Decoupling Taste-Based versus Statistical Discrimination in Elections

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Motivation

- A major challenge in political representation is the **persistent underrepresentation** of women & minorities in elected office.
  - As of 2025, women hold 27.3% of seats in national parliaments (Inter-Parliamentary Union).
  - Only 5 countries have achieved 50% or greater female representation in lower house.
- While various supply-side barriers exist, a **key demand-side factor is voter discrimination**.

Motivation

- Voter discrimination manifests in two distinct forms (Arrow 1973; Phelps 1972):
    - **Statistical discrimination** — voters form judgments based on group-level attributes or averages.
    - **Taste-based discrimination** — voters exhibit intrinsic biases against candidate identities, independent of observed behavior or qualifications.
- Distinguishing between two is essential for both academic understanding & policy
- Economic theory suggests that voter beliefs more responsive to targeted information than preferences
- If statistical discrimination dominates, information campaigns could significantly enhance representation

Motivation

- Distinguishing between statistical & taste-based voter discrimination is empirically challenging
- Two main obstacles:

1. $\rightarrow$ Beliefs & preferences are both latent and jointly shape vote choice
    - Statistical discrimination operates through beliefs
    - Taste-based through preferences
2. $\rightarrow$ Unlike standard models of labor market discrimination, voters evaluate candidates along both vertical attributes (e.g., competence) & horizontal attributes (e.g., policy alignment).
    - Horizontal attributes introduce non-monotonicities in voter behavior, complicating inference from aggregate vote share data, particularly if assume a linear model.

Our Paper

- We design & estimate a random utility voting model to tackle this complex identification problem.
- In our model, voters choose among candidates based on 3 key attributes:
  - *Gender Identity*
  - *Ability*
  - *Policy*
- Ability is a *vertical* attribute: voters uniformly prefer higher quality candidates
- Gender identity & policy are *horizontal*: voters evaluate these features differently depending on how closely they align with their own identity or policy ideal point

Framework

- Voters observe candidates' gender identity w/ certainty
- Ability & policy positions are uncertain; voters hold subjective & heterogeneous beliefs about these. Beliefs are the channel for statistical discrimination
- Voters differ in how they weight each attribute:
  - This state-dependent component of utility captures the psychological salience of attributes (i.e. campaign messages can influence independently of belief updating)
  - Weight on gender identity is the channel for taste-based gender discrimination

Framework

- We conduct an RCT, in partnership w/ a Brazilian nonpartisan NGO, micro-targeting voters via **Instagram** one week before Brazil's 2024 municipal elections.
- 1,000 municipalities. RCT is designed to identify statistical & taste-based discrimination within our framework.
- Voters randomly exposed to either informative or uninformative messages about female candidates.
  1. *Informative* messages provide hard information about female candidates' attributes, affecting both voter beliefs & the salience of these attributes in utility function
  2. *Uninformative* messages solely affect the salience of attributes without changing beliefs.

Literature Review

- Extensive literature in Economics and Political Science examines demand-side factors of women's under-representation in politics.
- Limited evidence of voter bias in Spain (Casas-Arce and Saiz, 2015; Gonzalez-Eiras and Sanz, 2021) and the United States (Broockman and Soltas, 2020; Anzia and Bernhard, 2022; Anzia and Berry, 2011; Ashworth et al., 2024).
- Strong evidence of voter bias in France (Fréchette et al., 2008; Le Barbanchon and Sauvagnat, 2022) and India (Beaman et al., 2009). We also find strong evidence of gender discrimination in Brazil's 2024 local elections.
- Extensive literature in labor economics seeks to estimate discrimination against minority groups and gender gap (e.g., Guryan and Charles, 2013; Bertrand and Duflo, 2018).

Literature Review

- A large literature estimates the reduced-form effects of informational campaigns on voter behavior, showing impacts on:
- voter turnout (Gerber and Green, 2000); voting decisions (DellaVigna & Gentzkow, 2010; Aker et al., 2011); vote-buying behavior (Vicente & Wantchekon, 2009; Fujiwara & Wantchekon, 2013; Vicente, 2014).
- Kendall et al. (2015), Cruz et al. (2024) show that campaign messages influence voter beliefs & choices, especially w/ appeals to valence. Do not focus on discrimination.

Setup

- Voter i characterized by gender $G_i \in \{0, 1\}$ and P_i policy position on a uni-dimensional progressive-conservative scale
- The voter chooses among a set of political candidates $j = 1, \ldots, J$ who are elected to a municipal legislature by open-list PR.
- Each candidate j is represented by three features:
  1. G_j - gender of the candidate
  2. A_j - ability in performing administrative tasks
  3. P_j - policy position on a uni-dimensional progressive-conservative scale

Utility Function

- Voters enjoy utility for supporting candidates w/ certain features (e.g. candidates who share their same identity or policy views)
- Voters may not know such features w/ certainty, or at least not for all candidates
- Voter i have subjective & heterogeneous beliefs over a candidate's features:
  1. $E_i[A_j] = A_{ij}$ - voter i's expectation about candidate j's ability
  2. $E_i[P_j] = P_{ij}$ - voter i's expectation about candidate j's policy position
  3. We assume that voters know the politician's gender identity w/ certainty

Utility Function

- Voters' utility is additively separable across the three features:

$$u_{ij} = -w_i^G \times |G_j - G_i| + w_i^A \times A_{ij} - w_i^P \times |P_{ij} - P_i| + \varepsilon_{ij}$$

- $w_i^k \geq 0$ - preference weights of gender identity, ability, and policy
- ε_{ij} - idiosyncratic preference shock, realized when the voter casts their ballot.
  1. Preferences are spatial in gender identity & policy; voters prefer candidates closer to their own position
  2. Preferences are vertical along the ability dimensions; everyone likes higher ability in their elected officials.
  3. These preferences combine both private value (gender, policy) horizontal dimensions & common value (ability) vertical dimensions.

