Social Image, Organisational Values and Inclusion: Evidence from a Field Experiment

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Institutions and Inclusivity

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- In particular in terms of access to finance

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How can institutional design promote the inclusion of underrepresented groups?

- By promoting these organizational objectives
- While incorporating individuals' expertise

Field Experiment: Institutional Barriers to Inclusivity

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Gendered inclusion

- We focus on equal opportunity for male and female entrepreneurs
- In a setting with limited access to finance for female entrepreneurs

Institutional Features

How does communicating organizational values (promoting equal opportunity) affect evaluators?

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How do these factors interact to shape inclusive decision-making?

- Treatment 3: Interacting these two treatments

Preview of results

Communicating organizational values benefits "good" female candidates

- Equalising their performance relative to "good" male candidates

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The assessments poorly predict the participants' future outcomes

Contributions

We contribute to the empirical behavioural literature on the role of social pressure

Dellavigna et al, 2012, 2016; Gerber, Green and Larim. 2008; Ai et al. 2016; Charness and Holder 2019; Garicano et al, 2005; Fan et al. 2022; Kelley, Hip and Protsch 2024

We contribute to the literature on organizational messaging

Ashraf, Bandiera and Jack 2014; Flammer and Luo 2017; Khan 2020

We contribute to the literature on discrimination in access to finance

Brock and De Haas, 2023; Fisman et al. 2020; Alibhai et al, 2023; Battaglia et al. 2024; Aydin, Bircan and De Haas, 2024; Jung 2025; Ubfal 2025; Heberg, Tookes and Yimfor 2025

Road map

The submissions

We invite 100 candidates to participate in the competition:

- Highly educated (80% bachelor)
- On average 31 years old
- Mostly wage-employed (67%) or self-employed (20%)
- Median income 10,000ETB

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- They submit a three-minute video as their proposal
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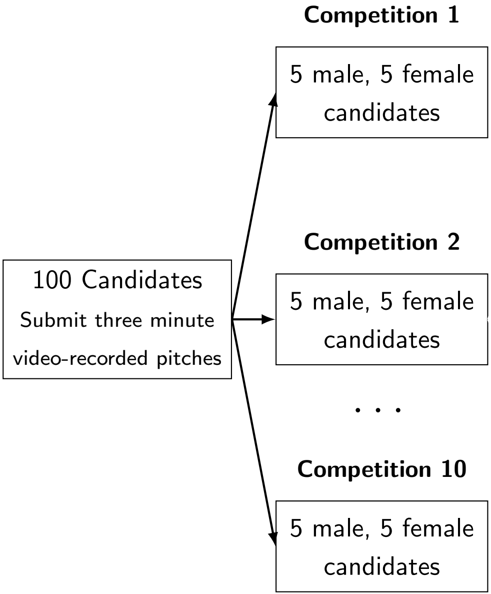
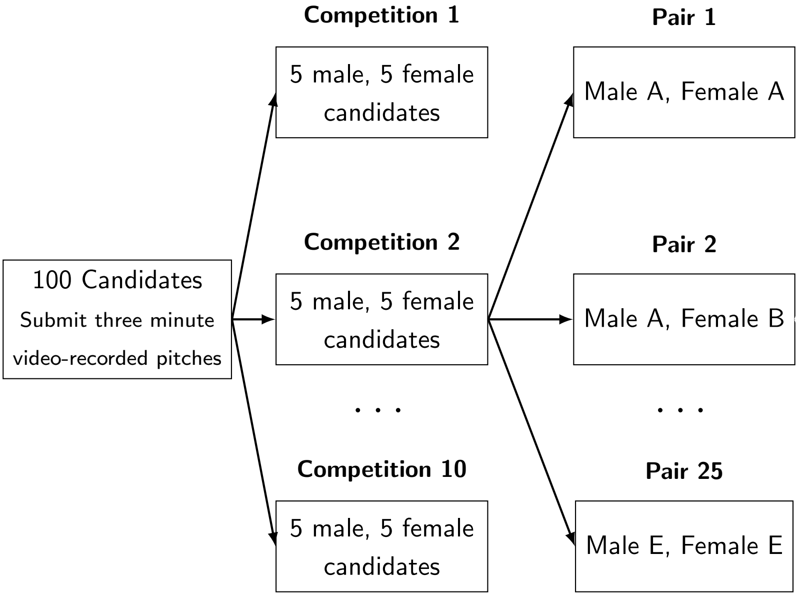
These videos are the inputs for our experiment

