Changing the Dialogue:
Descriptive Candidacies & Position-Taking in Campaigns for the U.S. House of Representatives

Online Appendix & Supplementary Information

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A Data Collection & Issue Classification

The data collected for this project belongs to a broader, longitudinal study about the nature of elite communication in contemporary congressional elections. At the time of our initial data collection, this paper's development was in a nascent stage; therefore, the initial collection and labeling of campaign platform text was completed agnostic to the researcher's objectives for this paper. In our data collection effort, we sought to collect and code the major topic area for all platform positions found on campaign websites for all primary election candidates who emerged in a given election year. To offer complete transparency, a full description of our data collection practices will be presented here. Before their coding task began, RAs were given a codebook and attended a two-hour training on the text collection process. Our data collection/classification was completed in the following stages:

A.1 Stage 1: Candidate & Website Identification

To collect text data from candidate campaign websites, we first identified the names of all major party candidates running in 2018 and 2020 using candidate filings with the Federal Election Commission (FEC), as well as state-level elections websites. Using this list of names, we sought to identify the campaign website URLs for all candidates in each election year by following links from online repositories like Politics1.com, visiting candidates' social media pages, and conducting simple Google searches.

A small group of candidates running in the 2018 and 2020 primaries either had no official campaign website or, if they did adopt a website, did not outline any policy positions on that site. To determine if this missingness was non-random, we regressed policy platform presence on a series of candidate characteristics and election-level covariates. The full model for this analysis can be found in Table A1 of the following page. Candidates who raised nominal funds (less than $2,000) prior to their primary were the least likely to adopt a platform. Campaign platform adoption was also weak among candidates who garnered less than 5% of the vote share in their primary. Generally, these kinds of poor performing candidates lack any campaign presence—online or otherwise—so a missing website is not at all surprising. Although these types of candidates were less likely to have a campaign platform, they are still well-represented in our data. Of the 1,477 Democratic candidates that ran in 2018 and 2020 who *either* raised nominal campaign funds *or* garnered less than 5% of the vote, 1,250 or 83% had a campaign website.

A.2 Website Text Archival & Segmentation

A team of twenty research assistants were tasked with cataloging campaign website text. Each RA was assigned a random selection of candidate names and website URLs. To ensure consistency, text was collected the day before or the day of each candidate's congressional primary. A visualization of the coding procedure taken by the team of RAs can be found in Figure 1. This includes screenshots taken of the Qualtrics tracking survey that was employed for text collection.

To collect campaign website text data, RAs would first navigate to a candidate's website and verify that the URL matched their candidate's profile (i.e., ensure the right website was assigned to the right candidate). Then, using a Qualtrics tracking survey, RAs were instructed to indicate whether or not a campaign platform could be identified on a candidate's campaign website. A platform page or pages could almost always be found

Table A1: Main Indicators for Missingness in Policy Platform Adoption on Congressional Campaign Website, 2018-2020

	DV: Presence of Policy Platform on Campaign Website
No Pre-Primary Election Campaign Receipts	-2.035^{*}
(Raised less than $2,000 prior to their primary)	(0.149)
Performed Poorly in the Primary	-0.579^{*}
(Garnered less than 5% of their primary's vote-share)	(0.191)
Current Member of Congress	0.297
	(0.279)
Ran Unopposed in the Primary	-0.250
	(0.217)
Previously Held Public Office	-0.274
(State-wide or local-level; prior Member of Congress)	(0.222)
Incumbent in Primary, Other Party	0.118
(Reference Category: Incumbent in Primary, Same Party)	(0.188)
Open Seat	0.357
	(0.208)
Constant	2.014^{*}
	(0.183)
Observations	1,718
Log Likelihood	-725.431
Akaike Inf. Crit.	1,466.863

Note: $^{*}p<0.05$

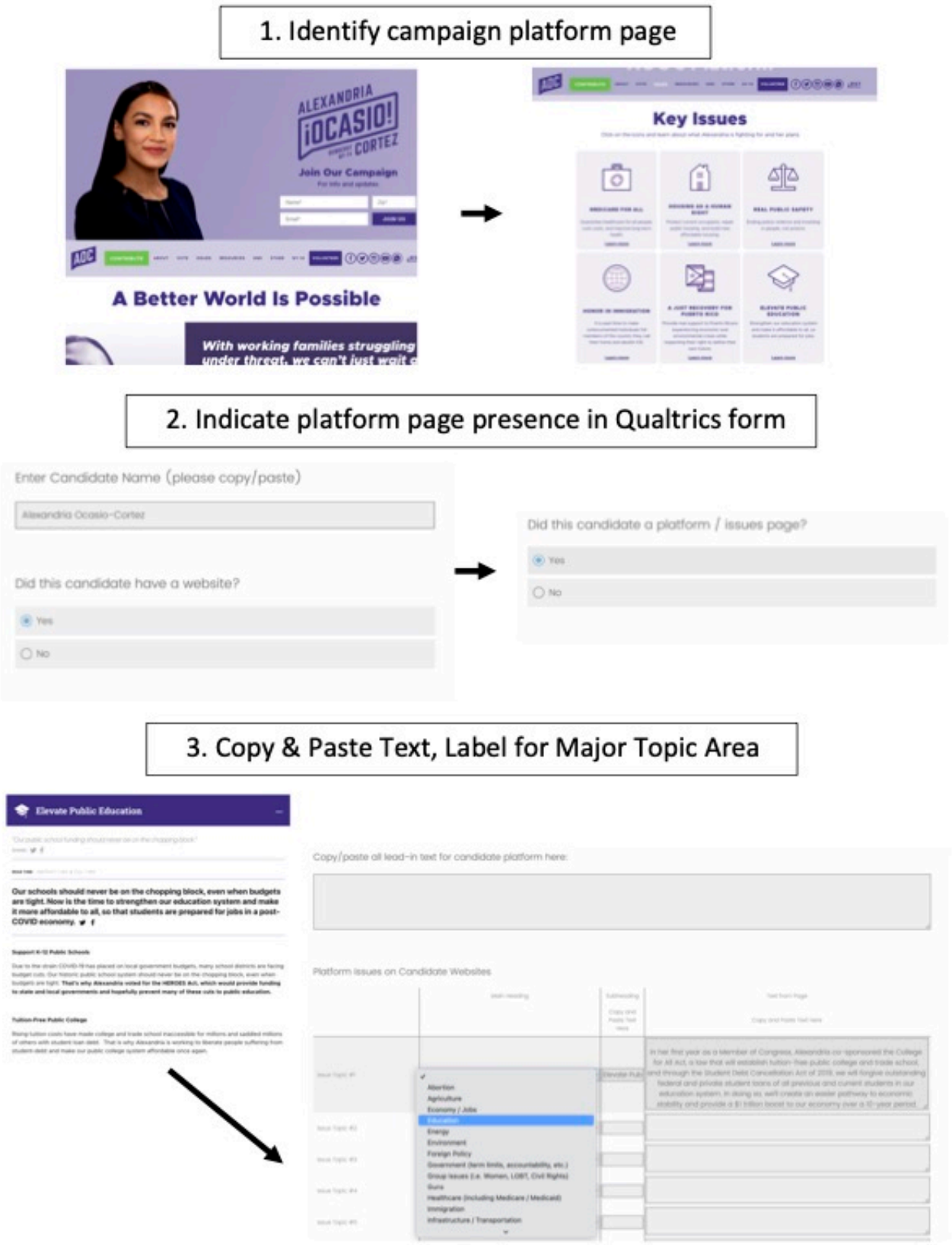
on the website's "main menu." This stage of data collection is illustrated as "Identify campaign platform page" in Figure 1. If the RA indicated that the web-page *did not* have a campaign platform, the Qualtrics tracking survey would direct coders to the end of the survey to answer a series of biographical questions about the candidate of interest (e.g., candidate partisanship or congressional district number). If the RA indicated that the website *did* have a campaign platform, the Qualtrics tracking survey would direct coders to a secondary page for text archival. This stage of data collection is illustrated as "Indicate platform page presence in Qualtrics form" in Figure 1.

