# Equitable Persuasion in Incentivized Deliberation

## An impossible tradeoff?

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**deliberation** (noun) / di-ˌli-bə-ˈrā-shən

extended conversation among two or more people to come to a better understanding of some issue

(Beauchamp, 2020)

# Deliberation Online

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## Talk:Coronavirus disease 2019

### Discretionary sanctions on the use of preprints [ edit ]

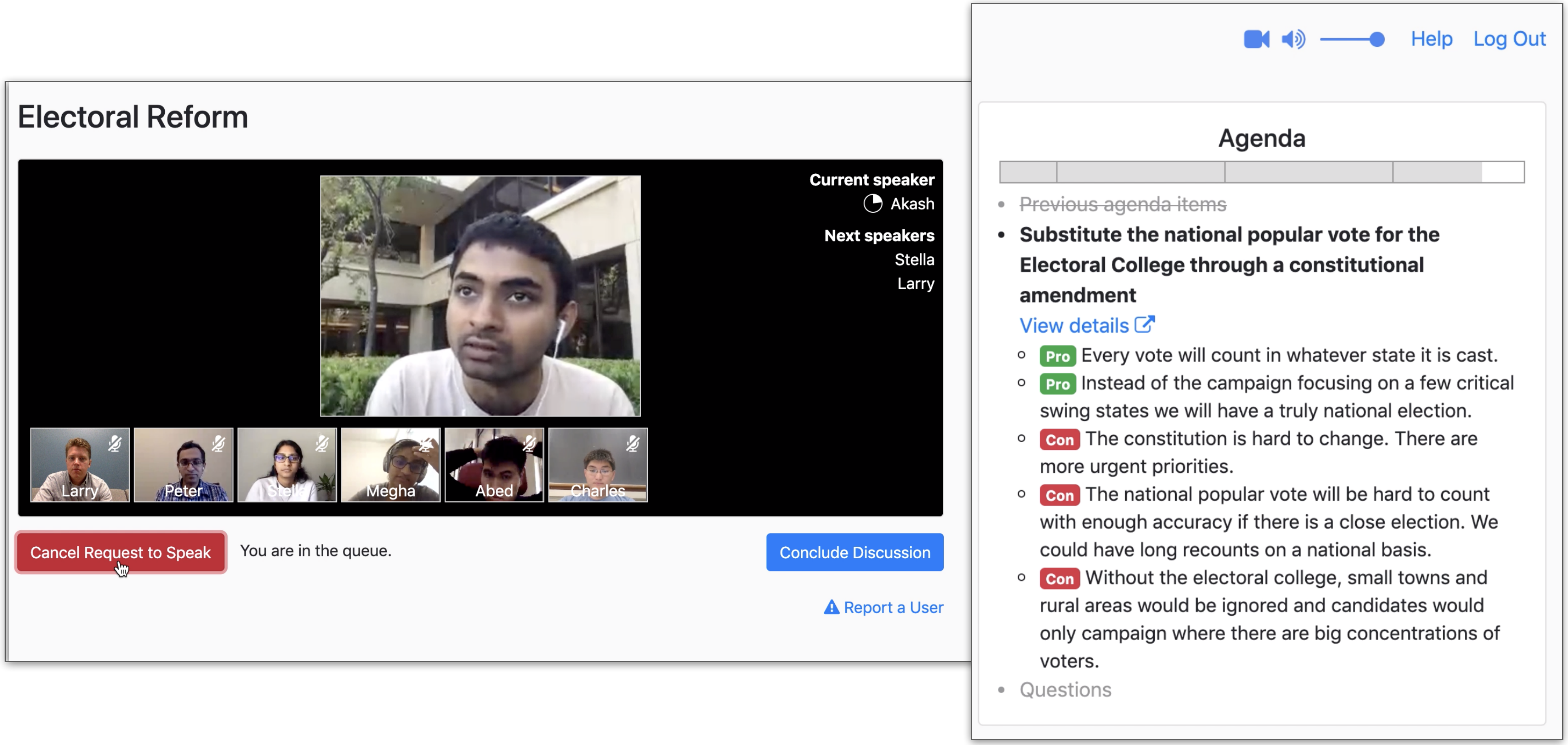
I am appalled by the use of preprints to support content in this article. The website MedRxiv displays a clear disclaimer:

> Caution: Preprints are preliminary reports of work that have not been certified by peer review. They should not be relied on to guide clinical practice or health-related behavior and should not be reported in news media as established information.

I'm giving notice that tomorrow I intend to place a general sanction on the page to prohibit the use of preprints as sources in this article. This ought to be simply a matter of respecting our guidelines on WP:Reliable sources and WP:MEDRS, but it now seems necessary. I'm naturally willing to hear reasons why discretionary sanctions should not be necessary to enforce our basic sourcing guidelines. --RexxS (talk) 21:51, 11 May 2020 (UTC)

- **Support**, obviously. Boing! said Zebedee (talk) 22:08, 11 May 2020 (UTC)
- **Support**. We should not be using preprints EVER. MartinezMD (talk) 22:53, 11 May 2020 (UTC)
- This is a WP:point, against WP:5P5, WP:5P4, WP:5P3 and potentially WP:5P2. This is an article about a current event. Our main source in the contested chapter (IFR) say I quote loosely : "Since yesterday [...] one research group has provided a correction of their estimate of the Infection-Fatality Ratio (IFR)". Since yesterday... Is that the pinnacle of peer review we strive for ? We have to deal with research that change daily, there is no need to put the big administrator boots and add yet another banner on top of this page. Just to state the obvious that peer reviewed source would be preferable. Everyone here agree. Iluvalar (talk) 22:56, 11 May 2020 (UTC)
- **Oppose**. What we're up against are bat shit crazy conspiracy theories. That's the reality of the situation. We're also at risk of irrelevancy due to the 24-hour news cycle and social media.

# Deliberation Online




## Stanford Online Deliberation Platform

cdd.stanford.edu

# Deliberation Online

## Project roadmap? #254

Open aatkinson opened this issue on Jan 29, 2019 · 8 comments

**aatkinson** commented on Jan 29, 2019 ···

Hi,

The goals are ambitious, the codebase is in flux, and future directions are outlined in your paper https://arxiv.org/pdf/1812.08729.pdf, but it's unclear what the roadmap is for this project.

What release cadence can we expect, and what features are prioritized?

I'm also curious if this has a substantial backing by Facebook / the PyTorch team.

Thanks

👍 3

**ahhegazy** commented on Jan 31, 2019 • edited Contributor ···

Great questions :)

As for the road map, we are mainly working on 5 main areas (roughly sorted according to priority):

- Enriching and Improving our stack with more tasks, models and techniques
- Improve Usability and have better integration with ipython notebooks
- Performance optimizations for training and inference
- Explore model interpretability techniques

For the release cadence, we will do our best to have a release every month. And yeah as we mentioned in our release blog post here this project powers some of the core projects in production at Facebook and it indeed has a substantial backing from different teams in Facebook AI.

**ibulu** commented on Feb 1, 2019 ···

> Thanks for the answer **@ahhegazy**! Does integration with fairseq fall under the 1st area?

I am curious about the fairest integration as well. Any plans on that?

**ahhegazy** commented on Feb 1, 2019 Contributor ···

Yes, we are working on integrating with translate: https://github.com/pytorch/translate/tree/master/pytorch_translate which is Fairseq models with production support

👍 3

**padipadou** commented on Feb 6, 2019 ···

Hello **@ahhegazy**, and thanks for sharing this amazing work, just a quick question, can we have an idea about timing regarding fairseq integration ? Thanks a lot !

👍 3

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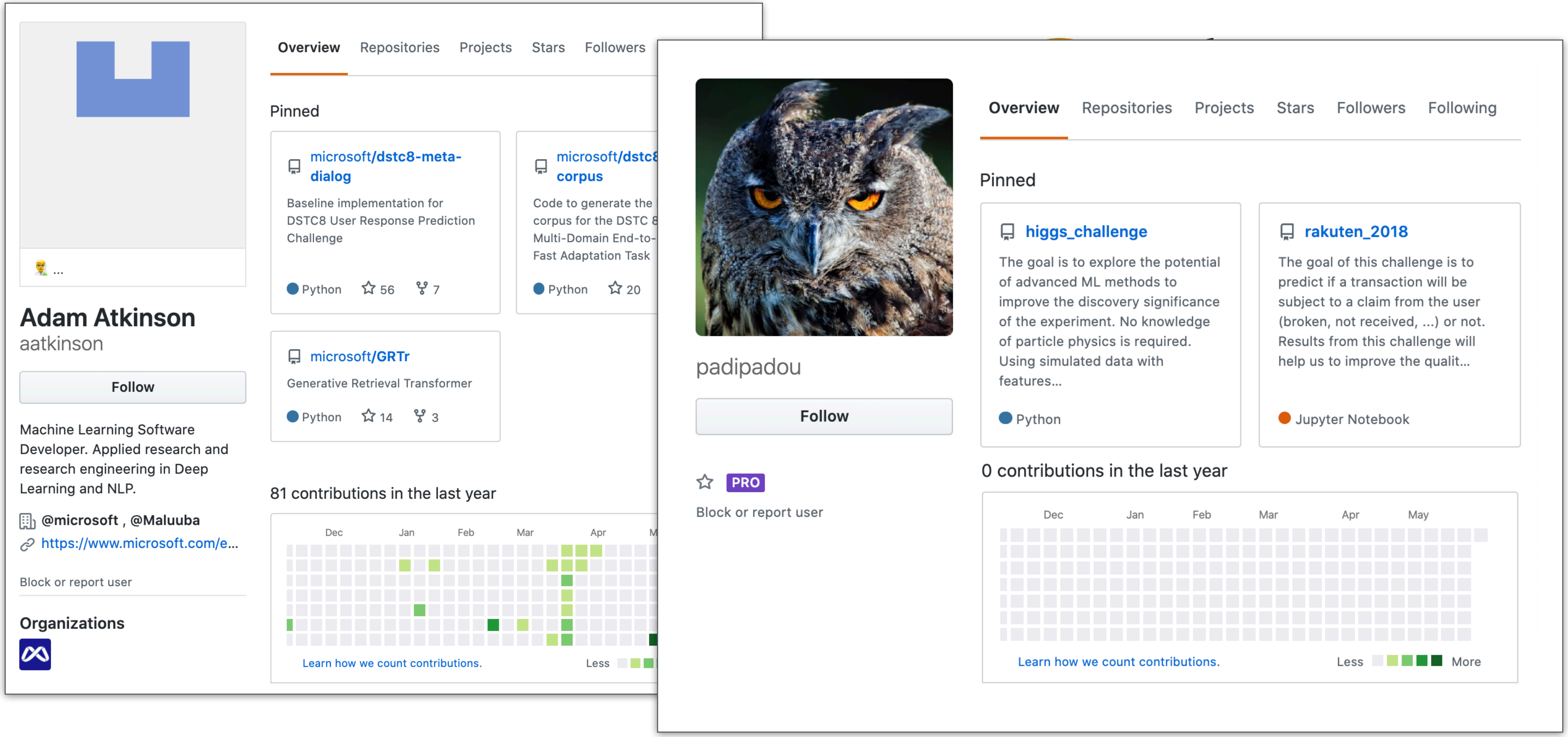
# Reputation Indicators

