymbol{\omega}$, plus a budget balancing constant:

$$u^r = \log p(\boldsymbol{\omega} \mid t^r) + C$$

<u>Corollary</u> If $\boldsymbol{\omega}$ contains enough information to establish a single objectively true answer, then BTS scores ranks respondents by probability they assign to truth.

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Theorem 3 The BTS score of a person with signal k equals the actual-to-prior frequency of k-signals:

$$u^r(t^r = k) = \log \omega_\kappa / p(\omega_\kappa) + D$$

Three distinct applications of truth serums in survey research

- To provide incentives for honest, careful responding
- To make more accurate population estimates of e.g., future voting behavior, or willingness-to-pay for goods and services
- Crowd wisdom: To improve on simple democratic averaging of opinions

The ‘intimidation’ method

The important property of the formula is that it rewards truthful answers. This means that truthful answers about your practices will increase the donation made on your behalf (and will also tend to increase the donations made on behalf of other respondents).

For the purpose of this survey it is not necessary for you to understand how the formula works, although the theoretical paper from Science, which includes a short abstract, is available here:

http://www.andrew.cmu.edu/user/lkjohn/Prelec04.pdf .

John, Loewenstein and Prelec, Psych. Science, 2012

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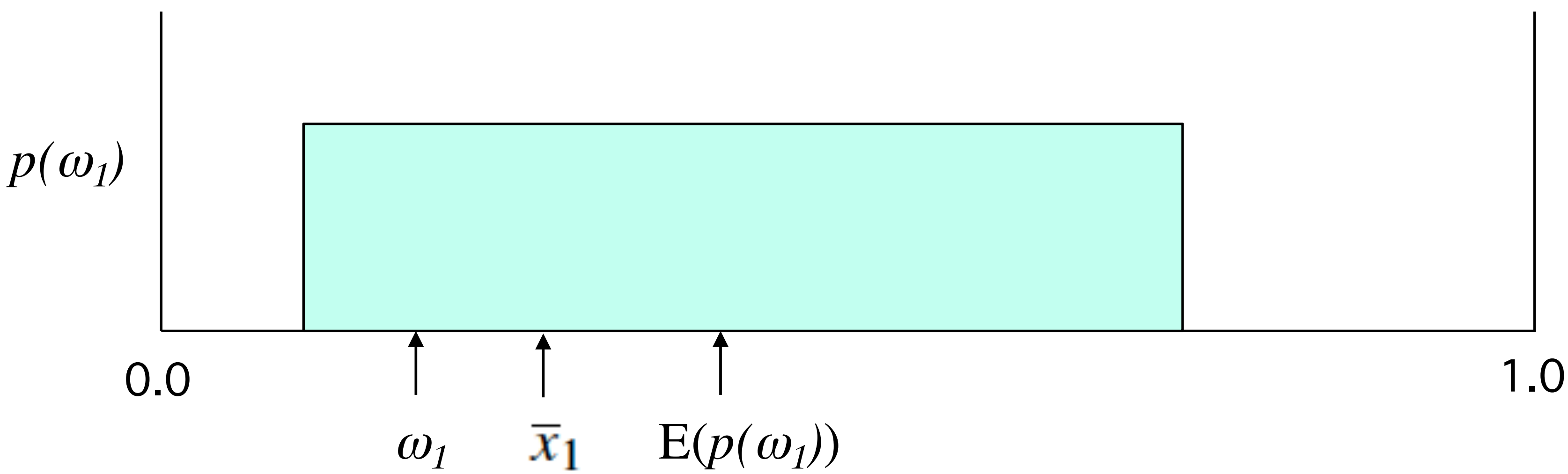
Rationale for weighting by BTS scores

A small fraction of 'noise respondents' are sampled according to the expectation of the prior distribution, $E(p(\omega_1,.., \omega_m))$. The remaining answers are sampled according to the true distribution, $\omega = (\omega_1,.., \omega_m)$.

Noise respondents don't consult their personal opinion, or are not competent to answer the question meaningfully.

The empirical frequencies will therefore be biased toward the prior mean.

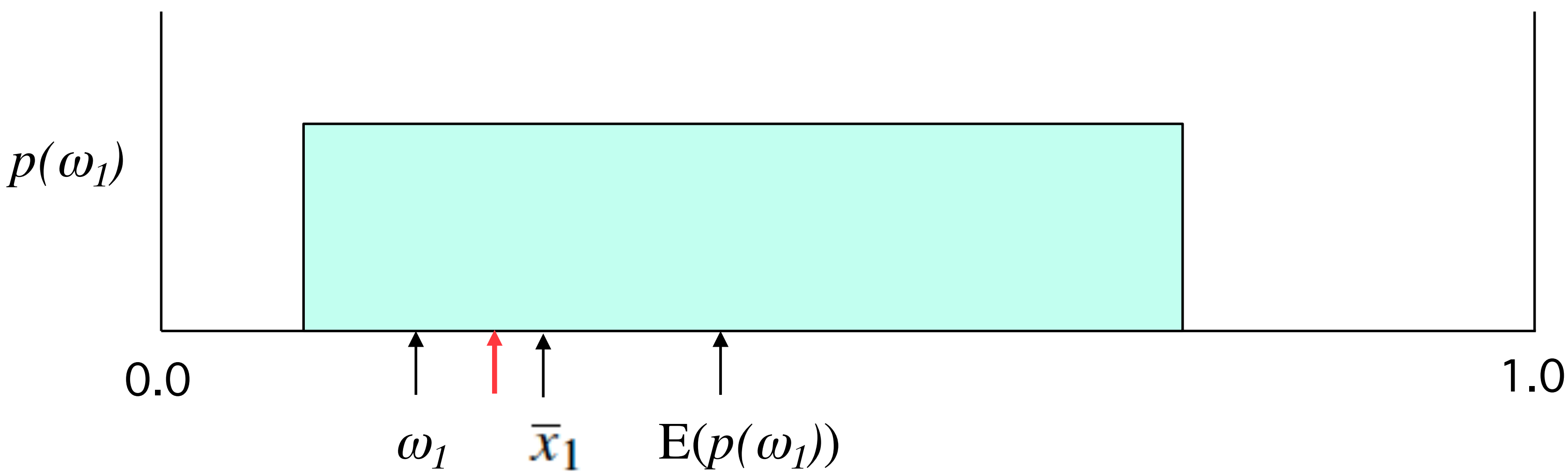


Rationale for weighting by BTS scores

Weighting by BTS scores moves the weighted average toward the true value.

$$\omega_1 < E(p(\omega_1)) \Longrightarrow u^r(t^r = 1) < u^s(t^s = 2)$$

However, aggressive weighting results in an overshoot.