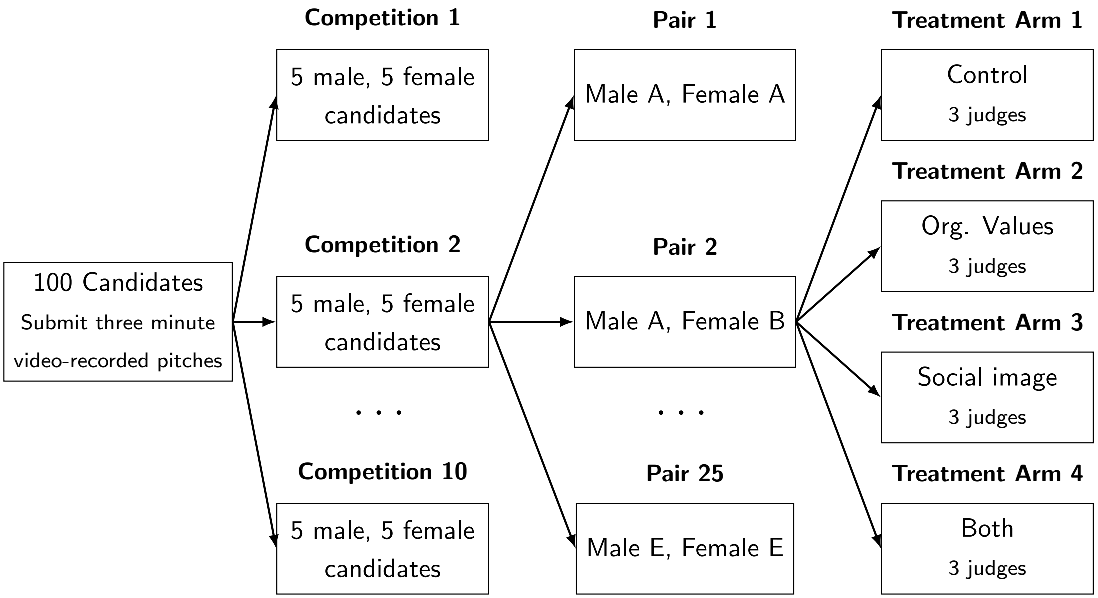
100 Candidates

Submit three minute

video-recorded pitches


Competition 1
5 male, 5 female candidates
Competition 2
5 male, 5 female candidates
...
Competition 10
5 male, 5 female candidates
100 Candidates
Submit three minute video-recorded pitches


Competition 1
5 male, 5 female candidates
Pair 1
Male A, Female A
Competition 2
5 male, 5 female candidates
Pair 2
Male A, Female B
100 Candidates
Submit three minute video-recorded pitches
. . .
. . .
Competition 10
5 male, 5 female candidates
Pair 25
Male E, Female E


Competition 1
5 male, 5 female candidates
Pair 1
Male A, Female A
Treatment Arm 1
Control
3 judges
Treatment Arm 2
Org. Values
3 judges
Competition 2
5 male, 5 female candidates
Pair 2
Male A, Female B
100 Candidates
Submit three minute video-recorded pitches
Treatment Arm 3
Social image
3 judges
. . .
. . .
Competition 10
5 male, 5 female candidates
Pair 25
Male E, Female E
Treatment Arm 4
Both
3 judges

The experimental sample: The judges

We invite 245 experienced human resource managers as judges:

- Responsible for HR decisions at medium-sized to large Ethiopian firms
- 25% female
- On average 41 years old
- On average 20 years of professional experience
- Range of sectors
- Balanced across treatments Table