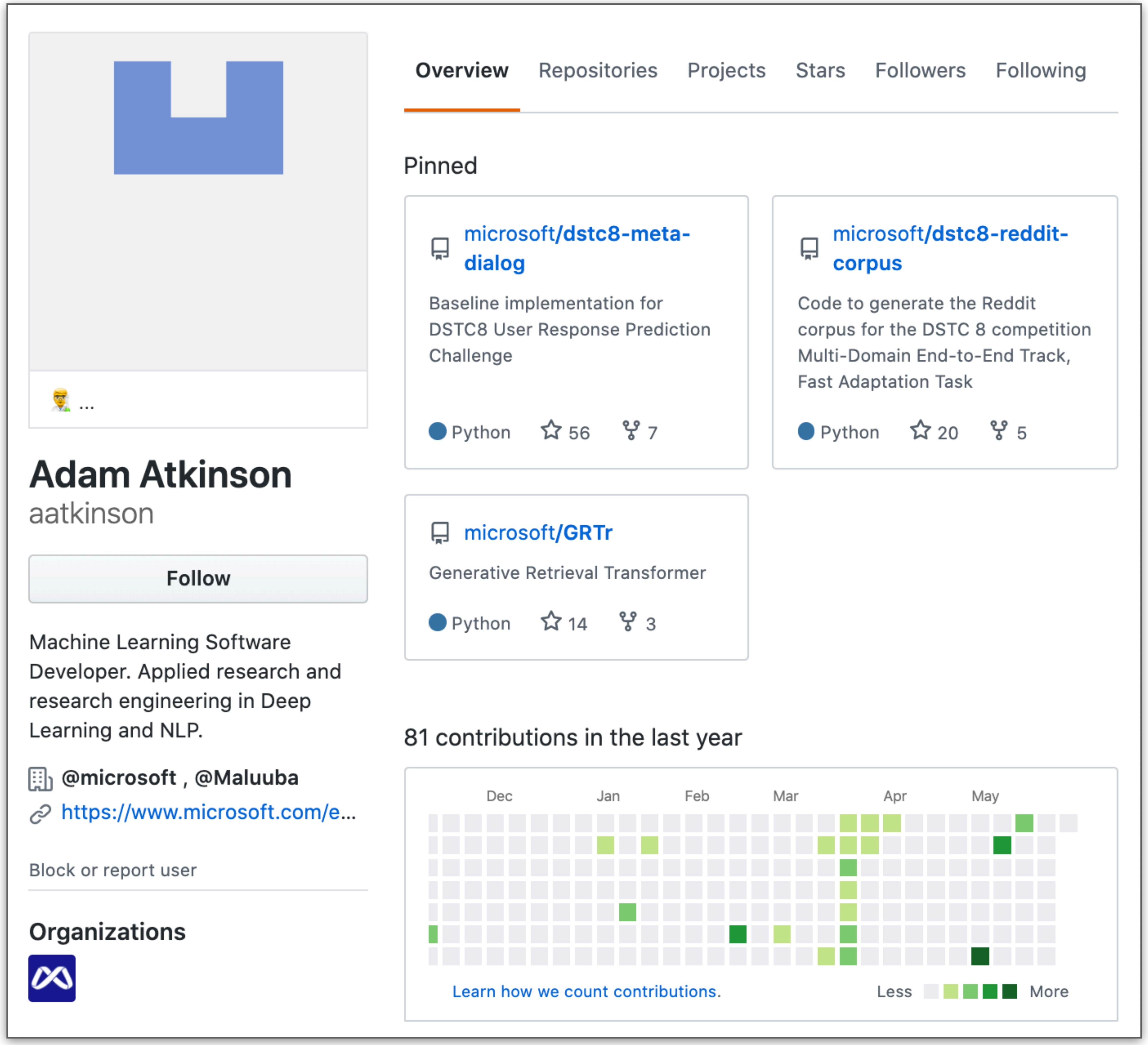



Used by project maintainers to prioritize issues and evaluate new contributors (Marlow et al, 2013)

# Reputation Indicators

+ Incentivize engagement

- Distort persuasive equity?



Q. Does reputation have persuasive power in deliberation online?

# Preview of Findings

Reputation is persuasive

+10 reputation units →
+26% persuasion rate

Patterns in effect heterogeneity consistent with **reference cues theory** (Bilancini & Boncinelli, 2018)

# Empirical Strategy

I. Identifying opinion-change
II. Disentangling non-reputation factors
III. Handling unobserved confounders
IV. Controlling for text

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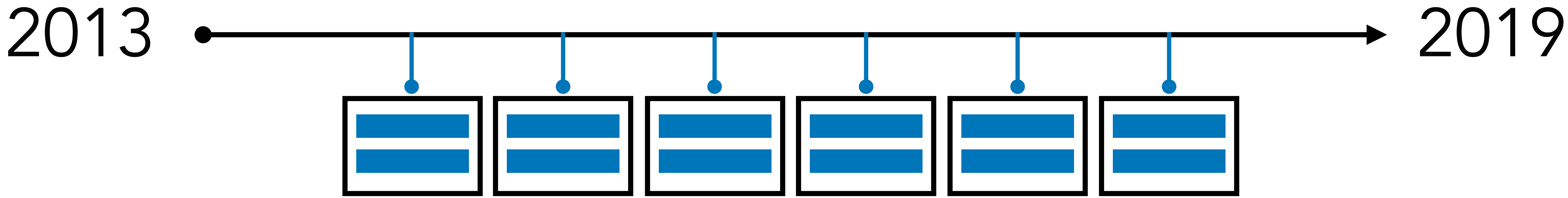
# I. Identifying Opinion-Change

**Persuasion: Empirical Evidence.**
DellaVigna & Gentzkow. *Annual Review of Economics*. 2010.

Typically **unobserved** — challenging to identify

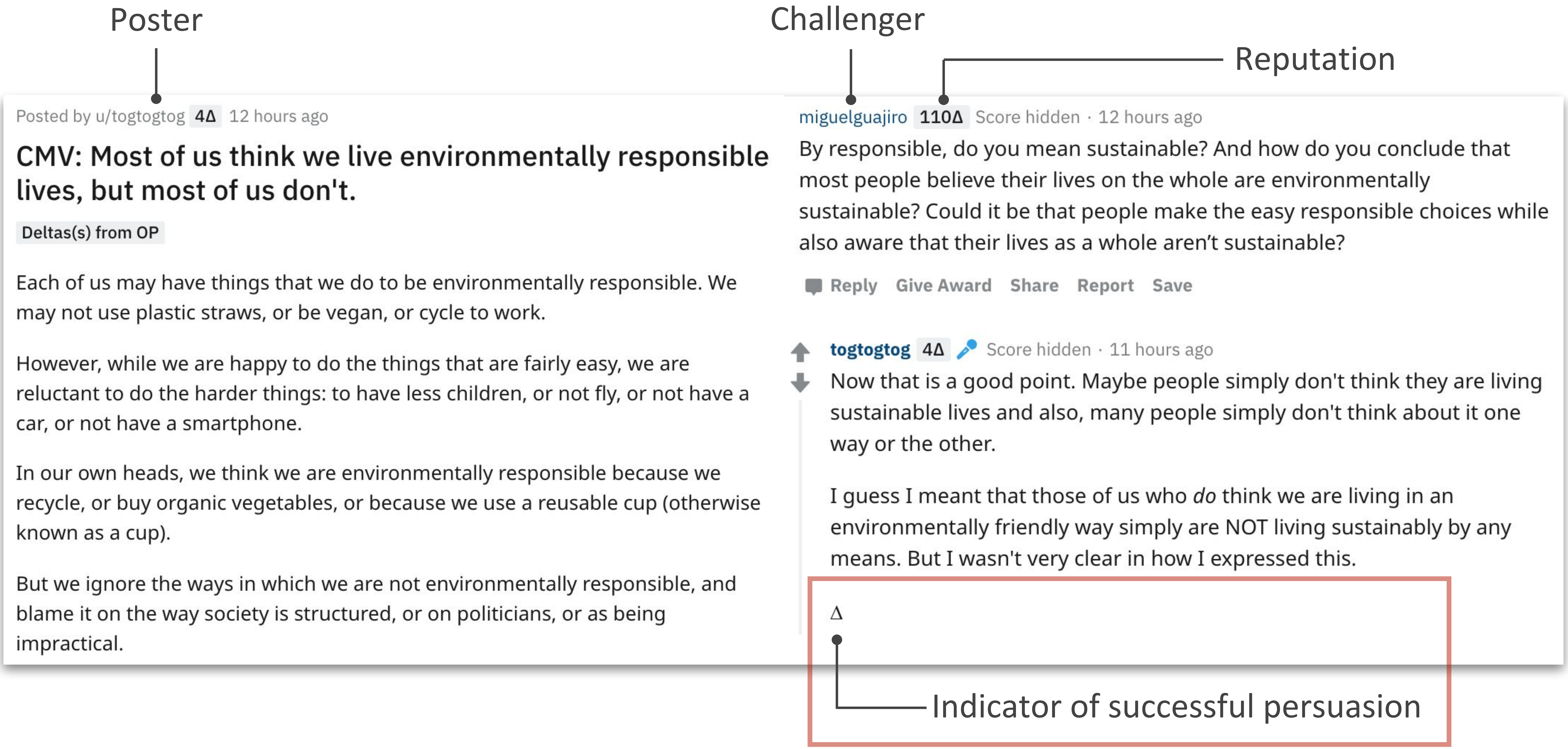
# I. Identifying Opinion-Change

**Our strategy:** Dataset of online deliberation from **ChangeMyView**



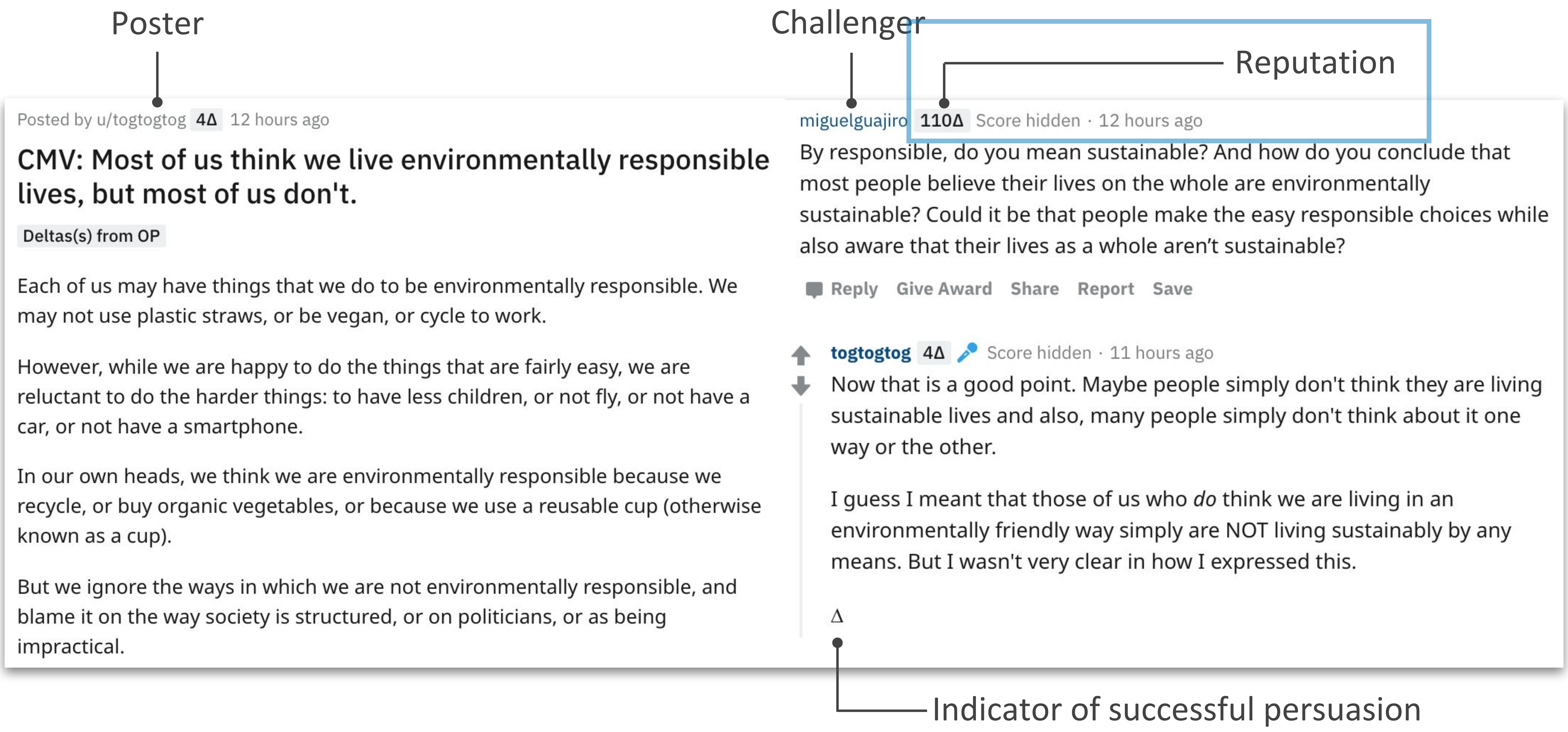

**>1 million** debates between **>800,000** members

**>20 moderators** enforce high-quality deliberation




**Explicit indicators** of successful persuasion

provided by opinion-holders (posters)




