

Do Stereotypes Explain Discrimination Against Minority Candidates or Discrimination
in Favor of Majority Candidates?

Appendix

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A Sample and data

Table 1: Number of observations in the experimental conditions

Candidate name	Manipulation of information	n
Italian	Control	202
Italian	Positive traits	202
Italian	Positive civic citizenship	201
Italian	Positive traits & positive civic citizenship	189
Algerian	Control	203
Algerian	Positive traits	205
Algerian	Positive civic citizenship	197
Algerian	Positive traits & positive civic citizenship	198

Table 2: Descriptive statistics of dependent variables

	Min	Max	Mean	SD
Nomination	0.00	10.00	5.41	2.57
Vote	0.00	10.00	5.25	2.70
Negative rating	0.00	1.00	0.19	0.40
Positive rating	0.00	1.00	0.41	0.49

B Experimental manipulations

B.1 Description of vignettes

Below, I describe my vignettes. Each vignette was presented either with the Algerian name, Ahmed Haddou, or the Italian name, Giuseppe Martinelli. First, the following introduction was presented to all subjects independent of experimental condition:

Given the recent tensions in the Conte government over infrastructure, it is possible that Italians may soon be called to new general elections. The experts agree that the person described below may have a good

chance of being nominated as a candidate for the “[respondent’s indicated closest party]” party in your district. Please read the description of the potential candidate carefully.

Before the respondents saw one of the following vignettes, they had the opportunity to retrieve information about the electoral system in Italy. In the description they also read that they could vote for the candidate in a first-past-the-post single member district.

Control condition: [Giuseppe Martinelli/Ahmed Haddou] is a 45-year-old and aspires to run for national parliamentary elections for the first time.

Positive trait description: [Giuseppe Martinelli/Ahmed Haddou] is a 45-year-old engineer who aspires to run for national parliamentary elections for the first time. He has a reputation as a sincere and honest politician, which was confirmed at this year’s Forum on Anti-Corruption where he received an honor for his commitment against corruption and fraud. Although he spent some time abroad, he has established ties to both entrepreneurs and unions in Italy. Recently, he was selected because of his experience by entrepreneurs and unions to serve as an expert for the development of a joint proposal to increase trade and growth. Besides his political activities, he likes to spend time with his children and to get socially involved, for example, he organizes holidays for disadvantaged families.

Positive civic citizenship description: [Giuseppe Martinelli/Ahmed Haddou] is a 45-year old commercial clerk who aspires to run for national parliamentary elections for the first time. He has placed his emphasize in the party on the issue of promoting local and regional economy and culture. This engagement also arose from his journey a couple of years ago, when he traveled through all the Italian regions to get to know the local cultures better. In his party, he is known for his exceptional interest in the Italian political system and political processes. Although some consider him as a quite harsh strategic, he has been in favor of

rejecting negotiations with a foreign company in his region because he feared that interests of the local community and Italy as a whole would be threatened.

Positive trait and positive civic citizenship description: [Giuseppe Martinelli/Ahmed Haddou] is a 45-year-old engineer who aspires to run for national parliamentary elections for the first time. He has a reputation as a sincere and honest politician, which was confirmed at this year's Forum on Anti-Corruption where he received an honor for his commitment against corruption and fraud. In his party, he is known for his exceptional interest in the Italian political system and political processes. Although some consider him as a quite harsh strategic, he has been in favor of rejecting negotiations with a foreign company in his region because he feared that interests of the local community and Italy as a whole would be threatened. He has placed his emphasize in the party on the issue of promoting local and regional economy and culture. This engagement also arose from his journey a couple of years ago, when he traveled through all the Italian regions to get to know the local cultures better. Although he spent some time abroad, he has established ties to both entrepreneurs and unions in Italy. Recently, he was selected because of his experience by entrepreneurs and unions to serve as an expert for the development of a joint proposal to increase trade and growth. Besides his political activities, he likes to spend time with his children and to get socially involved, for example, he organizes holidays for disadvantaged families.

Characteristics to measure traits and civic citizenship in the manipulation check:

Warmth: warm, trustworthy, helpful

Competence: skilled, competent, respected

Civic citizenship: knowledgeable of Italian politics, advocates Italian interests, values Italian culture

Warmth and competence ratings are combined into the indicator "traits" and are rescaled to the same scale

as the “civic citizenship” indicator (0-30).

B.2 Manipulation checks

Manipulation checks are based on two pilot studies. The first pilot study (N=442) shows that most respondents correctly identified whether the candidate name is native (0) or foreign (1): $M_{T_0} = 0.04$, $M_{T_1} = 0.84$, $p < 0.000$. In the second pilot study (N=242), respondents evaluated the candidate regarding a set of character trait and civic citizenship qualities, on the basis of which indicators for character traits and civic citizenship, respectively, have been built by adding the values from the individual evaluations (see online appendix Section B.1 for characteristics). Compared to the control group, respondents in the condition with the positive manipulation of character traits and civic citizenship allocated (on a scale from 0 to 30) significantly higher character trait ($M_{Control} = 16.64$, $M_{Positive\ traits} = 19.40$, $p < 0.006$) and civic citizenship ratings ($M_{Control} = 16.06$, $M_{Positive\ civic\ citizenship} = 18.92$, $p < 0.004$), respectively. In other words, my information manipulations influence the perception of candidates in the expected direction (see Table 3).