Pre-existing relationship through previous experiment

Control group protocol

Control group judges attend the experiment in groups of around 12 judges in a hotel in central Addis Ababa, they:

- Watch a video that explains the protocol
- Individually assess pairs of video-recorded proposals
  - Each pair consists of a male and female candidate
- Privately recommend one of the two candidates
- Each judge assesses 12 such pairs

The candidate in each competition with the most recommendations wins the prize

The assessments

The organisational values treatment

All judges watch a video of a well-known Ethiopian entrepreneur stressing the importance of access to capital

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The treatment extends this video with three statements:

- Female entrepreneurs have less access to capital
- This competition promotes equal opportunity for female entrepreneurs
- Judges need to consider many factors to make their decision

full statement

The social image treatment

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    - Stressing they may need to discuss their decision
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Judges without the social image treatment provide this feedback individually.

Discussing the decision

The HR Consultants

Two HR consultants – our “experts” – also assess the videos:

- CEO of a HR consultancy, and HR manager of a large for-profit enterprise
- Selected by local partners for their expertise
- They give a score for the quality of each proposal

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This allows us to define an "expert pick" to proxy for quality

- This is the candidate with the higher average score in each pair
- Judges are not aware of the experts and their assessments

Road map

Experimental design

Main Results

Interpreting the results

Policy implications

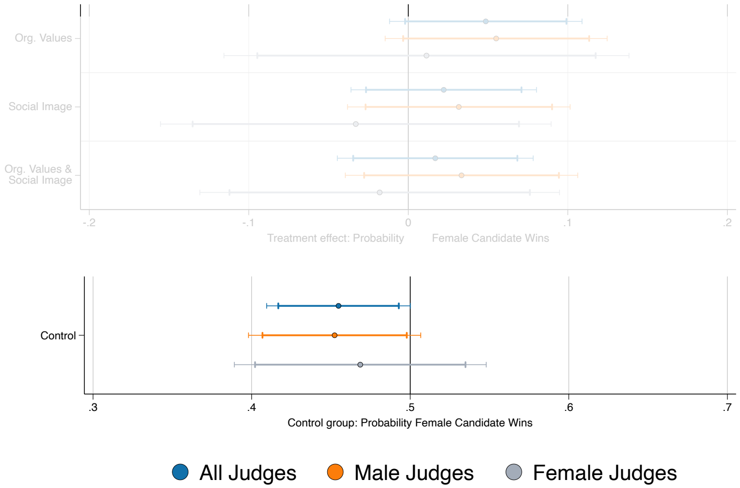
Result 1: No average effect on female candidates

We run the following regression:

$$\begin{aligned}\texttt{Female\_Wins}_{jp} = \;& \beta_1 \cdot \texttt{Organisational\_Values}_j + \beta_2 \cdot \texttt{Social\_Image}_j \\ + \;& \beta_3 \cdot \texttt{Combined\_Treatment}_j + \mu_p + \varepsilon_{jp},\end{aligned}$$

- j indexes judges and p indexes pairs of competing candidates
- We cluster errors at the judge level throughout
- We separately analyze the effect on male and female judges