Mechanisms

- Utility function combines:

$$u_{ij} = -w_i^G \times |G_j - G_i| + w_i^A \times A_{ij} - w_i^P \times |P_{ij} - P_i| + \varepsilon_{ij}$$

- Pure taste parameters (salience) w_i^k
  - This allows us to incorporate taste-based discrimination
- Candidate features over which learning may occur P_{ij} & A_{ij} (i's expectations depend on beliefs)
  - This allows us to incorporate statistical discrimination

Parameterization

- We use:

$$
\begin{aligned}
u_{i,j,m} = &-\exp\left(\sum_{g\in\{0,1\}}\left(\omega_g^G + \lambda_g^G \cdot V_{i,m}^G\right)\cdot \mathbf{1}\left\{G_i = g\right\} + \sigma_G \cdot \nu_{i,m}^G\right) \\
&\times \mathbf{1}\{G_i \neq G_j\} \\
&+ \exp\left(\omega^A + \lambda^A \max\{T_{i,m}^A, V_{i,m}^A\} + \sigma_A \nu_{i,m}^A\right) \\
&\times \left(\xi^A G_j + \rho^A T_{i,m}^A G_j + \eta^A X_m\right) \\
&- \exp\left(\omega^P + \lambda^P \max\{T_{i,m}^P, V_{i,m}^P\} + \sigma_P \nu_{i,m}^P\right) \\
&\times \left(\xi^P G_j + \rho^P T_{i,m}^P G_j + \eta^P X_m - \mu G_i\right)^2 + \epsilon_{i,j,m}
\end{aligned}
$$

Econometric Specification - Salience Weights

- The preference/salience weights (w_i^k) are designed to parsimoniously capture psychological components of choice (beyond learning)
- Examples are shifts in awareness (or neglect) of issues, or changes in voter attention occurring during the campaign.
  - Since these weights may be sensitive to multiple types of stimuli, we allow salience weights to respond to all signals, including uninformative ones:

$$w_i^k = exp(\omega^k + \lambda^k max\{T_{i,m}^k, V_{i,m}^k\} + \sigma_k v_{i,m}^k)$$

  - ω^k - dimension-specific intercept weight
  - $V_{i,m}^k$ - *uninformative* message about dimension k in municipality m
  - $v^{i,m}$ - unobserved heterogeneity preference shocks in municipality m

Econometric Specification - Voter Expectations

- Let $T^A_{i,m}$ and $T^P_{i,m}$ denote *informative* ability and policy messages about female politicians. We make the following additional functional form assumptions:
- Voter expectations about candidate ability are given by

$$A_{ij} = \xi^A G_j + \rho^A T^A_{i,m} G_j + \eta^A X_{j,m}$$

- Voter policy preferences are given by $|P_{ij} - P_i| = (P_{ij} - P_i)^2$, where voter expectations:

$$P_{ij} = \xi^P G_j + \rho^P T^P_{i,m} G_j + X^T_{j,m} \eta^P_j$$

voter ideal point:

$$P_i = \mu G_i + X^T_m \eta^P$$

- Notice: Vertical dimension is monotonic in the covariates. Horizontal dimension is spatial (i.e. non-monotonic) in the covariates. Theory-grounded difference that can be exploited for identification.

Vote Choice

- We assume $\epsilon_{i,j,m}$ is distributed Extreme Value Type I
- We model vote choice via a discrete choice, random utility framework

$$v_{i,m} = \mathbf{1}\{u_{i,1,m} > u_{i,0,m}\}$$

- Model-based total votes for female candidates in municipality m are then given by $v_m = \sum_{i=1}^{N_m} v_{i,m}$ and matched to empirical moments measured at the municipal level.
- Estimation is via Generalized Method of Moments (GMM)

Institutional Context

- 5,570 municipalities in Brazil
- Municipal elections are held every 4 years to elect mayors, vice mayors, and city councilors
- Voting is mandatory; turnout is typically above 80%
- Municipal elections are important
  1. Municipalities are responsible for essential services, including education, healthcare, urban planning, and infrastructure
  2. Mayors wield significant executive power, managing budgets and local public service delivery
  3. City councilors serve as the legislative body, enacting local laws and overseeing the administration
- Candidates for city council (our focus) are elected through an open-list proportional representation system (D'Hondt system) $\rightarrow$ mapping from votes to elected is not monotonic

Institutional Context

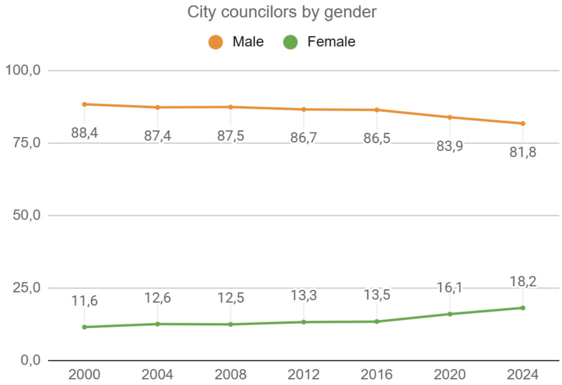


Figure: Share of Female Councilors Over Time

Institutional Context

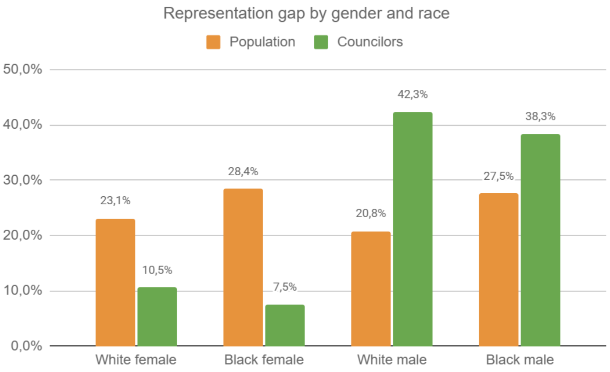


Figure: Representation Gap

Institutional Context

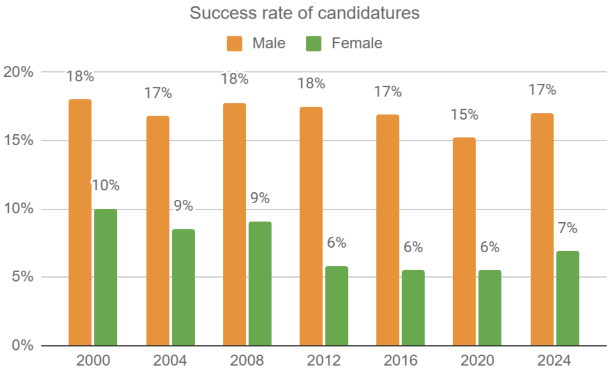


Figure: Election Rates

Institutional Context

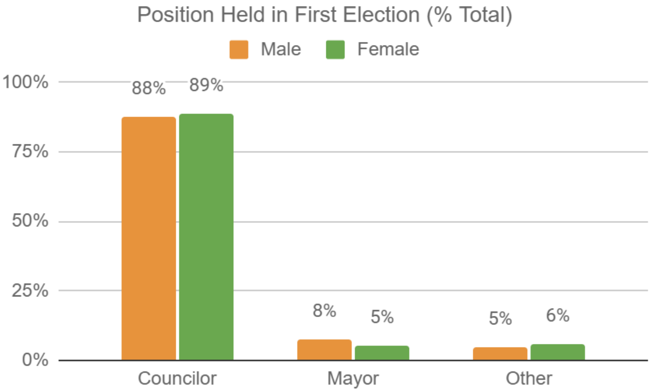


Figure: Career Ladder

Experimental Design

- The experiment was conducted 8 days prior to the 2024 municipal elections in 1,000 municipalities
- It was done in partnership with a NGO whose mission is to increase female political representation
- The campaign utilized Instagram to deliver tailored messages focusing on gender identity, ability, and policy.