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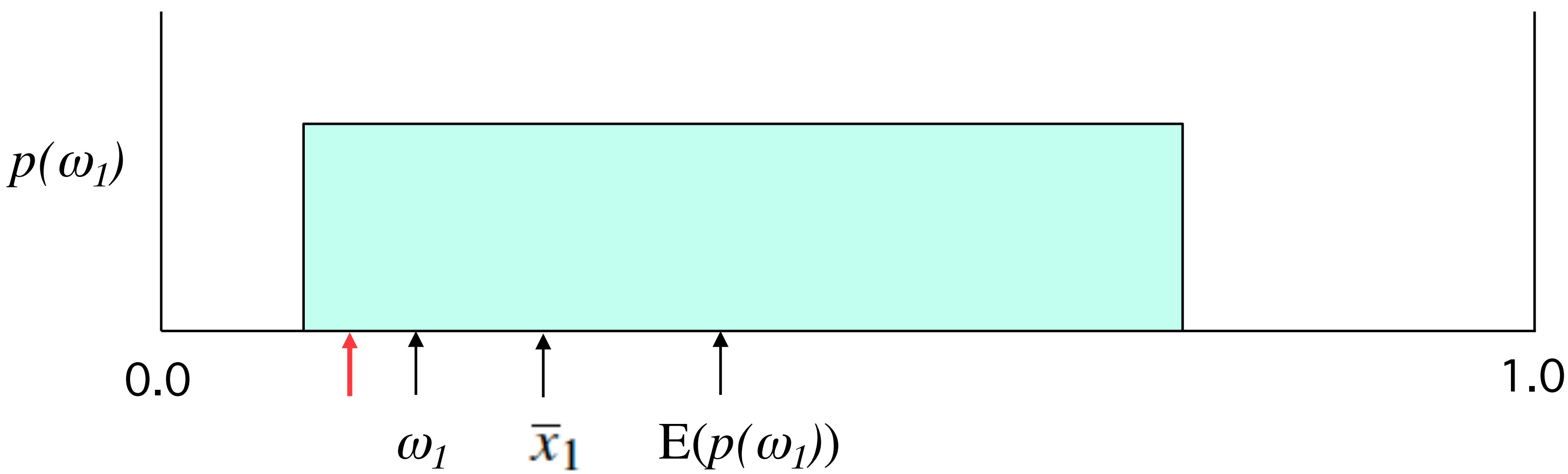


Study description

Understanding America Study at USC's Dornsife Center for Economic and Social Research: https://uasdata.usc.edu/index.php

All 50 states + DC

Four waves:

- Wave 1 N=4511, August 22 – September 11
- Wave 2 N=4259, September 14 – October 4
- Wave 3 N=5038, October 15 – November 5
- Wave 4 N=3217, after November 7

- 3156 respondents participated in all four waves

- Preregistered hypotheses; https://osf.io/a5fpb/

Olsson, Bruine de Bruin, Prelec and Galesic, 2019 (unpublished)

Information requested

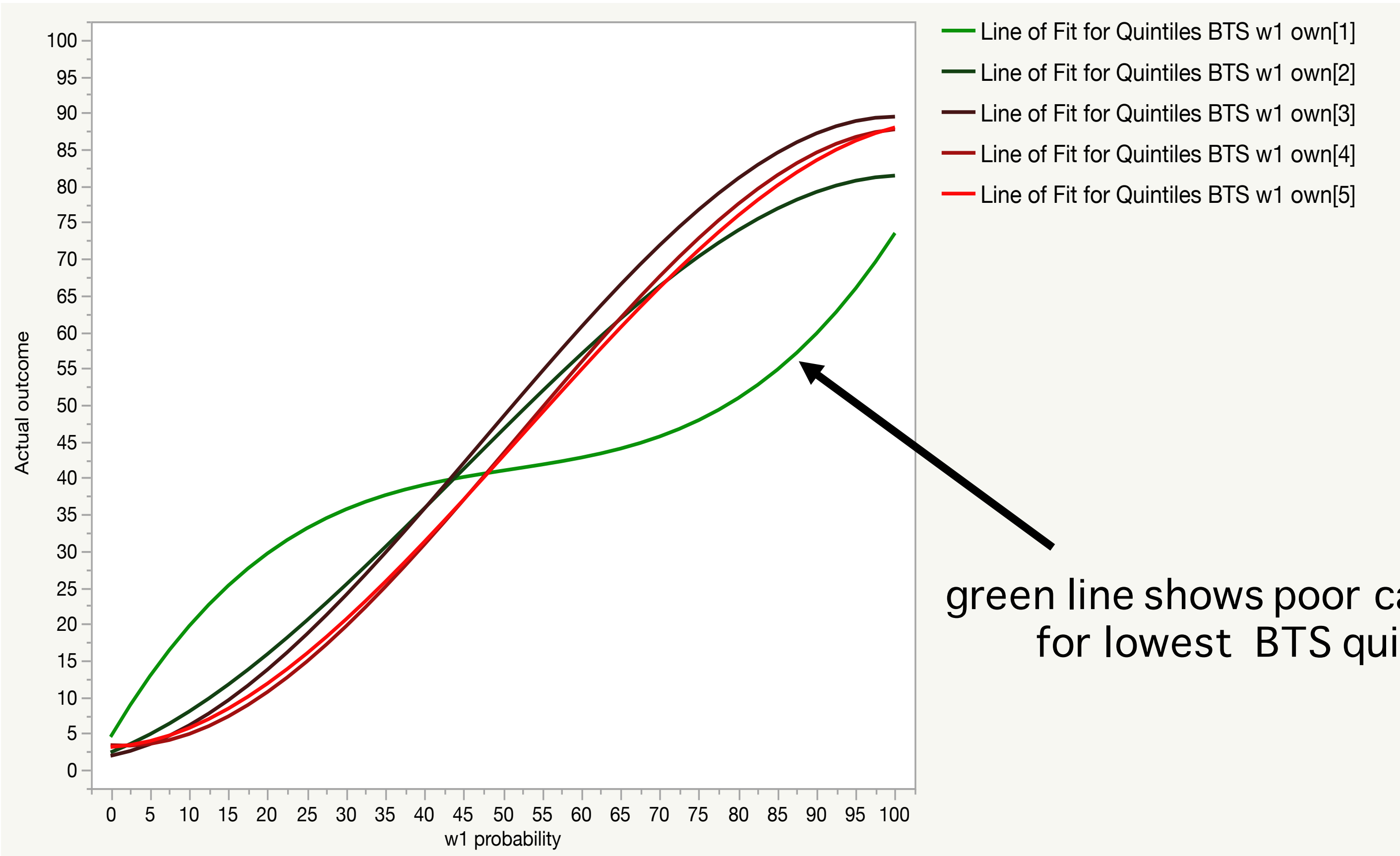
- Intention to vote expressed as probability (%)
- Voting for Democrat, Republican, Other (%)
- State level election predictions (%)
- Social circle predictions (%)

"... your friends, family, colleagues, and other acquaintances who live in your state, at at least 18 years of age, and who you have communicated with at least briefly within the last month, either face-to-face or otherwise..."

"Asking about social circles improves election predictions," Mirta Galesic et al., Nature Human Behavior, 2017

(improved predictions of the 2016 US Presidential elections, and the 2017 French Presidential elections).