At this point, RAs were instructed to copy and paste individual campaign platform positions into the Qualtrics tracking survey. The process of segmenting platform documents into platform points was straightforward; nearly all campaign platforms are organized into sets of paragraphs, where each paragraph addresses a specific platform topic or "point." Individual platform points are almost always nested under a label or heading describing that topic (i.e., Education, Healthcare, or Gun Rights). RAs were instructed to copy/paste a given platform point's body text and heading into the Qualtrics tracking survey. The most complex coding task assigned to RAs was the labeling of individual platform points for major topic area. Our goal with the labeling procedure was to classify individual platform points into broad categories to expedite future research (by ourselves or other researchers employing these text data). In the codebook, coders were provided with sample text that was illustrative of each major topic-area. If coders had questions about the classification of a particular text during their coding task, they were encouraged to reach out to one of the PIs for clarification. If coders were still unsure about text classification, they were encouraged to use the "Unknown/Don't Know" classifier; these texts were later classified by the PIs. This stage of data collection is illustrated as "Copy and Paste Text; Label for Major Topic Area" in Figure 1. A full list of major topic categories is presented below:

Table A2: Major Topic-Area Categories for Campaign Platform Segmentation

Healthcare & Entitlement Programs	Immigration
Agriculture	Infrastructure & Transportation
Crime & Public Safety	Military & Foreign Policy
Economy, Jobs & Trade	Support Troops / Veterans' Issues
Education	Local or District-Specific Issues
Energy and Environment	Political Opinions
Group Issues; Seniors & Vulnerable Populations	Religion
Government Reform & Constitution	Unknown / Don't Know / Other
Gun Rights & Reform	

Figure 1: Visualization of Initial Campaign Platform Collection & Segmentation Procedure



A.3 Qualitative Validation for Identity-Related Issues

Using this compilation of platform text from congressional campaign websites, the authors sought to identify which Democratic candidates adopted progressive positions on issues of race and gender; the authors additionally sought to identify which Democratic and Republican candidates adopted positions on veterans' issues. Across 2018 and 2020, we identified a total of 27,484 platform points across all candidates' platform documents. To reduce our task of reading this near thirty-thousand document corpus of individual platform points, several steps were taken. Using our major topic labels, we culled our corpus to only include those platform points labeled as belonging to the "Group Issues; Seniors & Vulnerable Populations" category and/or the "Support the Troops / Veterans' Issues." Moreover, in case these broad categories did not fully capture all platform text on gender/race/veterans' issues, we also did a simple string search across all texts for the inclusion of topic-specific keywords and key-phrases. If a platform point text was identified as having at least two of these keywords or phrases, it was included in our culled corpus. A full list of keywords is presented below:

Women's Issues Keywords: women, woman, reproductive, gender, sex, sexual, equal, equality, harassment, parental, parent, planned parenthood, abortion, pro-choice, breast

Black-associated Issues Keywords: african, black, minimums, prison, bail, incarceration, police, demilitarize, defund, color, racism, racist, bias, supremacy, white, minorities, minority, criminal, black lives matter, blm, voter, voting, vote, suppression, id, school to prison, pipeline

Veterans' Issues Keywords: veteran, veterans, vet, va, tricare, suicide, ptsd, homelessness, unemployment, unemployed, unemploy, homeless, gi, service, thank, thanks

This identification strategy reduced our corpus of platform points from nearly 30,000 documents to just over 10,000. However, this identification approach surely resulted in the inclusion of some texts that did not specifically discuss women's, Black-associated, or veterans' issues. For instance, the "Group Issues" topic employed in our initial coding of platform text encompassed texts about gender equality and anti-racial discrimination *as well as positions* positions advocating for other disadvantaged groups (e.g., individuals with disabilities). Similarly, women's issues keywords like "equal" and "sexual" resulted in the inclusion of platform positions about LGBTQ+ advocacy in our culled corpus. Platform positions such as these needed to be identified and removed to accurately measure which candidates did/did not discuss identity-related issues of interest. Therefore, to ensure the highest level of accuracy in text identification, two coders read through the totality of our 10,000-document culled corpus to identify which platform point texts specifically addressed women, racial, or veterans' issues. These coders also served as authors on the paper. It is important to note that, during coding, the coders were blind to candidate name, race, gender, and veterans' status.

For our purposes, we coded a platform point as pertaining to "women's issues" if it discussed any of the policies outlined by The Women's March Network—the group responsible for coordinating the 2017 Women's March on Washington. The goals put forward by Black Lives Matter and the NAACP provided a template for identifying platform points addressing "Black-associated issues." A list of example policies for both candidate types is provided in Table 1 of the main paper. We identified veterans' issues using the

Table A3: Proportion of Topic Coverage by Democratic Primary Election Candidates, 2018-2020

Healthcare (e.g., Affordable Care Act, Medicare-for-All)	92.23%
Education (e.g., College Debt, School Choice, Vocational Training)	79.21%
Protecting the Environment (e.g., Paris Accords, Climate Crisis)	75.76%
Immigration (e.g., Citizenship, Defund ICE, Border Wall)	54.24%
Ending Gun Violence (e.g., School Shootings, Background Checks)	51.26%
LGBTQ+ Rights (e.g., Discrimination; HIV/AIDS Prevention)	41.36%
Foreign Policy (e.g., World leadership, Combating terrorism)	28.22%
Infrastructure (e.g., Transportation, Broadband Internet)	25.36%

policy priorities put forward by two advocacy groups: Concerned Veterans for America and With Honor. A list of example veterans' issues is provided in Table 3 of the main paper. In addition to explicit policy priorities, our issue definitions include broader topics like healthcare or gun-rights that are framed in racial or gendered terms. For instance, if a candidate covers education reform in their platform while also discussing the racial achievement gap, we would consider that candidate to have taken up a Black-associated issue. To exclude these kinds of discussions would be to misrepresent the scope of topics related to race and gender. For issues with an ideological slant, candidates were only considered to have covered a women's or Black-associated issue if their position was left-leaning. For instance, in their discussion of abortion, if a Democratic candidate stated that they were in favor of repealing *Roe v. Wade*, we would *not* consider that candidate as having covered a women's issue.

Upon the completion of this secondary coding task, an inter-coder reliability metric of 0.92 was calculated. All disputed texts were reviewed, discussed, and classified based on a majority decision among the authors. This arbitration process was additionally completed blind to candidate characteristics. All texts classified as covering women's, racial, or veterans' issues were stored in a .rds dataframe. These texts are made available in Supplementary Resources and Harvard Dataverse for this paper. Across 1,373 Democratic candidate platforms, we determined that 66% of women and 55% of men discussed women's issues. Additionally, 39% of white, non-Hispanic Democrats, 59% of Black Democrats, and 49% of other racial/ethnic minorities discussed Black-associated issues. To place these proportions in perspective, we identified eight other topic categories and, additionally, assessed the propensity at which candidates covered these issues. We chose these issue-areas because they appeared in both the 2016 and 2020 Democratic Party platforms. If candidates take up any and all issues into their campaign platforms, then these topics should be especially prevalent. In Table A3, what we instead find is that candidates are variable in their uptake of issues important to their party. For instance, while over 90% of Democratic primary elections candidates discussed healthcare in their platforms, just over 40% talked about LGBTQ+ Rights.

A.4 Descriptive Survey of Race & Gender Text

To explore potential differences in how men/women and white/Black candidates discuss issues, we employ a semi-supervised machine learning approach called Structural Topic

Models (STM). At its core, an STM defines topics as distributions of semantically cohesive words and determines topical content based on word co-occurrences. Put differently, an STM is able to determine the types of topics or "themes" talked about within a text and groups words into topics based on how often they are used together. We employ these models to evaluate the comparative specificity/vagueness of candidates' platform statements on issues of race and gender.