Experimental Design

- It is common for politicians in Brazil to use Instagram for political campaigns and to connect with their constituents
- Instagram has approximately 141 million users in Brazil (64% of the population)
- It user base is diverse, with significant engagement across age groups
- Approximately 40% of city council candidates registered an Instagram account with the Brazil's Superior Electoral Court
  - But this likely underestimates actual usage
- Instagram's advertising algorithms enables advertisers to target users based on their municipality, gender, and age group.

Experimental Design - Sample Selection

- Medium-sized municipalities with populations between 5,000 and 30,000.
- Within this set, we calculated the minimum Instagram penetration rates and selected the top 1,000 municipalities with the highest minimum penetration.
    - To estimate minimum penetration rates, we conducted an independent data collection effort simulating a campaign before the experiment.
- We assigned treatment arms to the selected municipalities, stratifying on gender composition, education levels, racial composition, internet availability, past voting patterns for female candidates, GDP per capita, and age distribution.

Experimental Design - Treatments

Our experiment consisted of 6 treatments and control group randomly-assigned across 1,000 municipalities

1. Gender message targeted to women
2. Gender message targeted to men
3. Uninformative ability message
4. Informative ability message
5. Uninformative policy message
6. Informative policy message

Experimental Design - Gender Message

- "Did you know that women make up more than 50% the population, but they represent only 16% of the National Congress?"
- This messages was targeted to just women in some municipalities and to just men in other municipalities

Experimental Design - Uninformative Ability Message

- "What is important to you in this election? High quality and competent politicians that work hard for you make your local government and your community better. Vote for candidates who meet your quality standards."

Experimental Design - Informative Ability Message

- "What is important to you in this election? High quality and competent politicians that work hard for you make your local government and your community better. Did you know that studies show female politicians have higher quality,* are more competent and work harder** than male politicians? Vote for candidates who meet your quality standards."

Experimental Design - Uninformative Policy Message

- "What is important to you in this election? Education, health care, public safety? Vote for candidates who truly defend what is important for you every day."

Experimental Design - Informative Policy Message

- "What is important to you in this election? Education, health care, public safety? Did you know that studies show that female politicians invest 77% more on childcare*, welfare, employee flex time, and health care** than male politicians? Vote for candidates who truly defend what is important for you every day."

Data

- Electoral data come from the Superior Electoral Court (TSE)
  - total number of registered voters, votes for each candidate, and candidates' characteristics such as gender, race, education level and declared wealth
  - Main variable: the vote share for female candidates
- Census data from Brazilian Institute of Geography and Statistics (IBGE)
  - population size, age distribution, literacy rates, racial composition, per capita GDP, schooling levels, and the degree of urbanization
- Digital accessibility data from National Telecommunications Agency (Anatel)
  - population covered by broadband or mobile internet services and the percentage of households with internet access

Estimation Equation

- Regression

$$
\begin{aligned}
v_m \quad = \quad & \beta_0 + \beta_1 V_m^{G,1} + \beta_2 V_m^{G,0} + \beta_3 V_m^A + \beta_4 T_m^A \\
& + \beta_5 V_m^P + \beta_6 T_m^P + X_m^{'}\gamma + \delta_{s(m)} + \epsilon_m
\end{aligned}
$$

$V_m^{G,1} = 1$ - females in the municipality received the gender message
$V_m^{G,0} = 1$ - males in the municipality received the gender message
$V_m^A = 1$ - municipality received the uninformative ability message
$T_m^A = 1$ - municipality received the informative ability message
$V_m^P = 1$ - municipality received the uninformative policy message
$T_m^P = 1$ - municipality received the informative policy message
δ_s - strata fixed effects
X_m - vector municipal controls
ϵ_m error term, robust to heteroskedasticity

Reduced Form Estimates

	Vote Share for Female Candidates			
	(1)	(2)	(3)	(4)
Gender - Female	1.141	0.940	0.948	1.008
	(0.918)	(0.915)	(0.917)	(0.908)
Gender - Male	1.790*	1.879**	1.806*	1.800*
	(0.933)	(0.922)	(0.924)	(0.928)
Ability Uninformative	1.085	1.045	1.031	1.100
	(0.924)	(0.915)	(0.915)	(0.916)
Ability Informative	0.284	0.280	0.285	0.354
	(0.923)	(0.908)	(0.912)	(0.919)
Policy Uninformative	-0.298	-0.218	-0.216	-0.267
	(0.961)	(0.967)	(0.966)	(0.970)
Policy Informative	1.432	1.394	1.385	1.419
	(0.959)	(0.946)	(0.948)	(0.946)
DV Control Mean	22.97	22.97	22.97	22.97
R^2	0.03	0.05	0.05	0.06
Number of Obs.	1000	1000	1000	1000
Strata FE	Y	Y	Y	Y
Lagged DV	N	Y	Y	Y
Controls	N	N	Y	Y
Region FE	N	N	N	Y

Reduced Form Estimates - Issues

- The effects of the messages can be difficult to interpret in the reduced-form:
- Consider ability: voting depends on individuals' subjective prior beliefs about female candidates' abilities relative to male candidates
  - Depending on voters' priors, we can have opposite effects that wash out in aggregate
- Unobserved heterogeneity in the salience weights
  - If voters assign greater weight to gender than to ability, then even if our informative treatment alters beliefs about female candidates' ability, this may not manifest in vote choices.