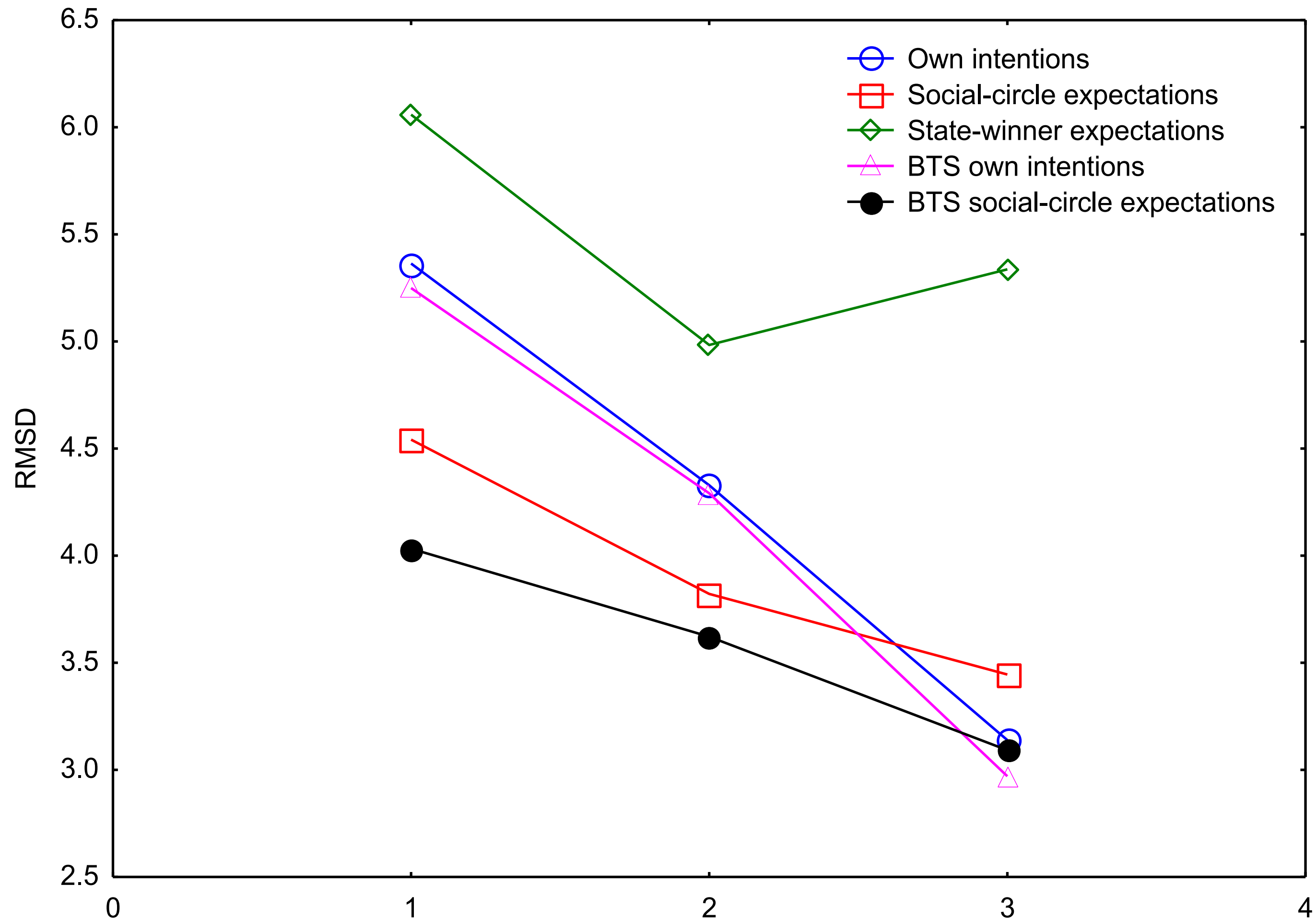
Identification of more credible answers with BTS scores
Calibration lines (intentions vs. actual self-reported behavior)



green line shows poor calibration
for lowest BTS quintile

Calibration curves, plotting action reported in post-election survey (including nonvoting) as function of stated probability for that action in Wave 1

Tracking error (RMS) by Wave, across all 3 voting options



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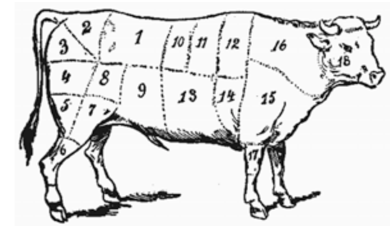
Wisdom of the crowd (WOC)



- New term, old idea; Condorcet, Galton.

  "The average competitor was probably as well fitted for making a just estimate of the dressed weight of the ox, as an average voter is of judging the merits of most political issues on which he votes, and the variety among the voters to judge justly was probably much the same in either case..

  According to the democratic principle of 'one vote one value' the middlemost [median] estimate expresses the *vox populi*, every other estimate being condemned as too low or too high by a majority of the voters…"

  Galton, "Vox Populi" Letter to Nature, 1907

- Today, a 'crowd wisdom' ideology:

  "Large groups of people are smarter than an elite few, no matter how brilliant — better at solving problems, fostering innovation, coming to wise decisions, even predicting the future."

  From The Wisdom of Crowds by James Surowiecki

‘Voting’ as unfiltered crowd wisdom

- Expert panels, juries, online ratings, Tripadvisor, Yelp, Google Local Guides
- Crucial limitations of unfiltered answers:

  No incentives for honesty or competence
  The average individual may hold wrong beliefs

- Examples (US Pollfish survey):

  What % of the US Federal budget is spent on foreign aid ?

  Average answer: 29 %
  Correct answer: <1 %

  What % of Syrian refugees are men of fighting age (18-59)?

  Average answer: 51 %
  Correct answer: 22 %

CAPITAL WHAT? ***Email: (for feedback & prizes)*** ______________________________

Here's a simple quiz that tests your knowledge of U.S. state capitals. For each statement, please answer whether you think it is **True (T)** or **False (F)** and then ***estimate what percentage of your workshop classmates will answer "True"***.

