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Issue salience and women's electoral performance: Theory and evidence from Google trends*

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Abstract

In this paper we study, theoretically and empirically, how the belief that the gender of politicians affects their competence on a range of issues may influence electoral outcomes depending on the salience of these issues. We propose a model of issue-specific gender bias in elections which can describe both the presence of a real comparative advantage ('kernel-of-truth' case, or stereotype) and the case of pure prejudice. We show that the bias influences electoral results but it can be partially reversed by successful information transmission during the electoral campaign. We then empirically investigate the relation between issue salience and women's performance, using US data on House and Senate elections. Estimates of issue salience are obtained using Google Trends data. Exploiting the longitudinal dimension of the dataset at district level and an IV strategy to rule out possible endogeneity, we show a positive correlation between the salience of feminine issues and women's electoral outcomes. The average effect is sizable with respect to the share of votes for women candidates, even if not large enough, on average, to increase the probability that women candidates win elections.

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1 Introduction

When in 2021 a former Berkeley economic professor and former Chair of the Federal Reserve was nominated secretary of treasury by newly elected President Biden the news made it to the headlines worldwide because that very important position in the cabinet was to be held by a woman for the first time in history. The same happened to former French Minister for the Economy and Managing Director of IMF, Christine Lagarde, when she became the first female president of the European Central Bank. And everybody remembers how Secretaries of State Madeleine Albright, Condoleeza Rice and Hillary Clinton stood out among their male colleagues at international summits.

Voters, and the public more in general, are becoming more accustomed to slightly more gender balanced cabinets and leadership roles but, truth be told, they are still more familiar with women holding portfolios like education, health and welfare policy.

In this paper we study, theoretically and empirically, how the belief that the gender of politicians affects their competence on a range of issues may influence electoral outcomes depending on the salience of these issues.

In spite of the remarkable examples mentioned above women are still a minority on the political scene in most countries (26.7% of members of parliament worldwide, Inter-Parliamentary Union database, July 2023) while they have been catching up and reducing the gap way faster in other sectors. Social scientists have been dissecting the possible causes for decades and many studies have focused on the possible bias that voters may held towards being represented by women. Despite this research effort, an open and conscious gender bias (preference based) has been difficult to uncover, maybe also because voters may not be willing to report clearly discriminatory positions in surveys and interviews.

There is instead evidence (Mo, 2015; Sanbonmatsu, 2002) of a belief based bias that induces less informed voters in believing that female politicians are less competent and so less fit for the job than male ones (see Cella and Manzoni, 2022, for a theoretical model). This is a consequence of a transposition of stereotypes about gendered personality traits to the electoral scene (Huddy and Terkildsen, 1993). Women are supposed to be more patient, loving and caring while men are tougher, more decisive and less emotional.

These characteristics, to the eyes of voters, make male candidates more electable because those personality traits ascribed to men are considered essential to be a good politician. Furthermore these beliefs about stereotypical personality traits have another effect, they divide the areas of expertise of politicians in feminine and masculine issues. Women are considered more competent when dealing with 'compassion' issues like education, health and welfare that remind of the domestic sphere where women have been confined until only a few decades ago. Men, instead, are believed to be more able to deal with more public sphere related issues like the economy, the defense and foreign policy (Lawless, 2004; Falk and Kenski, 2006).

The consequences of this stereotypical beliefs on electoral outcomes are not constant across electoral competitions. As a matter of fact, not all political campaigns are centered on the same topics, and the salience of specific issues may increase or decrease the probability of some candidates of being elected depending on their supposed competence in those areas. There is evidence (Lawless, 2004; Falk and Kenski, 2006) that in the post 9/11 phase when homeland security and defense were a top priority voters thought that male politicians were better suited to legislate on those matters. In 1992 instead, the first 'Year of the Woman', the salience of and interest about gender related issues was higher than it had been before (Dolan, 1998) and women performed greatly in the parliamentary elections and brought the women share of members of congress to an all time high of 10%.

We build an electoral model where candidates are evaluated on their expected competence over different issues. We have three (types of) issues that we call feminine, masculine or neutral depending on the prior belief held by voters on which gender is more likely to be competent on that issue. Voters during the electoral campaign (may) receive a signal and update their belief on the candidates' competences on specific issues. Based on these posterior beliefs, they will calculate the expected competence of each candidate using as weights the relative importance of the different issues. We find that, in such a model, a good campaign (positive signal) may succeed in changing the prior belief of voters, so that a woman may be considered competent on masculine issue with higher probability than a man.

We then test empirically the predictions of the model in the context of US House and Senate elections in the period 2006-2018. In order to investigate the effects of issue salience on women's political performance, we build a longitudinal dataset where issue salience is measured using Google Trends data and electoral results are retrieved from administrative sources. Using a district level fixed effects model, we find a positive and significant correlation between the salience of feminine issues and women's electoral outcomes.

The paper is structured as follows: Section 2 introduces and analyzes the theoretical model; Section 3 describes the data and discusses our measure of issue salience; Section 4 contains the empirical analysis and Section 5 concludes. The Appendix contains proofs, additional tables and Google Trends search keywords.

2 Model

We consider a one-period electoral competition in which two candidates, one from party L and one from party R, face each other. Politicians are characterised by their ideology x^k, and their (multidimensional) competence v^k, with $k = L, R$. Voters are heterogeneous in their policy preferences, while they all prefer higher competence. We model the potential trade-off between competence and ideology, as in Cella and Manzoni (2022) (which is a finite horizon version of Bernhardt et al., 2011).

Policy issues. We assume that the ideological position is one-dimensional. However, we depart from the existing literature in that we assume that the policy implementation occurs on three separate issues f, n, m. These issues are related to the competence dimension, in that a candidate may be differently able to implement policies in these areas. These issues have a different salience, ρ_j, $j = f, n, m$, in the policy phase.[1] As a consequence, a candidate is evaluated in terms of his/her weighted expected competence $\bar{v}^k = \sum_j \rho_j v_j^k$, where v_j^k is the competence of candidate from party k on issue j.

Politicians. Politicians are characterised by ideology and competence and they are policy oriented.

A politician from party L has ideology $x^L \sim U[-1, 0]$, and a politician from party R has ideology $x^R \sim U[0, 1]$. The competence of a candidate is described by a three-dimensional vector $v^k = \{v_f^k, v_n^k, v_m^k\}$ for $k = L, R$, where $v_j^k \in \{0, 1\}$ is the competence of candidate from party k in implementing issue j.

[1]The salience of an issue can be interpreted both as the weight that the issue has in the ex-post policy implementation, and as the probability that the issue is the most salient one. That is, the model accommodates both the interpretation that ex-post the policy is a combination of different issue, and the interpretation that ex-post there is one type of policy that is relevant.

Politicians receive utility from the implemented policy, $y \in \mathbb{R}$ and the competence of the elected politician, v^P, where $P = L, R$ is the identity of the elected politician. The utility of a politician from party k is:

$$u^k\left(y, v^P\right) = -\left(x^k - y\right)^2 + \bar{v}^P.$$

Voters. Each voter i has ideological preferences characterised by a bliss point x^i. Bliss points $x^i \sim U[-1, +1]$, so that the median voter has bliss point $x^m = 0$. Each voter's utility depends on the implemented policy y and on the weighted expected competence of the elected politician $\bar{v}^P$ as follows:

$$u^i\left(y, v^P\right) = -\left(x^i - y\right)^2 + \bar{v}^P.$$

Issues and gender bias. We assume that candidates are randomly selected from a gender-balanced population (male/female with equal probability). Our underlying assumption is that the gender of the candidate matters, and that it influences the expected competence on different issues. We classify policy issues in *feminine* (f), *neutral* (n), and *masculine* (m), depending on the voters' perception of the expected competence of candidates by gender. Specifically, we call an issue feminine (*resp.* masculine) if voters believe that a female candidate is more (*resp.* less) likely to be competent on it than a male candidate. We call an issue neutral if expected competence on that issue does not depend on gender. Assumption 1 formalizes this.

Assumption 1 *(i) The distribution of competence on the neutral issue n does not depend on gender.*

$$\begin{aligned} \Pr(v_n^k = 0|F) &= \Pr(v_n^k = 0|M), \\ \Pr(v_n^k = 1|F) &= \Pr(v_n^k = 1|M). \end{aligned}$$

(ii) Female (resp. male) candidates are perceived as more likely to be competent than male (resp. female) candidates on feminine (resp. masculine) issues.

$$\begin{aligned} \Pr(v_f^k = 1|F) &> \Pr(v_f^k = 1|M), \\ \Pr(v_m^k = 1|M) &> \Pr(v_m^k = 1|F). \end{aligned}$$

Note that this asymmetry in voters' beliefs could be induced both by a prejudice (as in Cella and Manzoni, 2022) or by a true underlying heterogeneity in the distribution of competences (Dolan, 2004). Later in the paper we will discuss where adopting either view changes the results.

In this general framework, we also make two simmetry assumptions on the distributions, for computational ease. First, we assume that high and low competence on the neutral issue are equally likely. Second, we assume that the perception of gender advantages on own issues and disadvantages on others' issues are the same across genders. Assumption 2 summarizes this.

Assumption 2 *(i) High and low competence on the neutral issue n are equally likely.*

$$\Pr(v_n^k = 0|G) = \Pr(v_n^k = 1|G) = \frac{1}{2}$$

for $G \in \{M, F\}$.

(ii) Symmetry across genders.

$$\Pr(v_f^k = 1|F) = \Pr(v_m^k = 1|M) = \Pr(v_f^k = 0|M) = \Pr(v_m^k = 0|F) = \gamma > \frac{1}{2}.$$

Signals. Before election, voters observe a signal σ^k on the candidate of each party k. $\sigma^k = (\sigma_j^k)_{j \in \{f,m\}}$. Each component σ_j^k is an independent signal on the competence of candidate k on issue j.[2] The signal has the following properties:

$$\sigma_j^k(v_j^k = 1) = \begin{cases} 1 & \text{with prob. } \frac{2}{3} \\ 0 & \text{with prob. } \frac{1}{3}, \end{cases} \qquad \sigma_j^k(v_j^k = 0) = \begin{cases} 0 & \text{with prob. } \frac{2}{3} \\ 1 & \text{with prob. } \frac{1}{3}. \end{cases}$$

The signal precision is $\frac{2}{3}$ for simplicity reasons, but any informative signal (precision larger than $\frac{1}{2}$) would deliver the same comparative statics.[3]

[2] We refrain from introducing a signal on the competence of the candidate on issue n for simplicity reasons. Given that the distribution of the competence on issue n is not affected by gender, a signal on n would not interact with our variable of interest.