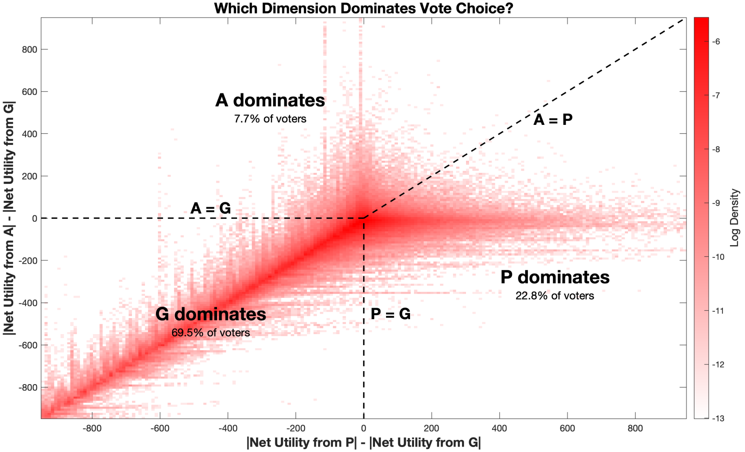
Reduced Form Estimates - Other Outcomes

	Turnout	Campaign Spending Males	Campaign Spending Females	Share Elected Females
	(1)	(2)	(3)	(4)
Gender - Female	-0.002	-10.643	21.877	0.014
	(0.003)	(174.848)	(153.136)	(0.013)
Gender - Male	-0.001	49.682	19.731	0.018
	(0.003)	(180.144)	(155.374)	(0.014)
Ability Uninformative	0.000	31.604	31.722	0.038**
	(0.003)	(184.925)	(156.190)	(0.016)
Ability Informative	-0.001	-21.038	2.883	-0.003
	(0.003)	(176.264)	(156.901)	(0.013)
Policy Uninformative	-0.001	298.856	182.369	0.023
	(0.003)	(221.219)	(186.854)	(0.016)
Policy Informative	0.003	154.277	77.181	0.028**
	(0.003)	(183.438)	(163.118)	(0.014)
DV Control Mean	0.85	1969.23	1680.76	0.12
R^2	0.63	0.23	0.22	0.10
Number of Obs.	998	1000	1000	1000
Strata FE	Y	Y	Y	Y
Lagged DV	Y	N	N	N
Controls	Y	Y	Y	Y

Structural Model - Parameter Estimates

Parameter	Description	Models (1)	(2)	(3)	(4)	(5)
ω_{GF}	Baseline weight G (F)	4.088***	3.878***	4.847***	6.772***	1498.302***
		(0.010)	(0.031)	(0.015)	(0.382)	(8.599)
ω_{GM}	Baseline weight G (M)	6.233***	7.049***	6.613***	13.404***	931.560***
		(0.012)	(0.028)	(0.023)	(0.663)	(0.000)
λ_{GF}	Effect of G message (F)	-0.018	-0.000	-0.003	0.068	48.147***
		(0.034)	(0.032)	(0.009)	(0.189)	(1.351)
λ_{GM}	Effect of G message (M)	-0.533***	-1.528***	-0.859***	-1.552***	-931.456***
		(0.015)	(0.018)	(0.014)	(0.361)	(0.000)
ω_{A0}	Baseline weight G	2.150***	1.995***	1.705***	0.312***	0.861***
		(0.519)	(0.412)	(0.593)	(0.036)	(0.003)
λ_{A}	Effect of unifo ability message	-0.162***	-0.168***	0.121***	-0.331***	-0.458***
		(0.022)	(0.026)	(0.012)	(0.078)	(0.002)
ω_{P0}	Baseline weight Policy	1.343**	-0.077	1.008*	0.663***	0.526***
		(0.564)	(0.600)	(0.598)	(0.028)	(0.001)
λ_{P}	Effect of uninfo policy message	0.083***	0.089***	0.064***	0.095***	0.036***
		(0.012)	(0.015)	(0.013)	(0.015)	(0.002)
ξ_{A}	Baseline net ability (F vs M)	0.120**	0.206**	-3.050*	-16.142***	-397.479***
		(0.059)	(0.096)	(1.847)	(2.231)	(2.558)
ρ_{A}	Effect of ability info	-0.092	-0.052	0.324	-1.562	-46.227***
		(0.064)	(0.185)	(0.218)	(2.354)	(1.530)
ξ_{P}	Baseline net policy (F vs M)	2.157***	-3.078***	4.084***	-3.855***	22.653***
		(0.624)	(0.857)	(1.212)	(0.235)	(0.071)
ρ_{P}	Effect of policy info	-0.192***	0.311***	-0.380***	0.470***	-0.953***
		(0.067)	(0.092)	(0.128)	(0.089)	(0.056)
μ	Relative policy (F voters)	-3.193***	8.216***	-2.886***	4.471***	-23.343***
		(0.876)	(2.952)	(0.905)	(0.245)	(0.121)
Region Fixed Effect		✓	-	✓	✓	✓
Candidate controls		✓	✓	✓	✓	✓
Municipio Characteristics		✓	✓	-	✓	✓
Salience-Weight functional Form		Exponential	Exponential	Exponential	Quadratic	Absolute
N	Number of Observations	1000	1000	1000	1000	1000
Obj Fun	Objective Function Value (MSE)	0.004	0.0041	0.0042	0.004	0.004

What determines vote choice?



Structural Model - Preference Parameters on Gender

- Women exhibit less gender bias (4.1) compared to men (6.2)
- Setting $\omega_{GM} = 0$ would increase female vote share by 7.98 p.p.
- Setting $\omega_{GF} = 0$ would decrease female vote share by 19.5 p.p.

Parameter	Description	Models (1)	(2)	(3)	(4)	(5)
ω_{GF}	Baseline weight G (F)	4.088***	3.878***	4.847***	6.772***	1498.302***
		(0.010)	(0.031)	(0.015)	(0.382)	(8.599)
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		(0.876)	(2.952)	(0.905)	(0.245)	(0.121)
Region Fixed Effect		✓	-	✓	✓	✓
Candidate controls		✓	✓	✓	✓	✓
Municipio Characteristics		✓	✓	-	✓	✓
Salience-Weight functional Form		Exponential	Exponential	Exponential	Quadratic	Absolute
N	Number of Observations	1000	1000	1000	1000	1000
Obj Fun	Objective Function Value (MSE)	0.004	0.0041	0.0042	0.004	0.004

Structural Model - Treatment Parameters on Gender

- The treatment reduced male voters' distaste for voting against their gender
- This lead to an increase in female vote share of 0.36 p.p. or about 1.5% relative to the mean female vote share. 1.5% is exactly the reduced-form (they should match on G)
- No effect on female voters