	Your Answer	% Answering "True"
Birmingham is the capital of Alabama.	_____	_______ %
Anchorage is the capital of Alaska.	_____	_______ %
Phoenix is the capital of Arizona.	_____	_______ %
Little Rock is the capital of Arkansas.	_____	_______ %
Los Angeles is the capital of California.	_____	_______ %
Denver is the capital of Colorado.	_____	_______ %
Bridgeport is the capital of Connecticut.	_____	_______ %
Wilmington is the capital of Delaware.	_____	_______ %
Jacksonville is the capital of Florida.	_____	_______ %
Atlanta is the capital of Georgia.	_____	_______ %
Honolulu is the capital of Hawaii.	_____	_______ %
Boise is the capital of Idaho.	_____	_______ %
Chicago is the capital of Illinois.	_____	_______ %
Indianapolis is the capital of Indiana.	_____	_______ %
Des Moines is the capital of Iowa.	_____	_______ %
Wichita is the capital of Kansas.	_____	_______ %
Lexington is the capital of Kentucky.	_____	_______ %
New Orleans is the capital of Louisiana.	_____	_______ %
Portland is the capital of Maine.	_____	_______ %
Baltimore is the capital of Maryland.	_____	_______ %
Boston is the capital of Massachusetts.	_____	_______ %
Detroit is the capital of Michigan.	_____	_______ %
Minneapolis is the capital of Minnesota.	_____	_______ %
Jackson is the capital of Mississippi.	_____	_______ %
Kansas City is the capital of Missouri.	_____	_______ %
Billings is the capital of Montana	_____	_______ %
Omaha is the capital of Nebraska.	_____	_______ %
Las Vegas is the capital of Nevada.	_____	_______ %
Manchester is the capital of New Hampshire.	_____	_______ %
Newark is the capital of New Jersey.	_____	_______ %
Albuquerque is the capital of New Mexico.	_____	_______ %
New York City is the capital of New York.	_____	_______ %
Charlotte is the capital of North Carolina.	_____	_______ %
Fargo is the capital of North Dakota.	_____	_______ %
Columbus is the capital of Ohio.	_____	_______ %
Oklahoma City is the capital of Oklahoma.	_____	_______ %
Portland is the capital of Oregon.	_____	_______ %
Philadelphia is the capital of Pennsylvania.	_____	_______ %
Providence is the capital of Rhode Island.	_____	_______ %
Columbia is the capital of South Carolina.	_____	_______ %
Sioux Falls is the capital of South Dakota.	_____	_______ %
Memphis is the capital of Tennessee.	_____	_______ %
Houston is the capital of Texas.	_____	_______ %
Salt Lake City is the capital of Utah.	_____	_______ %
Burlington is the capital of Vermont.	_____	_______ %
Virginia Beach is the capital of Virginia.	_____	_______ %
Seattle is the capital of Washington.	_____	_______ %
Charleston is the capital of West Virginia.	_____	_______ %
Milwaukee is the capital of Wisconsin.	_____	_______ %
Cheyenne is the capital of Wyoming.	_____	_______ %

*Prelec, D., Seung, H. S., & McCoy, J. Nature, 2017, 541(7638), 532-535

Diversity of problems

Largest city is not the capital:

Philadelphia — Pennsylvania
Los Angeles — California
Chicago — Illinois
New York — New York

Largest city is the capital:

Columbia — South Carolina
Atlanta — Georgia
Charleston — West Virginia
Des Moines — Iowa

Diversity of problems

Largest city is not the capital:

Philadelphia — Pennsylvania	Hard
Los Angeles — California	Easy
Chicago — Illinois	Hard
New York — New York	Easy

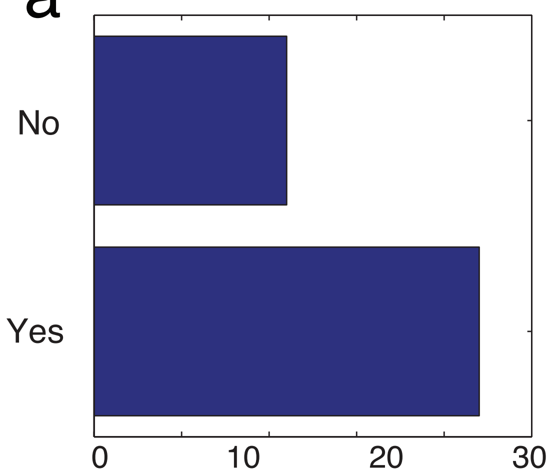
Largest city is the capital:

Columbia — South Carolina	Hard
Atlanta — Georgia	Easy
Charleston — West Virginia	Hard
Des Moines — Iowa	Easy

A question that most people in the US get wrong

(P) Philadelphia is the capital of Pennsylvania __Yes __No

a



Personal Votes

Probability of Yes confidence
------------>

Prediction of % that will agree with your opinion
------------>

Both sides are equally confident

(P) Philadelphia is the capital of Pennsylvania __Yes __No

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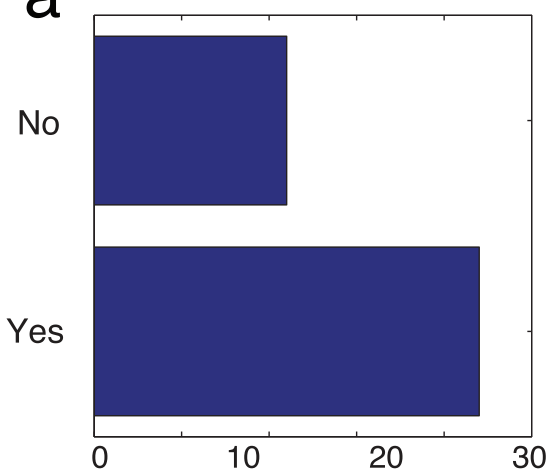

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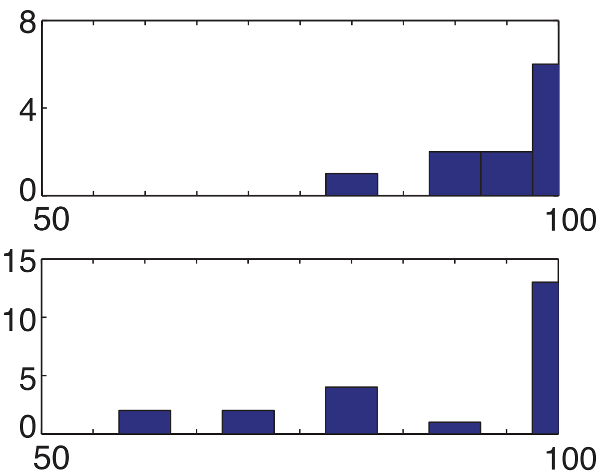


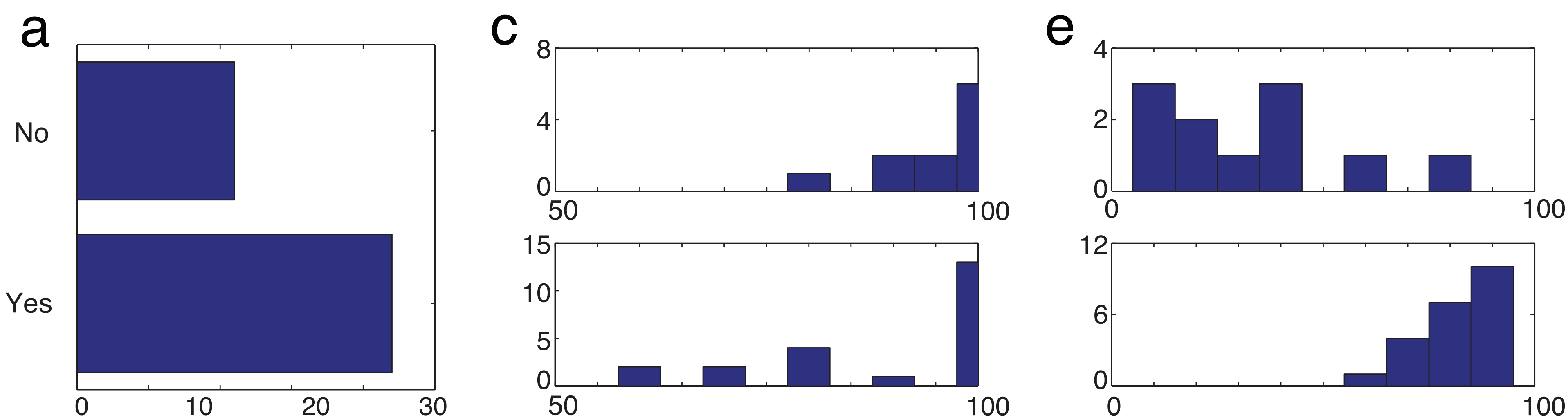
Personal
Votes

Probability of Yes
confidence
------------>

Prediction of
% that will agree
with your opinion
------------>

However, No voters expect to be the minority
Hence, there are more No votes than expected !