[3] A signal with precision $\frac{1}{2}$ would not be informative, and therefore would be equivalent to our benchmark case without signals. A signal with a precision lower than $\frac{1}{2}$ would simply inform the voters of the unlikely outcome.

Updating. Given the signal, σ_j^k, and the gender of the candidate, we derive the posterior distribution of voters' beliefs on the candidate's competence on issue j. Not surprisingly a positive signal on a specific issue shifts probability weight on high competence. Appendix A.1 reports the relevant probabilities (see Table A.1), and their derivations.

2.1 Expected competence and voting in absence of signals

Recall that, from the median voter's point of view, candidates are ex-ante symmetric in terms of ideology. Hence, the median voter will vote depending on which candidate has the higher expected competence. This expectation will be based on prior beliefs and updated with the observation of the candidate's gender and, possibly, the signals on his/her competence, using as weights the salience of the different issues. The presence of signals on competences is related to whether the campaign was successful in conveying information. We do not model the campaign itself, and the determinants of its effectiveness, but we consider different cases depending on the number of signals that a voter receives, so as to draw implications on the effects of information on gender equality.

To model the behavior of the median voter, we first compute the expected competences in absence of signals, when the only observed characteristic of the candidate is his/her gender. In this case, the expected competence will be based on the voter's prior belief. The expected competences of female and male candidates are as follows:

$$\begin{aligned}
\mathbb{E}(v^k|F,\emptyset,\emptyset) &= \rho_f\mathbb{E}(v_f^k|F,\sigma_f=\emptyset)+\rho_n\mathbb{E}(v_n^k|F)+\rho_m\mathbb{E}(v_m^k|F,\sigma_m=\emptyset)\\
&= \rho_f\gamma+\frac{\rho_n}{2}+\rho_m(1-\gamma),\\
\mathbb{E}(v^k|M,\emptyset,\emptyset) &= \rho_f\mathbb{E}(v_f^k|M,\sigma_f=\emptyset)+\rho_n\mathbb{E}(v_n^k|M)+\rho_m\mathbb{E}(v_m^k|M,\sigma_m=\emptyset)\\
&= \rho_f(1-\gamma)+\frac{\rho_n}{2}+\rho_m\gamma.
\end{aligned}$$

Note that without signals, the expected competence of a female politician is higher than the expected competence of a male politician if and only if $\rho_f > \rho_m$, that is if and only if feminine issues are more salient than masculine ones. We can therefore characterize the voting behavior of the median voter.

Proposition 1 *In absence of signals, if candidates are of different genders, the median voter chooses the female candidate whenever $\rho_f > \rho_m$, he chooses the male candidate if $\rho_m > \rho_f$ and he randomizes if $\rho_f = \rho_m$. Moreover, with no signals, the median voter* *randomizes between the two candidates if they are of the same gender, whenever no signal is available.*

Proof. Given the voting model, elections are decided by the median voter. From the median voter's point of view, candidates are ex-ante symmetric in terms of ideology, so that elections are decided by the expected competence of the candidates.

Without signals, if the two candidates are of the same gender, they have the same expected competence. If the two candidates are of different genders, the female candidate has higher expected competence if $\rho_f > \rho_m$, lower expected competence if $\rho_f < \rho_m$. Candidates have the same expected competence if $\rho_f = \rho_m$. ■

The proposition highlights that even when campaigns are ineffective at providing additional information, the salience of the different issues contributes to shaping the decision of the electorate, due to the asymmetry of the priors conditional on gender. For this reason, the salience of the neutral issue is irrelevant in the voters' decision, as the prior on issue n is gender independent.

Note that this behavior of the median voter implies that female politicians are more likely to be elected when the feminine issue is more salient than the male one, and male politicians are more likely to be elected in the opposite case. This is stated more precisely in the following Corollary.

Corollary 2 *In the absence of signals, the probability that the elected politician is female is* $\frac{1}{4}$ *if* $\frac{\rho_f}{\rho_m} < 1$, $\frac{1}{2}$ *when* $\frac{\rho_f}{\rho_m} = 1$, *and* $\frac{3}{4}$ *when* $\frac{\rho_f}{\rho_m} > 1$.

Note that the probability of electing a woman is weakly increasing with the relative salience of the feminine issue. Figure 1 shows graphically how this probability varies with γ and $\frac{\rho_f}{\rho_m}$.

2.2 Expected competence and voting in presence of two signals.

The assumption that voters do not observe any signal on candidates' competences is unrealistic. For this reason, we use the previous analysis as a benchmark and we now consider the effects of the interaction between the candidate's gender and the signals on his/her competence.

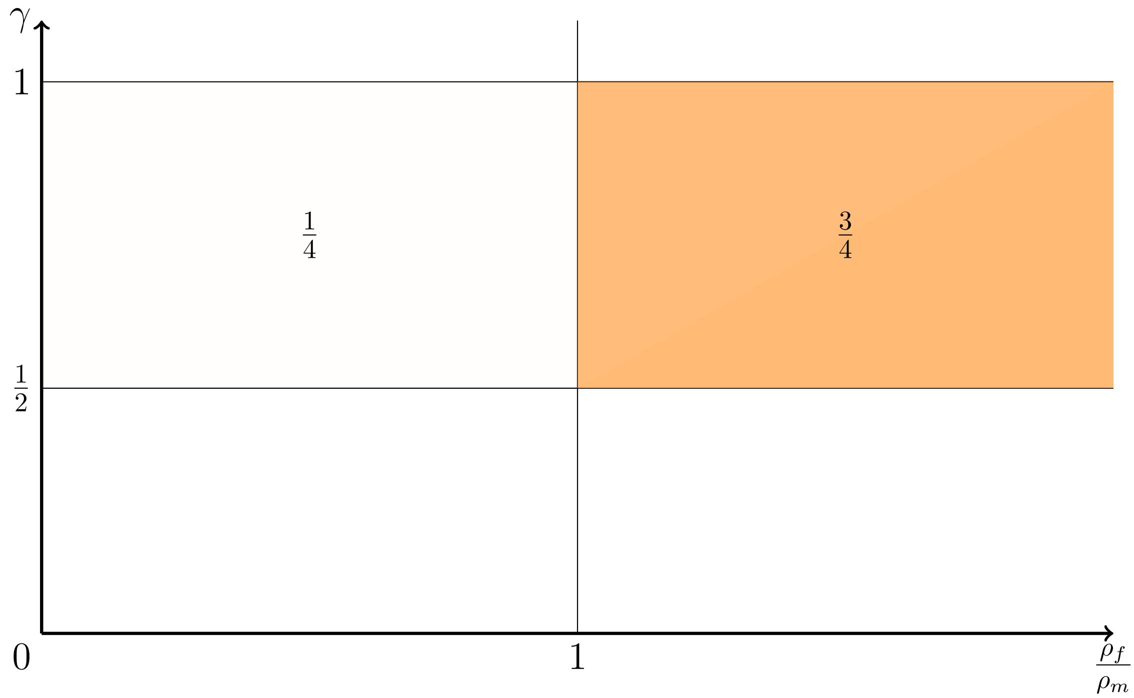


Figure 1: Probability of electing a woman in absence of signals, by strength of bias and relative salience of feminine issues

In order to analyze the effect of signals, we first need to compute the conditional expected competences given the candidate's gender, and the possible realizations of the two signals. Table A.2 in Appendix A.2 reports these expected competences.[4]

Then, we derive the median voter's optimal ranking of candidates given their gender-signal characteristics. The median voter chooses his/her preferred candidate on the basis of his/her observable characteristics, which in this case include both gender and the realization of the two signals (σ_f, σ_m). Lemma 4 in Appendix A.3 characterizes the full ranking of politicians for each set of relevant parameters, namely the relative salience $\left(\frac{\rho_f}{\rho_m}\right)$, and the prior bias γ. We highlight two features of these rankings: (i) the relative performance of females over males is increasing with the relative salience of feminine issues; (ii) when the bias on the prior is strong $\left(\gamma > \frac{2}{3}\right)$ we may observe a full separation of the ranking (either all male politicians preferred to female politicians, as in the first region of the proposition, or

[4]To help the reader, Table A.2 also reports the expected competences by gender in the case without signals.

all female politicians preferred to male politicians, as in the last region); this full separation is not possible when the prior bias is weak.

Lemma 4 allows us to prove Proposition 3 which characterizes the probability that the elected politician is female. This probability is computed under the assumption that all candidates are ex-ante equally likely to be competent on the different issues, regardless of their gender, and of the issue. In other words, we compute the probability that the elected politician is a woman when the bias comes from pure prejudice.[5]

Proposition 3 *Assume that candidates are randomly selected by each party. The probability of electing a female candidate is increasing with* $\frac{\rho_f}{\rho_m}$*. Specifically, such probability is equal to:*

- $\frac{1}{4}$ *when* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} \in \left(0, \frac{(3\gamma-2)(1+\gamma)}{(3\gamma-1)(2-\gamma)}\right)$;
- $\frac{9}{32}$ *when* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-2)(1+\gamma)}{(3\gamma-1)(2-\gamma)}, \frac{(3\gamma-2)(1+\gamma)}{4\gamma-2}\right)$;
- $\frac{11}{32}$ *when* $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-2)(1+\gamma)}{4\gamma-2}, \frac{4\gamma-2}{(3\gamma-1)(2-\gamma)}\right)$;
- $\frac{13}{32}$ *when* $\frac{\rho_f}{\rho_m} \in \left(\frac{4\gamma-2}{(3\gamma-1)(2-\gamma)}, 1, \right)$;
- $\frac{19}{32}$ *when* $\frac{\rho_f}{\rho_m} \in \left(1, \frac{(3\gamma-1)(2-\gamma)}{4\gamma-2}\right)$;
- $\frac{21}{32}$ *when* $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-1)(2-\gamma)}{4\gamma-2}, \frac{4\gamma-2}{(3\gamma-2)(1+\gamma)}\right)$;
- $\frac{23}{32}$ *when* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} \in \left(\frac{4\gamma-2}{(3\gamma-2)(1+\gamma)}, \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}\right)$;
- $\frac{3}{4}$ *when* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} > \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}$.