Parameter	Description	Models (1)	(2)	(3)	(4)	(5)
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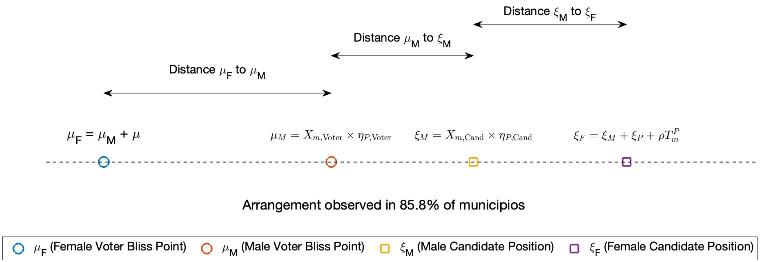
		(0.010)	(0.031)	(0.015)	(0.382)	(8.599)
ω_{GM}	Baseline weight G (M)	6.233***	7.049***	6.613***	13.404***	931.560***
		(0.012)	(0.028)	(0.023)	(0.663)	(0.000)
λ_{GF}	Effect of G message (F)	-0.018	-0.000	-0.003	0.068	48.147***
		(0.034)	(0.032)	(0.009)	(0.189)	(1.351)
λ_{GM}	Effect of G message (M)	-0.533***	-1.528***	-0.859***	-1.552***	-931.456***
		(0.015)	(0.018)	(0.014)	(0.361)	(0.000)
ω_{A0}	Baseline weight Ability	2.150***	1.995***	1.705***	0.312***	0.861***
		(0.519)	(0.412)	(0.593)	(0.036)	(0.003)
λ_A	Effect of unifo ability message	-0.162***	-0.168***	0.121***	-0.331***	-0.458***
		(0.022)	(0.026)	(0.012)	(0.078)	(0.002)
ω_{P0}	Baseline weight Policy	1.343**	-0.077	1.008*	0.663***	0.526***
		(0.564)	(0.600)	(0.598)	(0.028)	(0.001)
λ_P	Effect of uninfo policy message	0.083***	0.089***	0.064***	0.095***	0.036***
		(0.012)	(0.015)	(0.013)	(0.015)	(0.002)
ξ_A	Baseline net ability (F vs M)	0.120**	0.206**	-3.050*	-16.142***	-397.479***
		(0.059)	(0.096)	(1.847)	(2.231)	(2.558)
ρ_A	Effect of ability info	-0.092	-0.052	0.324	-1.562	-46.227***
		(0.064)	(0.185)	(0.218)	(2.354)	(1.530)
ξ_P	Baseline net policy (F vs M)	2.157***	-3.078***	4.084***	-3.855***	22.653***
		(0.624)	(0.857)	(1.212)	(0.235)	(0.071)
ρ_P	Effect of policy info	-0.192***	0.311***	-0.380***	0.470***	-0.953***
		(0.067)	(0.092)	(0.128)	(0.089)	(0.056)
μ	Relative policy (F voters)	-3.193***	8.216***	-2.886***	4.471***	-23.343***
		(0.876)	(2.952)	(0.905)	(0.245)	(0.121)
Region Fixed Effect		✓	-	✓	✓	✓
Candidate controls		✓	✓	✓	✓	✓
Municipio Characteristics		✓	✓	-	✓	✓
Salience-Weight functional Form		Exponential	Exponential	Exponential	Quadratic	Absolute
N	Number of Observations	1000	1000	1000	1000	1000
Obj Fun	Objective Function Value (MSE)	0.004	0.0041	0.0042	0.004	0.004

Structural Model - Policy Parameters

- Setting $\omega_P = 0$, increase vote shares substantially by 13.7 p.p.
- Significant mismatch between female voters' policy preferences (μ) and beliefs about female candidates' policy positions (ξ_P)
  - Female candidates are perceived as more conservative than female voters themselves
- Setting $\xi_P = 0$ increase female candidates' vote shares by 20.13 p.p.

Parameter	Description	Models (1)	(2)	(3)	(4)	(5)
ω_{GF}	Baseline weight G (F)	4.088***	3.878***	4.847***	6.772***	1498.302***
		(0.010)	(0.031)	(0.015)	(0.382)	(8.599)
ω_{GM}	Baseline weight G (M)	6.233***	7.049***	6.613***	13.404***	931.560***
		(0.012)	(0.028)	(0.023)	(0.663)	(0.000)
λ_{GF}	Effect of G message (F)	-0.018	-0.000	-0.003	0.068	48.147***
		(0.034)	(0.032)	(0.009)	(0.189)	(1.351)
λ_{GM}	Effect of G message (M)	-0.533***	-1.528***	-0.859***	-1.552***	-931.456***
		(0.015)	(0.018)	(0.014)	(0.361)	(0.000)
ω_{A0}	Baseline weight Ability	2.150***	1.995***	1.705***	0.312***	0.861***
		(0.519)	(0.412)	(0.593)	(0.036)	(0.003)
λ_A	Effect of unifo ability message	-0.162***	-0.168***	0.121***	-0.331***	-0.458***
		(0.022)	(0.026)	(0.012)	(0.078)	(0.002)
ω_{P0}	Baseline weight Policy	1.343**	-0.077	1.008*	0.663***	0.526***
		(0.564)	(0.600)	(0.598)	(0.028)	(0.001)
λ_P	Effect of uninfo policy message	0.083***	0.089***	0.064***	0.095***	0.036***
		(0.012)	(0.015)	(0.013)	(0.015)	(0.002)
ξ_A	Baseline net ability (F vs M)	0.120**	0.206**	-3.050*	-16.142***	-397.479***
		(0.059)	(0.096)	(1.847)	(2.231)	(2.558)
ρ_A	Effect of ability info	-0.092	-0.052	0.324	-1.562	-46.227***
		(0.064)	(0.185)	(0.218)	(2.354)	(1.530)
ξ_P	Baseline net policy (F vs M)	2.157***	-3.078***	4.084***	-3.855***	22.653***
		(0.624)	(0.857)	(1.212)	(0.235)	(0.071)
ρ_P	Effect of policy info	-0.192***	0.311***	-0.380***	0.470***	-0.953***
		(0.067)	(0.092)	(0.128)	(0.089)	(0.056)
μ	Relative policy (F voters)	-3.193***	8.216***	-2.886***	4.471***	-23.343***
		(0.876)	(2.952)	(0.905)	(0.245)	(0.121)
Region Fixed Effect		✓	-	✓	✓	✓
Candidate controls		✓	✓	✓	✓	✓
Municipio Characteristics		✓	✓	-	✓	✓
Salience-Weight functional Form		Exponential	Exponential	Exponential	Quadratic	Absolute
N	Number of Observations	1000	1000	1000	1000	1000
Obj Fun	Objective Function Value (MSE)	0.004	0.0041	0.0042	0.004	0.004