# **Prominent display** of reputation based on number of individuals persuaded previously

# Empirical Strategy

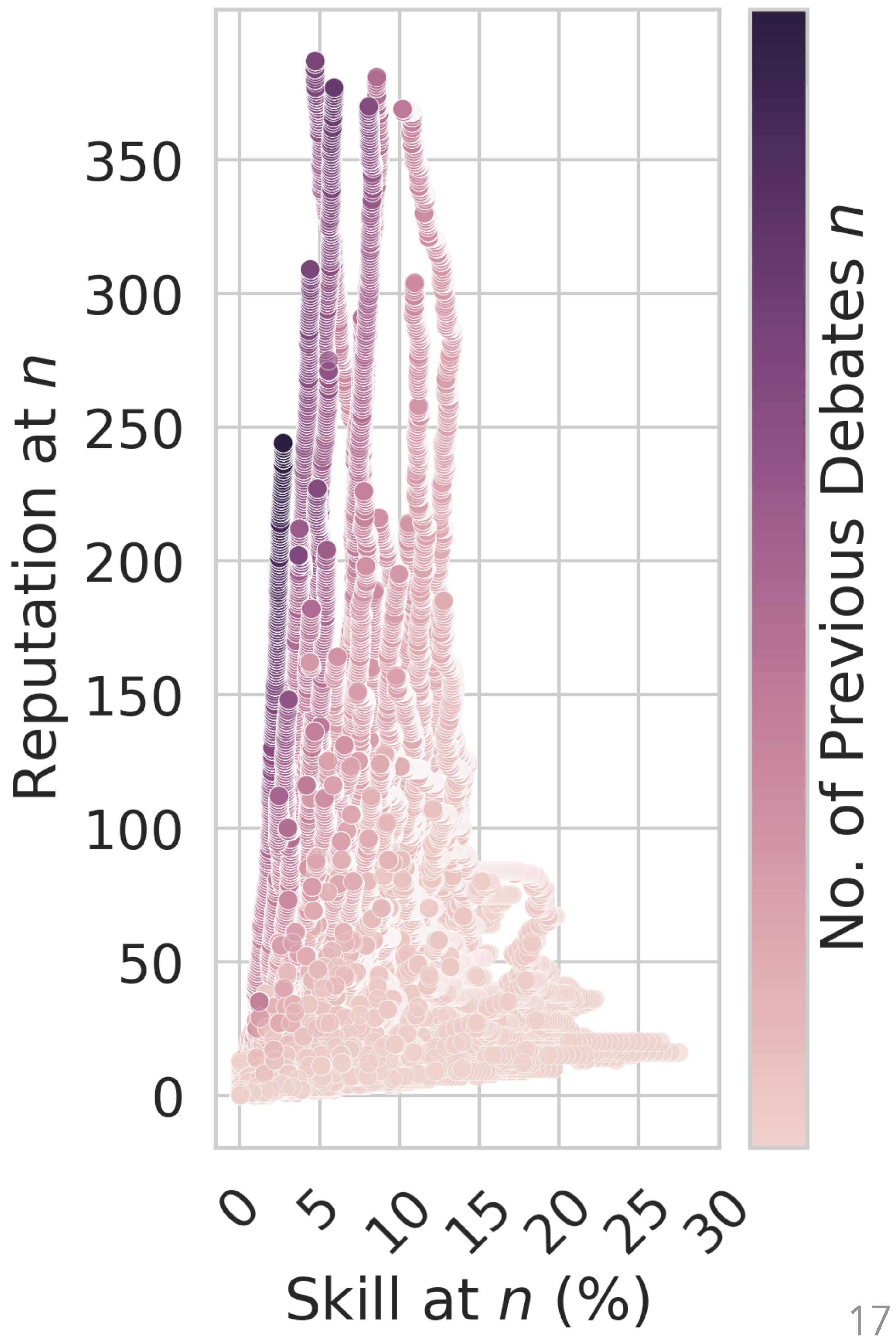
I. Identifying opinion-change
II. Disentangling non-reputation factors
III. Handling unobserved confounders
IV. Controlling for text

# II. Disentangling Non-Reputation Factors

Exploit **multiple debates per challenger**

$$\text{skill} = \frac{\text{no. posters persuaded previously}}{\text{no. previous debates}}$$

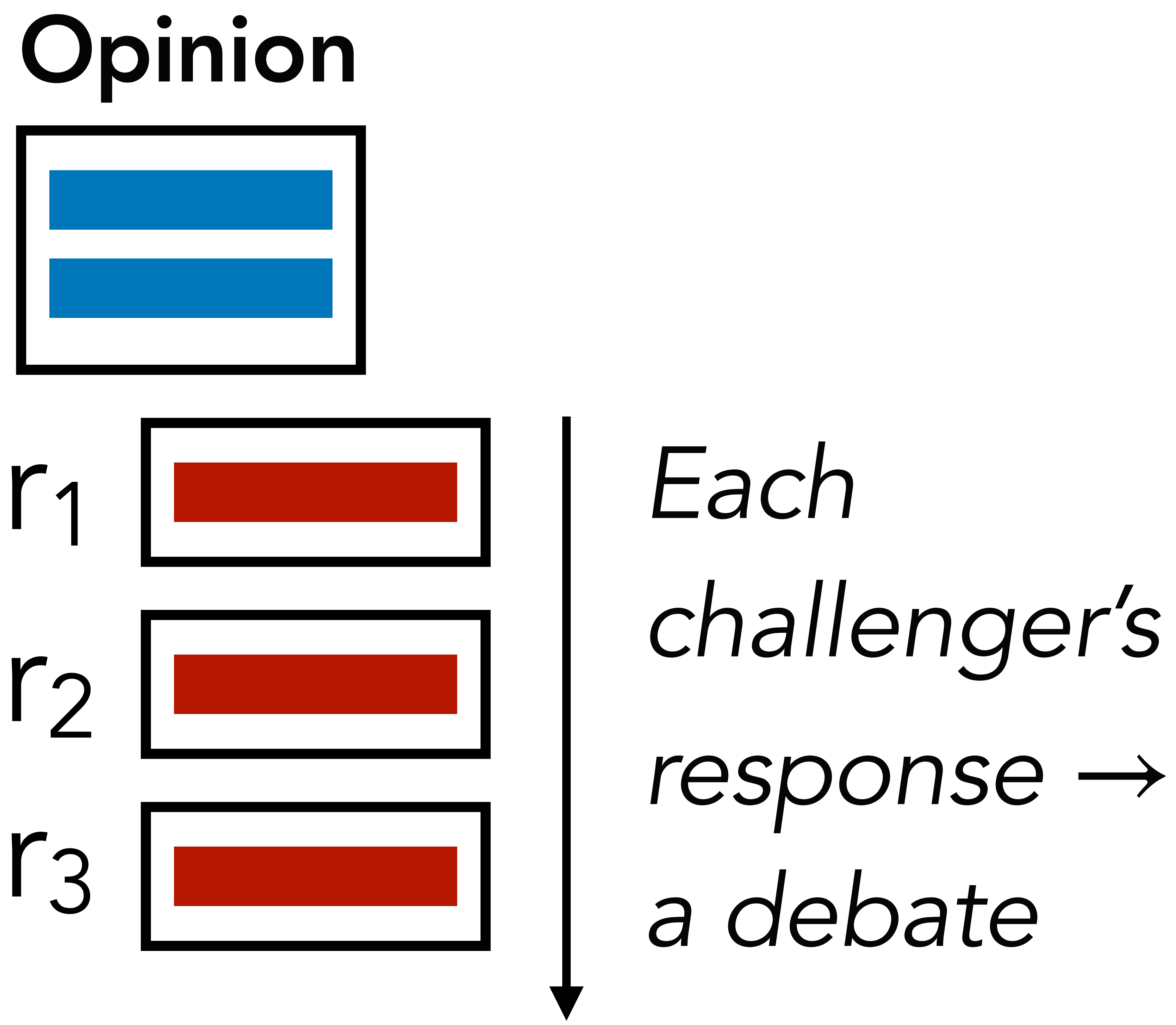
Controls for **time-invariant** challenger characteristics that affect persuasion



# II. Disentangling Non-Reputation Factors

Exploit **multiple responses per opinion** to control for opinion fixed-effects

Addresses confounding arising from **endogenous opinion selection**



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# III. Handling Unobserved Confounders