Proof. First, note that Lemma 4 proves that in the first region $\left(\gamma > \frac{2}{3} \text{ and } \frac{\rho_f}{\rho_m} \in \left(0, \frac{(3\gamma-2)(1+\gamma)}{(3\gamma-1)(2-\gamma)}\right)\right)$ each male candidate is preferred to each female candidate, regardless of their signals. Therefore, a female candidate can win the election only if she runs against another female, which occurs with probability $\frac{1}{4}$. Similarly, Lemma 4 proves that in the last region

[5] Our model can also describe a situation in which there is a true asymmetry in the distribution of competences. In this case, the median voter's behavior is unchanged, but the probability that the elected politician is female depends on γ as the probability of different types of candidates depends on γ as well. Specifically the probability that the elected politician is female changes monotonically: it increases with γ for $\rho_f > \rho_m$ and it decreases with γ for $\rho_f < \rho_m$ also within each parametric region.

$\left(\gamma > \frac{2}{3} \text{ and } \frac{\rho_f}{\rho_m} > \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}\right)$ each female candidate wins against each male candidate, and the probability of electing a female is $\frac{3}{4}$.

In intermediate regions the ranking of male and female candidates is not fully separated. Let us consider for example the second region, in which $\gamma > \frac{2}{3}$ and $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-2)(1+\gamma)}{(3\gamma-1)(2-\gamma)}, \frac{(3\gamma-2)(1+\gamma)}{4\gamma-2}\right)$. In this case, Lemma 4 shows that the median voter's ranking of candidates is the following:

$$(M,1,1) \succ (M,0,1) \succ (M,1,0) \succ (F,1,1) \succ (M,0,0) \succ (F,0,1) \succ (F,1,0) \succ (F,0,0).$$

In order to compute the probability of electing a female candidate we need to compute all possible occurrences of pair of candidates in terms of gender-signals characteristics, and determine the probability of those pairs in which a female wins.

Note that we have 8 types of candidates: $(M,1,1)$, $(M,0,1)$, $(M,1,0)$, $(M,0,0)$, $(F,1,1)$, $(M,0,0)$, $(F,0,1)$, $(F,1,0)$, $(F,0,0)$. Under the assumption that all candidates are equally likely to be competent on different issues (pure prejudice) all these types are equally likely. To see this, consider for example the probability that a candidate has type $(M,1,1)$: this is the product of the following probabilities:

- probability that the candidate is male $= \frac{1}{2}$;

- probability that the (male) candidate has a high signal on the feminine issue, which is the sum of the probability that the male candidate is competent on the feminine issue and has a high signal on it plus the probability that the male candidate is not competent on the feminine issue but has nonetheless a high signal on it $= \frac{1}{2} * \frac{2}{3} + \frac{1}{2} * \frac{1}{3} = \frac{1}{2}$;

- probability that the (male) candidate has a high signal on the masculine issue, obtained similarly $= \frac{1}{2} * \frac{2}{3} + \frac{1}{2} * \frac{1}{3} = \frac{1}{2}$;

Hence, the probability that the candidate is of type $(M,1,1)$ is $\frac{1}{8}$, and the probability of any pair of candidates is $\frac{1}{8} * \frac{1}{8} = \frac{1}{64}$.

Consider now the ranking of region 2 reported above. A female candidate wins in one of the following cases: (i) both candidates are female (probability $\frac{1}{4}$); (ii) candidate 1 is $(F,1,1)$ and candidate 2 is $(M,0,0)$ (probability $\frac{1}{64}$); (iii) candidate 1 is $(M,0,0)$ and candidate 2 is $(F,1,1)$ (probability $\frac{1}{64}$). Therefore, the probability that a female is elected in region 2 is $\frac{1}{4} + \frac{1}{64} + \frac{1}{64} = \frac{9}{32}$.

Election probabilities for the other regions can be derived similarly. ■

Proposition 3 shows that, for each $\gamma \in \left(\frac{1}{2}, 1\right)$, the probability that the elected politician is female is weakly increasing in the relative salience of the feminine issue. If we fix the relative salience, instead, the behavior of this probability depends on whether $\rho_f \lesseqgtr \rho_m$. Specifically, if $\rho_f > \rho_m$, the probability of having a female elected politician is increasing with γ, while it is decreasing when $\rho_f < \rho_m$. For example, when the masculine issue is relatively more important, this probability is higher when the bias is small, that is, when gender matters less in the eyes of the voters.

Figure 2 shows graphically how the probability of electing a woman varies with γ and $\frac{\rho_f}{\rho_m}$.

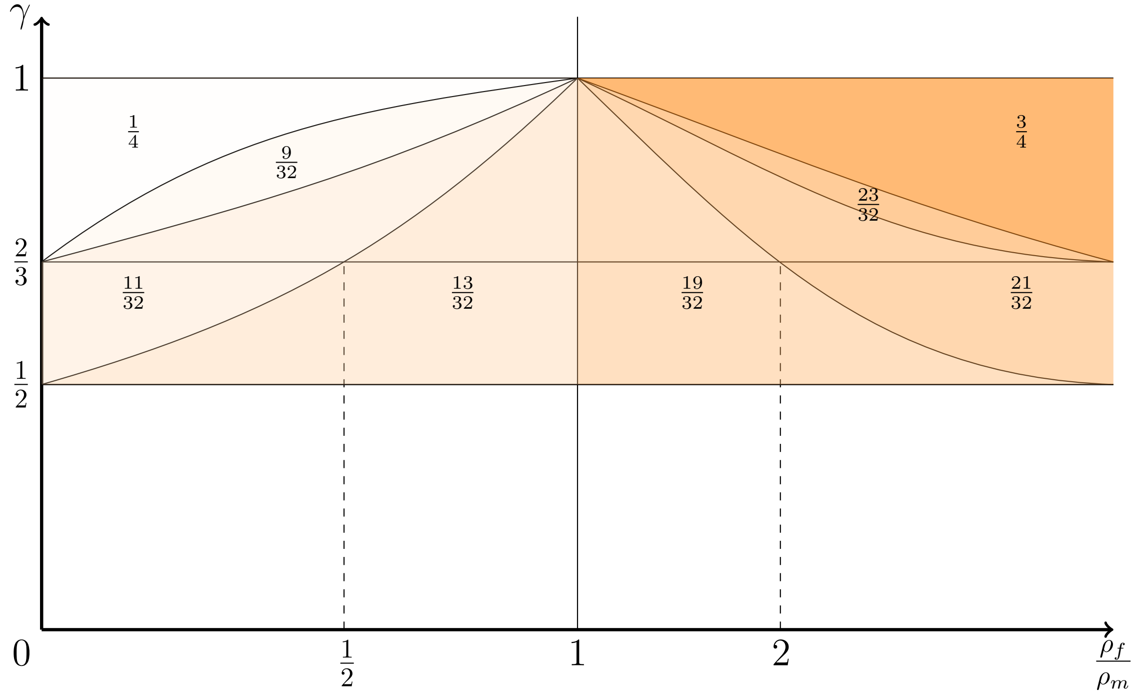


Figure 2: Probability of electing a woman in presence of both signals, by strength of bias and relative salience of feminine issues

2.3 Comparative statics

Let us now understand how the probability of electing a woman is affected by the strength of the bias, the relative salience of the issues, and the level of information on the candidates.

Effects of relative salience. Both in the benchmark model without signals and in the case with both signals the probability of electing a woman weakly increases with the relative salience of the feminine issues. Hence, women perform better in electoral competition when the relative salience of feminine issues over masculine issues is higher.

Effects of information on gender bias. The comparison of the case without signals and the case with signals allows us to analyze the effect of information on the interaction between issue salience and women's performance. We highlight two effects. First, the probability of electing a female politician is more sensitive to changes in the relative salience of feminine issues when there is more information on candidates' competences. This can be seen by comparing the Figure 1 and Figure 2. In the case without signals (Figure 1) the probability of electing a female politician changes only when the relative salience crosses the threshold 1. When more information is provided (Figure 2), the probability of electing a female politicians varies also when the relative salience is below or above 1. Second, information supports the disadvantaged candidates: it favors women when $\rho_m > \rho_f$, and men in the opposite case. This is quite intuitive, and yet reassuring: as voters gather more information on candidates, gender cues and prejudices are less relevant in forming an opinion on the candidate's competence. However, the gap is never closed unless competence itself is fully observed.[6]

3 Data description

The purpose of the empirical analysis is to test whether and to what extent the salience of different political issues affects the political gender gap, in terms of either women participation or electoral outcomes. This goal is ambitious and faces two main issues: the identification of the causal effect and the availability of reliable measures. In this section, we address the issue of data availability and collection, while we describe the details of the identification strategy in the next section.

To test our prediction we focus on the United States in the last two decades for several reasons. First of all, the United States are a unique case of state heterogeneity about social, political and ideological features, but within a common institutional framework and the

[6] In this one-period model voters never observe the true competence of the candidate. It may be reasonable to assume that competence is fully observed for elected politicians, as in Cella and Manzoni (2022). If this were the case, we would observe no gender distortion in incumbent re-election also in the presence of multiple issues.

same two-party system. This is a key aspect of the present analysis, that exploits exactly state and electoral district variability in contemporaneous nationwide elections. Second, issue salience itself can be very different across states and this guarantees enough variability in the variable of interest. In addition, high quality official data on United States elections are easily available from the Federal Election Commission. Finally, United States politics is very well-known worldwide and represents a case study that is very frequently used by scholars and researchers.

3.1 Electoral data

The main source of electoral data is the US public administration. By definition electoral offices have the primary role of tracking every single vote and attribute it unequivocally to one (or more) of the candidates for a seat. Moreover, in every democracy, such data are made available to citizens, voters, and mass media. Indeed, also the United States Federal Election Commission releases and makes the results of all House, Senate and President elections available in digital format shortly after the date of the elections.[7]

The main advantage of these administrative data is that they should not be subject to any measurement error[8] and that they cover all primary and general elections. The drawback is that no personal or socio-demographic information is provided, except for the full name of the candidates and the party or parties supporting them. Consequently, we need to retrieve the gender of each candidate from an external source. The Center for American Women and Politics (CAWP), based at the Eagleton Institute of Politics of the Rutgers University-New Brunswick, collects and makes available a list of female candidates for state and congressional elections since 1990. Moreover, we supplement this database matching the first name of each candidate to the list of masculine and feminine names given to newborn babies in the last seven decades (source: Social Security Administration).[9] In doing this, we rely on the algorithm developed by Blevins and Mullen (2015), that assigns to each first name a certain probability of being masculine or feminine. We define a candidate 'female' if she is listed in the CAWP database or if she has a name which is feminine with a probability larger than 75%; we define a candidate 'male' if he is not listed in the CAWP

[7] All the data in spreadsheet format are available on this website, as of Summer 2023.

[8] Of course, there are actual mistakes and errors in the count of votes, and recounts are frequent. However, such random errors should compensate and official data are the best approximation of the actual intentions of the voters.