Table 3: Manipulation check second pilot study

Manipulation of information	Traits	Civic citizenship
Control	16.64 (6.69)	16.06 (6.79)
Positive traits	19.40 (5.96)	18.62 (5.99)
Positive civic citizenship	18.49 (5.01)	18.92 (5.71)

Note: Means and standard deviations (in parentheses) are displayed.

C Measurement of dependent variables

Question wording:

(1) Dependent variable “support candidate nomination”

Q: In your opinion, should the party nominate [candidate name] as a candidate in the next Italian parliamentary elections?

A: Your support for the nomination: [I am not at all supportive of his nomination, 1, 2, ..., 8, 9, I am very supportive of his nomination]

(2) Dependent variable “likelihood voting for the candidate”

Q: Imagine that the party has nominated [candidate name] as an official candidate. How likely is it that you will vote for him?

A: Probability of voting for the candidate: [very unlikely, 1, 2, ..., 8, 9, very likely]

(3) Dependent variable “positive, neutral, or negative rating”

Q: You now have the opportunity to anonymously make another assessment of the potential candidate [candidate name]. Our aim is to send the party a comprehensive evaluation report on the potential candidate in question. Your answer will be included in the report on the overall evaluation of [candidate name] available to the party. Please choose one of the following options:

A: Your decision:

- o I am against the nomination of [candidate name]. This statement is included as a negative rating in the overall evaluation.
- o I am in favor of the nomination of [candidate name]. This statement is included as a positive rating

in the overall evaluation.

- o I am neither in favor of nor against the nomination of [candidate name]. This statement has no influence on the overall evaluation.
- o I prefer not to answer.

D Results regarding overall electoral discrimination

In order to assess electoral discrimination, irrespective of respondents' ideological position, I only include respondents in the control condition and regress the dependent variables on the name of the candidate, as shown in Equation 1:

$$Y_i = \beta_0 + \beta_1 CandidateName_i + \beta_2 (M_i = Control) + \epsilon_i \quad (1)$$

Do voters discriminate against candidates with a migration background? In line with expectations, Italian citizens were considerably less likely to cast their vote for the candidate if he had an Algerian as compared to an Italian name (see Table 4). The vote gap between the two candidates was a remarkable 8 percentage points on a 0-1 scale ($p=0.003$). This difference is even more striking, considering that the potential candidate was always (putatively) put forward by the party to which the respondent feels closest. This means that a considerable number of Italian citizens are willing either to abstain from voting or to vote for a party other than their preferred one due to the name of a candidate. Furthermore, I find strong evidence for discrimination *against* the candidate with a migration background in the finding that respondents were a staggering 20 percentage points more likely to send a negative rating of the potential candidate to the party when they evaluated a candidate with an Algerian name compared to one with an Italian name.

Interestingly, though, how strongly the respondents support their preferred party nominating a candidate is not evidently affected by his name ($p=0.100$), as shown in Table 4. Results also suggest that voters do not rate the potential candidate with an Algerian name positively less often than they do the potential candidate with an Italian name ($p=0.181$) (see Table 4). Put differently, while overall there is no evidence that voters discriminate *in favor of* a majority candidate, results suggest that voters strongly discriminate *against* a candidate with a migration background. These initial results contradict Hypothesis 1 regarding in-group favoritism, i.e. that voters have a tendency to preferentially treat a candidate with an Italian name over one with an Algerian name. The analyses that are provided in the paper, however, take a closer look at these results by distinguishing between the ideological position of Italian citizens.

Table 4: The effect of candidate names on electoral support and opposition

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.47*** (0.02)	0.49*** (0.02)	0.29*** (0.03)	0.14*** (0.03)
Candidate name (Algerian)	-0.04 (0.02)	-0.08** (0.03)	-0.06 (0.05)	0.20*** (0.04)
R ²	0.01	0.02	0.01	0.05
Adj. R ²	0.00	0.02	0.00	0.05
N	402	398	358	358
RMSE	0.25	0.26	0.44	0.42

Note: Coefficients and standard errors (in parentheses) from linear regression models. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

Findings in Tables 5 and 6 confirm that results do not change substantially if logit models are estimated (Table 5) or if immigrant-origin respondents are excluded from the analysis (Table 6).