## Main concern

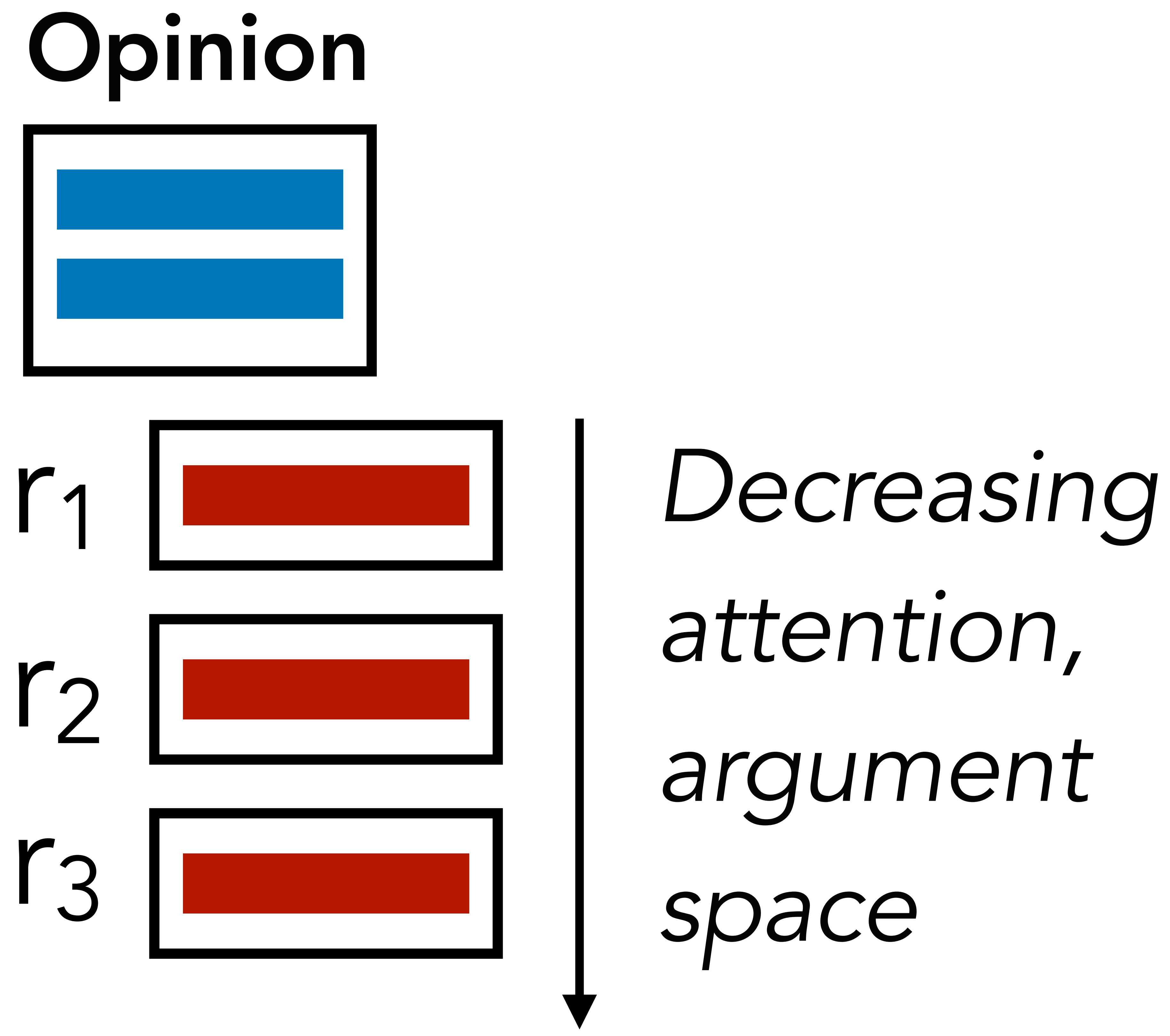
Time-varying challenger characteristics correlated with persuasion

Example: users improving their rhetorical ability with platform experience

# III. Handling Unobserved Confounders

**Instrument intuition**

- Higher (worse) position → lower persuasion probability
- Reputation ≈ no. of posters persuaded previously



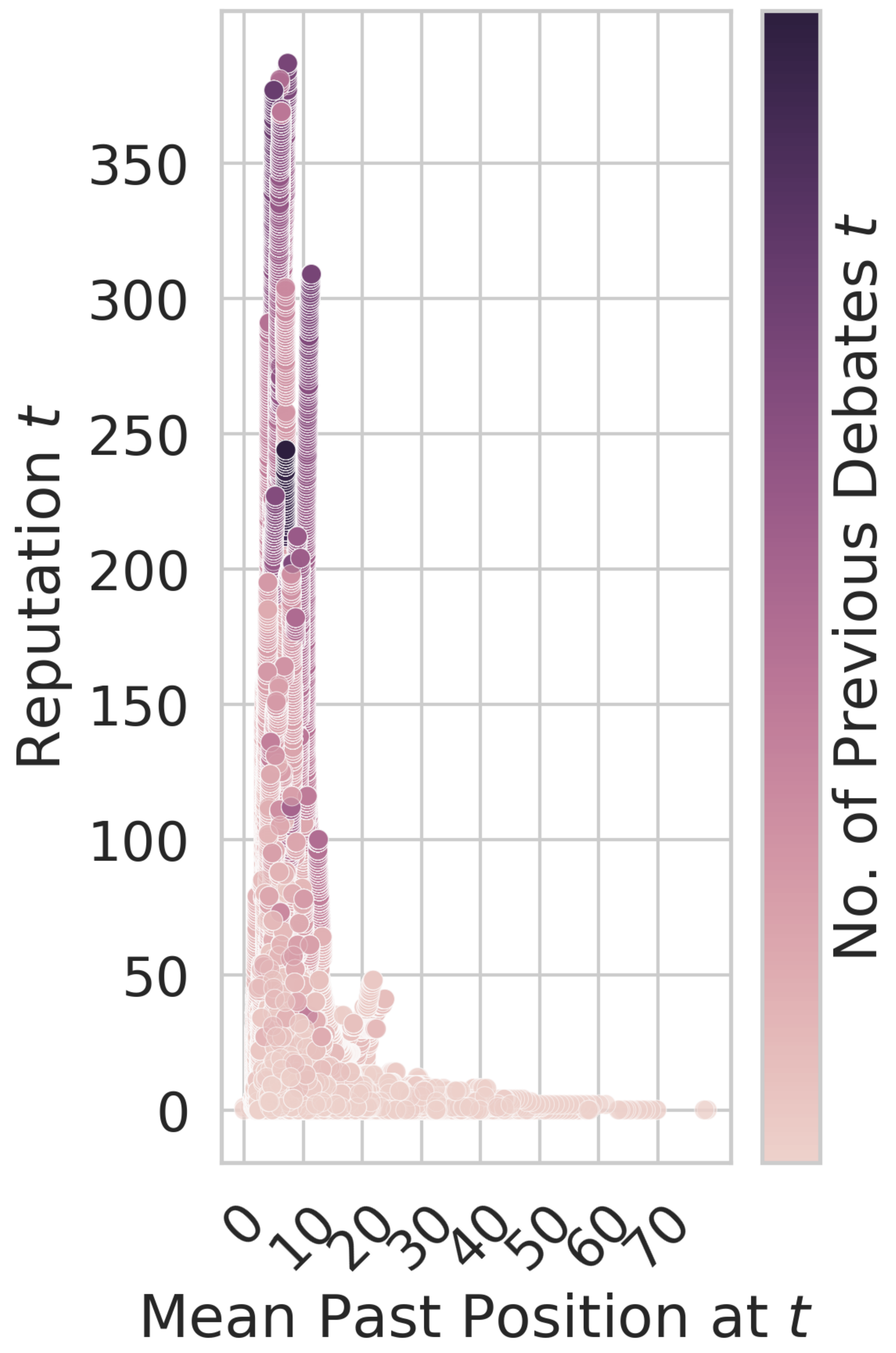
# III. Handling Unobserved Confounders

## Instrument definition

Mean past position of challenger before the present debate

First-stage F-statistic > 3000

Similar to the Fox News channel position instrument (Martin & Yurukoglu, 2017)



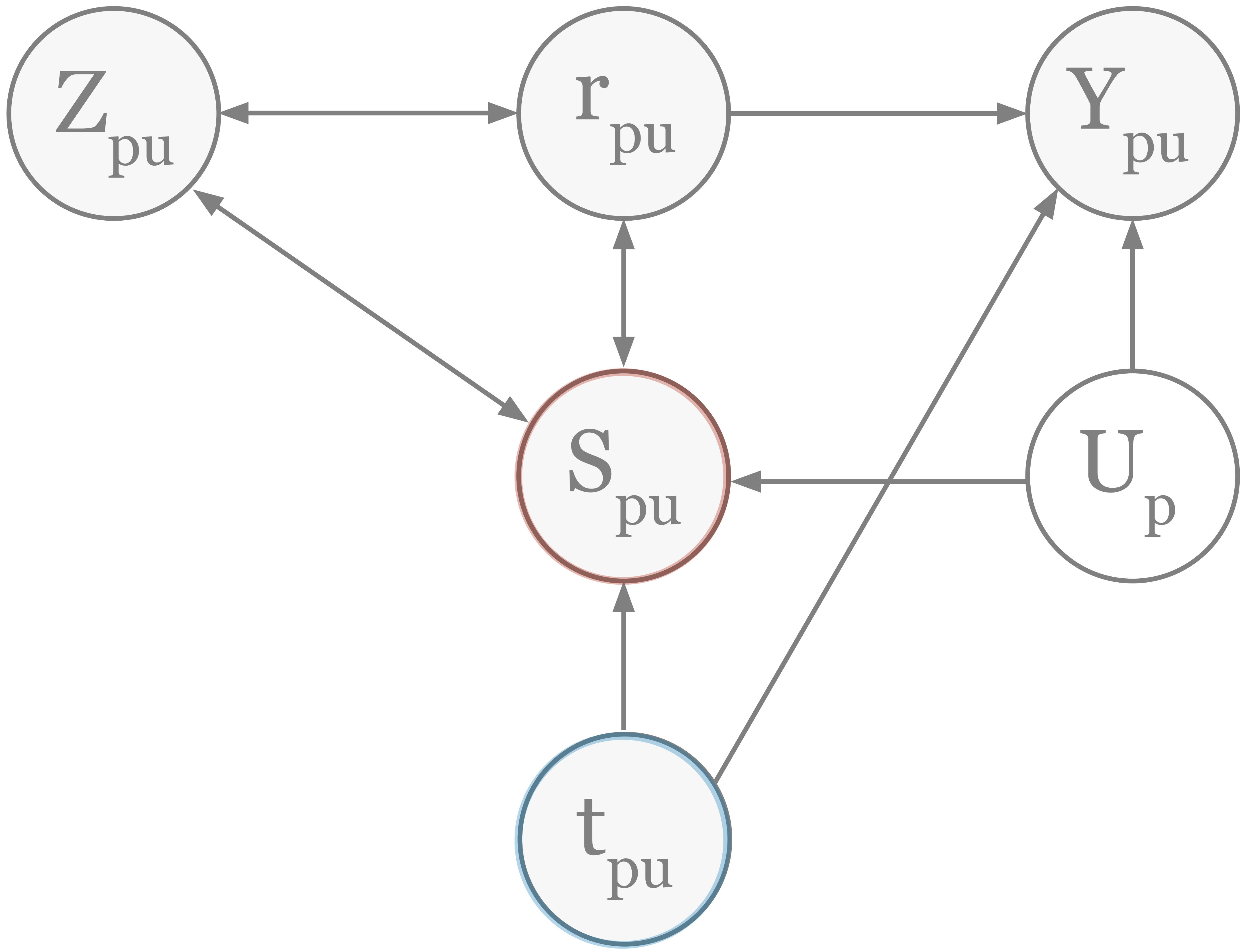
# III. Handling Unobserved Confounders

**Immediate concern**

Users selecting opinions to challenge based on their anticipated response position