[9] Available at this url: `https://www.ssa.gov/oact/babynames/` as of Spring 2023.

and if he has a name which is masculine with a probability larger than 75%; we leave undetermined the gender of candidates that are not listed in the CAWP and whose name is not assigned to any gender with a probability larger than 75%.[10] Table 1 displays the proportion of candidates by gender in House and Senate.

Table 1: Gender of candidates, general elections.

	House		Senate	
Gender	Freq.	Percent	Freq.	Percent
Males	9,094	81.47	1,259	81.70
Females	1,945	17.43	258	16.74
Undetermined	123	1.10	24	1.56
Total	11,162	100	1,541	100

3.2 Issue salience data

Issue salience is not straightforward to measure. We follow the growing literature that makes use of Google trends in similar frameworks (Mellon, 2013, 2014; Chykina and Crabtree, 2018) to measure the relative importance of different political issues over time. In order to identify the list of relevant queries, we proceed in two steps: first, we take an opinion survey run by IPSOS reporting a list of 'worrying issues' freely mentioned by at least 10% of the US sample.[11] Then, starting from each of these issues, we identify a set of (groups of) words that clearly refer to that specific issue. Last, we extend the list of relevant terms to the five most related queries identified by the algorithm of Google trends. Overall, we identify about 400 keywords related to 14 issues. Using the official API provided by Google, we retrieve the monthly time series since January 2004 for each search term in each US state. The procedure to compare the relative size of each term across US states and over time is that described in Castelnuovo and Tran (2017),[12] while the full list of terms by issue is in Appendix C.

[10]The high number of candidates and the heterogeneity of information available on the web makes it virtually impossible to check their gender manually.

[11]These issues are: Crime and violence, Healthcare, Terrorism, Immigration control, Financial/Political corruption, Moral decline, Poverty and social inequality, Unemployment, Education, Rise of extremism, Taxes, Climate change, Threats against the environment. We also add another category, Gender issues, due to the nature of the topic of the paper.

[12]Indeed, Google trends API allows to download only up to 5 terms in a single state over the entire period. By using a common keyword as a benchmark, it is possible to compare several different queries across states and over time.

To classify the 14 political issues as feminine/masculine/neutral we rely on the political science literature on gender gap in politics. This strand of literature identifies committees or ministries that are 'typically' assigned to men or women according to the perception about the relative competence on the specific subject (see for instance Michelle Heath et al., 2005; Krook and O'Brien, 2012; Pansardi and Vercesi, 2016). We follow the literature on the distinction among masculine, feminine and neutral issues to aggregate the 14 issues in three indices. Table 2 shows our classification of 'worrying issues', following closely the classifications in Krook and O'Brien (2012, Table 1, p.846) and Pansardi and Vercesi (2016, Table 1, p.72).

Table 2: Classification of political issues by gender.

Masculine	**Feminine**	**Neutral**
Crime and violence	Healthcare	Financial/Political corruption
Terrorism	Poverty and social inequality	Moral decline
Immigration control	Education	Rise of extremism
Unemployment	Gender issues	Climate change
Taxes		Treats against the environment

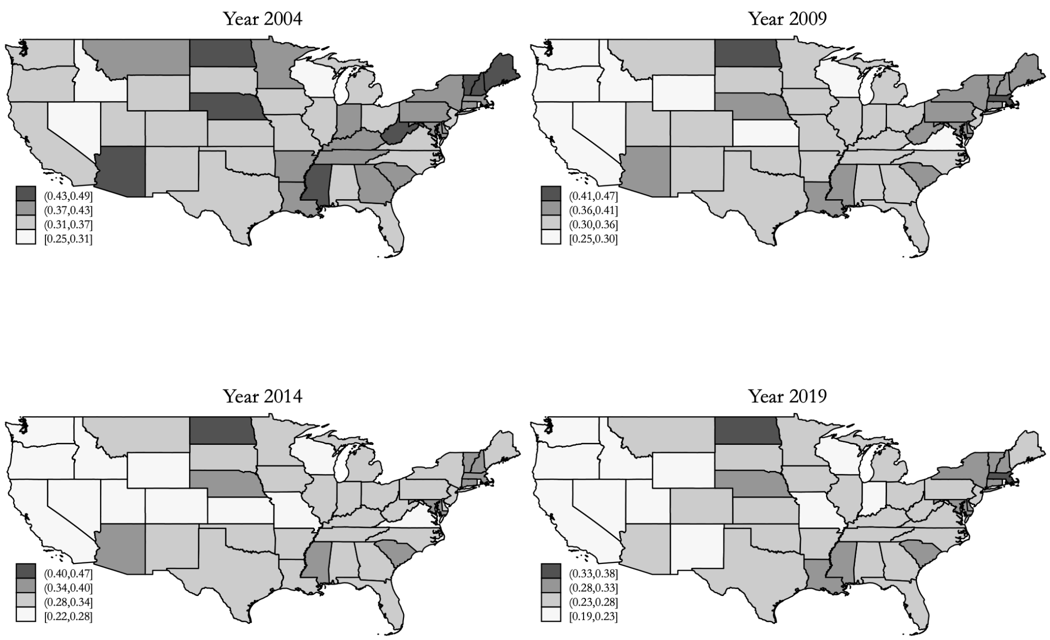
Finally, we compute the share of masculine, feminine and neutral issues over the total salience of the 14 topics listed above. Figure 3 shows the relative importance of feminine issues across states every five years since the start of Google trends data. We can observe a good heterogeneity both across states and over time, that is crucial for our identification strategy.

3.3 Other data

In addition to the administrative electoral data and Google trends, we consider other potential control variables. Specifically, we take demographic data (total population, share of males and females, share of ethnicities), educational data (share of population with high school and bachelor degree) and the share of eligible population actually registered in the electoral lists from the US Census Bureau, while per-capita GDP is taken from the Bureau of Economic Analysis. All these variables are registered at state and year level, spanning for the whole relevant period,[13] and matched to all the elections taking place in that state and year. Table 3 reports the descriptive statistics of the variables used in the baseline

[13] Educational data are an exception, as they are available at state level only since 2010.

Figure 3: Relative importance of feminine issues.



model and in the extended time span.

4 Empirical analysis

A clear-cut causal analysis of electoral phenomena is a very difficult task. On the one side, the number of observations is usually limited by the fact that elections take place every several years. On the other side, the electoral campaigns and dynamics involve features that can be hardly quantified and rationalized by a numerical variable. However, in the previous section we describe how we dealt with this issues using Google trends data and state-level House and Senate elections in the US, that take place every two years in more than 450 districts in the 51 states. As a results, we can rely on a panel of more than 3000 observations for House and Senate elections.

The panel structure of the data allows us to control for difficult-to-measure time-invariant characteristics of the states and districts that may influence the electoral results for women and are difficult to measure. Among these, for instance, there are cultural and value-based features of the electoral body, or local political events that may shape the preferences and attitudes of voters towards men and women.

Ideally, we would like to estimate a linear regression model like the following:

$$E_{d,s,t} = \alpha + \beta F_{s,t} + \Gamma X_{s,t} + \Lambda Z_{d,t} + \eta_t + \theta_d + \varepsilon_{d,s,t} \tag{1}$$

where E is the share of votes for female candidates in district d, state s and time t, F is the measure of 'feminine' issue salience in state s at time t, X is a set of state-specific controls, such as GDP, population, share of women, education, ethnic composition, Z is a set of district-specific political controls, such as the share of population registered for voting and the gender of candidates and incumbent, η and θ are time and district fixed-effects, respectively, and ε is the usual idiosyncratic error term. The sign and statistically significance of the parameter β represent the *ceteris paribus* effect of 'feminine' issue salience on the share of votes for female candidates.

However, the regression model in eq.(1) suffers from endogeneity issues, particularly due to the presence of an omitted variable bias. Indeed, while we can be reasonably sure that there is no reverse causality, e.g. election outcomes do not affect the relevance of feminine issues before elections,[14] there can be unobservable features that may jointly

[14]Since general elections usually take place in November, we define a year starting on November 1 and

Table 3: Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Electoral variables by district, since 2010					
Votes for women (share)	2324	.212	.304	0	1
Woman winner (dummy)	2324	.195	.396	0	1
Women candidates (share)	2324	.206	.281	0	1
Woman incumbent (dummy)	2324	.173	.378	0	1
Electoral variables by district, since 2004					
Votes for women (share)	3712	.198	.300	0	1
Woman winner (dummy)	3712	.184	.388	0	1
Women candidates (share)	3712	.190	.274	0	1
Woman incumbent (dummy)	3712	.166	.372	0	1
Other variables by state, since 2010					
Salience of feminine issues (ratio)	255	.3	.054	.164	.495
Total salience	255	719.4	279.9	179.4	1740.4
Population in electoral register (%)	255	68.8	5.6	51.3	84.2
Per capita GDP	255	46602	9142	30902	81243
Total population	255	6239539	7040867	564487	39461588
Males (share)	255	.494	.008	.472	.524
Females (share)	255	.506	.008	.476	.528
Asian (share)	255	.052	.092	.008	.669
Black (share)	255	.123	.109	.007	.526
Native (share)	255	.022	.033	.002	.174
White (share)	255	.803	.129	.302	.968
High school (total, %)	255	88.5	3.1	80.7	93.9
Bachelor (total, %)	255	30.0	6.3	17.5	60.4
Other variables by state, since 2004					
Salience of feminine issues (ratio)	407	.321	.06	.164	.501
Total salience	407	730.4	284.1	179.4	1740.4
Population in electoral register (%)	407	69.8	5.7	51.3	89.3
Per capita GDP	407	43022	9520	25192	81243
Total population	407	6107463	6854211	509106	39461588
Males (share)	407	.493	.008	.471	.524
Females (share)	407	.507	.008	.476	.529
Asian (share)	407	.049	.092	.007	.669
Black (share)	407	.122	.111	.006	.591
Native (share)	407	.021	.033	.002	.174
White (share)	407	.808	.131	.301	.974
High school (total, %)	255	88.5	3.1	80.7	93.9
Bachelor (total, %)	255	30.0	6.3	17.5	60.4

All the statistics refer to election years, that is any even year since 2004.

determine both dimensions and that cannot be captured even after controlling for district fixed effects, such as the characteristics of electoral campaigns. To address this concern, we employ a traditional instrumental variable strategy, using an approach similar in spirit to that in Autor et al. (2013): we instrument the relevance of feminine issues in state s in year t with the average relevance in all other states, weighted by (the inverse of) the distance between the capital cities, in the same year. This instrument satisfies both characteristics of a good instrument, being correlated to the endogenous variable and uncorrelated to the error term. As a consequence, we rely on a 2SLS regression model, as follows:

$$F_{s,t} = \alpha_1 + \beta_2 F_{-s,t} + \Gamma_1 X_{s,t} + \Lambda_1 Z_{d,t} + \eta_{1,t} + \theta_{1,d} + \varepsilon_{d,s,t} \quad (2)$$

$$E_{d,s,t} = \alpha_2 + \beta_2 \hat{F}_{s,t} + \Gamma_2 X_{s,t} + \Lambda_2 Z_{d,t} + \eta_{2,t} + \theta_{2,d} + \varepsilon_{d,s,t} \quad (3)$$

where $F_{-s,t}$ is the instrument described above.