Result 1: No average effect on female candidates



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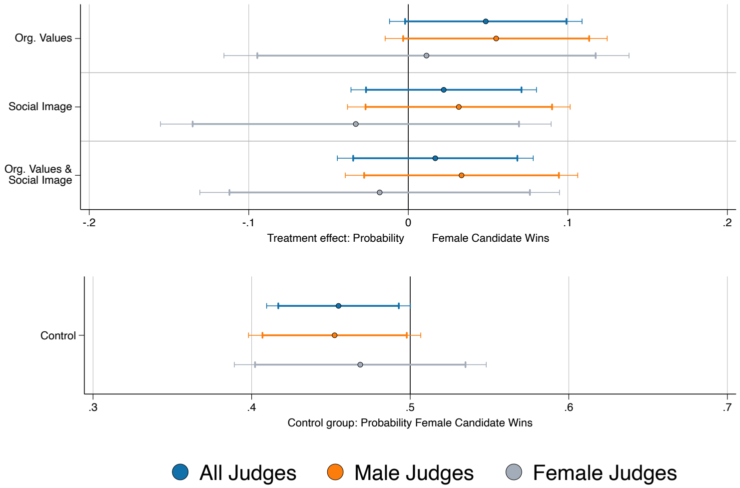
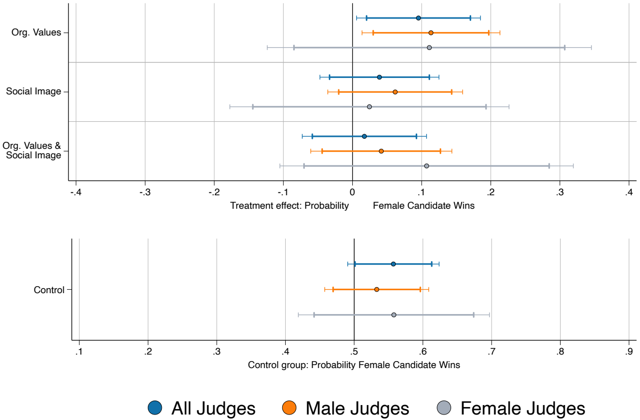


Table

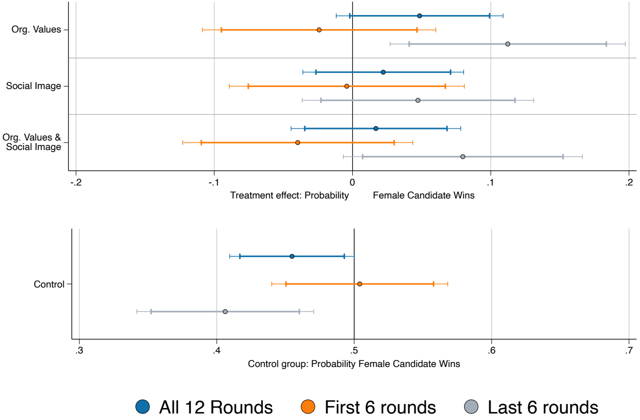
Result 2: Expert-favoured female candidates benefit from the org. values treatment

We run the same regression **for the subsample with a female expert pick**:

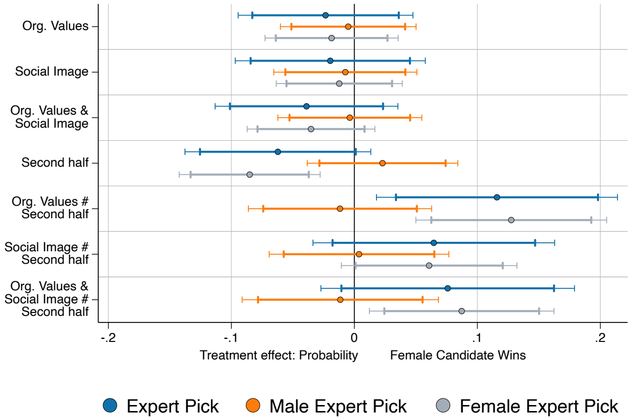


Result 3: Female candidates benefit from the treatments in later rounds

We run the same regression **separately for the first and last six rounds**:



Result 4: Treatments increase alignment with expert on female candidate in the last six rounds



Triplet-level results

We also study the effect on agreement among judges composition:

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And - for judges with the social image treatment - we study the effect of having a female member on the triplet on male judges:

- We find no evidence having a female triplet member affects male judges
- Either with or without the organisational values treatment

Who benefits?