↓

Must control for response position in the present debate




*(see paper for details)*

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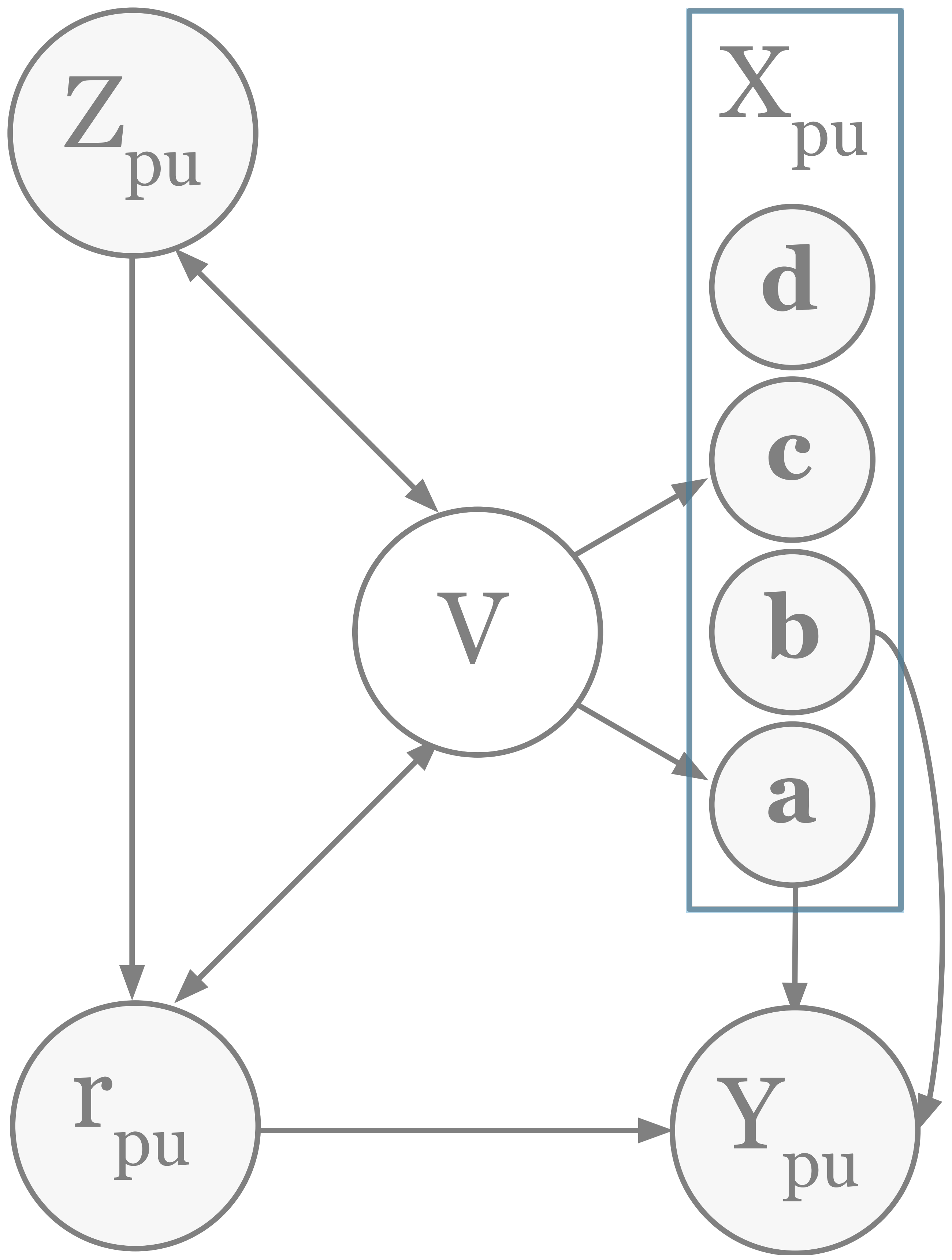
# IV. Controlling for Text

**Why control for text?**

Instrument confounders must affect both instrument **and** outcome

Are likely to affect the outcome through the response text

**NLP approaches:** No guarantees on retaining confounders or inference




*(see paper for details)*

# IV. Controlling for Text

**Our approach:** Partially-linear IV model, estimated via double machine-learning (Chernozhukov et. al., 2016)

$$Y_{pu} = \beta_1 r_{pu} + \beta_2 s_{pu} + \beta_3 t_{pu} + g(\tau_p, X_{pu}) + \epsilon_{pu} \qquad \mathbb{E}[\epsilon_{pu}|Z_{pu}, \tau_p, s_{pu}, t_{pu}, X_{pu}] = 0$$

$$Z_{pu} = \alpha_1 s_{pu} + \alpha_2 t_{pu} + h(\tau_p, X_{pu}) + \epsilon'_{pu} \qquad \mathbb{E}[\epsilon'_{pu}|\tau_p, s_{pu}, t_{pu}, X_{pu}] = 0$$

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$$\boxed{\begin{aligned} \mathbb{E}[\epsilon_{pu} | Z_{pu}, \tau_p, s_{pu}, t_{pu}, X_{pu}] &= 0 \\ \mathbb{E}[\epsilon'_{pu} | \tau_p, s_{pu}, t_{pu}, X_{pu}] &= 0 \end{aligned}}$$

Standard instrumental variable assumptions

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$$Y_{pu} = \beta_1 r_{pu} + \beta_2 s_{pu} + \beta_3 t_{pu} + g(\tau_p, X_{pu}) + \boxed{\epsilon_{pu}} \qquad \mathbb{E}[\epsilon_{pu} | Z_{pu}, \tau_p, s_{pu}, t_{pu}, X_{pu}] = 0$$

$$Z_{pu} = \alpha_1 s_{pu} + \alpha_2 t_{pu} + h(\tau_p, X_{pu}) + \boxed{\epsilon'_{pu}} \qquad \mathbb{E}[\epsilon'_{pu} | \tau_p, s_{pu}, t_{pu}, X_{pu}] = 0$$

**No distributional assumptions** placed on error terms (eg. Gaussian, Gumbel)

# IV. Controlling for Text

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**Non-parametric nuisance functions of the opinion fixed-effects $\tau_p$ and text $X_{pu}$**

Estimated via machine-learning

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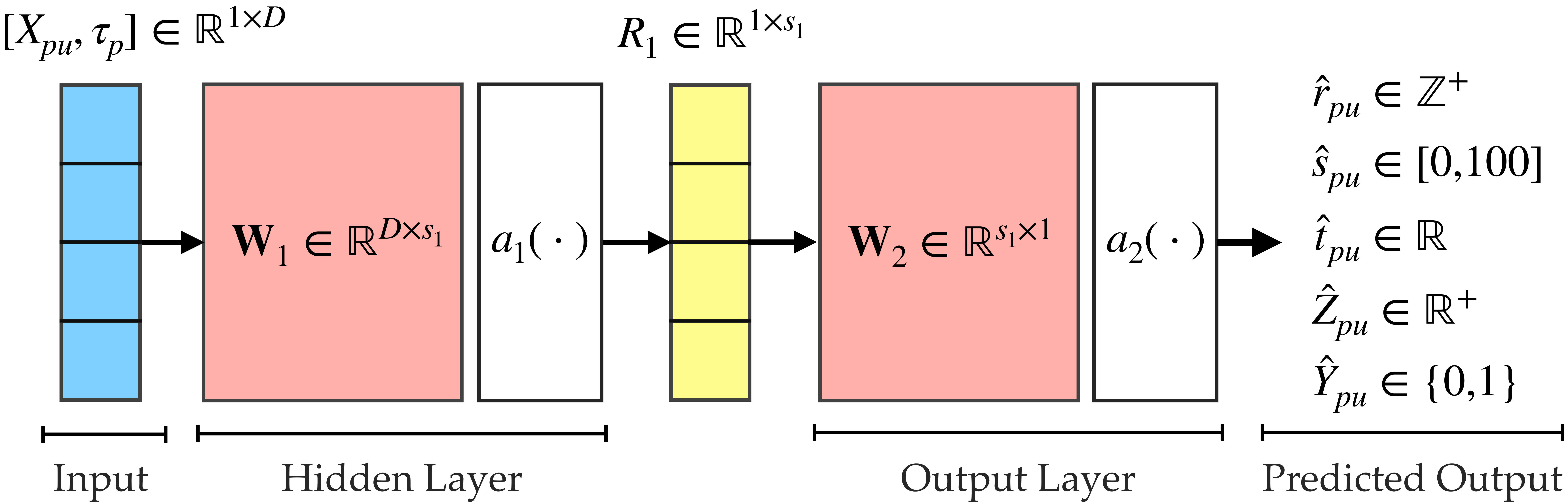
Consistent estimates, valid inference if **product** of nuisance function convergence rates is at least $n^{-1/2}$

# IV. Controlling for Text

## **Nuisance functions:** Deep ReLU neural networks

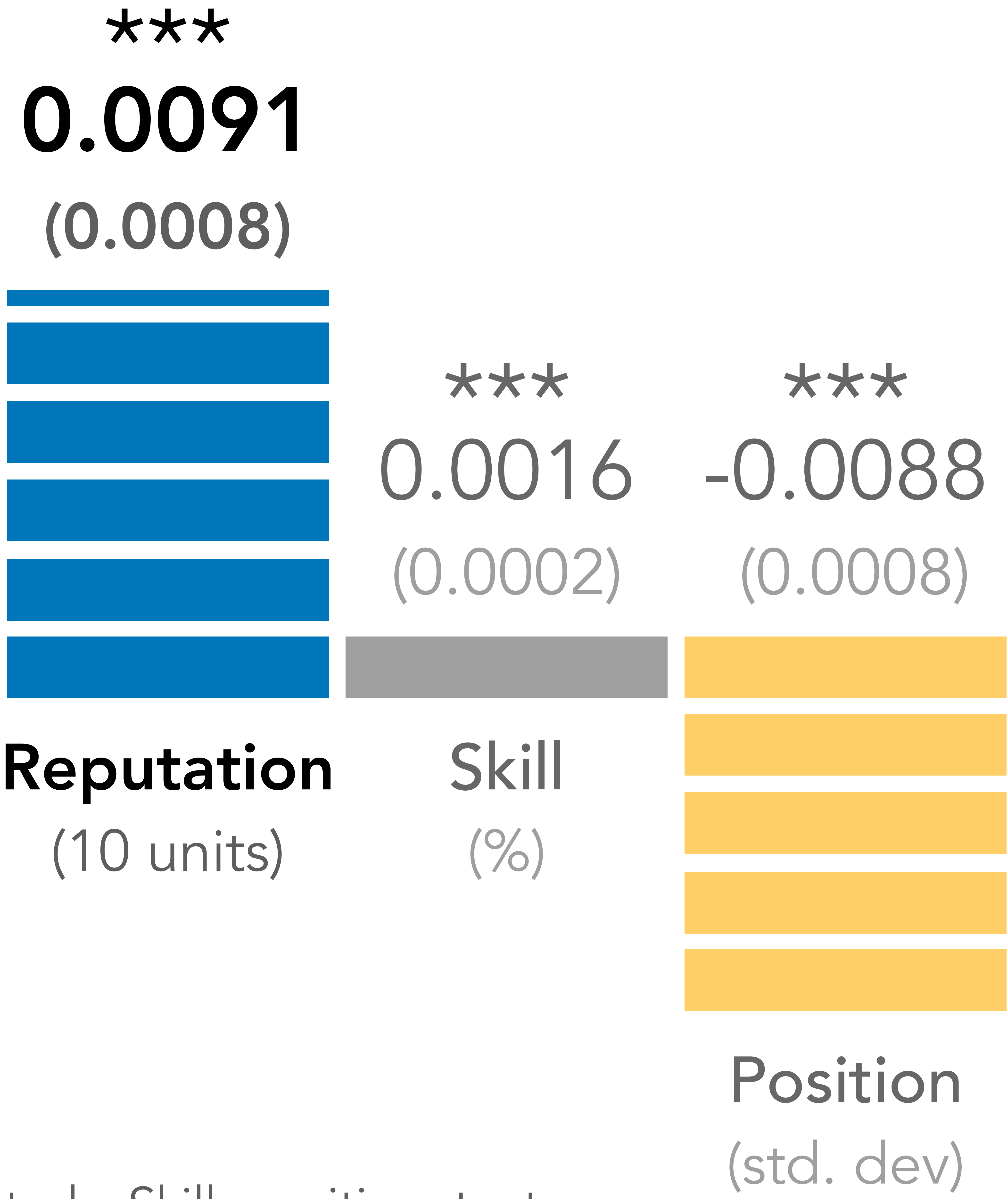



**Valid inference with double ML** (Farrell et. al., 2018)

# Results

Reputation is **persuasive**

+10 reputation units → +26% persuasion rate increase over the platform average persuasion rate (≈3.5%)