Table 4 displays the results for the 2SLS estimation in eq.(3). The salience of feminine issues is positively correlated to the share of votes for women candidates in all specifications, mostly independently of the set of control variables included. Although we must be very cautious in interpreting the magnitude of the coefficients in a IV-2SLS setting, a 1 standard deviation increase of the salience of feminine issue (about .043, 15% of the mean) leads to an increase of the share of votes for women candidates by about $13.5\% - 18.5\%$, depending on the specification.[15] Table 5 shows the results from an analogous model estimated with simple OLS with fixed effects, but without instrumental variables. We can observe that the size of the coefficients relative to salience of feminine issues is much lower and never statistically significant. This leads us to conclude that the omitted variable bias is negative, meaning that the effect of omitted variables on the share of votes for female candidates and the correlation between omitted variables and feminine issues have opposite sign. Table B.1 in Appendix B displays the full list of coefficients. We can observe that coefficients are fairly stable and can also notice that the share of female candidates and the presence of a female incumbent increase the share of votes for women, as expected. Moreover, time dummies are positive and significantly increasing over time, showing a positive 'exogenous' trend in the share of votes for women. Finally total population and the share of Black population has a negative effect, while other variables included in the model show no

ending on October 31. As an example, we match the results of elections taking place on November 2, 2010 with issue salience registered from November 1, 2009 to October 31, 2010.

[15] The first stage estimations are reported and commented in Table B.2 in Appendix B.

statistically significant effects.

Table 4: Dependent variable: % of votes for women candidates in general elections. IV-2SLS estimation.

	(1)	(2)	(3)	(4)	(5)
Salience of feminine issues	3.188*	4.179**	3.165**	4.281**	4.209**
	(1.859)	(1.906)	(1.380)	(1.905)	(1.900)
Controls:					
Political	No	Yes	Yes	Yes	Yes
Income	No	No	Yes	Yes	Yes
Demographic	No	No	No	Yes	Yes
Education	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2324	2324	2324	2324	2324

†: $p < 0.15$, *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors clustered at state level. Control variables: ‘Political’ include the share of women candidates, the share of population registered for voting and an indicator for a woman incumbent at district level; ‘Income’ include per-capita GDP at state level; ‘Demographic’ include total population and the shares of women, Asian, Black and Indian population at state level; ‘Education’ include the share of population with at least high school and at least college education at state level.

The choice of clustering standard errors at state level seems quite intuitive, since there can be some correlation among different districts in the same state. However, we test the robustness of the results when clustering standard errors at district level (Table 6, col.1), with robust standard errors (col.2) or not clustering at all (col.3), and results are virtually identical to the benchmark. Moreover, in the main model we put together House and Senate elections, controlling for the differences by including districts fixed effects and treating House and Senate as different districts. To analyze a neater model, we select only House elections (col.4). Even though the sample size is smaller, results are in line with the benchmark model. Finally, we select only those district with at least one female candidate (col.5). Also in this case, results are virtually unchanged, even if the sample size declines by about 60%.

Another concern we might have on our sample regards the time span. All the previous estimations include only elections since 2010 for two reasons: one, theoretical, regards gerrymandering: after 2010 Census, some districts were reshaped and this may affect the validity of the district fixed effects; the other, more practical, is the unavailability of data on education at state level before 2010. However, we test the time trend of our results

Table 5: Dependent variable: % of votes for women candidates in general elections. OLS estimation.

	(1)	(2)	(3)	(4)	(5)
Salience of feminine issues	0.112	-0.059	-0.033	-0.159	-0.235
	(0.285)	(0.253)	(0.269)	(0.291)	(0.272)
Controls:					
Political	No	Yes	Yes	Yes	Yes
Income	No	No	Yes	Yes	Yes
Demographic	No	No	No	Yes	Yes
Education	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.781	0.828	0.828	0.828	0.829
Observations	2324	2324	2324	2324	2324

*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors clustered at state level. Control variables: 'Political' include the share of women candidates, the share of population registered for voting and an indicator for a woman incumbent at district level; 'Income' include per-capita GDP at state level; 'Demographic' include total population and the shares of women, Asian, Black and Indian population at state level; 'Education' include the share of population with at least high school and at least college education at state level.

by running regression models without education for different time spans, starting from the first elections in 2004. Results represented in Figure 4 show that the effect seems to be fairly stable, with a slight increase in the statistical significance in the latest elections.

Another sensible political outcome is the probability that a female candidate actually wins elections. We modify the baseline model by replacing the dependent variable with a dummy indicating whether the winner of general election is a woman. The coefficients of this linear probability model should be then interpreted as the change in probability that a female candidate wins elections due to an increase in feminine issue salience. Results reported in Table 7 show that the sign of the main coefficient is positive, as expected, while significance is lower. Therefore, even though issue salience has a significant effect on the share of votes for female candidates, this effect is not strong enough to significantly change the outcome of elections and to change in a significant number of cases the gender of the winner. This result is consistent with the fact that winners have a large average margin on the runner-up, about 33% in our sample, meaning that, on average, a change of about 2 standard deviations is needed to reverse the result of an election.

Finally, we run a set of sensitivity and falsification tests by changing the definitions of masculine, feminine and neutral issues with respect to the definition in Table 2. In

Table 6: Dependent variable: % of votes for women candidates in general elections. IV-2SLS estimation.

	(1)	(2)	(3)	(4)	(5)
Standard errors	Clustered at district level	Robust	Non adjusted	Clustered at state level	Clustered at state level
Sample	Full	Full	Full	House only	See notes
Salience of feminine issues	4.209**	4.209**	4.209**	5.638**	4.274**
	(1.898)	(1.887)	(1.667)	(2.641)	(1.684)
Controls:					
Political	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Demographic	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2324	2324	2324	2158	934

*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors clustered at district level in column 1, robust in column 2, non adjusted in column 3, clustered at state level in columns 4 and 5. The sample is full in columns 1-3, only House elections in column 4 and only districts with at least one female candidate in column 5. Control variables: 'Political' include the share of women candidates, the share of population registered for voting and an indicator for a woman incumbent at district level; 'Income' include per-capita GDP at state level; 'Demographic' include total population and the shares of women, Asian, Black and Indian population at state level; 'Education' include the share of population with at least high school and at least college education at state level.

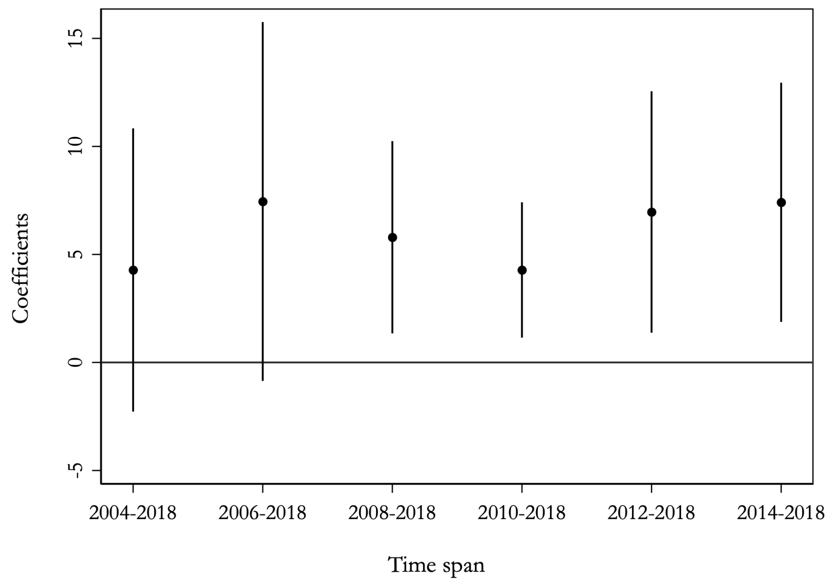


Figure 4: Effect of feminine issue salience on the share of votes for female candidates. Main equation, by time span.

Table 7: Dependent variable: Probability that a female candidate wins general elections. IV-2SLS estimation.

	(1)	(2)	(3)	(4)	(5)
Salience of feminine issues	1.258	3.802	2.872	4.179	5.188
	(4.662)	(4.758)	(3.862)	(4.035)	(4.348)
Controls:					
Political	No	Yes	Yes	Yes	Yes
Income	No	No	Yes	Yes	Yes
Demographic	No	No	No	Yes	Yes
Education	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2324	2324	2324	2324	2324

*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors clustered at state level. Control variables: 'Political' include the share of women candidates, the share of population registered for voting and an indicator for a woman incumbent at district level; 'Income' include per-capita GDP at state level; 'Demographic' include total population and the shares of women, Asian, Black and Indian population at state level; 'Education' include the share of population with at least high school and at least college education at state level.

general, shifting some of the neutral issues to masculine or feminine issues does not have a significant impact on the results, while moving more relevant issues makes the results completely insignificant. For instance, if we classify as 'feminine' the issues of Crime and violence and Terrorism, results disappear, and the same is true if we move Education and Gender issues to masculine issues. This is reassuring of the fact that our indicators are good proxies of gender issue relevance.

5 Conclusion

In this paper we consider how issue salience affects women's political participation and performance, both from a theoretical and empirical point of view.

Theoretically, we introduce a model of issue-specific gender bias in elections, which can be interpreted as a description of a real comparative advantage over some issues (in the spirit of Bordalo et al., 2019) as well as a pure prejudice (as in Cella and Manzoni, 2022). We show how the bias influences electoral results, favoring female candidates when the salience of feminine issues is higher, and male candidates when the salience of masculine issues is higher. We also show when successful information transmission during the electoral campaign may partially contrast and reverse this phenomenon.

From the empirical point of view, employing a novel panel dataset of issue salience and administrative electoral data, we are able to show a robust positive effect of the relevance of feminine issues on the share of votes in the general elections. This evidence is consistent with and supportive of the main conclusions of the theoretical model and sheds some further light on the relevant topic of equal gender representation in the political framework.