The important question is what candidates benefit from the treatments

We evaluate this heterogeneity in two ways:

1. Based on expected performance *without* the treatment [Abadie, Chingos and West, 2018]
2. Based on the characteristics that predict a female candidate winning [Lasso-Logit]

Endogenous stratification

We take a large set of covariates X: experts' scores; expert and enumerator assessments; facial-expression features; measures of gendered-language

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We use the Abadie, Chingos and West (2018) procedure for valid inference

Heterogeneity in treatment effects in the last six rounds

	Control	Org. Values	Social Image	Both
Low control performance		6.75%	-0.18%	0.03%
		$[-1.44\%,\ 18.24\%]$	$[-8.68\%,\ 10.77\%]$	$[-8.95\%,\ 8.48\%]$
High control performance		15.71%	2.14%	6.43%
		$[6.88\%,\ 22.39\%]$	$[-6.26\%,\ 10.00\%]$	$[0.04\%,\ 13.85\%]$

	Control	Org. Values	Social Image	Both
Low control performance	36.51%	43.26%	36.33%	36.54%
High control performance	49.00%	64.71%	51.14%	55.43%

Heterogeneity in treatment effects in the first six rounds

	Control	Org. Values	Social Image	Both
Low control performance		-2.72% $[-10.73\%,\ 6.67\%]$	0.67% $[-9.04\%,\ 10.33\%]$	-2.39% $[-11.66\%,\ 7.87\%]$
High control performance		-1.01% $[-11.67\%,\ 9.73\%]$	2.58% $[-8.02\%,\ 11.54\%]$	1.08% $[-8.15\%,\ 10.73\%]$

	Control	Org. Values	Social Image	Both
Low control performance	41.66%	38.94%	42.33%	39.27%
High control performance	56.24%	55.23%	58.82%	57.32%

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$$\text{Woman\_Wins}_{jp} \;=\; \alpha \;+\; X_p^\top \boldsymbol{\beta}_1 \;+\; Z_j\,\beta_2 \;+\; (Z_j X_p)^\top\,\boldsymbol{\beta}_3\,. \tag{1}$$

Using a lasso-logit framework

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Using a lasso-logit framework

We use stability selection (Meinhausen and Bullmann, 2010) to select the most relevant set of predictors

Who benefits from the organisational values treatment

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- Giving specific examples
- Being articulate

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The algorithm captures no heterogeneity in treatment effects in the first six rounds

Policy implications

Huge (mixed) evidence base on interventions to reduce gender bias

Gender-blinded assessments (Goldin and Rouse 2000); Messaging to applicants (Delfino 2024, Leibrandt and List 2025); Quotas and peer review (Leibrandt 2018); Artificial intelligence (Hoffman 2018, Li 2020); Affirmative Action (Arcidiacono, P, 2005; Bleemer, 2022); Mission-driven motivation: Ashraf (2014a), Burbano (2016), Tonin and Vlassopoulos (2015), Khan (2025); Social distance and monetary incentives (Berg et al, 2017); Debiasing

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Work to be done on this low-cost intervention to:

- See whether this replicates
- See how it affects morale and inclusion in organizations

Full statement

As you know, access to capital is limited for entrepreneurs in Ethiopia. This competition will provide an opportunity for entrepreneurs to access capital to start or grow their business. Considering equal opportunity: I realise you need to take into account a large number of factors when making your decision but would like you to keep in mind that when starting a business, female entrepreneurs face additional constraints due to lenders' biases. A recent World Bank report finds that male entrepreneurs are more likely to take out loans than female entrepreneurs. In terms of loan sizes, male entrepreneurs borrow about 50 percent more than female entrepreneurs. In this competition, we are committed to gender equality and want to promote male and female entrepreneurs equally. Your vote is important in deciding which individual will win the 50,000 Ethiopian birr prize; please consider your choices carefully.

back

Table: Judge-level summary statistics Back

	Overall	Control	Social Image	Org. Values	Both Treatments	p-value
Gender (1=male)	.74	.70	.80	.72	.74	.679
Has a bachelor's degree	.78	.77	.8	.81	.72	.672
Has formal management education	.76	.77	.78	.72	.79	.804
Judge age (years)	41	39	43	41	43	.246
Experience in current job (years)	6.1	6.5	6.8	5.9	5.3	.474
Total experience (years)	20	19	20	20	20	.981
Position of manager						
Most senior manager or owner	33%	30%	42%	28%	32%	.318
Finance and administration	15%	16%	15%	13%	16%	.941
HR Manager	32%	39%	25%	33%	32%	.505
Other	20%	16%	17%	26%	21%	.43
Department of manager						
Human resources	40%	49%	34%	40%	39%	.409
Administration	34%	28%	42%	31%	35%	.373
Finance	13%	14%	10%	13%	14%	.914
Other	13%	9%	14%	17%	12%	.621
Number of judges	245	57	59	72	57	