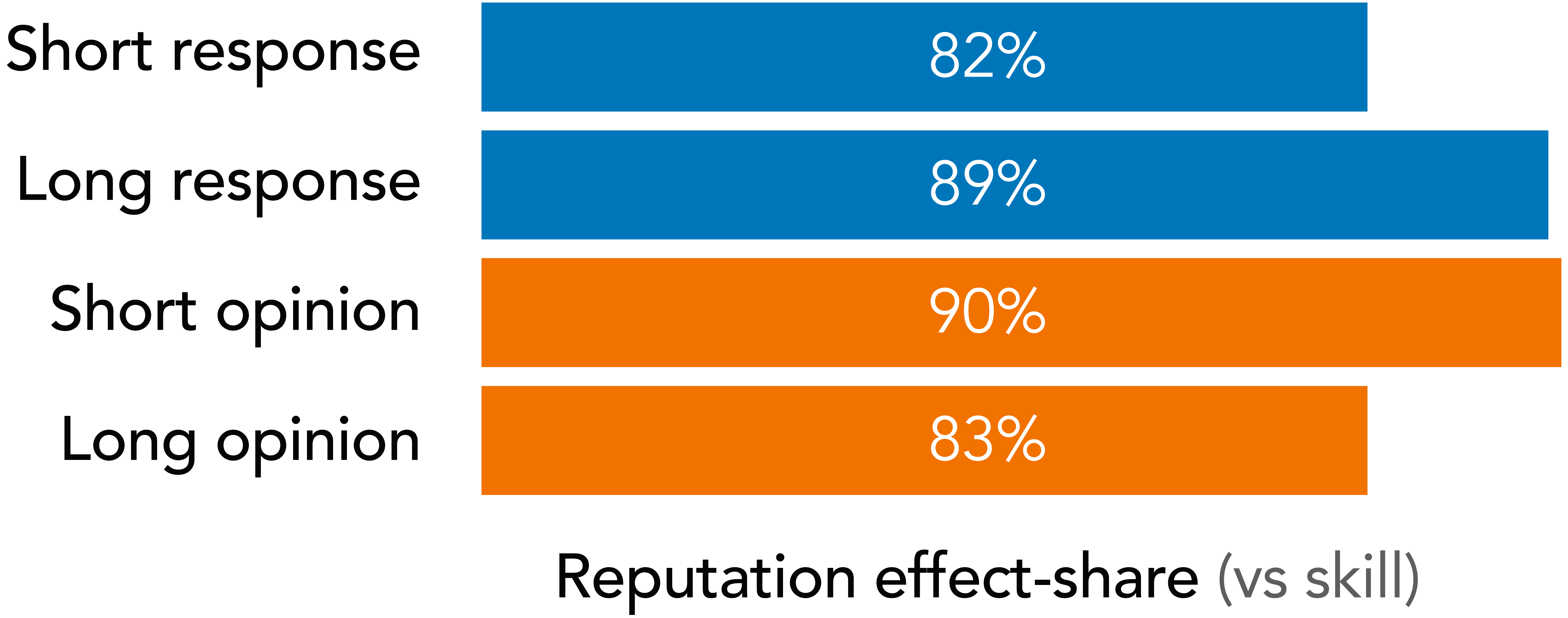

Estimated Local Average Treatment Effect (LATE)

Outcome: Debate success
Treatment: Reputation

Controls: Skill, position, text
Includes opinion fixed-effects

# Results

Persuasive power **increases** with cognitive load and **decreases** with issue-involvement of opinion-holder

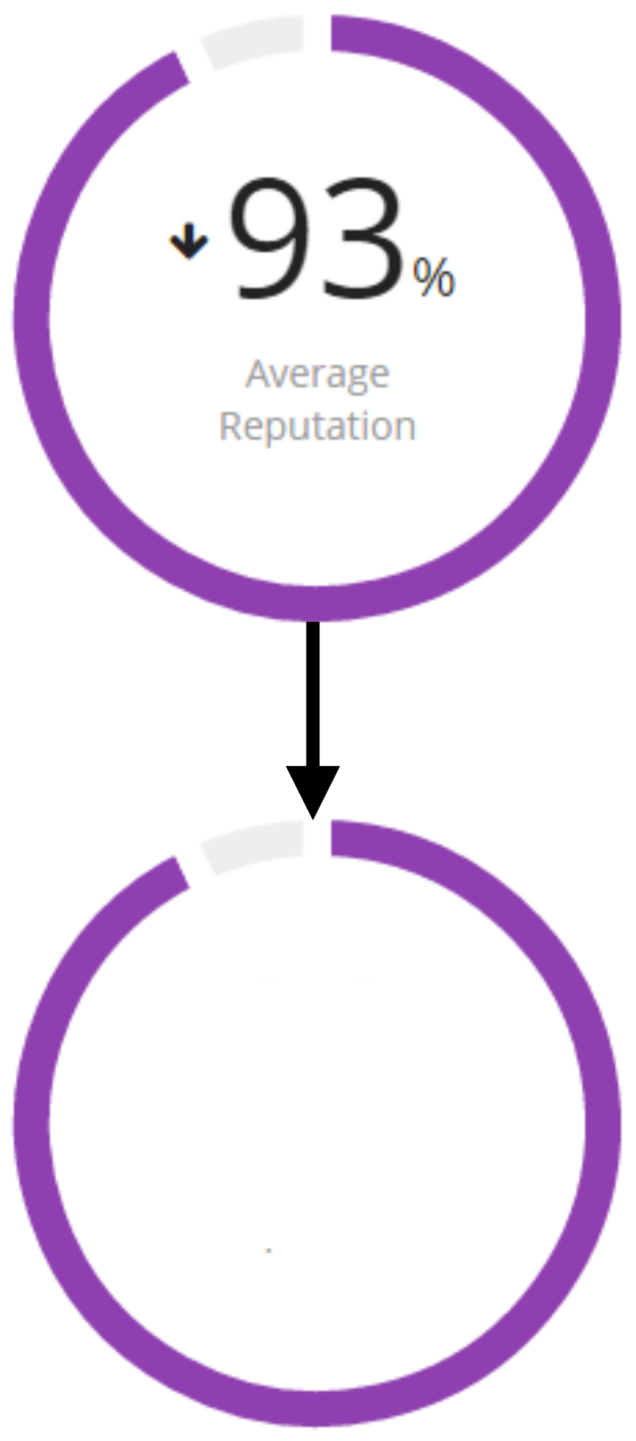


# Implications for Deliberation Platforms

Consistent with reference cues theory of persuasion (Bilancini & Boncinelli, 2018)

Reference cues used if they (i) have **lower cognitive cost**, and (ii) are **accurate proxies**

**Potential strategy:** Manipulate perceived reference cue accuracy



*Preprint, code & data:*

emaadmanzoor.com/ethos/

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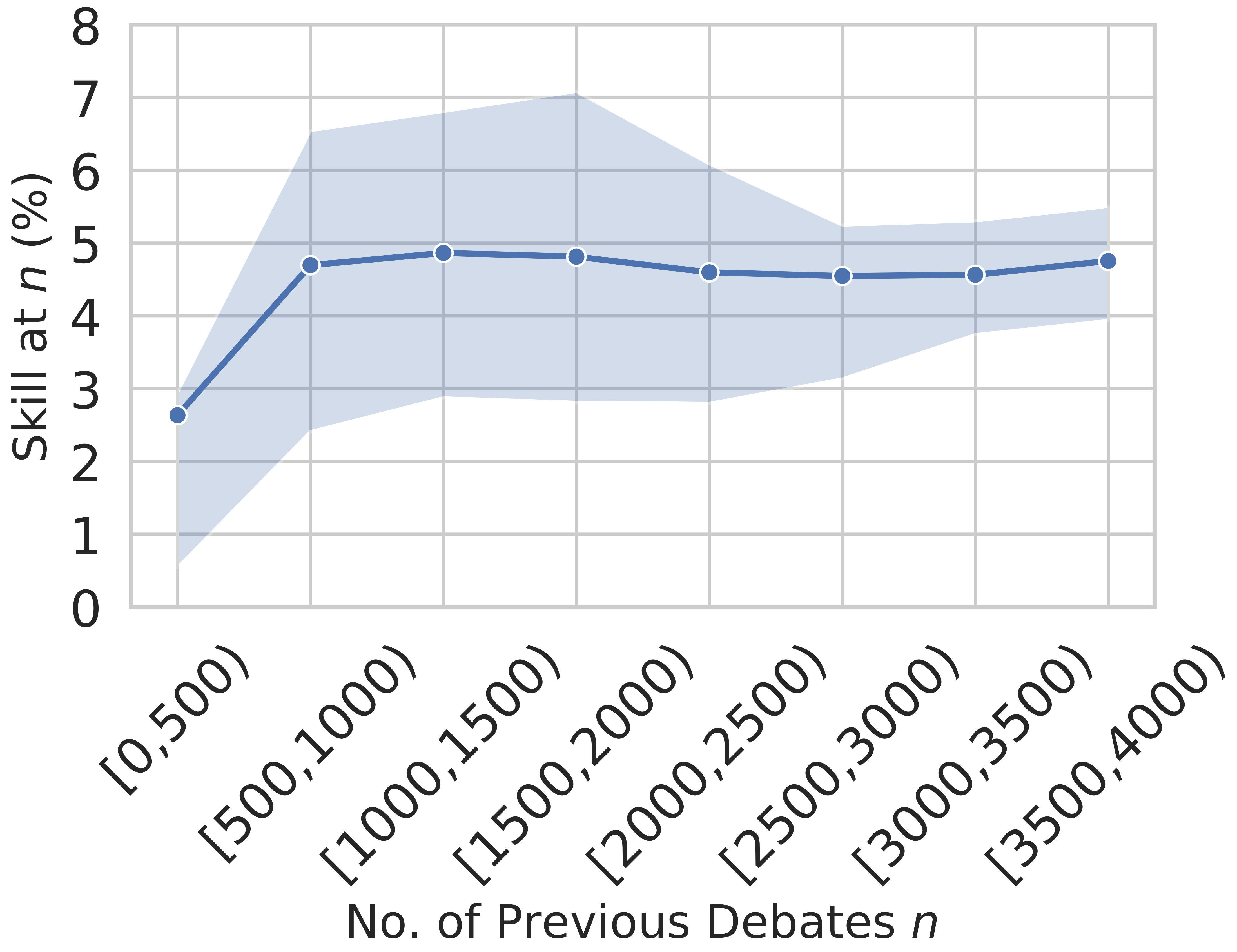
Dokyun Lee
Michael D. Smith
Carnegie Mellon University