To prepare the text for modeling, we took several pre-processing steps standard in text analysis (Grimmer and Stewart, 2013). First, we removed any stop words—commonly used words such as "the," "a," or "in" that have no substantive meaning but rather serve a purely grammatical function. Second, we discarded punctuation, numbers, and removed capitalization. Third, we simplified platform text vocabulary by stemming words, which removes word endings to reduce the dimensionality of text. For instance, using stemming, words like *legislative*, *legislator*, and *legislation* would simplify to *legislat-*. Finally, we removed infrequent words, dropping any terms that did not appear in at least twenty-five texts. Using a variety of metrics for model quality (e.g., held-out likelihood and semantic coherence), we specified seven topics in our Gender STM and six in our Race STM.

Topics identified in our Gender Model are presented in Table A4; topics identified in our Race Model are presented in Table A5. The left column in both tables is a topic label assigned by the authors based upon that topic's common theme; these labels were informed by the top word stems associated with that topic, presented in the middle column of Tables A4 and A5. The right column of both tables specifies the average amount of text dedicated to that topic across platform texts related to women's or Black-associated issues. For example, per Table A5, 17.78% of candidates' text about Black-associated issues was, on average, dedicated to the topic of "Voter Suppression."

For our purposes, several topics of note emerge. The topic "Broad Equality" in Tables A4 and A5 includes references broad-base discrimination within a variety of social groups (e.g., the Race STM in Table A5 features stems about racial justice *as well as* stems for equality based on gender and sexual orientation). Given these topics' broader focus, text associated with "Broad Equality" may more likely include vague overtures about equality and discrimination rather than specific policy proposals. On the other hand, the topic "Action & Advocate" in Table A4 embodies specific references to legislative action and advocacy through the inclusion of stems like *fight*, *vote*, and *congress-*. Accordingly, text associated with this topic may more likely discuss specific policy proposals about women's issues. No topic well-encapsulates legislative advocacy in Table A5 for our Race Model.

Table A4: Gender Model Topics

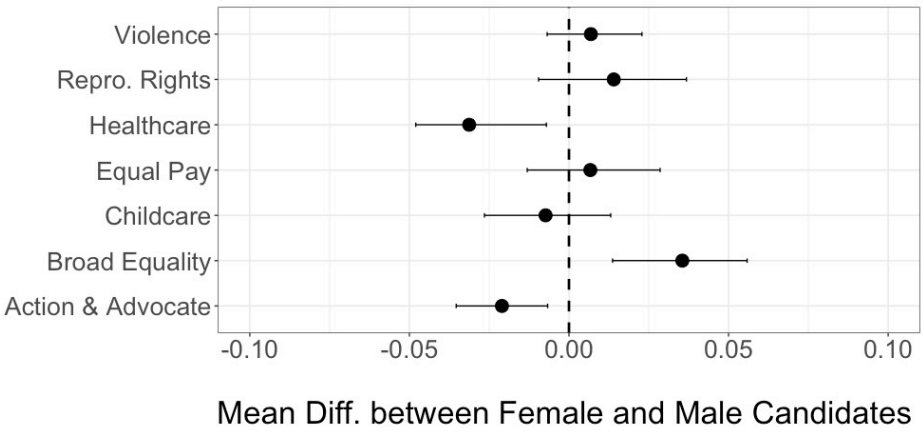
Description	**Stems**	**%**
Equal Pay	women, equal, pay, leav, cent, men, workplac, make, gap, paid fair, earn	20.11
Reproductive Rights	abort, right, access, reproduct, control, pregnanc, decis, bodi, birth, safe	18.30
Action & Advocate	fight, stand, effort, congress, protect, oppos, washington, vote, voic, defend	15.15
Broad Equality	right, equal, protect, discrimin, gender, human, person, justic, lgbtq, race	12.70
Healthcare	health, access, equal, healthcar, breast, medic, servic, cancer, qualiti, coverag	12.45
Childcare	child, worker, care, childcar, job, program, school, pre-k, infrastructur	11.68
Violence	violenc, sexual, domest, victim, abus, gun, support, assault, campus, survivor	9.62

Table A5: Race Model Topics

Description	**Stems**	**%**
War on Drugs	drug, marijuana, sentenc, war, send, color, sentenc, cannabi, offend, black	19.30
Broad Equality	right, equal, racial, discrimin, protect, gender, hate, lgbtq, ethnic, dream	18.33
Voter Suppression	suppress, vote, id, gerrymand, right, civil, holiday, registr, racis, interfer	17.78
Criminal Justice	justic, system, incarcer, rehabilit, recidiv, school-to-prison, nonviol, offend	17.27
Racial Inequality	black, white, gap, health, wage, access, district, color, unequ, repar	14.83
Law Enforcement	polic, oversight, train, reform, investig, camera, floyd, misconduct, de-escal	12.49

In Figure 2 we evaluate gendered difference in the proportion of text dedicate to each of the seven topics in Table A4. Point estimates falling to the left of the dashed line indicate that Democratic female candidates talked more about that particular topic in their platform text about women's issues than did Democratic male candidates. Point estimates falling to the right of the dashed line indicate that Democratic male candidates talked more about that particular topic than did Democratic female candidates. Point estimates are accompanied by 95% confidence intervals. Perhaps unsurprisingly, we see that women dedicate a statistically significantly greater proportion of their campaign platform text on women's issues to the "Action & Advocate" topic than do men. Conversely, male candidates dedicate a statistically significantly greater proportion of their text to the "Broad Equality" topic than do women. It is important to note that these effect sizes are fairly small; gendered differentials in the proportion of text dedicated to the "Action & Advocate" and "Broad Equality" topics are less than five percent.

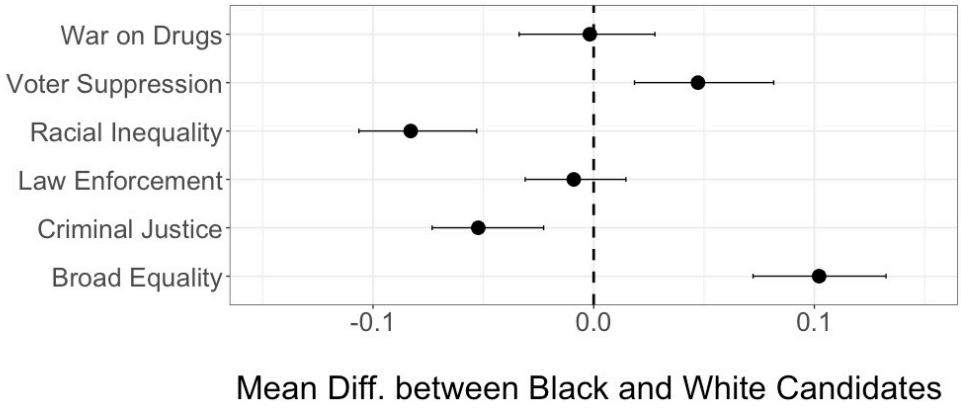
Figure 2: Difference in Topic Prevalence by Gender in Platform Text on Women's Issues



In Figure 3 we evaluate racial difference in the proportion of text dedicate to each of the six topics in Table A5. Point estimates falling to the left of the dashed line indicate that Democratic Black candidates talked more about that particular topic in their platform text about Black-associated issues than did Democratic white candidates. Point estimates falling to the right of the dashed line indicate that Democratic white candidates talked more about that particular topic than did Democratic Black candidates. Point estimates are accompanied by 95% confidence intervals. Figure 3 depicts a much larger difference in

white/Black candidate's inclusion of the "Broad Equality" topic than did Figure 2; white candidates dedicated ten percent more of their campaign platform text on race issues to this topic than did Black candidates. This finding suggests that white candidates' text is more likely to feature vague statements about race than are texts from Black candidates.