Table 5: Effect of candidate names on electoral support and opposition

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.47*** (0.02)	0.49*** (0.02)	-0.90*** (0.17)	-1.78*** (0.22)
Candidate name (Algerian)	-0.04 (0.02)	-0.08** (0.03)	-0.33 (0.24)	1.12*** (0.27)
Adj. R ²	0.00	0.02		
N	402	398	358	358
AIC			410.23	384.24

Note: Coefficient and standard errors from linear regression models (models "Nominate" and "Vote") and logistic regression models (models "Positive rating" and "Negative rating"). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

Table 6: Effect of candidate name on electoral support and opposition, only respondents without a migration background

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.49*** (0.02)	0.51*** (0.02)	0.28*** (0.04)	0.16*** (0.04)
Candidate name (Algerian)	-0.05 (0.03)	-0.09** (0.03)	-0.06 (0.05)	0.20*** (0.05)
R ²	0.01	0.03	0.01	0.05
Adj. R ²	0.01	0.03	0.00	0.05
Num. obs.	319	317	298	298
RMSE	0.24	0.26	0.43	0.43

Note: Coefficients and standard errors (in parentheses) from linear regression models. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

E Regression outputs tables main analyses

Table 7: The effect of candidate names on electoral support and opposition, by ideological position of respondents

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.48*** (0.03)	0.50*** (0.03)	0.22*** (0.06)	0.08 (0.06)
Candidate name (Algerian)	0.05 (0.05)	0.02 (0.05)	0.18* (0.08)	0.16 (0.08)
Ideological position = center	-0.04 (0.05)	-0.05 (0.05)	0.00 (0.08)	0.16 (0.08)
Ideological position = right	0.03 (0.04)	0.02 (0.05)	0.23** (0.08)	0.05 (0.08)
Candidate name x ideol. pos.= center	-0.04 (0.06)	-0.03 (0.07)	-0.10 (0.12)	-0.06 (0.12)
Candidate name x ideol. pos. = right	-0.23*** (0.06)	-0.26*** (0.06)	-0.62*** (0.11)	0.18 (0.11)
R ²	0.07	0.11	0.11	0.09
Adj. R ²	0.06	0.10	0.09	0.08
N	357	355	318	318
RMSE	0.24	0.25	0.42	0.42

Note: Coefficients and standard errors (in parentheses) from linear regression models. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

Table 8: Effect of candidate names on electoral support and opposition, by ideological position of respondents

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.48*** (0.03)	0.50*** (0.03)	-1.27*** (0.34)	-2.44*** (0.52)
Candidate name (Algerian)	0.05 (0.05)	0.02 (0.05)	0.86* (0.44)	1.27* (0.61)
Ideological position = center	-0.04 (0.05)	-0.05 (0.05)	-0.00 (0.48)	1.29* (0.62)
Ideological position = right	0.03 (0.04)	0.02 (0.05)	1.08* (0.44)	0.52 (0.66)
Candidate name x ideol. pos. = center	-0.04 (0.06)	-0.03 (0.07)	-0.44 (0.64)	-0.78 (0.76)
Candidate name x ideol. pos. = right	-0.23*** (0.06)	-0.26*** (0.06)	-4.72*** (1.13)	0.52 (0.78)
Adj. R ²	0.06	0.10		
N	357	355	318	318
AIC			338.39	341.30

Note: Coefficients and standard errors from linear regression models (models "Nominate" and "Vote") and logistic regression models (models "Positive rating" and "Negative rating"). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

Table 9: Mediating effect of stereotypes, respondents in the ideological center

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.44*** (0.03)	0.46*** (0.03)	0.22** (0.07)	0.24*** (0.05)
Candidate name (Algerian)	0.02 (0.04)	-0.01 (0.05)	0.08 (0.10)	0.10 (0.08)
Positive traits	0.21*** (0.04)	0.18*** (0.05)	0.40*** (0.09)	-0.19* (0.08)
Positive civic citizenship	0.12** (0.04)	0.09 (0.05)	0.22* (0.10)	-0.08 (0.08)
Positive traits and civic citizenship	0.16*** (0.04)	0.09 (0.05)	0.25* (0.10)	-0.11 (0.08)
Candidate name x traits	-0.10 (0.06)	-0.09 (0.07)	-0.21 (0.14)	0.00 (0.11)
Candidate name x civic citizenship	-0.04 (0.06)	-0.05 (0.07)	-0.19 (0.14)	0.03 (0.11)
Candidate name x traits & civ. cit.	-0.03 (0.06)	0.04 (0.07)	-0.01 (0.14)	-0.04 (0.11)
R ²	0.09	0.06	0.07	0.05
Adj. R ²	0.07	0.04	0.05	0.03
N.	427	428	378	378
RMSE	0.23	0.25	0.48	0.39

Note: Coefficients and standard errors (in parentheses) from linear regression models. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

Table 10: Mediating effect of stereotypes, respondents on the ideological left

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.48*** (0.03)	0.50*** (0.03)	0.22** (0.07)	0.08 (0.04)
Candidate name (Algerian)	0.05 (0.04)	0.02 (0.05)	0.18 (0.09)	0.16* (0.06)
Positive traits	0.19*** (0.05)	0.16*** (0.05)	0.44*** (0.10)	-0.02 (0.06)
Positive civic citizenship	0.07 (0.04)	0.07 (0.05)	0.23* (0.09)	0.03 (0.06)
Positive traits and civic citizenship	0.19*** (0.05)	0.19*** (0.05)	0.38*** (0.10)	-0.06 (0.06)
Candidate name x traits	-0.10 (0.06)	-0.08 (0.07)	-0.28* (0.14)	-0.07 (0.09)
Candidate name x civic citizenship	-0.03 (0.06)	-0.07 (0.07)	-0.17 (0.13)	-0.08 (0.09)
Candidate name x traits & civ. cit.	-0.02 (0.06)	-0.04 (0.07)	-0.14 (0.13)	-0.11 (0.09)
R ²	0.09	0.08	0.08	0.04
Adj. R ²	0.07	0.06	0.06	0.03
N	442	440	413	413
RMSE	0.24	0.25	0.49	0.32