# Descriptive Statistics

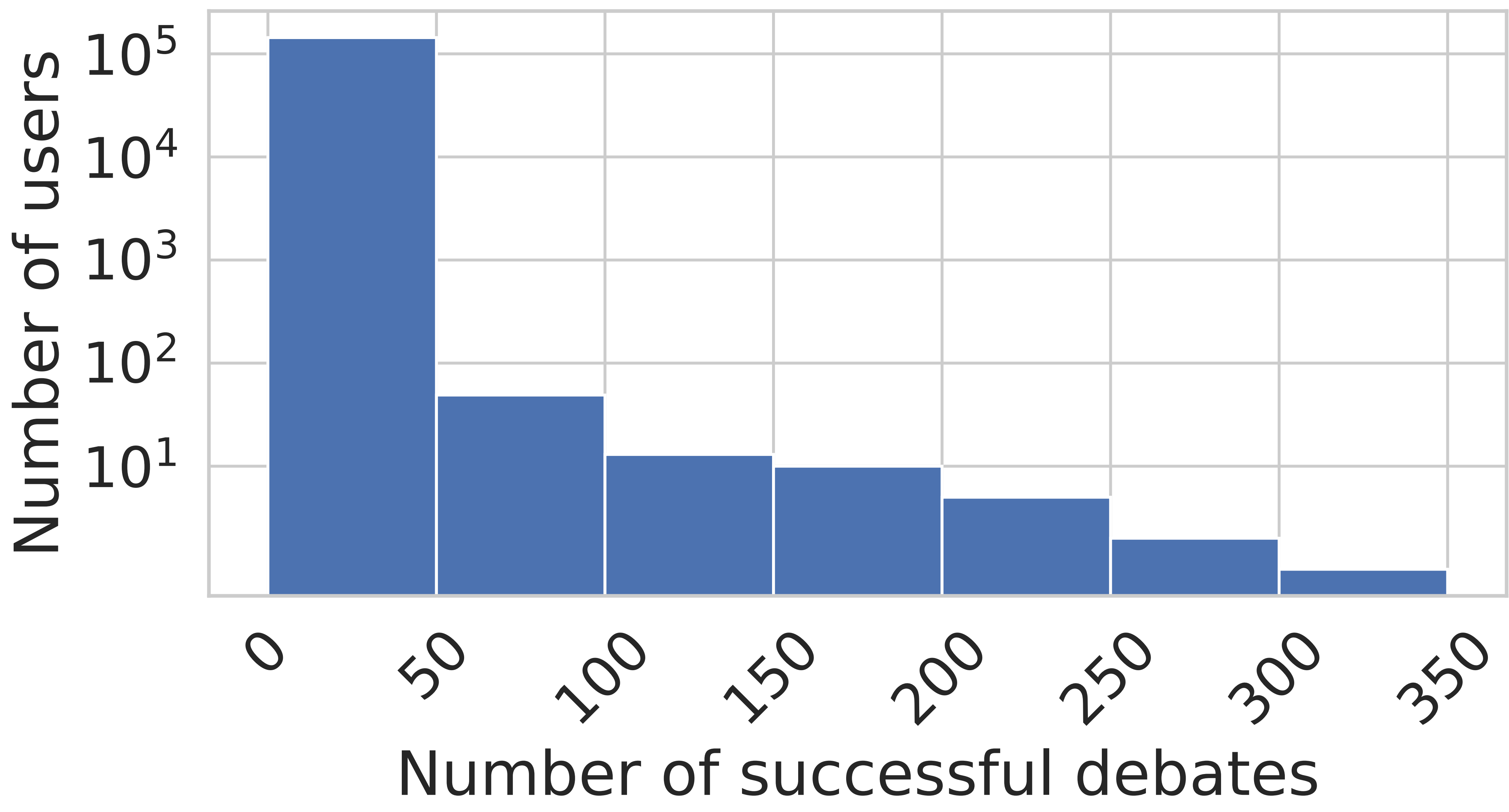
| | Mean | Standard Deviation | Median |
|---|---|---|---|
| *Statistics of challengers in each debate* | | | |
| Reputation $r_{pu}$ | 15.9 | 43.4 | 1.0 |
| Skill $s_{pu}$ (%) | 3.0 | 3.7 | 1.6 |
| Position $t_{pu}$ | 14.8 | 24.3 | 8.0 |
| Mean past position $Z_{pu}$ | 10.4 | 13.0 | 7.5 |
| Number of past debates $\sum_{p'<p} S_{p'u}$ | 244.4 | 591.7 | 24.00 |
| *Statistics of overall dataset* | | | |
| Number of opinions | 91,730 | | |
| Opinions conceded | 21,576 | | |
| Opinions leading to more than 1 debate | 84,998 | *(number of clusters with opinion fixed-effects)* | |
| Number of debates | 1,026,201 | | |
| Successful debates | 36,187 | | |
| Multi-party debates | 348,041 | | |
| Number of debates per opinion | 11.2 | 12.7 | 9 |
| Successful debates per opinion | 0.4 | 0.9 | 0 |
| Number of unique posters | 60,573 | | |
| Opinions per poster | 1.5 | 2.4 | 1 |
| Number of unique challengers | 143,891 | | |
| Challengers with more than 1 debate | 64,871 | *(number of clusters with user fixed-effects)* | |
| Number of debates per challenger | 7.1 | 58.5 | 1 |
| Successful debates per challenger | 0.3 | 3.2 | 0 |

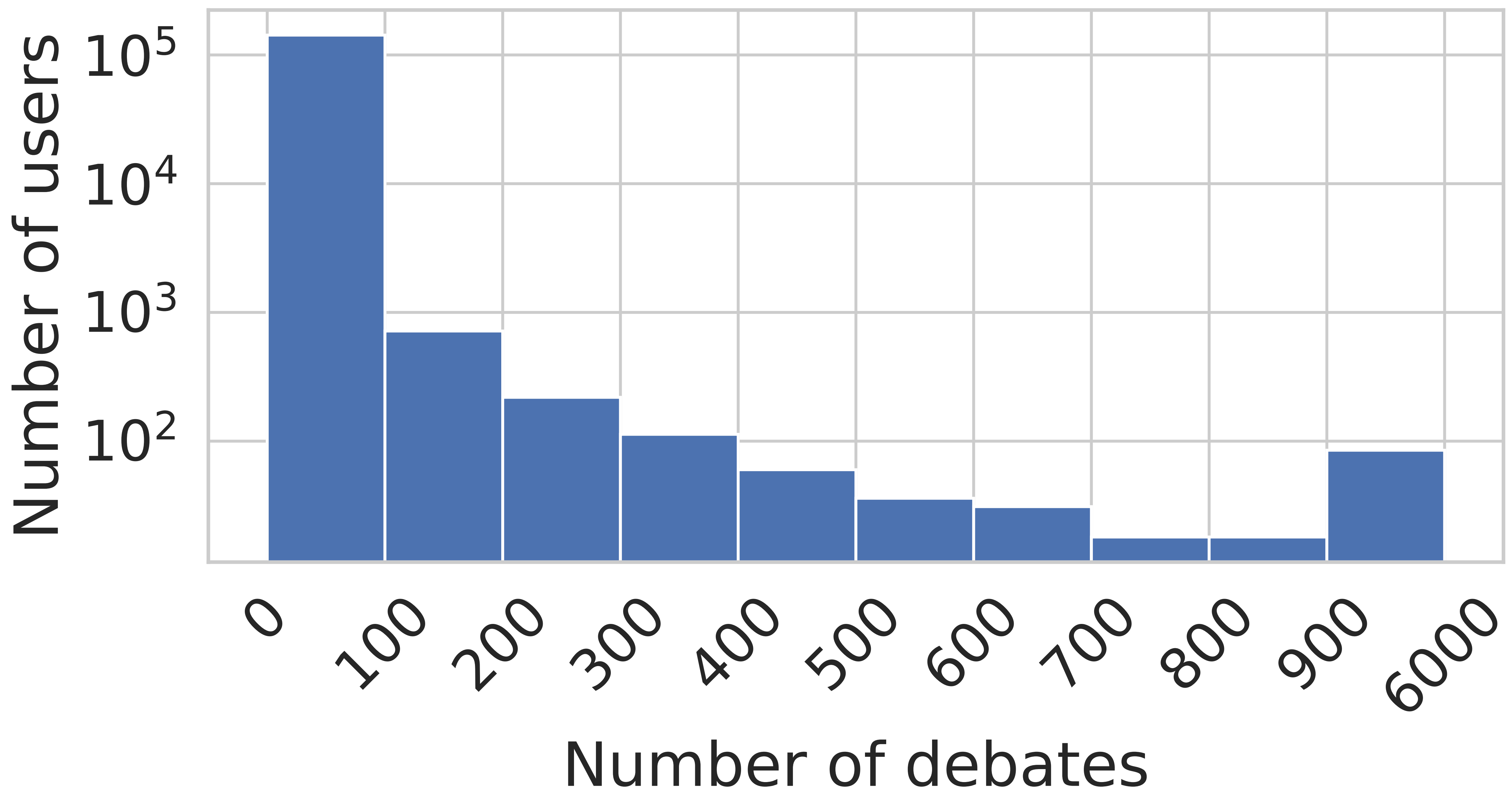
**Table 1: Descriptive Statistics.** Debates from March 1, 2013 to October 10, 2019.