Figure 3: Difference in Topic Prevalence by Race in Platform Text on Black-Associated Issues



B Entropy Balancing

Before model estimation, we employ a non-parametric method for data preprocessing. This procedure endeavors to make our subsequent estimation for the effect of female/Black candidate presence more accurate and considerably less model-dependent (Ho et al. 2007). Methods such as matching and weighting achieve this aim by accounting for differences in covariates that, in our application, measure (1) a candidate's intrinsic likelihood to take up women's or Black-associated issues, and (2) indicate in which types of races a female and Black candidates may be more likely to emerge. This adjustment is done through the estimation of observational weights, which seek to achieve "balance" across covariates so candidates who *did* run against a descriptive competitor and those who *did not* are sufficiently similar. After the assignment of weights, a candidate's status as having run against a female/Black competitor is closer to being independent from previously specified covariates and, thus, model dependence is greatly reduced.

Although there are a number of methods for inducing balance across covariates, we employ a weighting methodology called entropy balancing (EB) developed by Hainmueller (2012). Entropy balancing purports a key advantage over more traditional matching methods (i.e. propensity score matching) in that it makes balance the primary target of intent. Put diferently, this approach eliminates the need to cyclically model propensity scores and check for covariate balance—what Imai et al. (2008) call the "propensity score tautology"—by directly incorporating covariate balance into the weight estimation procedure. Entropy balancing also (1) keeps estimates for observational weights as close as possible to their base weights to prevent loss of information and (2) is doubly robust (Zhao and Percival 2017). This means that if either the true outcome model corresponds to a linear regression on the covariates or the true treatment assignment model corresponds to a logistic regression on the covariates, the effect estimated using EB weights is unbiased.[14]

[14]For a deeper discussion of the advantages of covariate balancing methods, see Imai et al. (2008).

Using the WeightIt package developed by Greifer (2020), we estimate balancing weights using the covariates described below. We estimate four sets of observational weights for our four candidate samples:

- Male Professional Democrats (Gender Model I)
- Male Amateur Democrats (Gender Model II)
- White Professional Democrats (Race Model I)
- White Amateur Democrats (Race Model II)

B.1 Observational Weight Estimation

In our analysis, we seek to achieve balance on covariates that measure a candidate's intrinsic likelihood to take up women's or Black-associated issues (the outcome) and covariates that indicate in which types of races a female or Black candidate may be more likely to run (key IV). Across all three models, we balance over some basic district conditions. Candidates tend to run in races where they perceive themselves as possessing an advantage (Maisel and Stone 1997; 2014). Accordingly, Black and female Democrats may be more likely to emerge in safely partisan congressional districts where they have greater clout with voters. To capture voter sentiment, we include a covariate that indicates partisan seat safety, captured through average presidential vote-share for that congressional district across 2016 and 2020. Moreover, incumbents tend to win reelection at overwhelming rates, therefore it is often most strategic for a candidate to emerge when a seat becomes vacant (Jacobson 1983). Therefore, in our covariate balancing, we include an indicator for "incumbent in race" (0) or "open seat" (1). Finally, there is competing research on the effects of a state's primary system (i.e. openness) on strategic candidate behavior (see McGhee et al. 2014; Hill 2015). To ensure our definition of balancing covariates is comprehensive, we include a binary indicator for whether or not a state's primary election system is "closed" (i.e. only registered partisans can vote in the primary).

B.1.1 IV: Female Candidate Emergence

To determine the effect of a female candidate's presence on male Democrats' campaign behavior, we balance over covariates that indicate in which types of races a female candidate may be more likely to emerge. Democratic female candidates are especially calculated in their decision to run, choosing to emerge only when they think that they have a good shot at winning (Fox and Lawless 2005; Fulton et al. 2006; Kanthak and Woon 2014). Therefore, we expect women to be more likely to run in districts that are safely-Democratic. These are the kinds of races where voters are especially receptive to female candidates (Dolan 2014) and where women may find greater success in building their donor networks (Thomsen and Swers 2017). Studies also suggest that women may be especially likely to emerge in districts without an incumbent (Palmer and Simon 1998). The presence of an incumbent is indicated by our "open race" covariate.

B.1.2 IV: Black Candidate Emergence

To determine the effect of a Black candidate's presence on white Democrats' campaign behavior, we balance over covariates that indicate in which types of races a Black candidate may be more likely to emerge. Similar to women, Black candidates are incredibly judicious in their decision to run and, therefore, less likely to emerge (Fox and Lawless 2005). The absence of Black candidates, however, may also be rooted in explanations irrespective of political ambition. Supply-side theories on minority candidate emergence note that, in districts with a small minority population, there may be no viable Black candidate to run for office—absent any hesitations that candidate may have about running (Canon 1996; Branton 2009; Shah 2014). To account for the baseline supply of potential Black candidates we include a continuous measure for the percent of Black residents in a congressional district, as reported by the 2018 American Community Survey. Moreover, Juenke and Shah (2016) find that district conditions like seat vacancy and partisanship are key predictors for Black candidate electoral success. Our measure for presidential vote-share and binary indicator for open race status capture these important factors which predict where Black candidates may be more likely to win and, therefore, where they may be especially likely to run.

B.1.3 Outcome Variable: Likelihood of Issue Coverage

We expect that a candidate's likelihood to cover Black-associated issues will be mediated by the number Democratic-leaning constituents in a district (captured by presidential vote-share), prevalence of Black constituents in a district (captured by % Black residents in district), and whether or not that candidate is running in a southern state. We expect that a candidate's likelihood to cover women's issues will be similarly mediated by whether or not a district leans Democratic. There may be some male or white Democrats who have a personal stake in an issue and, therefore, may be more likely to take up these issues. This is problematic because candidate intention is nearly impossible to observe; therefore, our ability to condition on this covariate is limited. We expect, however, that each individual candidate's inclination to take up a given issue will—to some extent—be mediated by whether or not he is "strategic." For instance, even if a male Democrat genuinely cares about advocating for women's equality, he should be far less likely to cover this topic if he is running in a Republican-controlled district. In such a race, covering "women's issues" presents no advantage to that candidate and, in all likelihood, discussing this topic would serve as a liability (e.g. Thomsen 2015; McDonald et al. 2020). Therefore, by controlling for candidate strategic intent, we can (somewhat) account for a candidate's unobserved personal convictions towards a policy.

B.2 Love Plots: Covariate Distributional Balance

We establish balance across all covariates identified in Table 2 on the main paper. Plots of covariate distributions are presented in Figures 4 through 7. These figures depict—before and after weighting—the absolute mean differences in the covariate distributional balance for white and male Democratic candidates who did and did not run against a descriptive opponent in their partisan primary election. To best approximate the conditions of a controlled experiment using observational data, these mean difference between candidate types should be close to zero. The dotted line indicates a 0.05 threshold; points falling to the left of this line indicates balance has been achieved for that covariate. To

provide a mode of comparison beyond unweighted data, covariate distributions weighted with the covariate balancing propensity score methodology (CBPS) proposed by Imai and Ratkovic (2012) are also plotted. In each instance plotted, entropy balancing outperforms unweighted data and CBPS in achieving covariate distributional balance.