(P) Philadelphia is the capital of Pennsylvania __Yes __No



Personal
Votes

Probability of Yes
confidence
------------>

Prediction of
% that will agree
with your opinion
------------>

The correct answer is the answer that is more popular than the group predicts

Philadelphia is the capital of Pennsylvania __Yes ✓No

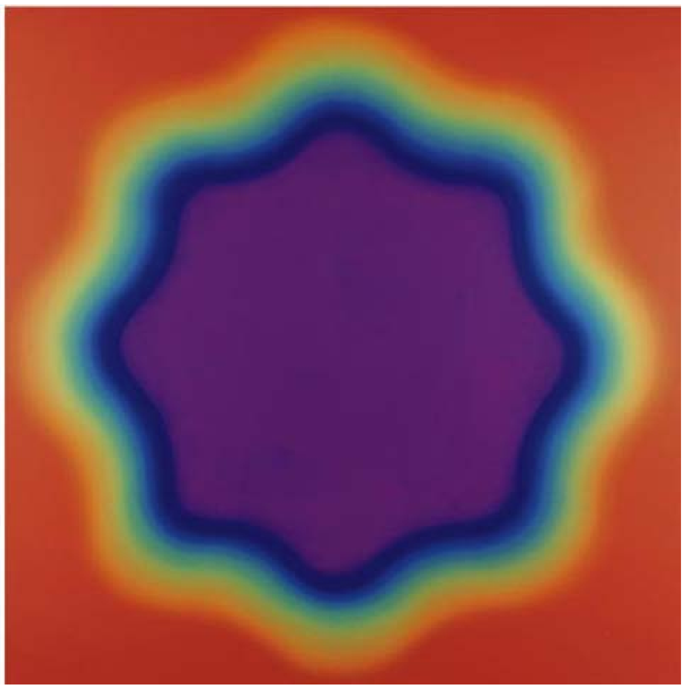
	Yes	No
Actual vote frequency	67%	33%

Columbia is the capital of South Carolina ✓Yes __No

	Yes	No
Actual vote frequency	64%	36%

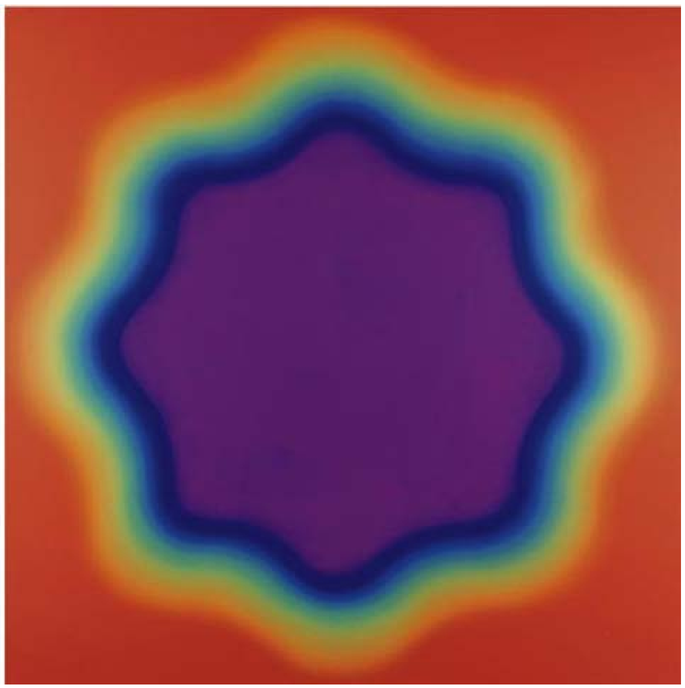
*Prelec, D., Seung, H. S., & McCoy, J. Nature, 2017, 541(7638), 532-535

Illustration 2
What is the value of a modern artwork?

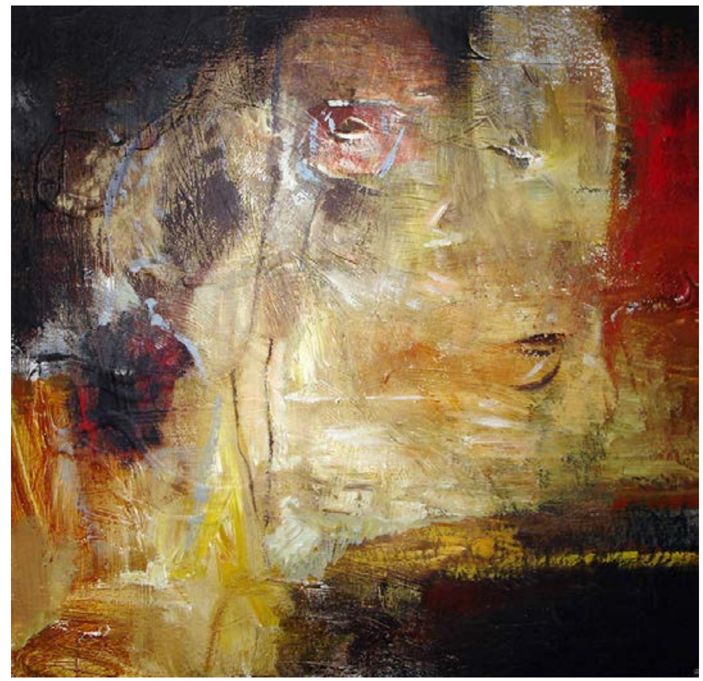


Prelec, Seung and McCoy, Nature, 2017

What is the value of a modern artwork?



$ 96,000



$ 85

Prelec, Seung and McCoy, Nature, 2017

What is the value of a modern artwork?

Prelec, Seung and McCoy, Nature, 2017

What is the value of a modern artwork?

$ 17,400,000

$ 89

Prelec, Seung and McCoy, Nature, 2017

What is the value of a modern artwork?