Note: Coefficients and standard errors (in parentheses) from linear regression models. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

Table 11: Mediating effect of stereotypes, respondents on the ideological right

	Nominate	Vote	Positive rating	Negative rating
Intercept	0.51*** (0.03)	0.52*** (0.03)	0.45*** (0.06)	0.13* (0.06)
Candidate name (Algerian)	-0.17*** (0.04)	-0.24*** (0.05)	-0.44*** (0.09)	0.34*** (0.08)
Positive traits	0.11* (0.04)	0.11* (0.05)	-0.02 (0.08)	-0.02 (0.08)
Positive civic citizenship	0.05 (0.04)	0.04 (0.05)	0.01 (0.08)	0.01 (0.08)
Positive traits and civic citizenship	0.16*** (0.04)	0.09* (0.05)	0.05 (0.08)	-0.03 (0.08)
Candidate name x traits	0.00 (0.06)	0.02 (0.06)	0.28* (0.12)	-0.09 (0.11)
Candidate name x civic citizenship	0.06 (0.06)	0.09 (0.06)	0.26* (0.12)	-0.10 (0.11)
Candidate name x traits & civ. cit.	-0.03 (0.06)	0.08 (0.06)	0.19 (0.12)	-0.08 (0.11)
R ²	0.14	0.15	0.10	0.10
Adj. R ²	0.12	0.14	0.09	0.09
N	541	539	492	492
RMSE	0.25	0.26	0.45	0.42

Note: Coefficients and standard errors (in parentheses) from linear regression models. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$.

F The prevalence of positive and negative stereotypes

F.1 Measurements

As an additional analysis I directly analyze the prevalence of positive stereotypes of majority (or minority) candidates and negative stereotypes of immigrant-origin candidates (or majority) candidates in two ways. Specifically, I use an (a) implicit association test and (b) latent profile analysis based on ratings of candidates on a bipolar scale regarding characteristics capturing traits and civic citizenship. In the following I

describe the two approaches to measure stereotypes in more detail.

F.1.1 Implicit association test

An Implicit Association Test (IAT) is designed to identify stereotypes that operate at an unconscious level through automatic psychological processes (e.g., Greenwald et al. 1998).¹ In the IAT, respondents were instructed to classify attributes and candidate names that appeared on the screen as rapidly and accurately as possible. The test assesses strengths of associations between concepts by measuring how long respondents take to categorize words. The twist is that a certain key is always assigned to both one name category (e.g., Italian) and one category of attributes (e.g., positive). Specifically, for the purpose of this study, respondents classified (a) attributes that capture character traits (and in a second round civic citizenship) as either positive or negative and (b) candidate names as either Italian and Algerian. From a mixed list of a) attributes and b) candidate names to classify, it is calculated how long the respondents take. The categories of names and attributes are then switched (e.g., Italian + negative & Algerian + positive) and the response times between the different pairings are compared. Because taking part in the IAT requires a keyboard, only those respondents who took the survey on a computer (and not on a mobile phone) were able to participate in the IAT (N=791).

Specifically, the procedure was structured as follows. In a first practice block, Algerian and Italian candidate names appeared on the computer screen and respondents were asked to classify them rapidly as either Algerian or Italian names, by pressing the correct key (e for Algerian and i for Italian). Next, in a second practice block, respondents classified a series of positive and negative character traits as either positive or negative by using the same two keys (e for positive and i for negative). Then, in a combined task, re-

1. There has, however, also been criticism of the IAT. For instance an influential meta-analysis by Oswald et al. (2013) shows that the IAT does not predict discriminatory behavior more accurately than explicit measurements of stereotypes.

spondents classified words of all four categories (Algerian names, Italian names, positive character traits, negative character traits). The task was split into a practice block (20 combined trials) and a critical block (40 combined trials). Again respondents were asked to press the e key for Algerian or positive and i for Italian or negative. Then the keys for the categories of attributes were reversed (e for Algerian and negative and i for Italian and positive). Respondents went through another practice block in which they categorized only character traits with the new keys. Finally, participants went through another combined task with the new pairing, consisting again of a practice block and a critical one (see Table 12 for an overview). In all tasks, respondents were forced to correct errors before proceeding, and time was measured until the respondent pressed the correct key. The combination of attributes and names that were initially assigned to a given key varied randomly between respondents. The respondents went through two rounds of the IAT, one with positive and negative attributes regarding character traits and one with positive and negative attributes regarding civic citizenship.