Figure 4: Covariate Balance: Love Plot for Male Democratic Professional Candidates

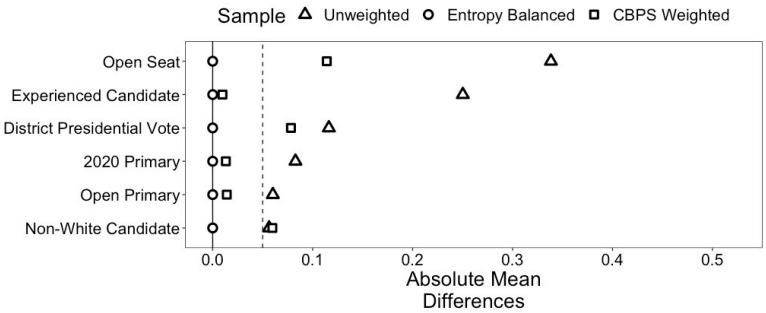


Figure 5: Covariate Balance: Love Plot for Male Democratic Amateur Candidates

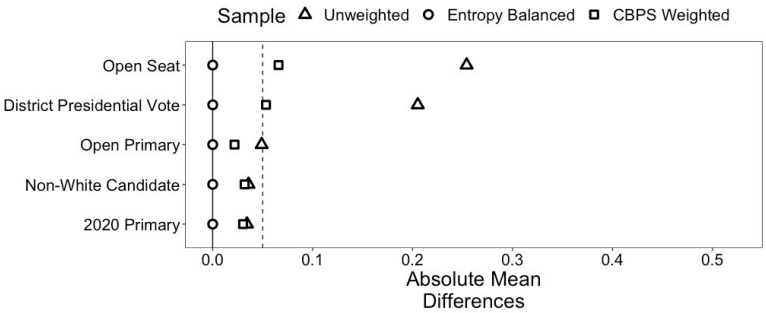


Figure 6: Covariate Balance: Love Plot for White Democratic Professional Candidates

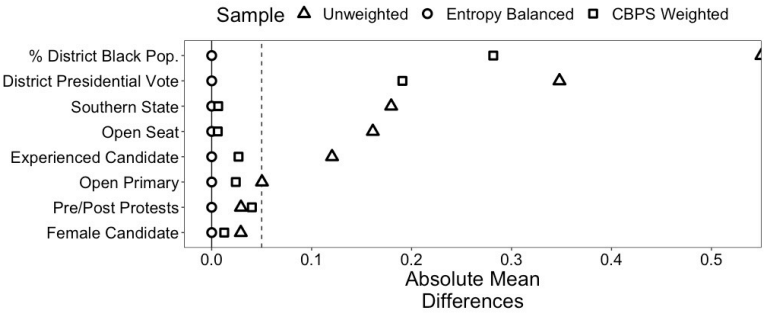


Figure 7: Covariate Balance: Love Plot for White Democratic Amateur Candidates

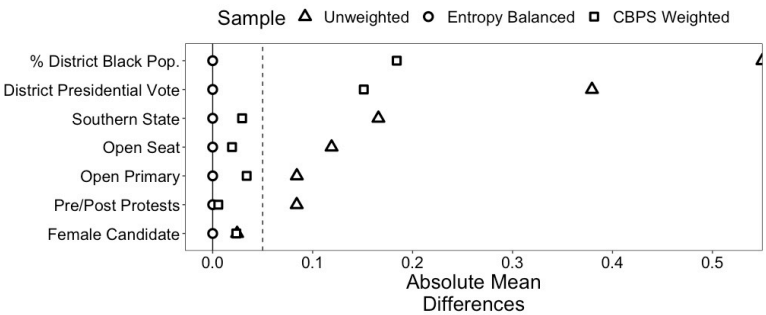


Table A6: Full Results: Logistic Regression for Male Professional Democrats' Coverage of Women's Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Women's Issues in Campaign Platforms				
	(Model 1)		(Model 2)		(Model 3)
Balancing Weights	✓	✗	✓	✗	✓
Presence of Female Candidate	1.218*	0.793*	1.250*	0.821*	1.079*
	(0.325)	(0.230)	(0.314)	(0.238)	(0.328)
Experience in Elected Office	−0.855*	−0.661*	−0.919*	−0.757*	−1.025*
	(0.291)	(0.239)	(0.366)	(0.296)	(0.324)
Current Member of Congress			−0.819*	−0.607*	
			(0.373)	(0.303)	
Open Race	−0.674	−0.185	−0.646	−0.128	−0.664
	(0.370)	(0.282)	(0.415)	(0.311)	(0.381)
Dem. Presidential Vote	0.008	−0.001	0.008	−0.001	
	(0.011)	(0.008)	(0.012)	(0.009)	
Seat Safety: Democratic					0.251
(Reference: Competitive)					(0.494)
Seat Safety: Republican					−0.782
(Reference: Competitive)					(0.488)
Primary Type: Open	−0.145	−0.141	−0.147	−0.143	0.152
	(0.337)	(0.212)	(0.336)	(0.212)	(0.309)
2020	−0.182	0.091	−0.176	0.089	−0.193
	(0.293)	(0.209)	(0.299)	(0.211)	(0.283)
Non-White Candidate	0.193	0.197	0.186	0.188	0.209
	(0.370)	(0.330)	(0.371)	(0.331)	(0.381)
Constant	−0.045	0.397	−0.045	0.435	0.583
	(0.615)	(0.457)	(0.635)	(0.470)	(0.550)
Observations	430	430	430	430	430
Log Likelihood		−278.299		−277.961	
Akaike Inf. Crit.		572.598		573.922	
Pseduo R^2	0.16		0.16		0.17

Note: *p<0.05

Table A7: Full Results: Logistic Regression for Male Amateur Democrats' Coverage of Women's Issues in Online Campaign Platforms, 2018-2020

	(Model 1)		(Model 2)
Balancing Weights	✓	✗	✓
Presence of Female Candidate	0.573*	0.284	0.550*
	(0.268)	(0.213)	(0.265)
Open Race	−0.248	−0.061	−0.270
	(0.280)	(0.240)	(0.281)
Dem. Presidential Vote	0.004	0.001	
	(0.008)	(0.007)	
Seat Safety: Democratic			−0.244
(Reference: Competitive)			(0.387)
Seat Safety: Republican			−0.268
(Reference: Competitive)			(0.338)
Primary Type: Open	0.016	0.051	−0.002
	(0.266)	(0.220)	(0.258)
2020	−0.094	0.116	−0.057
	(0.236)	(0.203)	(0.240)
Non-White Candidate	−0.224	−0.274	−0.211
	(0.310)	(0.281)	(0.310)
Constant	−0.337	−0.080	0.099
	(0.461)	(0.394)	(0.386)
Observations	425	425	425
Log Likelihood		−291.405	
Akaike Inf. Crit.		596.811	
Pseudo R^2	0.03		0.03
Note:			*p<0.05

Table A8: Full Results: Logistic Regression for White Professional Democrats' Coverage of Black-Associated Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Issues in Campaign Platforms					
	(Model 1)		(Model 2)		(Model 3)	(Model 4)
Balancing Weights	✓	✗	✓	✗	✓	✗
Presence of Black Candidate	0.937*	0.860*	0.749*	0.690*	1.026*	0.947*
	(0.327)	(0.271)	(0.282)	(0.277)	(0.335)	(0.402)
Experience in Elected Office	−1.689*	−0.915*	−0.039	−0.451	−1.707*	−0.920*
	(0.402)	(0.229)	(0.355)	(0.269)	(0.419)	(0.230)
Current Member of Congress			−2.176*	−1.611*		
			(0.488)	(0.325)		
Open Race	0.304	0.048	−0.131	−0.268	0.497	0.054
	(0.503)	(0.251)	(0.328)	(0.271)	(0.491)	(0.252)
Dem. Presidential Vote	0.028	0.029*	0.059*	0.047*		0.029*
	(0.020)	(0.011)	(0.017)	(0.013)		(0.011)
Seat Safety: Democratic					0.298	
(Reference: Competitive)					(0.471)	
Seat Safety: Republican					−0.343	
(Reference: Competitive)					(0.531)	
Primary Type: Open	0.223	−0.332	−0.143	−0.350	0.332	−0.321
	(0.384)	(0.205)	(0.296)	(0.208)	(0.385)	(0.209)
Pre/Post George Floyd	0.514	0.656*	1.112*	0.800*	0.616	0.662*
	(0.469)	(0.237)	(0.316)	(0.247)	(0.447)	(0.239)
Female	0.108	0.163	0.514	0.088	0.097	0.161
	(0.394)	(0.200)	(0.276)	(0.203)	(0.384)	(0.200)
District % Black Population	0.004	0.007		0.010		0.011
	(0.024)	(0.015)		(0.016)		(0.021)
Above Average Black Pop.					0.781	
					(0.454)	
South	0.088	0.066	0.068	0.123	−0.164	0.053
	(0.467)	(0.249)	(0.306)	(0.253)	(0.445)	(0.253)
Presence of Black Candidate×						−0.008
District % Black Population						(0.026)
Constant	−1.783	−1.757*	−3.353*	−2.465*	−0.884	−1.800*
	(1.114)	(0.562)	(0.869)	(0.620)	(0.606)	(0.581)
Observations	505	505	505	505	505	505
		−308.181		−302.925		−308.138
Akaike Inf. Crit.		636.361		627.849		638.275
Pseduo R^2	0.19		0.21		0.21	