# Skill vs. Experience

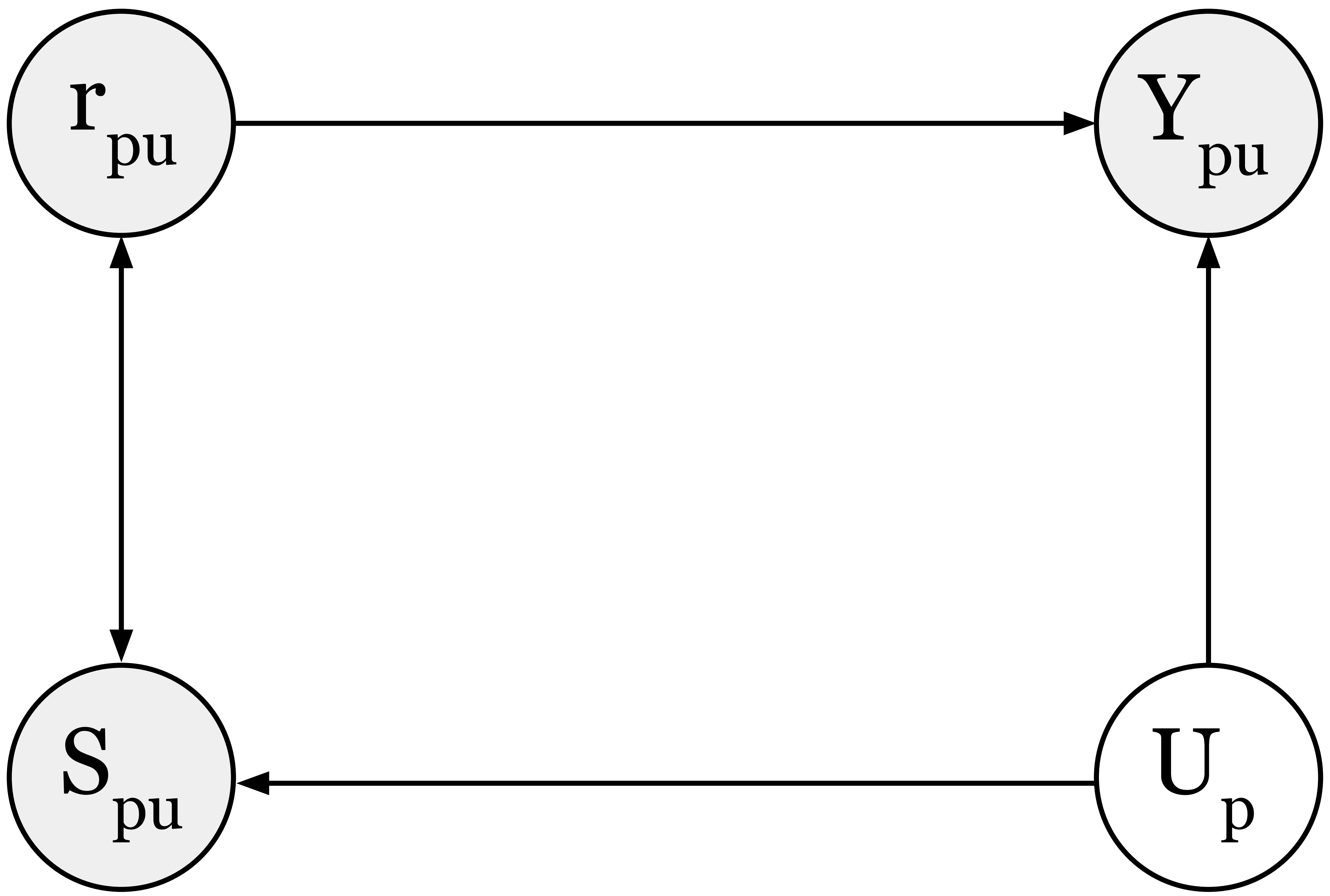


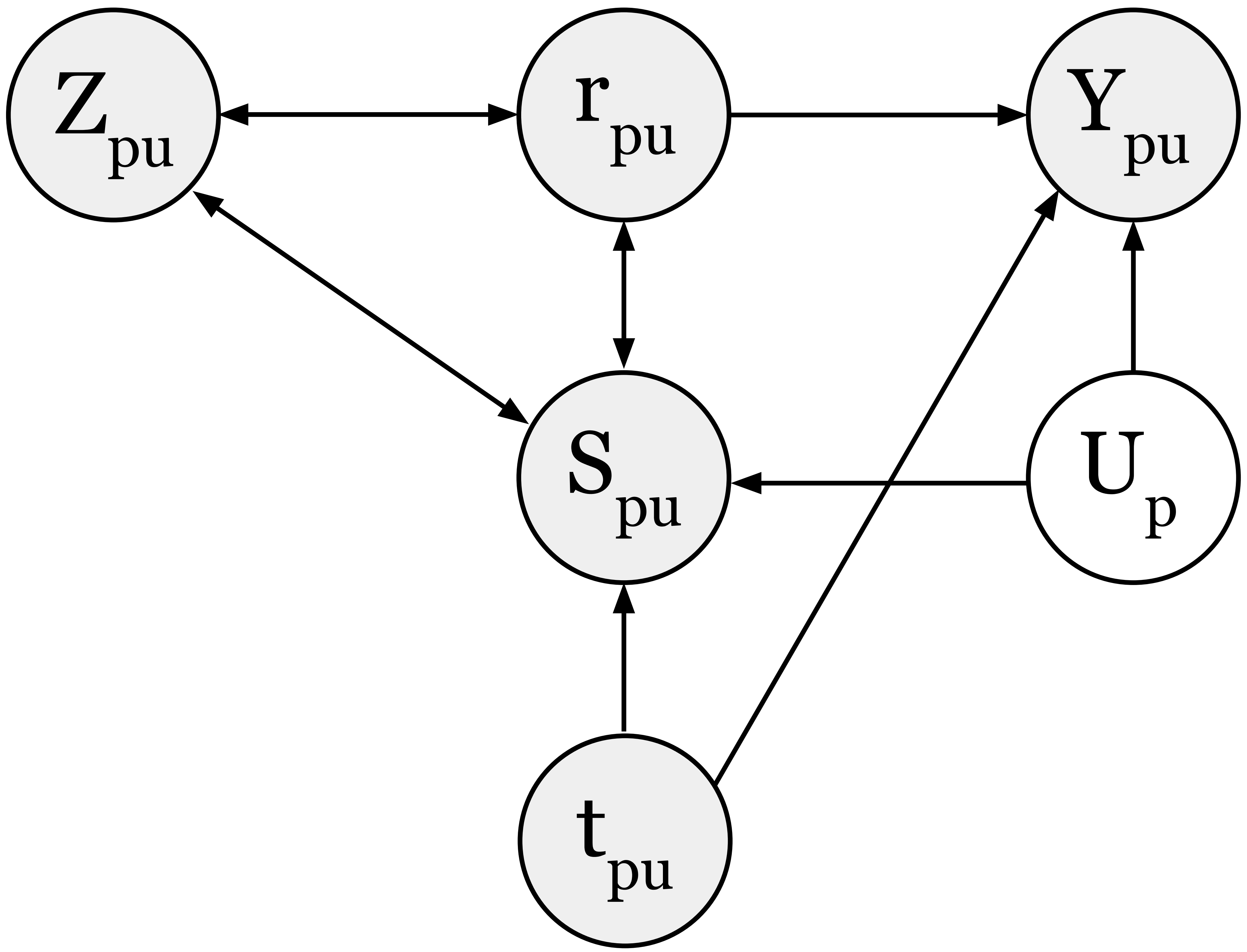
# Debate Participation and Success



# Endogenous Opinion Selection



# Instrument First-Stage

| | Dependent Variable: Reputation $r_{pu}$ |
|---|---|
| Mean past position $Z_{pu}$ | $-0.1833$ $(0.003)^{***}$ |
| Skill $s_{pu}$ (percentage) | $2.3055$ $(0.012)^{***}$ |
| Position $t_{pu}$ (std. deviations) | $-1.7354$ $(0.067)^{***}$ |
| Opinion fixed-effects ($\tau_p$) | ✓ |
| Instrument F-Statistic | $3,338.7$ |
| No. of debates | $1,019,469$ |
| $R^2$ | $0.22$ |

Note: Standard errors displayed in parentheses. $^{***}p < 0.001;^{**} p < 0.01;^{*} p < 0.05$

**Table 5: First-stage estimates.** Mean past position as an instrument for reputation.

# Double ML Estimation Procedure

1. Estimate the following conditional expectation functions on sample $\mathcal{S}'$:

   i. $l(X_{pu}, \tau_p) = \mathbb{E}[Y_{pu}|X_{pu}, \tau_p]$ to get $\hat{l}(\cdot)$.

   ii. $q(X_{pu}, \tau_p) = \mathbb{E}[Z_{pu}|X_{pu}, \tau_p]$ to get $\hat{q}(\cdot)$.

   iii. $m_r(X_{pu}, \tau_p) = \mathbb{E}[r_{pu}|X_{pu}, \tau_p]$ to get $\hat{m}_r(\cdot)$.

   iv. $m_s(X_{pu}, \tau_p) = \mathbb{E}[s_{pu}|X_{pu}, \tau_p]$ to get $\hat{m}_s(\cdot)$.

   v. $m_t(X_{pu}, \tau_p) = \mathbb{E}[t_{pu}|X_{pu}, \tau_p]$ to get $\hat{m}_t(\cdot)$.

2. Estimate the following residuals on sample $\mathcal{S}$:

   i. $\tilde{Y}_{pu} = Y_{pu} - \hat{l}(X_{pu}, \tau_p)$.

   ii. $\tilde{Z}_{pu} = Z_{pu} - \hat{q}(X_{pu}, \tau_p)$.

   iii. $\tilde{r}_{pu} = r_{pu} - \hat{m}_r(X_{pu}, \tau_p)$.

   iv. $\tilde{s}_{pu} = s_{pu} - \hat{m}_s(X_{pu}, \tau_p)$.

   v. $\tilde{t}_{pu} = t_{pu} - \hat{m}_t(X_{pu}, \tau_p)$.

3. Run a two-stage least-squares regression of $\tilde{Y}_{pu}$ on $\tilde{r}_{pu}, \tilde{s}_{pu}, \tilde{t}_{pu}$ using $\tilde{Z}_{pu}$ as an instrument for $\tilde{r}_{pu}$ to obtain the estimated local average treatment effects of reputation, skill and position on debate success.

# Neural Models of Text

| Prediction target | Number of Hidden layers | Activation Functions: Hidden Layer | Activation Functions: Output Layer | Loss Function |
|---|---|---|---|---|
| Debate success $Y_{pu} \in \{0, 1\}$ | 5 | ReLU | Sigmoid | Binary Cross-Entropy |
| Reputation $r_{pu} \in \mathbb{Z}^+$ | 3 | ReLU | Rectifier | Mean squared error |
| Skill $s_{pu} \in [0, 100]$ (percentage) | 3 | ReLU | Sigmoid | Mean squared error |
| Position $t_{pu} \in \mathbb{R}$ (standardized) | 3 | ReLU | Identity | Mean squared error |
| Instrument $Z_{pu} \in \mathbb{R}^+$ | 5 | ReLU | Rectifier | Mean squared error |

**Table 7: Architectural hyperparameters.** The input layer matrix $\boldsymbol{W}_1$ of each neural network has size 89,924 $\times$ 4,926, where 89,924 is the dimensionality of the input vector (the vocabulary size + the number of unique opinion clusters) and 4,926 is the dimensionality of $X_{pu}$ (the vocabulary size). Each of the $h$ hidden layer matrices $\boldsymbol{W}_2, \ldots \boldsymbol{W}_h$ has size 4,926 $\times$ 4,926, and the output layer matrix $\boldsymbol{W}_{h+1}$ has size 4,926 $\times$ 1.

# Neural Models of Text

| Prediction target | Learning Rate | Batch Size | Weight-Decay | Subsample Loss | | |
|---|---|---|---|---|---|---|
| | | | | Train | Validation | Inference |
| Debate success $Y_{pu} \in \{0, 1\}$ | 0.0001 | 50,000 | 10000 | 0.148 | 0.155 | 0.152 |
| Reputation $r_{pu} \in \mathbb{Z}^+$ | 0.0001 | 50,000 | 10 | 39.801 | 40.406 | 39.842 |
| Skill $s_{pu} \in [0, 100]$ (percentage) | 0.0001 | 50,000 | 10 | 3.672 | 3.764 | 3.707 |
| Position $t_{pu} \in \mathbb{R}$ (standardized) | 0.0001 | 50,000 | 10 | 0.658 | 0.789 | 0.796 |
| Instrument $Z_{pu} \in \mathbb{R}^+$ | 0.0001 | 50,000 | 10000 | 12.389 | 13.370 | 13.217 |

**Table 8: Optimization hyperparameters.** The subsample losses on $S'_{\text{train}}$, $S'_{\text{val}}$ and $S$ are reported after training each neural network with the selected hyperparameters for at most 5,000 mini-batch iterations (with early-stopping) on $S'_{\text{train}}$. The binary cross-entropy subsample loss is reported for the network predicting $Y_{pu}$ and the *root* mean squared prediction error is reported for the other networks.

# Effect of Experience

$$Y_{pu} = \rho_u + m_{pu} + \theta_1 \sum_{p'<p} S_{p'u} + \theta_2 t_{pu} + \epsilon_{pu}$$

| | Dependent Variable: Debate Success $Y_{pu}$ |
|---|---|
| No. of opinions challenged previously $\sum_{p'<p} S_{p'u}$ | $-1 \times 10^{-6}$ $(0.7 \times 10^{-6})$ |
| Position $t_{pu}$ (std. deviations) | $-0.0107$ $(0.0003)^{***}$ |
| User fixed-effects ($\rho_u$) | ✓ |
| Month-year fixed-effects ($m_{pu}$) | ✓ |
| No. of debates | $947,181$ |
| $R^2$ | $0.07$ |

Note: Standard errors displayed in parentheses. $^{***}p < 0.001;^{**} p < 0.01;^{*} p < 0.05$

**Table 3: Estimated effect of past experience on debate success.**