Table 12: Blocks in the Implicit Association Test (IAT)

Block	Function (trials)	Items assigned to left key (e)	Items assigned to right key (i)
B1	Practice (20)	Algerian names	Italian names
B2	Practice (20)	Positive	negative
B3	Practice (20)	Algerian + positive	Italian + negative
B4	Critical (40)	Algerian + positive	Italian + negative
B5	Practice (40)	Negative	positive
B6	Practice (20)	Algerian + negative	Italian + positive
B7	Critical (40)	Algerian + negative	Italian + positive

Note: The table provides an example of the IAT process. The block numbers show the order in which the respondents went through the IAT. Trials describe the number of words that the respondents assigned in a given block.

The difference in average time between the two combined tasks provides the basis for the IAT measure, referred to as D-value. The R package *iatgen* is used to perform the data cleaning and calculating of

D-values. The scoring is based on the algorithm suggested by Greenwald et al. (2003). First, trials over 10,000 ms and IAT data from participants with more than 10 percent of trials having latency less than 300 ms were scored as missing.

Then, within-person difference scores were derived based on each respondent's mean latency times of the combined blocks. Based on Greenwald et al. (2003), I used scores from the combined practice blocks and the critical blocks. This results in two mean differences ($\text{Mean}_{B6} - \text{Mean}_{B3}$ and $\text{Mean}_{B7} - \text{Mean}_{B4}$). The two difference scores of both practice and critical blocks are then divided by their associated "inclusive" standard deviations. Finally, the average of the two scores corresponds to the D-value (see Carpenter et al. 2019; Greenwald et al. 2003).

A positive D-value indicates that the respondent needed longer for presumably "incompatible" combinations (positive/Algerian name & negative/Italian name) than "compatible" combinations (negative/Algerian name & positive/Italian name). For example, faster responses for the (Algerian name/positive & Italian name/negative) task than for the (Italian name/positive & Algerian name/negative) task result in a negative D-value, indicating a stronger association of candidates with Algerian names than of candidates with Italian names with positive traits (see also Greenwald et al. 2009).

F.1.2 Description of latent profile analysis and finite normal mixture models

I measure stereotypes in an additional way, relying on openly expressed assessments of the candidates (see also Piston 2010; Sniderman et al. 2000; Sniderman and Hagendoorn 2007). To measure such stereotypes, I consider recommendations in the literature on how to measure attitudes in a way that allows me to disentangle in-group favoritism and out-group hostility (Hewstone et al. 2002; Greenwald and Pettigrew 2014). Based on the claim by Greenwald and Pettigrew (2014) that such measures should include a

neutral point, respondents evaluated the candidates on a scale ranging from a negative evaluation (e.g., incompetent) to a positive evaluation (e.g., competent) with a clear neutral middle starting point instead of applying a “unipolar conception of attitudes toward minorities” (Sniderman et al. 2014, 121; for a similar approach see Sniderman and Stiglitz 2008). Using these ratings, I conduct model-based cluster analysis to identify different *types* of biases in the population. Cluster analysis allows me to identify cohesive and distinct groups of respondents that show similar response patterns. Given that respondents evaluated both a candidate with an Algerian name and one with an Italian name, a comparison between the ratings of the candidates allows me to discern different biases. For instance, it may disentangle individuals with a pure in-group favoritism (a combination of neutral/positive evaluations of the immigrant-origin candidate and a *more* positive evaluation of the majority candidate) from those with both an in-group and an out-group bias (a combination of a negative evaluation of the immigrant-origin candidate with a positive evaluation of the majority candidate).

This specific form of cluster analysis relies on mixture models and is based on the assumption that the observed data is the result of some unknown finite set of subpopulations with their unique probability distributions (Ahlquist and Breunig 2012, 96). Finite mixture models are a statistical method to model the overall population as a mixture of these separate subpopulations (Jang and Hitchcock 2012, 299). The approach identifies hidden groups in the data based on a statistical model and can thereby be considered probability-based. Each individual has a certain probability to be allocated to each of the clusters. The number of clusters (as well as their shape and volume) are derived by comparing the model fit of a series of estimated mixture models and choosing the most suitable model solution. I rely on the standard approach and use normal finite mixture models. Following the terminology in the literature, I label the mixture models used here that reduce a set of *continues* variables to a few subgroups latent profile analysis (as

distinct from latent class analysis which refers to the reduction of *categorical* variables; see e.g., Oberski (2016).

The following description of mixture models is based on Fraley and Raftery (2002) and estimation is conducted in R using the package *mclust* (see Scrucca et al. 2016).