Note: *p<0.05

Table A9: Full Results: Logistic Regression for White Amateur Democrats' Coverage of Black-Associated Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Issues in Campaign Platforms		
	(Model 1)		(Model 2)
Balancing Weights	✓	✗	✓
Presence of Black Candidate	0.246	−0.106	0.064
	(0.305)	(0.269)	(0.281)
Open Race	−0.318	−0.287	−0.140
	(0.358)	(0.250)	(0.360)
Dem. Presidential Vote	0.043*	0.026*	
	(0.017)	(0.011)	
Seat Safety: Democratic			−0.006
(Reference: Competitive)			(0.505)
Seat Safety: Republican			−0.965
(Reference: Competitive)			(0.499)
Primary Type: Open	0.291	0.028	−0.033
	(0.408)	(0.241)	(0.326)
Pre/Post George Floyd Protests	0.341	0.382	0.189
	(0.400)	(0.286)	(0.389)
Female	0.552	0.242	0.132
	(0.327)	(0.228)	(0.311)
District % Black Population	−0.001	0.044*	
	(0.018)	(0.017)	
Above Average District Black Pop.			0.823*
			(0.301)
South	1.572*	0.689*	1.030*
	(0.392)	(0.251)	(0.373)
Constant	−3.346*	−2.178*	−0.623
	(0.970)	(0.559)	(0.473)
Observations	429	429	429
Log Likelihood		−269.449	
Akaike Inf. Crit.		556.899	
Pseudo R^2	0.20		0.15
Note:			*p<0.05

Table A10: Issue Adoption Among Professional Candidates Running Against a Female/Black Candidate

	DV: Adopted Issues in Campaign Platform	
	(Male Professional) Candidate	(White Professional) Candidate
Experience in Elected Office	−1.344*	−1.203*
	(0.370)	(0.635)
Open Race	0.276	−0.729
	(0.359)	(0.651)
Dem. Presidential Vote	0.014	0.019
	(0.014)	(0.034)
District % Blck Population		0.006
		(0.029)
Primary Type: Open	−0.174	−1.455*
	(0.341)	(0.637)
2020	−0.493	
	(0.333)	
Pre/Post George Floyd Protests		1.499*
		(0.799)
Non-White	−0.431	
	(0.468)	
Female		−0.469
		(0.555)
Substantive Issue Coverage	0.723	0.252
	(0.453)	(0.588)
Strategic Descriptive Opponent	−0.206	0.823
	(0.402)	(0.548)
# of Candidates in Race	−0.077	0.052
	(0.058)	(0.116)
Constant	0.918	0.918
	(0.751)	(0.751)
Observations	210	95
Log Likelihood	−119.638	−49.799
Akaike Inf. Crit.	259.277	123.597

Note: *p<0.05

C Sensitivity Analysis

We endeavor to understand to what extent unobserved cofounders may be responsible for our findings for the effect of descriptive candidate presence, as presented in Tables A6 through Table A8. To do so, we employ the sensmakr package developed by Cinelli et al. (2020). A sensitivity analysis examining the fragility of our estimates for professional male Democratic responsiveness is presented in Table A11. A sensitivity analysis examining the fragility of our estimates for amateur male Democratic responsiveness is presented in Table A12. Moreover, a sensitivity analysis examining the fragility of our estimates for professional white Democratic responsiveness is presented in Table A13.

C.1 Robustness: Male Democratic Candidates

Table A11: Sensitivity Analysis: Professional Male Democrat Responsiveness to the Presence of a Female Candidate

Outcome: Probability of Discussing Women's Issues (0,1)

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Presence of Female Candidate	0.278	0.046	6.112	8.1%	25.7%	18.2%
Observations = 430				*Bound (3x Previously Held Elected Office)*		

Table A12: Sensitivity Analysis: Amateur Male Democrat Responsiveness to the Presence of a Female Candidate

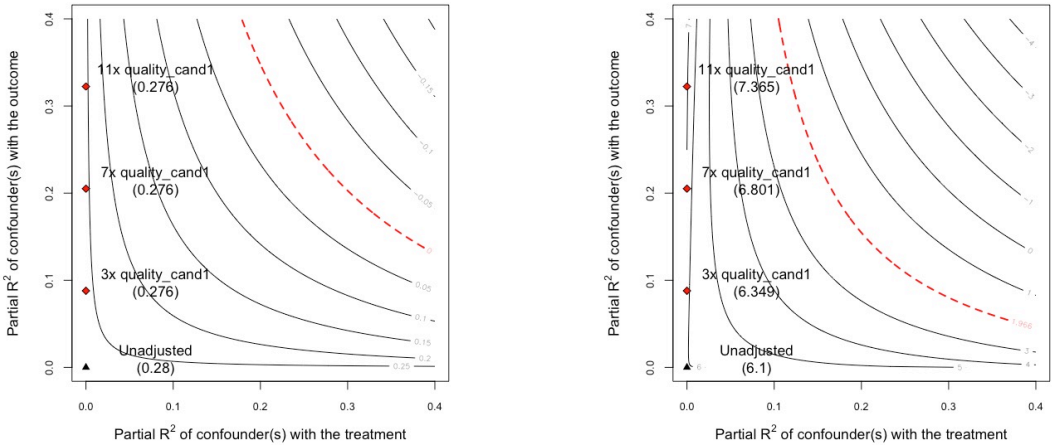
Outcome: Probability of Discussing Women's Issues (0,1)

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Presence of Female Candidate	0.141	0.05	2.835	1.9%	12.9%	4.2%
Observations = 425				*Bound (3x Non-White Candidate)*		

The partial R^2 of descriptive candidate presence (treatment) with candidate issue uptake (outcome) presented in column 4 of Table A11 demonstrates that an extreme confounder (orthogonal to the covariates) that explains 100% of the residual variance of the outcome, would need to explain at least 8.1% of the residual variance of the treatment to fully account for the observed estimated effect. Per column 5 of Table A11, unobserved confounders (orthogonal to the covariates) that explain more than 25.7% of the residual variance of both the treatment and the outcome to fully account for our findings (i.e. bring the point estimate to 0). If unobserved cofounders were to explain 18.2% of the residual variance of both the treatment and outcome, these factors would be sufficiently strong enough to make our results indifferent from zero at the significance level of 0.05.