Voter Bliss Points - Case 1

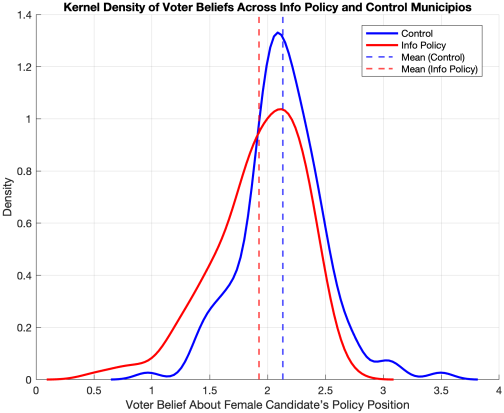


Structural Model - Policy Treatment Parameters

- Uninformative policy message increased the salience of policy dimension
- But how this translates into votes depends on relative positions
- Informative policy message reduced the perceived distance between female voters' bliss points and female candidates' positions, increasing female vote shares by 0.54 p.p.

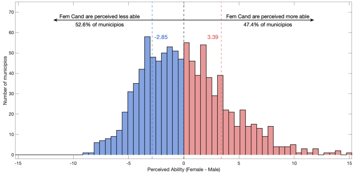
Parameter	Description	Models (1)	(2)	(3)	(4)	(5)
ω_{GF}	Baseline weight G (F)	4.088***	3.878***	4.847***	6.772***	1498.302***
		(0.010)	(0.031)	(0.015)	(0.382)	(8.599)
ω_{GM}	Baseline weight G (M)	6.233***	7.049***	6.613***	13.404***	931.560***
		(0.012)	(0.028)	(0.023)	(0.663)	(0.000)
λ_{GF}	Effect of G message (F)	-0.018	-0.000	-0.003	0.068	48.147***
		(0.034)	(0.032)	(0.009)	(0.189)	(1.351)
λ_{GM}	Effect of G message (M)	-0.533***	-1.528***	-0.859***	-1.552***	-931.456***
		(0.015)	(0.018)	(0.014)	(0.361)	(0.000)
ω_{A0}	Baseline weight Ability	2.150***	1.995***	1.705***	0.312***	0.861***
		(0.519)	(0.412)	(0.593)	(0.036)	(0.003)
λ_A	Effect of unifo ability message	-0.162***	-0.168***	0.121***	-0.331***	-0.458***
		(0.022)	(0.026)	(0.012)	(0.078)	(0.002)
ω_{P0}	Baseline weight Policy	1.343**	-0.077	1.008*	0.663***	0.526***
		(0.564)	(0.600)	(0.598)	(0.028)	(0.001)
λ_P	Effect of uninfo policy message	0.083***	0.089***	0.064***	0.095***	0.036***
		(0.012)	(0.015)	(0.013)	(0.015)	(0.002)
ξ_A	Baseline net ability (F vs M)	0.120**	0.206**	-3.050*	-16.142***	-397.479***
		(0.059)	(0.096)	(1.847)	(2.231)	(2.558)
ρ_A	Effect of ability info	-0.092	-0.052	0.324	-1.562	-46.227***
		(0.064)	(0.185)	(0.218)	(2.354)	(1.530)
ξ_P	Baseline net policy (F vs M)	2.157***	-3.078***	4.084***	-3.855***	22.653***
		(0.624)	(0.857)	(1.212)	(0.235)	(0.071)
ρ_P	Effect of policy info	-0.192***	0.311***	-0.380***	0.470***	-0.953***
		(0.067)	(0.092)	(0.128)	(0.089)	(0.056)
μ	Relative policy (F voters)	-3.193***	8.216***	-2.886***	4.471***	-23.343***
		(0.876)	(2.952)	(0.905)	(0.245)	(0.121)
Region Fixed Effect		✓	-	✓	✓	✓
Candidate controls		✓	✓	✓	✓	✓
Municipio Characteristics		✓	✓	-	✓	✓
Salience-Weight functional Form		Exponential	Exponential	Exponential	Quadratic	Absolute
N	Number of Observations	1000	1000	1000	1000	1000
Obj Fun	Objective Function Value (MSE)	0.004	0.0041	0.0042	0.004	0.004

Structural Model - Policy Treatment Parameters



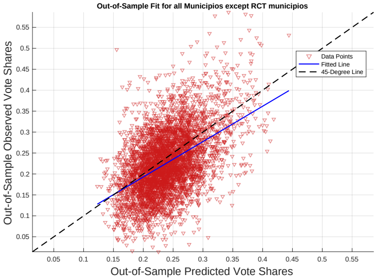
Structural Model - Ability Parameters

- Setting $\omega_A = 0$, increases female vote shares modestly by 1.2 p.p.
- We don't find a significant treatment effect
- Voters perceive female candidates as having higher ability (but depends on the controls)
- Substantial heterogeneity in beliefs