If we have a data set with n observations (y_1, \dots, y_n) , the likelihood for a mixture model with G mixture components can be expressed with the following equation:

$$L_{MIX}(\theta_1, \dots, \theta_G; \tau_1, \dots, \tau_G | y) = \prod_{i=1}^n \sum_{k=1}^G \tau_k f_k(y_i | \theta_k) \quad (2)$$

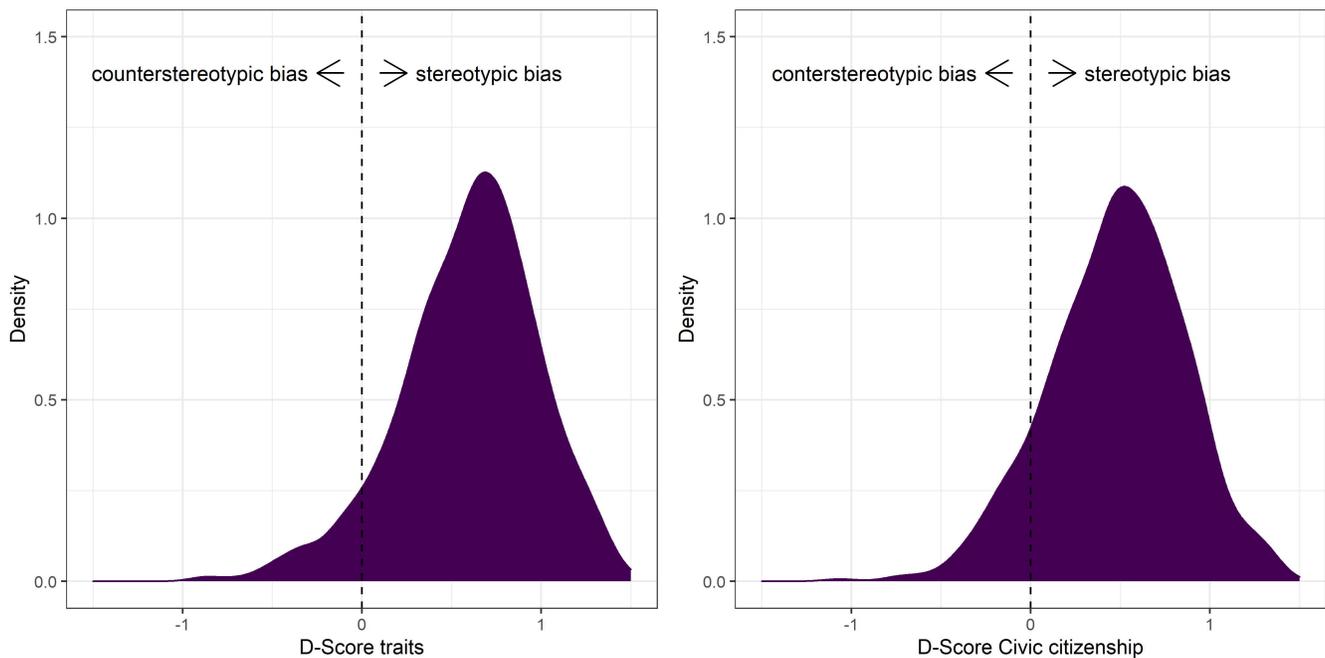
f_k stands for the density function of component k for observation y_i (with parameters θ) and τ captures the probability that an observation belongs to the k th component. The parameters θ and τ are unknown and are estimated by the model. Each component of the finite mixture model corresponds to a cluster/profile. In the present analysis, f_k is (for all components) a multivariate normal (Gaussian) density function, having a mean μ_k and covariance matrix Σ_k . Groups or clusters resulting from this model have an ellipsoidal form, are centered at the means μ_k and the density for observations is increasing with their closeness to the mean. Geometric features (shape, volume, orientation) of the clusters are determined by the parameters of the covariances Σ_k . Finally, the number of parameters of the covariance matrix (e.g., whether shape, volume, and/or orientation should be allowed to vary across clusters) is obtained in *mclust* by using eigenvalue decomposition (see Banfield and Raftery 1993). Concretely, the *mclust* function in R then obtains the maximum likelihood estimator (MLE) of the mixture model that is parameterized via the eigenvalue composition by using the EM algorithm.

F.2 Results

F.2.1 Implicit association test

Figure 1 illustrates the findings from the implicit association test by providing densities of the D-scores. Illustrations in these figures show that a clear majority of respondents associated positive traits and civic citizenship more with Italian names than with Algerian names and/or negative characteristics more with Algerian than Italian names (if D-score > 0).