The conclusions of this study can also suggest some interpretation of the actual behavior of candidates and parties. On the one hand, parties may decide to strategically candidate men (women) whenever masculine (feminine) issues are perceived as more salient in a specific electoral campaign. On the other hand, once candidacies are settled, parties and candidates may direct the electoral campaign on specific issues according to the gender of candidates. We observe, in fact, that right wing parties often campaign on national security, crime and immigration while left wing parties typically focus on redistribution, health and education. A similar process may happen according to the gender of candidates, if they decide to exploit and reinforce the stereotypes.

From another perspective, in order to increase gender equality, policy makers may want to break the stereotype and the vicious cycle that relegates female politicians to feminine issues. According to the results of our models, more information may help to reduce the gender gap. In previous work (Cella and Manzoni, 2022) we argued that gender quotas may reduce the bias against women by providing more information on the distribution of their competences by increasing sample size (i.e., by allowing voters to observe the competence of a higher number of female politicians). This paper suggests that gender bias may also be reduced by intervening on media: balancing the gender of 'experts' invited to talk about specific issues may prove that men and women are equally skilled.

To conclude, issue salience is one of the possible mechanisms behind female representation in politics. This paper is a first attempt to rigorously isolate its effects.

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A Updating

A.1 Posterior distribution of competences

In this section we derive the ex-post distribution of $v_j^k|\sigma_j, G$. We compute the values explicitly for the feminine issue f. For what concerns the masculine issues, $\mathbb{P}(v_m^k|\sigma_m, M) = \mathbb{P}(v_f^k|\sigma_f, F)$, and $\mathbb{P}(v_m^k|\sigma_m, F) = \mathbb{P}(v_f^k|\sigma_f, M)$ if $\sigma_m = \sigma_f$. Table A.1 summarizes the posterior distribution.

Table A.1: Probability of v_j^k, given the gender of the candidate, and the realization of the signal on issue j.

	F		M	
	$v_j^k = 1$	$v_j^k = 0$	$v_j^k = 1$	$v_j^k = 0$
$(j = f, \sigma_f = 1)$	$\frac{2\gamma}{1+\gamma}$	$\frac{1-\gamma}{1+\gamma}$	$\frac{2-2\gamma}{2-\gamma}$	$\frac{\gamma}{2-\gamma}$
$(j = f, \sigma_f = 0)$	$\frac{\gamma}{2-\gamma}$	$\frac{2-2\gamma}{2-\gamma}$	$\frac{1-\gamma}{1+\gamma}$	$\frac{2\gamma}{1+\gamma}$
$(j = m, \sigma_m = 1)$	$\frac{2-2\gamma}{2-\gamma}$	$\frac{\gamma}{2-\gamma}$	$\frac{2\gamma}{1+\gamma}$	$\frac{1-\gamma}{1+\gamma}$
$(j = m, \sigma_m = 0)$	$\frac{1-\gamma}{1+\gamma}$	$\frac{2\gamma}{1+\gamma}$	$\frac{\gamma}{2-\gamma}$	$\frac{2-2\gamma}{2-\gamma}$

Conditional probability of $v_f^k = 1$

$$\begin{aligned}
\mathbb{P}(v_f^k = 1|\sigma_f = 1, F) &= \frac{\mathbb{P}(\sigma_f = 1|v_f^k = 1, F)\mathbb{P}(v_f^k = 1|F)}{\mathbb{P}(\sigma_f = 1|v_f^k = 1, F)\mathbb{P}(v_f^k = 1|F) + \mathbb{P}(\sigma_f = 1|v_f^k = 0, F)\mathbb{P}(v_f^k = 0|F)} \\
&= \frac{\frac{2}{3}\gamma}{\frac{2}{3}\gamma + \frac{1}{3}(1-\gamma)} = \frac{2\gamma}{1+\gamma}.
\end{aligned}$$

$$\begin{aligned}
\mathbb{P}(v_f^k = 1|\sigma_f = 1, M) &= \frac{\mathbb{P}(\sigma_f = 1|v_f^k = 1, M)\mathbb{P}(v_f^k = 1|M)}{\mathbb{P}(\sigma_f = 1|v_f^k = 1, M)\mathbb{P}(v_f^k = 1|M) + \mathbb{P}(\sigma_f = 1|v_f^k = 0, M)\mathbb{P}(v_f^k = 0|M)} \\
&= \frac{\frac{2}{3}(1-\gamma)}{\frac{2}{3}(1-\gamma) + \frac{1}{3}\gamma} = \frac{2-2\gamma}{2-\gamma}.
\end{aligned}$$

$$\begin{aligned}
\mathbb{P}(v_f^k = 1|\sigma_f = 0, F) &= \frac{\mathbb{P}(\sigma_f = 0|v_f^k = 1, F)\mathbb{P}(v_f^k = 1|F)}{\mathbb{P}(\sigma_f = 0|v_f^k = 1, F)\mathbb{P}(v_f^k = 1|F) + \mathbb{P}(\sigma_f = 0|v_f^k = 0, F)\mathbb{P}(v_f^k = 0|F)} \\
&= \frac{\frac{1}{3}\gamma}{\frac{1}{3}\gamma + \frac{2}{3}(1-\gamma)} = \frac{\gamma}{2-\gamma}.
\end{aligned}$$

$$\begin{aligned}\mathbb{P}(v_f^k = 1|\sigma_f = 0, M) &= \frac{\mathbb{P}(\sigma_f = 0|v_f^k = 1, M)\mathbb{P}(v_f^k = 1|M)}{\mathbb{P}(\sigma_f = 0|v_f^k = 1, M)\mathbb{P}(v_f^k = 1|M) + \mathbb{P}(\sigma_f = 0|v_f^k = 0, M)\mathbb{P}(v_f^k = 0|M)} \\ &= \frac{\frac{1}{3}(1-\gamma)}{\frac{1}{3}(1-\gamma) + \frac{2}{3}\gamma} = \frac{1-\gamma}{1+\gamma}.\end{aligned}$$

Conditional probability of $v_f^k = 0$

$$\begin{aligned}\mathbb{P}(v_f^k = 0|\sigma_f = 1, F) &= \frac{\mathbb{P}(\sigma_f = 1|v_f^k = 0, F)\mathbb{P}(v_f^k = 0|F)}{\mathbb{P}(\sigma_f = 1|v_f^k = 0, F)\mathbb{P}(v_f^k = 0|F) + \mathbb{P}(\sigma_f = 1|v_f^k = 1, F)\mathbb{P}(v_f^k = 1|F)} \\ &= \frac{\frac{1}{3}(1-\gamma)}{\frac{1}{3}(1-\gamma) + \frac{2}{3}\gamma} = \frac{1-\gamma}{1+\gamma}.\end{aligned}$$

$$\begin{aligned}\mathbb{P}(v_f^k = 0|\sigma_f = 1, M) &= \frac{\mathbb{P}(\sigma_f = 1|v_f^k = 0, M)\mathbb{P}(v_f^k = 0|M)}{\mathbb{P}(\sigma_f = 1|v_f^k = 0, M)\mathbb{P}(v_f^k = 0|M) + \mathbb{P}(\sigma_f = 1|v_f^k = 1, M)\mathbb{P}(v_f^k = 1|M)} \\ &= \frac{\frac{1}{3}\gamma}{\frac{1}{3}\gamma + \frac{2}{3}(1-\gamma)} = \frac{\gamma}{2-\gamma}.\end{aligned}$$

$$\begin{aligned}\mathbb{P}(v_f^k = 0|\sigma_f = 0, F) &= \frac{\mathbb{P}(\sigma_f = 0|v_f^k = 0, F)\mathbb{P}(v_f^k = 0|F)}{\mathbb{P}(\sigma_f = 0|v_f^k = 0, F)\mathbb{P}(v_f^k = 0|F) + \mathbb{P}(\sigma_f = 0|v_f^k = 1, F)\mathbb{P}(v_f^k = 1|F)} \\ &= \frac{\frac{2}{3}(1-\gamma)}{\frac{2}{3}(1-\gamma) + \frac{1}{3}\gamma} = \frac{2-2\gamma}{2-\gamma}.\end{aligned}$$

$$\begin{aligned}\mathbb{P}(v_f^k = 0|\sigma_f = 0, M) &= \frac{\mathbb{P}(\sigma_f = 0|v_f^k = 0, M)\mathbb{P}(v_f^k = 0|M)}{\mathbb{P}(\sigma_f = 0|v_f^k = 0, M)\mathbb{P}(v_f^k = 0|M) + \mathbb{P}(\sigma_f = 0|v_f^k = 1, M)\mathbb{P}(v_f^k = 1|M)} \\ &= \frac{\frac{2}{3}\gamma}{\frac{2}{3}\gamma + \frac{1}{3}(1-\gamma)} = \frac{2\gamma}{1+\gamma}.\end{aligned}$$

A.2 Expected competences with two signals

Table A.2 B reports the expected competences in presence of two signals. To help the reader, Table A.2 also reports the expected competences by gender in the case without signals.

Table A.2: Expected competence of a candidate, given his/her gender, and the realization of the signals.