Prelec, Seung and McCoy, Nature, 2017

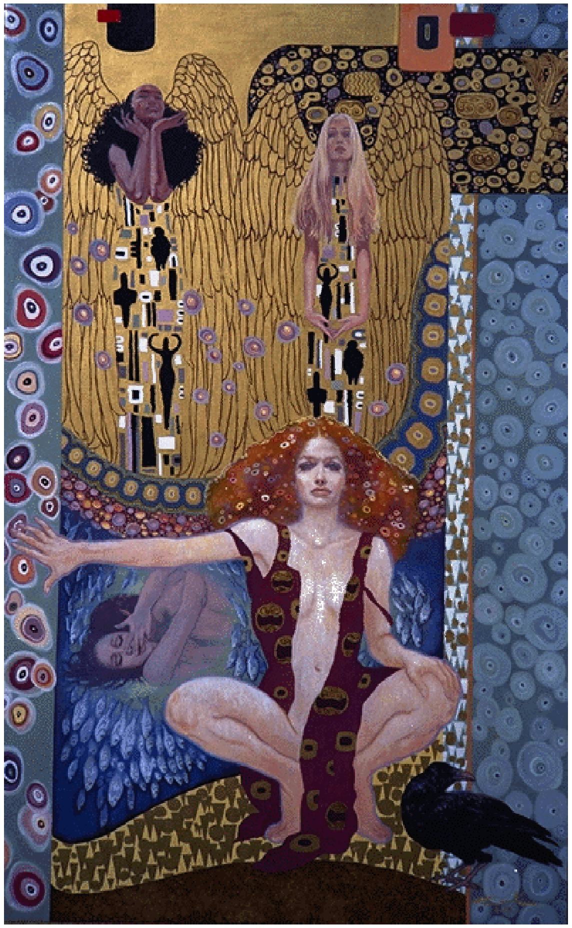
What is the value of a modern artwork?

$ 1,810,276

$ 4,408,000

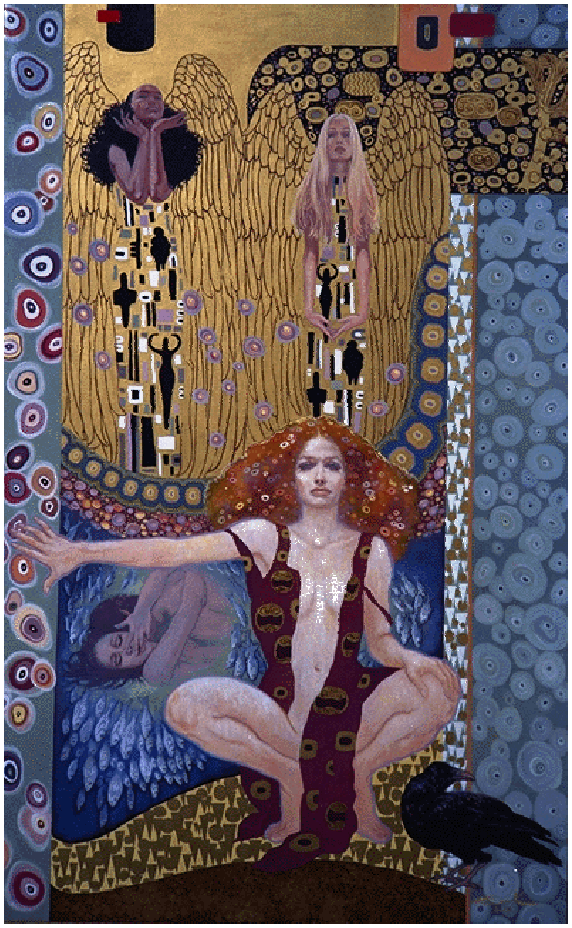
Prelec, Seung and McCoy, Nature, 2017

What is the value of a modern artwork?



Prelec, Seung and McCoy, Nature, 2017

What is the value of a modern artwork?