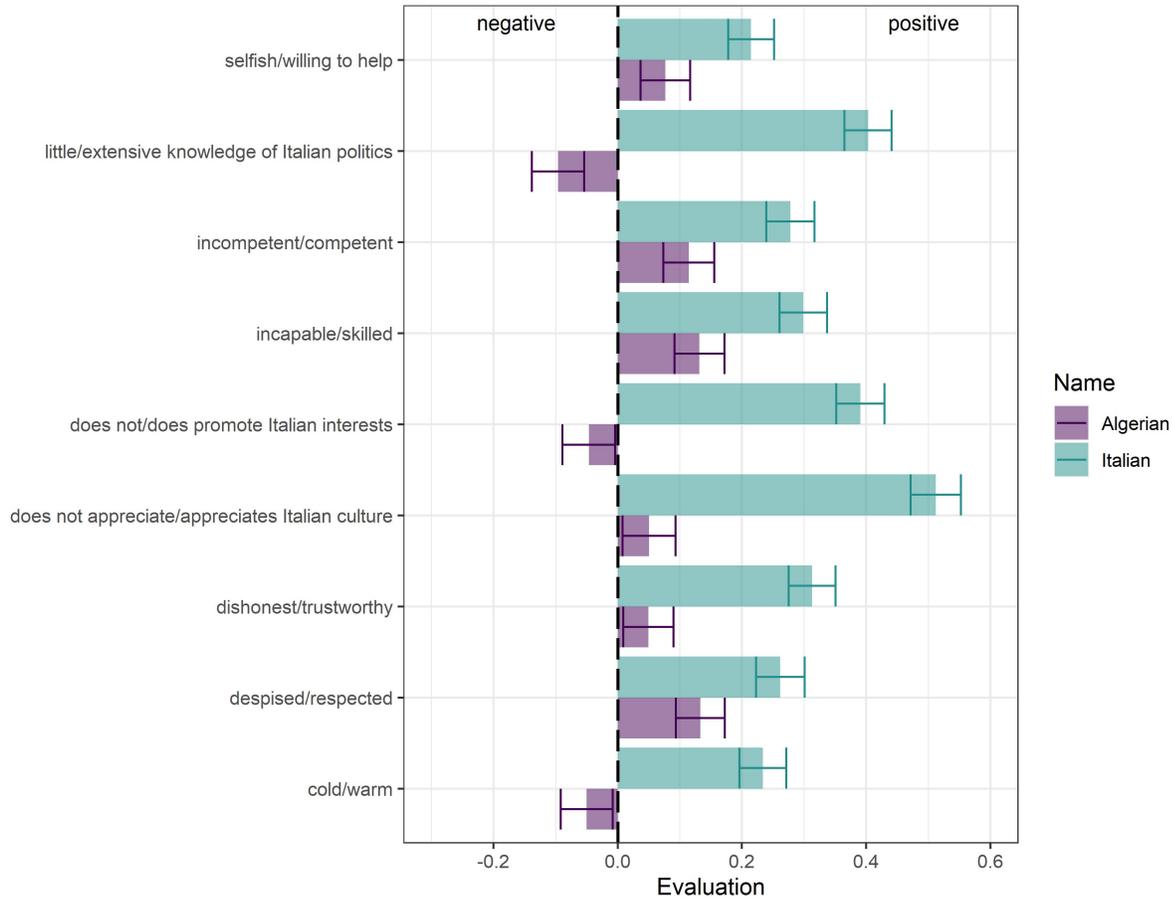
Figure 1: D-scores from Implicit Association Tests



Note: The figures show densities of D-scores derived from the implicit association test (N=791 respondents). Calculation of D-scores are based on Greenwald et al. (2003). A D-score > 0 indicates that a respondent holds a bias in the direction of common stereotypes (negative stereotypes of immigrant-origin candidates and/or positive stereotypes of majority candidates). The left figure displays results regarding characteristics capturing traits and the right figure with respect to characteristics measuring civic citizenship.

F.2.2 Explicit stereotypes

Figure 2: Explicit stereotypes, two-dimensional scale



Note: Results from evaluations of two candidates, one with an Algerian name (Omar Zidane) and one with an Italian name (Lorenzo Marino). Traits and civic citizenship characteristics are measured on a scale ranging from -4 (most negative) to 4 (most positive). Means and standard errors are displayed. A difference in evaluations between the two candidates provides evidence of explicit stereotypes.

F.2.3 Latent profile analysis of explicit stereotypes

Table 13: Best model fits according to BIC

Model	Groups	BIC
EEV	3	-67621.39
EEE	5	-67736.63
EEE	9	-67738.93

Note: The three models with the largest BIC (Bayesian information criterion) are displayed. In contrast to common usage, the BIC in *mclust* is calculated in a way that a higher value represents a better model fit. The models are: EEV = ellipsoidal distribution, equal volume, equal shape, variable orientation; EEE = ellipsoidal distribution, equal volume, equal shape, equal orientation.

G Survey text

This section displays the survey flow including the question, answer choices as well as information about pre-screening, variables considered for the quota, and randomization. Questions that were not used explicitly in the study are not displayed here (the full survey text in Italian is available upon request).

Introduction

Thank you for participating in this survey, which contains questions about your political behavior. The aim of the survey is to analyze voter behavior in different contexts. This questionnaire is developed at the University of Lucerne, Switzerland.

We ask you to read the questions carefully and indicate your opinions and personal data.

Data will be treated confidentially. Results will be reported on an aggregated level without any identification possible.

Thank you very much for your participation and contribution to this research project.

Question 1: Please indicate your age:

- Less than 18 years
- 18-34 years
- 35-54 years
- 55-74 years
- more than 74 years

Question 2: Please indicate your nationality:

- Italian (including dual citizenship)
- Foreign

↳ Respondents who are younger than 18 years or have (only) foreign nationality are excluded from the survey.

Question 3: Please indicate your gender:

- Male
- Female
- Not classifiable

↳ Quota is applied according to frequency of gender and age in the enfranchised Italian population.

Question 4: In political matters, many people often talk of “left” and “right”. Thinking about your opinion, where would you place yourself on a scale from left to right?