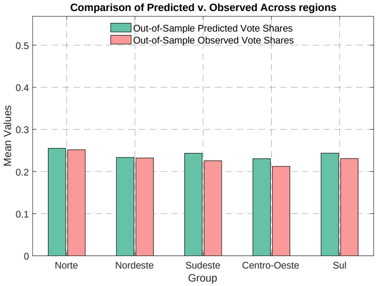


		Models				
Parameter	Description	(1)	(2)	(3)	(4)	(5)
ω_{GF}	Baseline weight G (F)	4.088***	3.878***	4.847***	6.772***	1498.302***
		(0.010)	(0.031)	(0.015)	(0.382)	(8.599)
ω_{GM}	Baseline weight G (M)	6.233***	7.049***	6.613***	13.404***	931.560***
		(0.012)	(0.028)	(0.023)	(0.663)	(0.000)
λ_{GF}	Effect of G message (F)	-0.018	-0.000	-0.003	0.068	48.147***
		(0.034)	(0.032)	(0.009)	(0.189)	(1.351)
λ_{GM}	Effect of G message (M)	-0.533***	-1.528***	-0.859***	-1.552***	-931.456***
		(0.015)	(0.018)	(0.014)	(0.361)	(0.000)
ω_{A0}	Baseline weight Ability	2.150***	1.995***	1.705***	0.312***	0.861***
		(0.519)	(0.412)	(0.593)	(0.036)	(0.003)
λ_A	Effect of unifo ability message	-0.162***	-0.168***	0.121***	-0.331***	-0.458***
		(0.022)	(0.026)	(0.012)	(0.078)	(0.002)
ω_{P0}	Baseline weight Policy	1.343**	-0.077	1.008*	0.663***	0.526***
		(0.564)	(0.600)	(0.598)	(0.028)	(0.001)
λ_P	Effect of uninfo policy message	0.083***	0.089***	0.064***	0.095***	0.036***
		(0.012)	(0.015)	(0.013)	(0.015)	(0.002)
ξ_A	Baseline net ability (F vs M)	0.120**	0.206**	-3.050*	-16.142***	-397.479***
		(0.059)	(0.096)	(1.847)	(2.231)	(2.558)
ρ_A	Effect of ability info	-0.092	-0.052	0.324	-1.562	-46.227***
		(0.064)	(0.185)	(0.218)	(2.354)	(1.530)
ξ_P	Baseline net policy (F vs M)	2.157***	-3.078***	4.084***	-3.855***	22.653***
		(0.624)	(0.857)	(1.212)	(0.235)	(0.071)
ρ_P	Effect of policy info	-0.192***	0.311***	-0.380***	0.470***	-0.953***
		(0.067)	(0.092)	(0.128)	(0.089)	(0.056)
μ	Relative policy (F voters)	-3.193***	8.216***	-2.886***	4.471***	-23.343***
		(0.876)	(2.952)	(0.905)	(0.245)	(0.121)
Region Fixed Effect		✓	-	✓	✓	✓
Candidate controls		✓	✓	✓	✓	✓
Municipio Characteristics		✓	✓	-	✓	✓
Salience-Weight functional Form		Exponential	Exponential	Exponential	Quadratic	Absolute
N	Number of Observations	1000	1000	1000	1000	1000
Obj Fun	Objective Function Value (MSE)	0.004	0.0041	0.0042	0.004	0.004

Out-of-Sample Fit



(a)



(b)

Validation

A high quality in-sample fit should be a given for structural models, while validation+out-of-sample performance are key to assess model misspecification. We show

1. Performance of two-fold validation w/ 80-20 training sample-testing sample split
2. Additional out-of-sample fit performances, including municipios at the boundaries of RCT sample, far, etc.

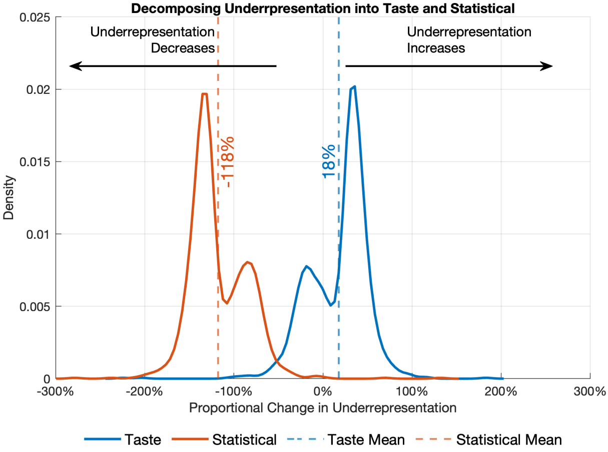
Decomposing Statistical vs. Taste-Based Discrimination

- Because vote choices are nonlinear in discrimination sources, decomposition depends on the order in which each is shut down.
- Evaluate both: shutting down statistical first (ST) & statistical after taste-based (TS).
- Underrepresentation is: $\Delta_{base} = \text{Fem Pop Share} - s(\hat{\theta})$.
- Compute marginal changes for ST:
  1. $\Delta_{ST,stat} = s(\hat{\theta}) - s(\hat{\theta}; \text{no-stat})$
  2. $\Delta_{ST,taste} = s(\hat{\theta}; \text{no-stat}) - s(\hat{\theta}; \text{no-stat, no-taste})$
  3. And analogously for TS
- Final decomposition:

$$\text{Decomp}_{stat} = \frac{\Delta_{ST,stat} + \Delta_{TS,stat}}{2 \cdot \Delta_{base}}; \ \text{Decomp}_{taste} = \frac{\Delta_{TS,taste} + \Delta_{ST,taste}}{2 \cdot \Delta_{base}}$$

By construction: $\text{Decomp}_{stat} + \text{Decomp}_{taste} = 100\%$.
We compute these for each municipality & plot the resulting densities.

Statistical vs. Taste-Based Discrimination



Counterfactual Simulations

Counterfactual Name	Description	Vote-Share Est (p.p.)	Vote-Share Diff (p.p.)	Vote-Share p-value	Votes Est	Votes Diff	Votes p-value
Baseline	No messages sent to voters	24.005			6665.976		
		(2.266)			(703.590)		
Gender	Gender messages sent to all voters	24.114	0.109	0.804	6674.492	8.517	0.946
		(2.265)	(0.438)		(703.158)	(124.604)	
Gender - Females	Gender messages sent to all female voters	23.78	-0.23	0.600	6600.54	-65.23	0.600
		(2.26)	(0.43)		(701.24)	(124.38)	
Gender - Males	Gender messages sent to all male voters	24.34	0.34***	0.000	6739.53	73.76***	0.000
		(2.27)	(0.09)		(705.81)	(20.15)	
Info Ability	Informative Ability message sent to all voters	23.828	-0.177	0.187	6577.587	-88.388*	0.055
		(2.305)	(0.134)		(711.761)	(46.097)	
Uninformative Ability	Uninformative Ability message sent to all voters	24.038	0.033	0.513	6639.738	-26.237*	0.064
		(2.292)	(0.050)		(712.030)	(14.165)	
Informative Policy	Informative Policy message sent to all voters	24.533	0.528**	0.045	6775.417	109.442	0.131
		(2.190)	(0.263)		(685.951)	(72.499)	
Uninformative Policy	Uninformative Policy message sent to all voters	22.993	-1.012***	0.000	6347.957	-318.019***	0.000
		(2.329)	(0.163)		(721.330)	(50.774)	
All Treatments	All messages sent	24.405	0.400	0.418	6674.022	8.047	0.955
		(2.218)	(0.494)		(691.008)	(143.317)	

Optimal Campaign Design

- Previous counterfactuals show not all messages increase female vote shares; voter heterogeneity plays a key role.
- We analyze the potential of an optimal campaign to maximize female electoral support.

Setup:

- Define a campaign as a binary vector $D \in \{0,1\}^{10}$:

$$D = \left(V^{G,0}, V^{A,0}, T^{A,0}, V^{P,0}, T^{P,0}, V^{G,1}, V^{A,1}, T^{A,1}, V^{P,1}, T^{P,1}\right)$$

- $g = 0$ for male voters, $g = 1$ for female voters.
- $s_m(D, X_m; \hat{\theta})$ = predicted female vote share in municipality m under campaign D.