Table: The effects of treatments on the probability of voting for a female candidate

	All judges	All judges	Male judges	Male judges	Female judges	Female judges
	b/se	b/se	b/se	b/se	b/se	b/se
Org. Values	0.049	0.045	0.055	0.051	0.011	-0.118
	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.11)
Social Image	0.022	0.014	0.032	0.020	-0.033	-0.135
	(0.03)	(0.03)	(0.04)	(0.03)	(0.06)	(0.12)
Org. Values	0.017	0.013	0.033	0.036	-0.018	-0.151
& Social Image	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.11)
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.455	0.459	0.452	0.458	0.469	0.586
N	2631	2631	1962	1962	628	628

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Table: The effects of treatments on the probability of voting for an expert-favoured candidate

	All judges		Male judges		Female judges	
	b/se	b/se	b/se	b/se	b/se	b/se
Org. Values	0.073**	0.063*	0.094**	0.088**	0.101	0.039
	(0.03)	(0.03)	(0.04)	(0.04)	(0.08)	(0.08)
Social Image	0.047	0.037	0.062	0.061	0.066	0.050
	(0.03)	(0.03)	(0.04)	(0.04)	(0.08)	(0.07)
Org. Values &	0.036	0.021	0.049	0.046	0.108*	0.054
Social Image	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.570	0.580	0.545	0.549	0.572	0.617
N	2331	2331	1708	1708	583	583

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Table: The effects of treatments on making a unanimous decision

	unanimous	unanimousWomanWins	unanimousManWins	unanimousExpertPickWins
	b/se	b/se	b/se	b/se
Org. Values	0.078	0.057	0.021	0.106**
	(0.05)	(0.04)	(0.04)	(0.05)
Social Image	0.098*	0.053	0.045	0.123**
	(0.05)	(0.04)	(0.04)	(0.05)
Org. Values &	0.080	0.034	0.046	0.083*
Social Image	(0.05)	(0.04)	(0.04)	(0.05)
Control mean	0.298	0.129	0.169	0.197
N	823	823	823	762

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Table: The effects on probability of voting for the experts' pick by score difference

	Expert pick wins					
	Bottom tercile		Middle tercile		Top tercile	
	b/se	b/se	b/se	b/se	b/se	b/se
Org. Values	0.042	0.041	0.032	0.010	0.144**	0.140**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Social Image	0.039	0.048	-0.013	-0.040	0.114**	0.102*
	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
Org. Values &	0.008	-0.005	-0.001	-0.029	0.099	0.090
Social Image	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.481	0.480	0.618	0.640	0.617	0.624
N	831	831	699	699	801	801

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Table: The effects of treatments on unanimity by score difference

	Unanimous decision					
	Bottom tercile		Middle tercile		Top tercile	
	b/se	b/se	b/se	b/se	b/se	b/se
Org. Values	0.037	0.051	-0.086	-0.096	0.278***	0.279***
	(0.08)	(0.08)	(0.11)	(0.11)	(0.10)	(0.10)
Social Image	0.014	0.026	0.076	0.071	0.242**	0.235**
	(0.07)	(0.08)	(0.11)	(0.11)	(0.09)	(0.09)
Org. Values &	0.018	0.032	0.060	0.052	0.191*	0.195**
Social Image	(0.08)	(0.08)	(0.10)	(0.10)	(0.10)	(0.10)
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.254	0.243	0.362	0.368	0.287	0.287
N	335	335	225	225	263	263

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Random Forest & Predictive Accuracy in Treatment Arms

Do judges coordinate on some different set of characteristics?