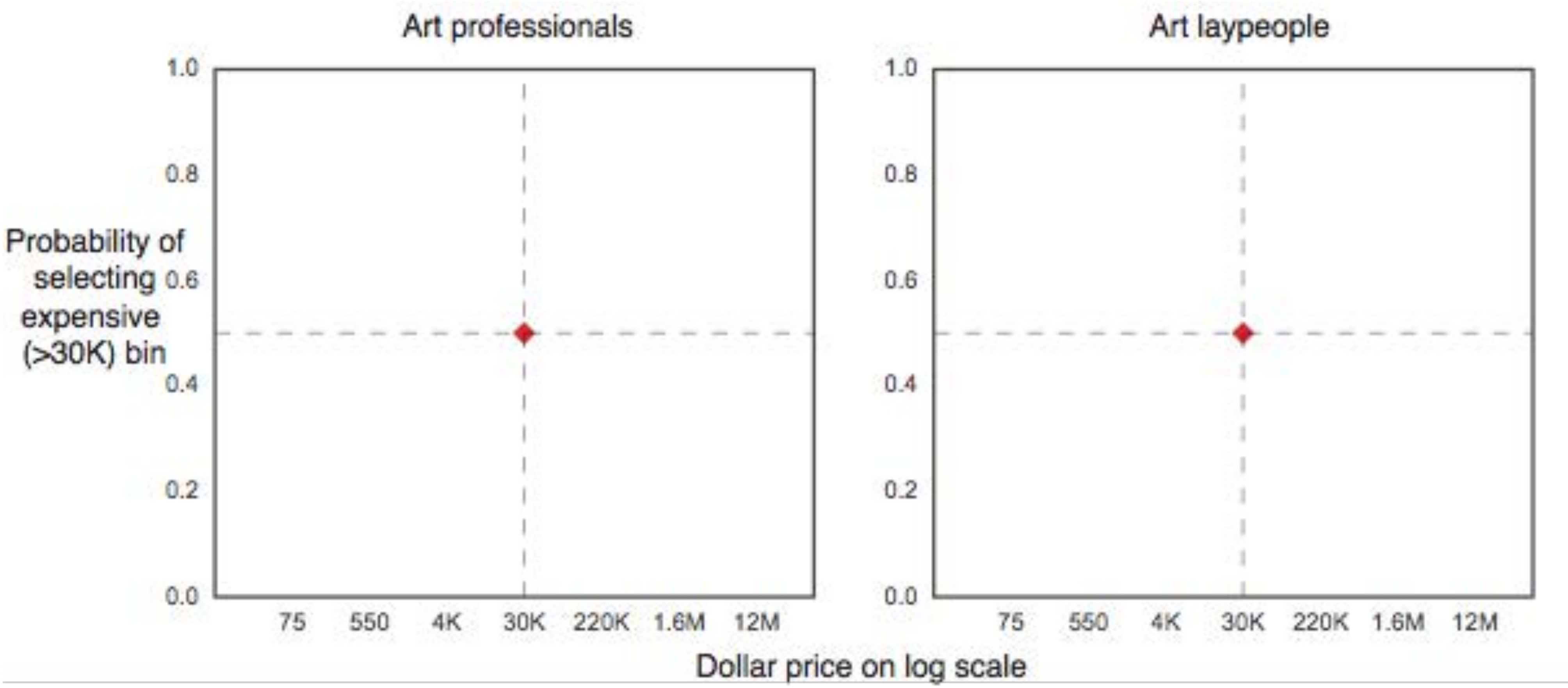


$4,200

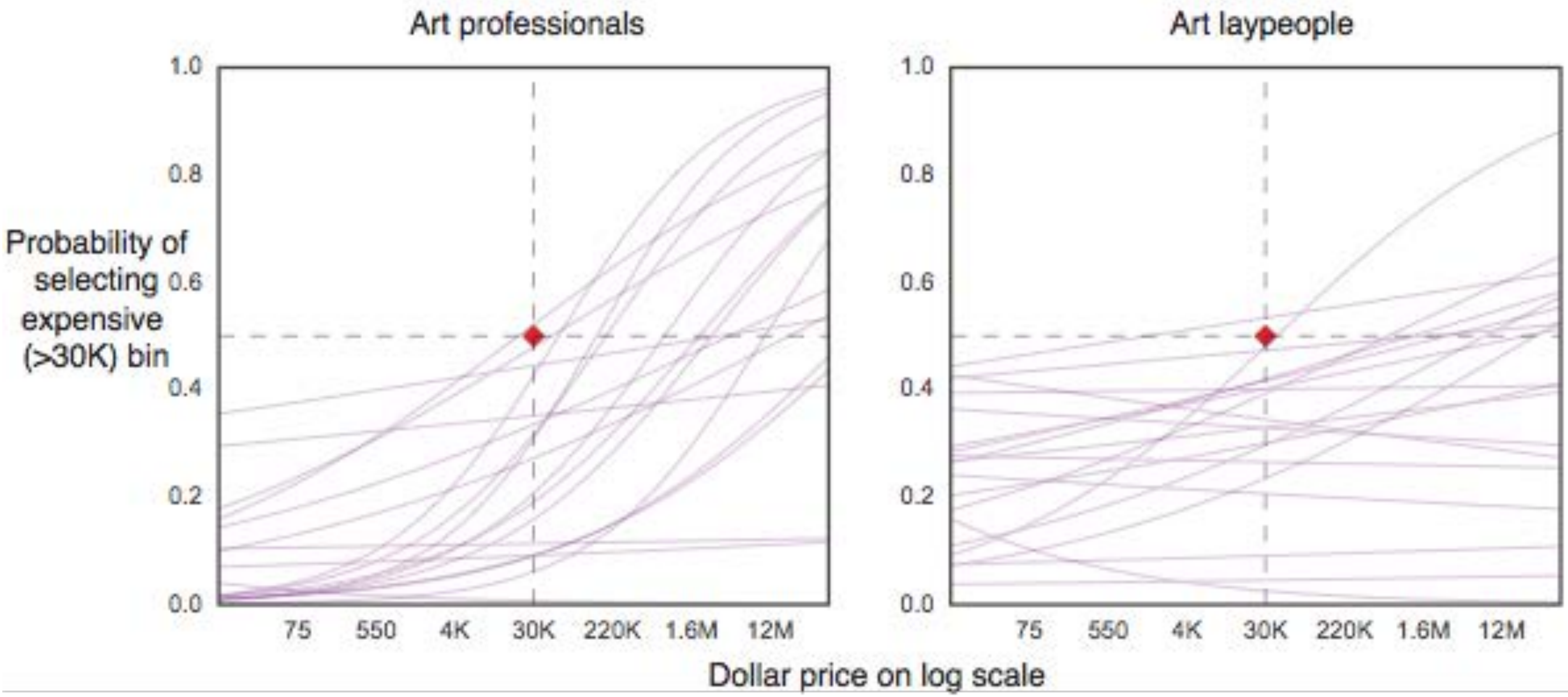
$2,618,925

Prelec, Seung and McCoy, Nature, 2017

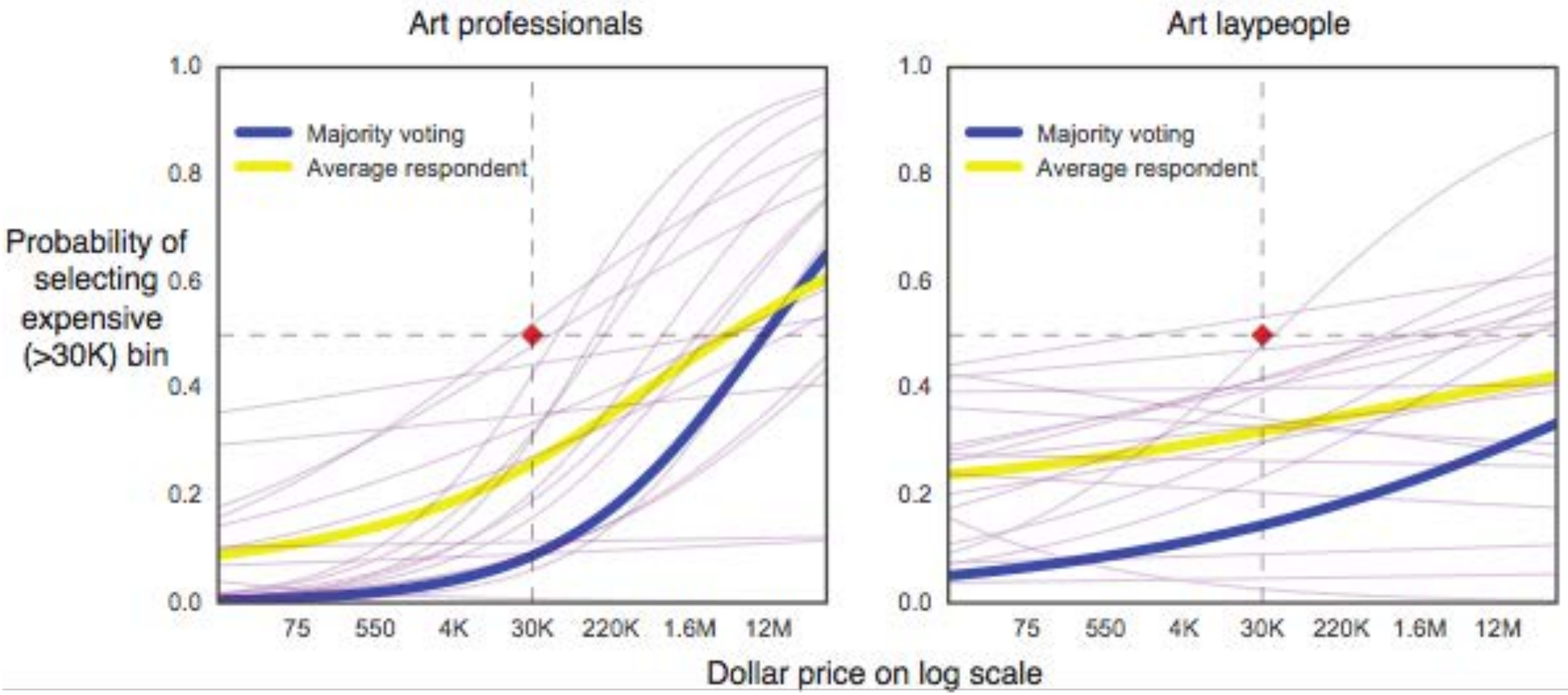
Data from art studies



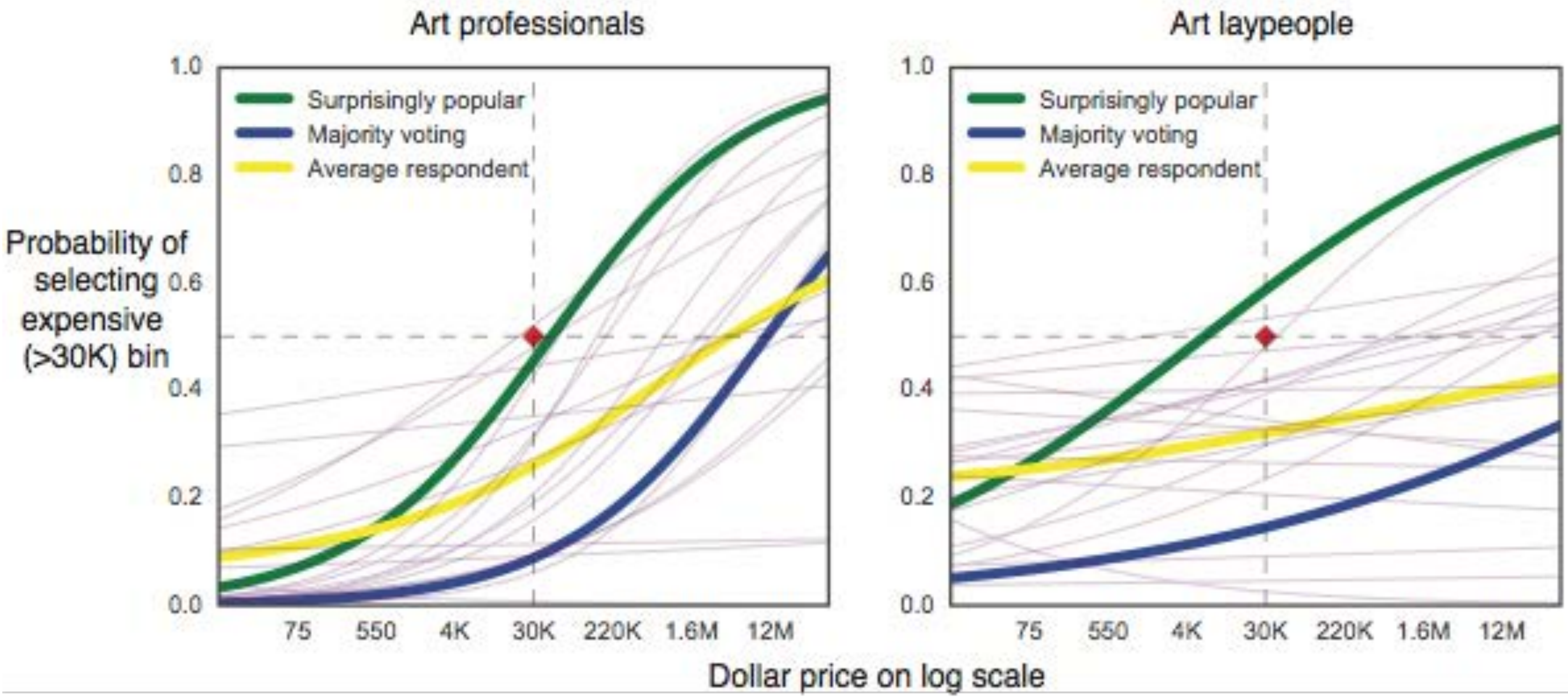
Many individuals show poor discrimination & calibration



Majority vote amplifies individual 'bias' for low prices



The surprisingly popular answer removes the crowd bias



Thank you to other collaborators

MIT

Christopher Long
Danica Mijovic-Prelec
Alex Huang
Daniele Suh

Wharton

John McCoy

Draper Labs

John Irvine
Sarah Miller
Cliff Forlines
S. R. Prakash

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Institute of Economics Zagreb

Sonja Radas

Northwestern University

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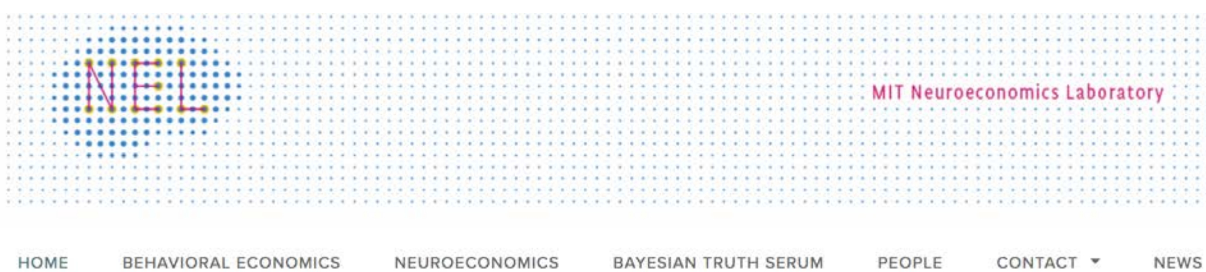
Caltech

Jaksa Cvitanic



nel.mit.edu/

An example of a 'survey of the field '
~ 2,000 philosophers on 30 disputed theses in philosophy