	$G = F$	$G = M$
$\mathbb{E}(v^k \mid G, \emptyset, \emptyset)$	$\rho_f \gamma + \rho_n \frac{1}{2} + \rho_m(1-\gamma)$	$\rho_f(1-\gamma) + \frac{\rho_n}{2} + \rho_m \gamma$
$\mathbb{E}(v^k \mid G, \sigma_f = 0, \sigma_m = 0)$	$\rho_f \frac{\gamma}{2-\gamma} + \frac{\rho_n}{2} + \rho_m \frac{1-\gamma}{1+\gamma}$	$\rho_f \frac{1-\gamma}{1+\gamma} + \frac{\rho_n}{2} + \rho_m \frac{\gamma}{2-\gamma}$
$\mathbb{E}(v^k \mid G, \sigma_f = 1, \sigma_m = 0)$	$\rho_f \frac{2\gamma}{1+\gamma} + \frac{\rho_n}{2} + \rho_m \frac{1-\gamma}{1+\gamma}$	$\rho_f \frac{2-2\gamma}{2-\gamma} + \frac{\rho_n}{2} + \rho_m \frac{\gamma}{2-\gamma}$
$\mathbb{E}(v^k \mid G, \sigma_f = 0, \sigma_m = 1)$	$\rho_f \frac{\gamma}{2-\gamma} + \frac{\rho_n}{2} + \rho_m \frac{2-2\gamma}{2-\gamma}$	$\rho_f \frac{1-\gamma}{1+\gamma} + \frac{\rho_n}{2} + \rho_m \frac{2\gamma}{1+\gamma}$
$\mathbb{E}(v^k \mid G, \sigma_f = 1, \sigma_m = 1)$	$\rho_f \frac{2\gamma}{1+\gamma} + \frac{\rho_n}{2} + \rho_m \frac{2-2\gamma}{2-\gamma}$	$\rho_f \frac{2-2\gamma}{2-\gamma} + \frac{\rho_n}{2} + \rho_m \frac{2\gamma}{1+\gamma}$

A.3 Lemma 4

Lemma 4 *Assume that candidates are randomly selected by each party. The median voter's ranking of politicians according to their gender and signal depends on the ratio* $\frac{\rho_f}{\rho_m}$ *as follows:*

- *if* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} \in \left(0, \frac{(3\gamma-2)(1+\gamma)}{(3\gamma-1)(2-\gamma)}\right)$ *the ranking is*

  $$(M,1,1) \succ (M,0,1) \succ (M,1,0) \succ (M,0,0) \succ (F,1,1) \succ (F,0,1) \succ (F,1,0) \succ (F,0,0);$$

- *if* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-2)(1+\gamma)}{(3\gamma-1)(2-\gamma)}, \frac{(3\gamma-2)(1+\gamma)}{4\gamma-2}\right)$ *the ranking is*

  $$(M,1,1) \succ (M,0,1) \succ (M,1,0) \succ (F,1,1) \succ (M,0,0) \succ (F,0,1) \succ (F,1,0) \succ (F,0,0);$$

- *if* $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-2)(1+\gamma)}{4\gamma-2}, \frac{4\gamma-2}{(3\gamma-1)(2-\gamma)}\right)$ *the ranking is*

  $$(M,1,1) \succ (M,0,1) \succ (F,1,1) \succ (M,1,0) \succ (F,0,1) \succ (M,0,0) \succ (F,1,0) \succ (F,0,0);$$

- *if* $\frac{\rho_f}{\rho_m} \in \left(\frac{4\gamma-2}{(3\gamma-1)(2-\gamma)}, 1,\right)$ *the ranking is*

  $$(M,1,1) \succ (F,1,1) \succ (M,0,1) \succ (M,1,0) \succ (F,0,1) \succ (F,1,0) \succ (M,0,0) \succ (F,0,0);$$

- *if* $\frac{\rho_f}{\rho_m} \in \left(1, \frac{(3\gamma-1)(2-\gamma)}{4\gamma-2}\right)$ *the ranking is*

  $$(F,1,1) \succ (M,1,1) \succ (F,1,0) \succ (F,0,1) \succ (M,1,0) \succ (M,0,1) \succ (F,0,0) \succ (M,0,0);$$

- *if* $\frac{\rho_f}{\rho_m} \in \left(\frac{(3\gamma-1)(2-\gamma)}{4\gamma-2}, \frac{4\gamma-2}{(3\gamma-2)(1+\gamma)}\right)$ *the ranking is*

  $$(F,1,1) \succ (F,1,0) \succ (M,1,1) \succ (F,0,1) \succ (M,1,0) \succ (F,0,0) \succ (M,0,1) \succ (M,0,0);$$

- *if* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} \in \left(\frac{4\gamma-2}{(3\gamma-2)(1+\gamma)}, \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}\right)$ *the ranking is*

  $$(F,1,1) \succ (F,1,0) \succ (F,0,1) \succ (M,1,1) \succ (F,0,0) \succ (M,1,0) \succ (M,0,1) \succ (M,0,0);$$

- *if* $\gamma > \frac{2}{3}$ *and* $\frac{\rho_f}{\rho_m} > \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}$ *the ranking is*

  $$(F,1,1) \succ (F,1,0) \succ (F,0,1) \succ (F,0,0) \succ (M,1,1) \succ (M,1,0) \succ (M,0,1) \succ (M,0,0);$$

Proof.

1. Due to the symmetry of the problem, the following relations hold iff $\rho_f > \rho_m$ (for any γ)

$$\begin{aligned}
\mathbb{E}(v^k|F,\sigma_f=0,\sigma_m=0) &> \mathbb{E}(v^k|M,\sigma_f=0,\sigma_m=0)\\
\mathbb{E}(v^k|F,\sigma_f=1,\sigma_m=0) &> \mathbb{E}(v^k|M,\sigma_f=0,\sigma_m=1)\\
\mathbb{E}(v^k|F,\sigma_f=0,\sigma_m=1) &> \mathbb{E}(v^k|M,\sigma_f=1,\sigma_m=0)\\
\mathbb{E}(v^k|F,\sigma_f=1,\sigma_m=1) &> \mathbb{E}(v^k|M,\sigma_f=1,\sigma_m=1)
\end{aligned}$$

2. The following relations hold for any value of $\rho = (\rho_f, \rho_n, \rho_m)$ and γ

   - $\mathbb{E}(v^k|F,\sigma_f=1,\sigma_m=1) \geq \mathbb{E}(v^k|F,\sigma_f=1,\sigma_m=0) \geq \mathbb{E}(v^k|F,\sigma_f=0,\sigma_m=0)$;
   - $\mathbb{E}(v^k|F,\sigma_f=1,\sigma_m=1) \geq \mathbb{E}(v^k|F,\sigma_f=0,\sigma_m=1) \geq \mathbb{E}(v^k|F,\sigma_f=0,\sigma_m=0)$;
   - $\mathbb{E}(v^k|M,\sigma_f=1,\sigma_m=1) \geq \mathbb{E}(v^k|M,\sigma_f=1,\sigma_m=0) \geq \mathbb{E}(v^k|M,\sigma_f=0,\sigma_m=0)$;
   - $\mathbb{E}(v^k|M,\sigma_f=1,\sigma_m=1) \geq \mathbb{E}(v^k|M,\sigma_f=0,\sigma_m=1) \geq \mathbb{E}(v^k|M,\sigma_f=0,\sigma_m=0)$;

   Moreover:

   - $\mathbb{E}(v^k|F,\sigma_f=1,\sigma_m=0) > \mathbb{E}(v^k|F,\sigma_f=0,\sigma_m=1)$ if $\rho_f > \rho_m$.

- $\mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 0) > \mathbb{E}(v^k|M, \sigma_f = 0, \sigma_m = 1)$ if $\rho_f > \rho_m$

3. If $\gamma < \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 0) < \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 1)$, for any ρ.
   If $\gamma > \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 0) > \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 1)$ iff $\frac{\rho_f}{\rho_m} > \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}$.
4. If $\gamma < \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 0) < \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 0)$, for any ρ.
   If $\gamma > \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 0) > \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 0)$ iff $\frac{\rho_f}{\rho_m} > \frac{4-2\gamma}{(3\gamma-2)(1+\gamma)}$.
   Note that $1 \leq \frac{4-2\gamma}{(3\gamma-2)(1+\gamma)} \leq \frac{(3\gamma-1)(2-\gamma)}{(3\gamma-2)(1+\gamma)}$ for $\gamma \in \left[\frac{1}{2}, 1\right]$.
5. If $\gamma < \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 1) < \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 1)$, for any ρ.
   If $\gamma > \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 1) > \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 1)$ iff $\frac{\rho_f}{\rho_m} > \frac{4-2\gamma}{(3\gamma-2)(1+\gamma)}$.
6. If $\gamma < \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 1) > \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 0)$, iff $\rho_m > \rho_f$.
   If $\gamma > \frac{2}{3}$, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 1) > \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 0)$ iff $\rho_f > \rho_m$.
7. For any γ, $\mathbb{E}(v^k|F, \sigma_f = 0, \sigma_m = 0) > \mathbb{E}(v^k|M, \sigma_f = 0, \sigma_m = 1)$, iff $\frac{\rho_f}{\rho_m} > \frac{(3\gamma-1)(2-\gamma)}{4-2\gamma}$
8. For any γ, $\mathbb{E}(v^k|F, \sigma_f = 1, \sigma_m = 0) > \mathbb{E}(v^k|M, \sigma_f = 1, \sigma_m = 1)$, iff $\frac{\rho_f}{\rho_m} > \frac{(3\gamma-1)(2-\gamma)}{4-2\gamma}$

■

B Additional tables

Table B.1 displays all the estimated coefficients of the baseline model reported in Table 4 in the main text.

Table B.2 shows in column (1) the simple correlation between the instrument and the instrumented variable, without any control variables. The coefficient is intuitively positive and strongly significant ($t - stat = 31.02$) and 92.5% of the variance of the endogenous variable is explained by the instrument. Next columns show the first stages of the respective models in Table 4. While the presence of year fixed effects reverses the sign, the instrument remains highly significant.

Table B.1: Dependent variable: % of votes for women candidates in general elections. IV-2SLS estimation.

	(1)	(2)	(3)	(4)	(5)
Salience of feminine issues	3.188*	4.179**	3.165**	4.281**	4.209**
	(1.859)	(1.906)	(1.380)	(1.905)	(1.900)
Share of female candidates	0.817***	0.737***	0.737***	0.739***	0.739***
	(0.026)	(0.030)	(0.030)	(0.030)	(0.030)
Salience of relevant issues	-0.000*	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of pop. registered	.	0.001	0.001	0.001	0.001
	.	(0.002)	(0.002)	(0.002)	(0.002)
Female incumbent	.	0.194***	0.195***	0.195***	0.195***
	.	(0.018)	(0.018)	(0.018)	(0.018)
Per capita GDP	.	.	-0.000*	-0.000	-0.000
	.	.	(0.000)	(0.000)	(0.000)
Population	.	.	.	0.000**	0.000**
	.	.	.	(0.000)	(0.000)
Share of female population	.	.	.	5.649	7.269
	.	.	.	(6.699)	(7.010)
Share of Asian population	.	.	.	-1.995	-2.162
	.	.	.	(2.407)	(2.280)
Share of Black population	.	.	.	-3.838**	-4.094*
	.	.	.	(1.917)	(2.090)
Share of native population	.	.	.	6.912	7.071
	.	.	.	(7.785)	(8.302)
Share of pop. with high school	.	.	.	.	-0.007
	.	.	.	.	(0.010)
Share of pop. with bachelor	.	.	.	.	0.007
	.	.	.	.	(0.008)
Year 2012	0.056*	0.071*	0.068**	0.083*	0.085*
	(0.030)	(0.040)	(0.033)	(0.043)	(0.050)
Year 2014	0.073†	0.098*	0.096**	0.127**	0.127†
	(0.047)	(0.050)	(0.043)	(0.062)	(0.078)
Year 2016	0.163*	0.210*	0.190**	0.252**	0.249*
	(0.095)	(0.107)	(0.085)	(0.122)	(0.144)
Year 2018	0.238*	0.313**	0.287**	0.377**	0.373*
	(0.133)	(0.140)	(0.114)	(0.162)	(0.196)
Constant	-0.745†	-1.060**	-0.705**	-3.607	-3.973
	(0.474)	(0.452)	(0.327)	(3.610)	(3.564)
Observations	2324	2324	2324	2324	2324

†: $p < 0.15$, *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors clustered at state level.