Aggregate Optimal Campaign:

- Find $D^{\text{agg-optimal}}$ that maximizes the average female vote share:

$$D^{\text{agg-optimal}} = \arg \max_{D \in \{0,1\}^{10}} \frac{1}{M} \sum_{m=1}^{M} s_m(D, X_m; \hat{\theta})$$

Counterfactual Simulations

		Vote-Share			Votes		
Counterfactual Name	Description	Est (p.p.)	Diff (p.p.)	p-value	Est	Diff	p-value
Baseline	No messages sent to voters	24.005			6665.976		
		(2.266)			(703.590)		
Aggregate Optimal	Optimal campaign at the country level	25.015	1.011***	0.001	6842.793	177.019**	0.038
		(2.807)	(0.304)		(885.929)	(85.276)	
Municipal Optimal	Municipal Optimal campaign	25.412	1.408***	0.000	6956.087	290.313***	0.000
		(2.763)	(0.293)		(877.416)	(74.544)	
Municipal - Aggregate Optimal	Difference b/w municipal and national		0.397***	0.001		113.294***	0.002
			(0.118)			(36.178)	

Optimal Campaign Design

Optimal messages:

- Males: $V^{G,0} = 1$, $V^{P,0} = 1$, others $= 0$.
- Females: $T^{A,1} = 1$, $V^{P,1} = 1$, others $= 0$.

Results:

- Increase in female vote share:
  - $+1.05$ p.p. (s.e. $= 0.281$) in RCT sample.
  - $+1.01$ p.p. (s.e. $= 0.304$) in full Brazil sample.
- Translates to $+72{,}000$ votes (RCT) and $+975{,}000$ votes (nationwide).

Cost Efficiency:

- 1.6 votes per dollar (RCT sample),
- 0.96 votes per dollar (full sample).

Municipality Optimal Campaign

- Tailoring campaigns to local context may enhance effectiveness.
- We define the Municipality Optimal Campaign by selecting, for each municipality m, the campaign D_m^* that maximizes predicted female vote share:

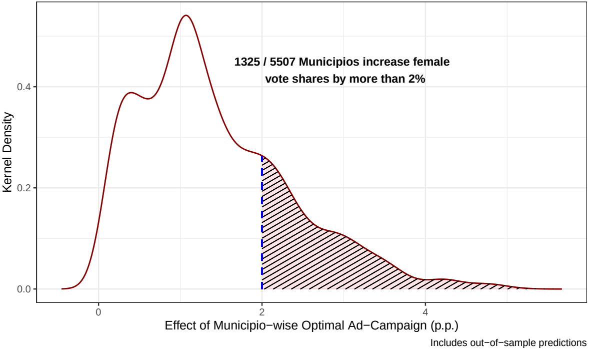
$$D_m^* = \arg \max_{D \in \{0,1\}^{10}} s_m(D, X_m; \hat{\theta})$$

$$s^{\text{mun-optimal}}(\hat{\theta}) = \frac{1}{M} \sum_{m=1}^{M} s_m(D_m^*, X_m; \hat{\theta})$$

Counterfactual Simulations

		Vote-Share			Votes		
Counterfactual Name	Description	Est (p.p.)	Diff (p.p.)	p-value	Est	Diff	p-value
Baseline	No messages sent to voters	24.005			6665.976		
		(2.266)			(703.590)		
Aggregate Optimal	Optimal campaign at the country level	25.015	1.011***	0.001	6842.793	177.019**	0.038
		(2.807)	(0.304)		(885.929)	(85.276)	
Municipal Optimal	Municipal Optimal campaign	25.412	1.408***	0.000	6956.087	290.313***	0.000
		(2.763)	(0.293)		(877.416)	(74.544)	
Municipal - Aggregate Optimal	Difference b/w municipal and national		0.397***	0.001		113.294***	0.002
			(0.118)			(36.178)	

Counterfactual Simulations



Municipality Optimal Campaign: Results

Vote share gains:

- +1.463 p.p. (s.e. = 0.281) in RCT sample
- +1.408 p.p. (s.e. = 0.293) in full Brazil sample
- ≈0.4 p.p. improvement over Aggregate Optimal Campaign

Vote totals:

- +99,727 votes (RCT), +1,598,754 votes (national)
- 24% of municipalities see ≥2 p.p. increase

Message prevalence in optimal mix (Brazil sample):

- Male: Gender (75.5%), Inf. Ability (0%), **Uninf. Ability (27.8%)**, Inf. Policy (71.9%), Uninf. Policy (0%)
- Female: Gender (0%), Inf. Ability (0%), **Uninf. Ability (52.7%)**, Inf. Policy (85.7%), Uninf. Policy (0%)

Cost efficiency:

- Avg. messages/municipality: 3.07 (vs. 4 in Aggregate Campaign)
- Votes per dollar: 2.97 (RCT), 1.91 (Brazil)

Persuasion Rates

		Vote-Share			Persuasion Rates		
Counterfactual Name	Description	Est (p.p.)	Diff (p.p.)	p-value	Est (p.p.)	Diff (p.p.)	p-value
Baseline	No messages sent to voters	23.846			23.846		
		(2.266)			(2.266)		
Aggregate Optimal	Optimal campaign at the RCT-sample level	24.898	1.051***	0.000	24.898	1.381***	0.000
		(2.253)	(0.281)		(2.253)	(0.374)	
Municipio-wise Optimal	Municipio-wise Optimal campaign	25.309	1.463***	0.000	25.309	1.921***	0.000
		(2.218)	(0.281)		(2.218)	(0.369)	

- Municipio-wise optimal → persuasion rate is ˜2%
  Green and Gerber - GOTV - 11.5-15.6%
  Enikolopov et al. 2010 - Independent Media in Russia - 7.7%
  Gentzkow (2006) - TV - 4.4%
  DellaVigna and Kaplan (2007) - Fox News - 11.6%

Conclusions

- Workhorse empirical model of political behavior $\Rightarrow$ quantitative assessment of discrimination in elections
- Evidence of both taste-based & statistical discrimination against female candidates
- In Brazil, our counterfactual analysis shows that substantial gains in gender representation can be achieved (over 2 p.p.)
- The analysis also identifies specific messages that may backfire
- Future research in Political Economy & Political Science can extend our framework to explore alternative dimensions of identity (Gennaioli & Tabellini, 2025)