Aesthetic value: objective or subjective?

Option	Predicted votes	Actual votes
Subjective		34.5%
Objective		41.0%
Other		24.5%

Mind: physicalism or non-physicalism?

Option	Predicted votes	Actual votes
Physicalism		56.5%
Non-physicalism		27.1%
Other		16.4%

*David Bourget and David Chalmers "What philosophers believe"
Philosophical Studies, 2014, 170 (3):465-500.

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Other	15.2%	24.5%

Odds ratio on Truth = 2.56
for Objectivists vs.
Subjectivists

Mind: physicalism or non-physicalism?

Option	Predicted votes	Actual votes
Physicalism	64.2%	56.5%
Non-physicalism	23.9%	27.1%
Other	11.9%	16.4%

Odds ratio on Truth = 1.29
for Non-physicalists
vs. Physicalists

*David Bourget and David Chalmers “What philosophers believe”
Philosophical Studies, 2014, 170 (3):465-500.

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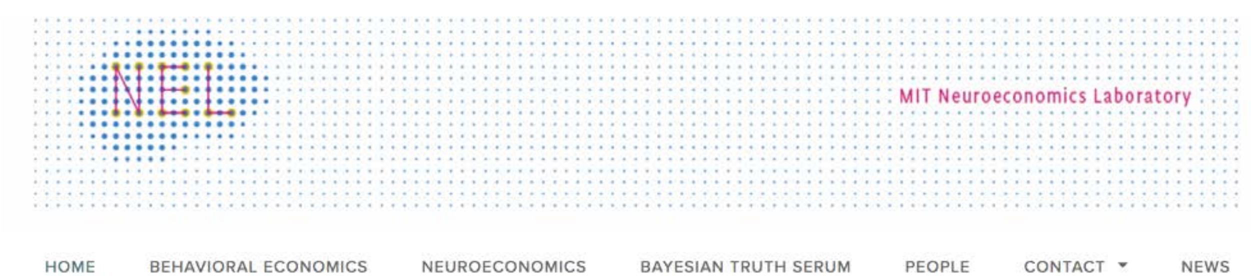

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