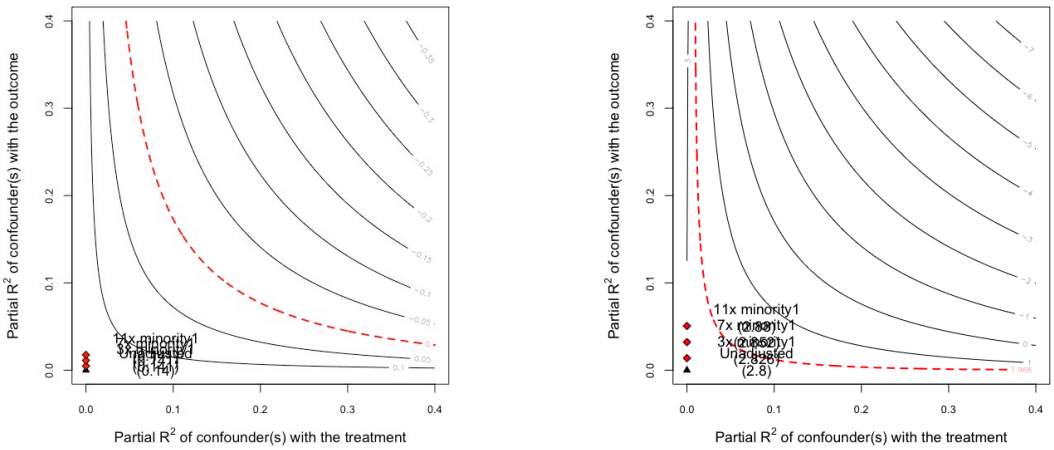
The partial R^2 of descriptive candidate presence (treatment) with candidate issue uptake (outcome) presented in column 4 of Table A12 demonstrates that an extreme confounder (orthogonal to the covariates) that explains 100% of the residual variance of the outcome, would need to explain at least 1.9% of the residual variance of the treatment to fully account for the observed estimated effect. Per column 5 of Table A12, unobserved confounders (orthogonal to the covariates) that explain more than 12.9% of the residual variance of both the treatment and the outcome to fully account for our findings (i.e.

Figure 8: Sensitivity contour plots in the partial R2 scale with benchmark bounds for Professional Male Democrats



(a) Sensitivity of the Point Estimate (b) Sensitivity of the T-Value

Figure 9: Sensitivity contour plots in the partial R2 scale with benchmark bounds for Amateur Male Democrats



(a) Sensitivity of the Point Estimate (b) Sensitivity of the T-Value

bring the point estimate to 0). If unobserved cofounders were to explain 4.2% of the residual variance of both the treatment and outcome, these factors would be sufficiently strong enough to make our results indifferent from zero at the significance level of 0.05.

Next, in Figure 8(a) Figure 8(b), we visually demonstrate how confounders of different types would affect point estimates and t-values for our professional Democratic male model. The horizontal axis describes the fraction of the residual variation in the treatment (partial R^2) explained by the confounder; the vertical axis describes the fraction of the residual variation in the outcome explained by the confounder. The contours show the adjusted estimate that would be obtained for an unobserved confounder (in the full model) with hypothesized values of the sensitivity parameters. The three reference points show that a confounder 3x, 7x, or 11x stronger than observed covariate *Previously Held Elected Office* still produce robust findings. Figure 8(b) shows the sensitivity of the t-value of the treatment effect. As we move along the horizontal axis, the adjusted effect and standard-errors remain fairly consistent. This plot shows that the statistical significance of our

treatment remains robust to a confounder 3x, 7x, or 11x stronger than observed covariate *Previously Held Elected Office*.

Similarly, in Figure 9(a) Figure 9(b), we visually demonstrate how confounders of different types would affect point estimates and t-values for our amateur Democratic male model. The horizontal axis describes the fraction of the residual variation in the treatment (partial R^2) explained by the confounder; the vertical axis describes the fraction of the residual variation in the outcome explained by the confounder. The contours show the adjusted estimate that would be obtained for an unobserved confounder (in the full model) with hypothesized values of the sensitivity parameters. The three reference points show that a confounder 3x, 7x, or 11x stronger than observed covariate *Non-White Candidate* still produce robust findings. Figure 9(b) shows the sensitivity of the t-value of the treatment effect. As we move along the horizontal axis, the adjusted effect and standard-errors remain fairly consistent. This plot shows that the statistical significance of our treatment remains robust to a confounder 3x, 7x, or 11x stronger than observed covariate *Non-White Candidate*.

C.2 Robustness: White Democratic Candidates

Table A13: Sensitivity Analysis: Professional White Democrat Responsiveness to the Presence of a Black Candidate

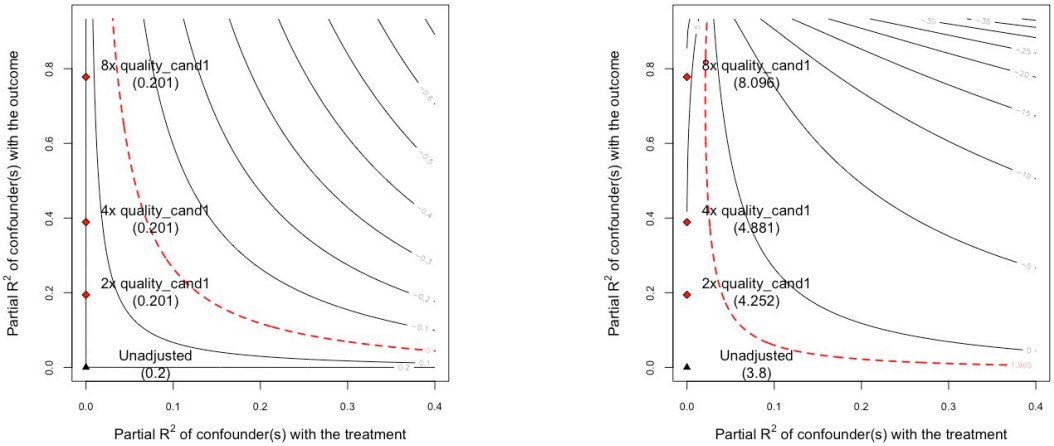
Outcome: Probability of Discussing Black-Associated Issues (0,1)

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Presence of Black Candidate	0.201	0.053	3.82	2.9%	15.8%	8%
Observations = 429				*Bound (2x Previously Held Elected Office)*		

The partial R^2 of descriptive candidate presence (treatment) with candidate issue uptake (outcome) presented in column 4 of Table A13 demonstrates that an extreme confounder (orthogonal to the covariates) that explains 100% of the residual variance of the outcome, would need to explain at least 2.9% of the residual variance of the treatment to fully account for the observed estimated effect. Per column 5 of Table A13, unobserved confounders (orthogonal to the covariates) that explain more than 15.8% of the residual variance of both the treatment and the outcome to fully account for our findings (i.e. bring the point estimate to 0). If unobserved cofounders were to explain 8% of the residual variance of both the treatment and outcome, these factors would be sufficiently strong enough to make our results indifferent from zero at the significance level of 0.05.

Next, in Figure 10(a) Figure 10(b), we visually demonstrate how confounders of different types would affect point estimates and t-values for our professional Democratic male model. The horizontal axis describes the fraction of the residual variation in the treatment (partial R^2) explained by the confounder; the vertical axis describes the fraction of the residual variation in the outcome explained by the confounder. The contours show the adjusted estimate that would be obtained for an unobserved confounder (in the full model) with hypothesized values of the sensitivity parameters. The three reference points show that a confounder 4x, 6x, or 8x stronger than observed covariate *Previously Held Elected Office* still produce robust findings. Figure 10(b) shows the sensitivity of the t-value of the treatment effect. As we move along the horizontal axis, the adjusted effect and standard-errors remain fairly consistent. This plot shows that the statistical

Figure 10: Sensitivity contour plots in the partial R2 scale with benchmark bounds for Professional Male Democrats



(a) Sensitivity of the Point Estimate

(b) Sensitivity of the T-Value

significance of our treatment remains robust to a confounder 4x, 6x, or 8x stronger than observed covariate *Previously Held Elected Office*.