Table B.2: Dependent variable: Salience of feminine issues. First stage of IV-2SLS estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
Instrument	1.240***	-0.698***	-0.692**	-0.961***	-0.734***	-0.690***
	(0.040)	(0.261)	(0.262)	(0.283)	(0.246)	(0.237)
Share of female candidates	.	0.000	-0.000	-0.000	-0.001	-0.000
	.	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Salience of relevant issues	.	0.000***	0.000***	0.000***	0.000***	0.000***
	.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of pop. registered	.	.	0.000	0.000	0.000	0.000
	.	.	(0.000)	(0.000)	(0.000)	(0.000)
Female incumbent	.	.	0.001	0.001	0.000	0.000
	.	.	(0.001)	(0.001)	(0.000)	(0.000)
Per capita GDP	.	.	.	0.000***	0.000	0.000
	.	.	.	(0.000)	(0.000)	(0.000)
Population	.	.	.	.	-0.000***	-0.000***
	.	.	.	.	(0.000)	(0.000)
Share of female population	.	.	.	.	-1.983*	-2.181**
	.	.	.	.	(1.006)	(1.013)
Share of Asian population	.	.	.	.	0.850***	0.863***
	.	.	.	.	(0.295)	(0.302)
Share of Black population	.	.	.	.	0.575**	0.662***
	.	.	.	.	(0.245)	(0.240)
Share of native population	.	.	.	.	0.392	0.893
	.	.	.	.	(1.320)	(1.436)
Share of pop. high school	.	.	.	.	.	0.002*
	.	.	.	.	.	(0.001)
Share of pop. bachelor	.	.	.	.	.	0.001
	.	.	.	.	.	(0.001)
Year 2012	.	-0.029***	-0.031***	-0.042***	-0.034***	-0.037***
	.	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
Year 2014	.	-0.041***	-0.041***	-0.056***	-0.049***	-0.054***
	.	(0.006)	(0.006)	(0.009)	(0.008)	(0.008)
Year 2016	.	-0.084***	-0.085***	-0.110***	-0.097***	-0.103***
	.	(0.011)	(0.011)	(0.016)	(0.013)	(0.014)
Year 2018	.	-0.115***	-0.115***	-0.150***	-0.133***	-0.142***
	.	(0.016)	(0.015)	(0.022)	(0.019)	(0.020)
Constant	0.010	0.436***	0.414***	0.439***	1.353**	1.223**
	(0.009)	(0.061)	(0.075)	(0.069)	(0.517)	(0.508)
R^2	0.925	0.955	0.955	0.958	0.965	0.965
Observations	2324	2324	2324	2324	2324	2324

†: $p < 0.15$, *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors clustered at state level. Instrument is the average salience of feminine over total in all other states.

C List of keywords

Crime & violence: Gun control; Shooting; Violence; Crime; Homicide; NRA; stabbing; Burglary; Murder; for gun control; gun laws; gun control laws; obama gun control; guns; school shooting; vegas shooting; police shooting; texas shooting; shooting today; domestic violence; gun violence; what is violence; family violence; school violence; crime rate; crime news; crime map; crime city; crime statistics; homicide rate; homicide news; what is homicide; the nra; nra membership; nra store; what is nra; nra news; school stabbing; back stabbing; the burglary; burglary robbery; robbery; what is burglary; burglary crime; theft

Healthcare: Healthcare; Health insurance; Medicare; Medicaid; Obamacare; healthcare insurance; health care; family healthcare; health care insurance; medical insurance; health insurance plans; what is health insurance; medicare medicaid; medicare insurance; medicare advantage; what is medicare; obamacare insurance; medicaid insurance; what is obamacare; obamacare health insurance

Terrorism: Terrorism; National security; Homeland security; Al qaeda; ISIS; Terrorist attack; beheading; terrorism definition; terrorist; war on terrorism; what is terrorism; domestic terrorism; national security council; national security act; what is national security; national security agency; us national security; terrorist attacks; new terrorist attack; news terrorist attack; homeland security department; department of homeland security; homeland and security; homeland security us; taliban; taliban al qaeda; isis al qaeda; bin laden; isis news; isis video; what is isis

Immigration control: dreamers act; Immigrants; Immigration; Illegal migration; Mexican border; Wall; daca; the immigrants; illegal immigrants; new immigrants; immigrants in the us; how many immigrants; immigration us; immigration news; immigration reform; immigration law; illegal immigration; us immigration; immigrant; illegal immigration statistics; immigration statistics; us mexican border; mexican wall; mexican border wall; border wall; mexican border crossing; border crossing; trump border wall; daca dreamers

Financial/political corruption: Corruption; Superpac; Lobbying; Bribe; police corruption; government corruption; what is corruption; political corruption; corruption definition; the bribe; bribe definition ; bribery; bribe money; what is bribe; lobbying is; what is lobbying; lobbying groups; lobbying group; political lobbying; lobbyist; lobbying disclosure; interest groups; superpac colbert; super pac; what is superpac; what is a superpac

Moral decline: Transgender; lgbt; lgbtq; Gay; Same sex marriage; Abortion; what is transgender; transgender woman; transgender surgery; transgender man; lgbt rights; what is lgbt; lgbt center; lgbt community; lgbt pride; what lgbtq; what does lgbtq; lgbtq stand for; what is lgbtq; lgbtq meaning; gay marriage; gay pride; same sex marriage states; legal same sex marriage; is same sex marriage legal; same sex marriage supreme court; us same sex marriage; pill abortion; abortion clinic; abortion clinics; what is abortion; abortion law

Poverty & soclai inequality: Poverty; Inequality; child poverty; Top 1%; Homeless; Food stamps; poverty level; what is poverty; poverty line; poverty rate; us poverty; what is inequality; income inequality; social inequality; child in poverty; children poverty; what is child poverty; child poverty rate; child poverty in america; the top 1%; Top 1% net worth; Top 1% taxes; Top 1% salary; Top 1% income; homeless help; homeless housing; homeless children; homeless people; homeless shelter

Unemployment: Unemployment; Job; Job search; Unemployment benefit; Recession; Job loss; unemployment benefits; unemployment login; claim unemployment; unemployment rate; unemployment number;

jobs; job description; job openings; job application ; get a job; jobs search; job search engines; indeed; indeed job search; job sites; maximum unemployment benefit; what is unemployment; unemployment weekly benefit; unemployment benefit amount; unemployment benefit claim; the recession; great recession; what is recession; us recession; economic recession; loss of job; job loss insurance; us job loss; job loss depression; job loss statistics

Education: Education; Waiver / Scholarship; College fees; Public school; Private school; University fees; Student loan; Admissions; department of education; board of education; special education; higher education; continuing education; fee waiver; waiver program; tuition waiver; college fee waiver; scholarships; college scholarship; foundation scholarship; scholarship application; scholarship for college; tuition; college tuition; tuition and fees; college application; college application fees; public schools; public charter school; public school ranking; private schools; private high schools; private elementary school; christian private school; private school tuition; college; colleges; student loans; student loan forgiveness; loan forgiveness; federal loan; federal student loan; college admissions; admissions office; office of admissions; admission; graduate admissions

Rise of extremism: Black lives matter; Nazi; Communist; KKK; Riot; White supremacy; Socialism; Incel; black lives matter protest; blm; black lives matter movement; black lives matter shirt; what is black lives matter; trump nazi; the nazi; nazi party; nazi symbol; neo nazi; communist manifesto; communist party; communist china; china; communism; the kkk; trump kkk; black kkk; what is kkk; kkk klan; the riot; riots; prison riot; chicago riot; riot police; the white supremacy; white supremacy trump; black white supremacy; black supremacy; white supremacy groups; socialism communism; definition socialism; what is socialism; socialist; democratic socialism; incel meaning; definition incel; what is incel; what is an incel; define incel

Taxes: Taxes; Shutdown; Public debt; Federal budget; Tax cuts; Inflation; Mortgage; file taxes; state taxes; income taxes; property taxes; federal taxes; tax; government shutdown; government; the government shutdown; state shutdown; what is public debt; bureau public debt; us debt; us public debt; national debt; the federal budget; federal government budget; federal government; government budget; us federal budget; bush tax cuts; trump tax cuts; tax cuts jobs act; tax cuts and jobs act; tax cuts obama; inflation rate; inflation calculator; what is inflation; rate of inflation ; us inflation; mortgage calculator; mortgage rates; mortgage loan; mortgage rate; mortgage refinance

Climate change: Climate; Climate change; Global warming; Emission control; Carbon tax; Renewable energy; Floods; Hurricanes; climate is; what is climate; climate change is; climate control; global climate change; what is climate change; global warming climate change; how does climate change; climate change effects; trump climate change; climate change causes; what is global warming; global warming effects; global warming causes; global warming facts; global warming definition; what is carbon tax; cap and trade; carbon emission tax; us carbon tax; what is the carbon tax; solar energy renewable; what is renewable energy; solar energy; energy resources; renewable resources; hurricane; carolina hurricanes; hurricanes schedule; florida hurricanes; what are hurricanes; flood; flooding; flash floods; texas floods; what are floods

Threats against the environment: Pollution; Air pollution; Clean air; Nuclear waste; Fracking; water pollution; water ; what is pollution; environmental pollution; pollution control; pollution in the air; what is air pollution; air quality; air pollution effects; air pollution control; how to clean air; clean air act; the clean air act; clean water act; epa; epa clean air act; Nuclear energy waste; Nuclear power waste; what is nuclear waste; what is fracking; oil fracking; fracking water; gas fracking; fracking definition

Gender: Gender bias; Gender inequality; mansplaining; gender pay gap; women glass ceiling; what is gender bias; gender bias definition; gender bias examples; gender bias in the workplace; gender bias in education; the gender pay gap; gender gap in pay; gender wage gap; what is the gender pay gap; gender pay gap statistics; what is mansplaining; mansplaining definition; mansplaining meaning; mansplaining examples; mansplaining define; women inequality; gender equality; what is gender inequality; gender inequality in the workplace; gender inequality definition; gender discrimination; women discrimination; gender based discrimination