- 0 (Left)

- 1
- 2
- 3
- 4
- 5 (Center)
- 6
- 7
- 8
- 9
- 10 (Right)
- I prefer not to answer
- I cannot place myself on this scale

Question 5: Is there a political party (movement) to which you feel close (or even less distant than the others)? If so, can you please indicate which one?

- Partito Democratico
- Forza Italia
- Lega
- Movimento Cinque Stelle
- Fratelli d'Italia
- Liberi e Uguali
- +Europa

- o CasaPound
- o Potere al Popolo!
- o Nessuno
- o Altro

↳ Answer is piped into Question 6. Respondents who did not indicate to feel close to any party are excluded from the survey.

↳ Blocking based on ideological placement (Question 4).

Question 6: Given the recent tensions in the Conte government over infrastructure, it is possible that Italians may soon be called to new general elections. The experts agree that the person described below may have a good chance of being nominated as a candidate for the “[respondent’s indicated closest party]” party in your district. Please read the description of the potential candidate carefully.

↳ Respondents are randomly (within block) presented one of the eight vignettes that describe a candidate. Before they saw one of the vignettes, they had the opportunity to retrieve information about the electoral system in Italy.

Question 7: In your opinion, should the party nominate [candidate name] as a candidate in the next Italian parliamentary elections?

Your support for the nomination: [I am not at all supportive of his nomination, 1, 2, ..., 8, 9, I am very supportive of his nomination]

Question 8: Imagine that the party has nominated [candidate name] as an official candidate. How likely is it that you will vote for him?

Probability of voting for the candidate: [very unlikely, 1, 2, ..., 8, 9, very likely]

Question 9: You now have the opportunity to anonymously make another assessment of the potential candidate [candidate name]. Our aim is to send the party a comprehensive evaluation report on the potential candidate in question. Your answer will be included in the report on the overall evaluation of [candidate name] available to the party. Please choose one of the following options:

- o I am against the nomination of [candidate name]. This statement is included as a negative rating in the overall evaluation.
- o I am in favor of the nomination of [candidate name]. This statement is included as a positive rating in the overall evaluation.
- o I am neither in favor of nor against the nomination of [candidate name]. This statement has no influence on the overall evaluation.
- o I prefer not to answer.

Question 10: The next questions will no longer concern this candidate, but we will show you the names of two hypothetical candidates. Please evaluate the two hypothetical candidates with regard to the characteristics indicated.

↳ Randomization of candidate names (a and b)

(a) Lorenzo Marino:

↳ Randomization of the following characteristics

- [selfish, -3,-2, -1, 0, 1, 2, 3, willing to help]

- [little knowledge of Italian politics, -3,-2, -1, 0, 1, 2, 3, extensive knowledge of Italian politics]
- [incompetent, -3,-2, -1, 0, 1, 2, 3, competent]
- [incapable, -3,-2, -1, 0, 1, 2, 3, capable]
- [does not promote Italian interests, -3,-2, -1, 0, 1, 2, 3, promotes Italian interests]
- [does not appreciate Italian culture, -3,-2, -1, 0, 1, 2, 3, appreciates Italian culture]
- [dishonest, -3,-2, -1, 0, 1, 2, 3, trustworthy]
- [despised, -3,-2, -1, 0, 1, 2, 3, respected]
- [cold, -3,-2, -1, 0, 1, 2, 3, warm]

(b) Omar Zidane:

↳ Randomization of the following characteristics

- [selfish, -3,-2, -1, 0, 1, 2, 3, willing to help]
- [little knowledge of Italian politics, -3,-2, -1, 0, 1, 2, 3, extensive knowledge of Italian politics]
- [incompetent, -3,-2, -1, 0, 1, 2, 3, competent]
- [incapable, -3,-2, -1, 0, 1, 2, 3, capable]
- [does not promote Italian interests, -3,-2, -1, 0, 1, 2, 3, promotes Italian interests]
- [does not appreciate Italian culture, -3,-2, -1, 0, 1, 2, 3, appreciates Italian culture]
- [dishonest, -3,-2, -1, 0, 1, 2, 3, trustworthy]
- [despised, -3,-2, -1, 0, 1, 2, 3, respected]
- [cold, -3,-2, -1, 0, 1, 2, 3, warm]

Question 11: Would you describe yourself as having a migration background?

- o No, I don't have a migration background.
- o Yes, I have a migration background. Please specify which one: -----
- o I prefer not to answer.

↳ Respondents who took the survey on a computer were guided to the IAT.

Debriefing

Thank you for participating in our survey. Our study focuses on discrimination against candidates with a migration background. Specifically, our survey examines the extent to which Italians tend to vote for a candidate with an Italian name or for a candidate with a foreign name. In this study, we asked you a few questions about a person your preferred party intends to nominate as a candidate. The candidate described to you is our invention. Other survey participants were able to evaluate other potential candidates so that we could compare responses for different candidates. By consequence, we will also not send evaluations of the candidates to political parties. In addition, we evaluate explicit and implicit stereotypes, the latter with the test you have just carried out in case you take the survey from a computer.

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