- Methodology:
  - Random forest algorithm run separately for each treatment arm
  - Measure out-of-bag (OOB) predictive accuracy (performance on unseen data)
- Interpretation of OOB Accuracy:
  - Higher accuracy → More consistent mapping from characteristics to votes
  - Lower accuracy → More idiosyncratic decision-making

Back

Random forest algorithm

Results are consistent with more idiosyncratic decision making in the control group:

- 55% in control
- 61% in organizational values
- 64% in social image
- 65% in combined treatment

Judges are not coordinating on some other set of characteristics in the control group.

Back

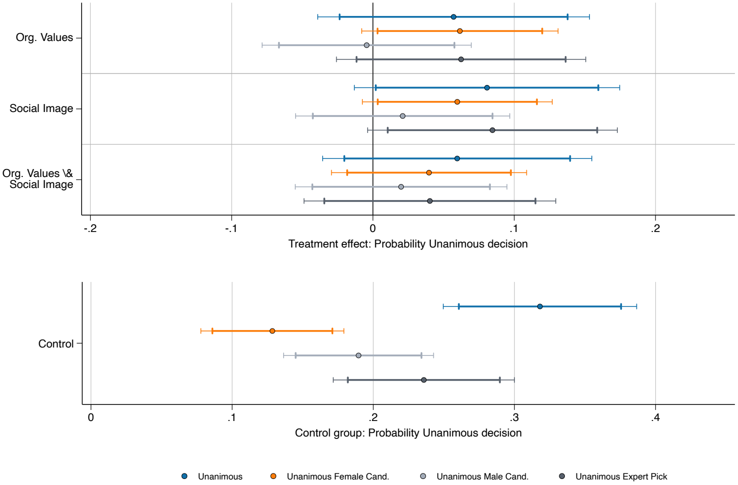
Result 3: Treatments slightly increase agreement among judges

We run the following regression at the triplet-level:

$$\begin{aligned}\texttt{Unanimous}_{cp} = \ & \beta_1 \cdot \texttt{Organisational\_Values}_c + \beta_2 \cdot \texttt{Social\_Image}_c \\ & + \beta_3 \cdot \texttt{Combined\_Treatment}_c + \mu_p + \varepsilon_{cp},\end{aligned}$$

- c indexes triplets and p indexes pairs of competing candidates
- We cluster errors at the grouped triplet level within a treatment throughout

Result 3: Treatments slightly increase agreement among judges



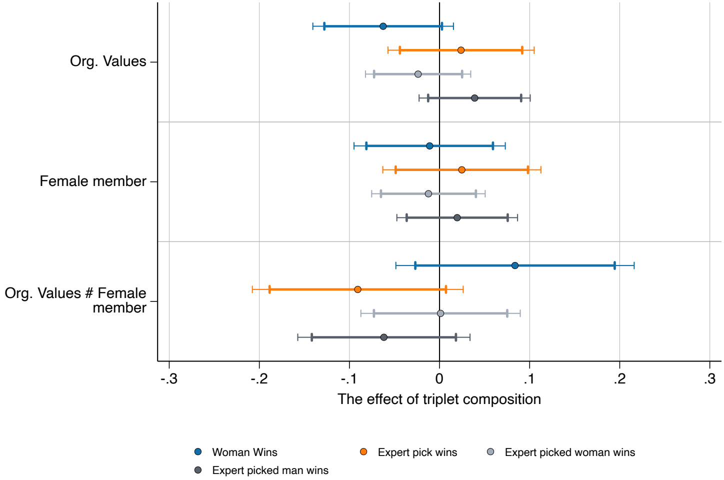
Result 4: There is no heterogeneity by triplet's gender composition

We run the following regression for the subset of male judges:

$$\begin{aligned} y_{jp} = \; & \beta_1 \cdot \texttt{Organisational\_Values}_j + \beta_2 \cdot \texttt{Female\_Member}_j \\ & + \beta_3 \cdot \texttt{Organisational\_Values}_j \cdot \texttt{Female\_Member}_j + \theta \cdot \texttt{Score\_Difference}_p + \varepsilon_{jp}, \end{aligned} \tag{2}$$

We control for the difference in the average expert score difference

Result 4: There is no heterogeneity by triplet's gender composition



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