D Analysis Extension: Military Veterans

Table A14: Covariates for Military Veteran Democratic and Republican Models

Model Covariate	Covariate Values	
Unit of Analysis: Non-Veteran Primary Election Candidates		
Dependent Variable: Discussed Veterans' Issues in Congressional Campaign Platform		
Independent Variables:		
Presence of a Military Veteran	0 (No Veteran)	1 (Veteran)
Open Seat	0 (Incumbent in Race)	1 (Open Seat)
Primary Election Rules	0 (Closed Primary)	1 (Open Primary)
Candidate Gender	0 (Male)	1 (Female)
# of Military Installations	0 (Min)	21 (Max)
District % Military Veterans	0-100 (reported by U.S. Army, 2015)	
District Seat Safety	0-100 (2016 and 2020 same-party presidential vote, averaged)	

D.1 Entropy Balancing

To determine the effect of a military veteran's presence on non-veteran Republicans' campaign behavior, we balance over covariates that indicate in which types of races a military veteran may be more likely to emerge. Supply-side explanations may also provide a rationale for the emergence patterns of Republican military veterans. Certain congressional districts—particularly those with a military base or resources for veterans—tend to have larger populations of veterans and, therefore, have a larger supply of potential candidates.

Aside from an elevated presence of veterans, these kinds of installations also provide jobs for the local community and support the local economy, making defense-related issues especially salient to constituents. Studies on the strategic campaign behavior of veterans are limited. However, the nascent body of work dedicated to this topic indicates military vets tend to run in "high opportunity" environments (e.g. Collens 2020). Districts with constituent populations who care deeply about veterans and policies related to the military seem to fit this description. For all of these reasons, we include count for the number of a military base in a district and the presence of a VA hospital to approximate the salience of veteran-related issues to that district's constituency.

D.2 Love Plots: Covariate Distributional Balance

We establish balance across all covariates identified in Table A14. Plots of covariate distributions are presented in Figures 11 through 14. These figures depict—before and after weighting—the absolute mean differences in the covariate distributional balance for non-veteran Democratic and Republican candidates who did and did not run against a military veteran in their partisan primary election. To best approximate the conditions of a controlled experiment using observational data, these mean difference between candidate types should be close to zero. The dotted line indicates a 0.05 threshold; points falling to the left of this line indicates balance has been achieved for that covariate. To provide a mode of comparison beyond unweighted data, covariate distributions weighted with the covariate balancing propensity score methodology (CBPS) proposed by Imai and Ratkovic (2012) are also plotted. In each instance plotted, entropy balancing outperforms unweighted data and CBPS in achieving covariate distributional balance.

Figure 11: Covariate Balance: Love Plot for Non-Vet. Republican Professional Candidates

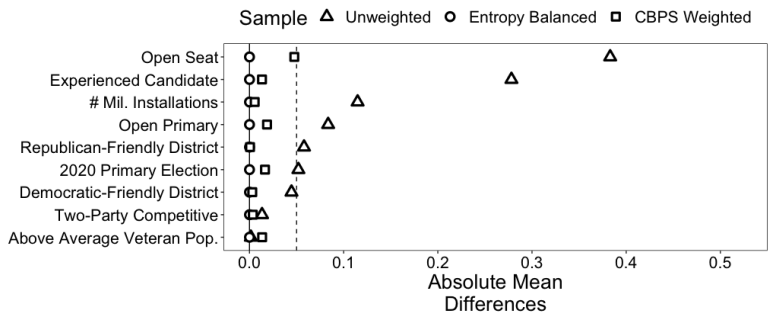


Figure 12: Covariate Balance: Love Plot for Non-Vet. Republican Amateur Candidates

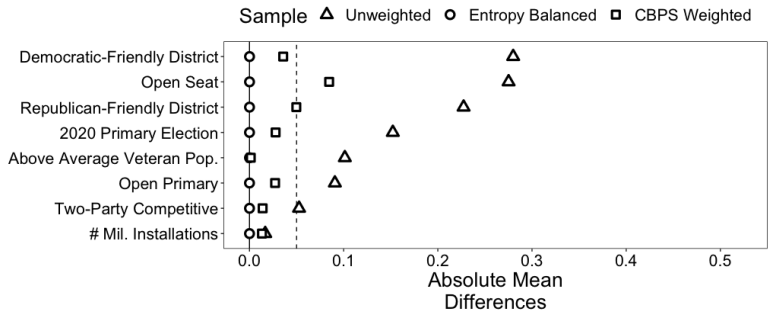


Figure 13: Covariate Balance: Love Plot for White Democratic Professional Candidates

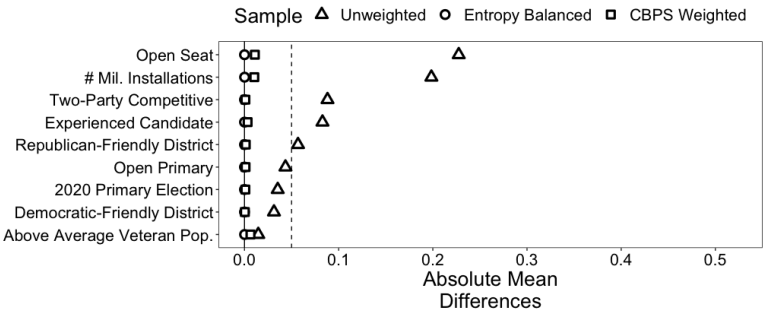


Figure 14: Covariate Balance: Love Plot for White Democratic Amateur Candidates

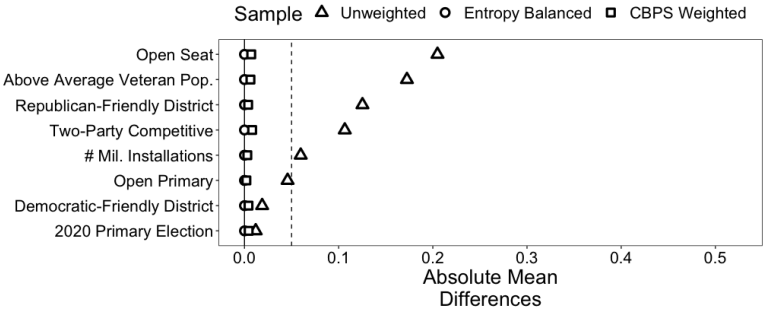


Table A15: Full Results: Logistic Regression for Non-Veteran Professional Republicans' Coverage of Veterans' Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Veterans' Issues in Campaign Platforms				
	(Model 1)		(Model 2)		(Model 3)
Balancing Weights	✓	✗	✓	✗	✓
Presence of Military Veteran	0.784*	0.424*	0.958*	0.660*	0.778*
	(0.241)	(0.214)	(0.252)	(0.228)	(0.244)
Experience in Elected Office	−0.269	0.123	−0.633*	−0.353	−0.429
	(0.304)	(0.232)	(0.318)	(0.262)	(0.303)
Current Member of Congress			0.366	0.904*	
			(0.402)	(0.318)	
Open Race	−0.772*	−0.292	−0.095	0.382	−0.878*
	(0.266)	(0.235)	(0.352)	(0.297)	(0.259)
Rep. Presidential Vote	−0.011	−0.011	−0.027	−0.024*	
	(0.014)	(0.011)	(0.016)	(0.012)	
Seat Safety: Democratic (Reference: Competitive)					−0.580
					(0.509)
Seat Safety: Republican (Reference: Competitive)					−0.167
					(0.314)
Primary Type: Open	−0.051	−0.158	−0.277	−0.252	−0.102
	(0.293)	(0.212)	(0.308)	(0.217)	(0.274)
2020	−0.816*	−0.254	−0.761*	−0.120	−0.779*
	(0.256)	(0.190)	(0.266)	(0.196)	(0.258)
District % Veteran Population	0.572	0.868*	0.442	0.769*	
	(0.294)	(0.241)	(0.301)	(0.246)	
Above Average Veteran Population					1.158*
					(0.291)
# of Military Installations	0.068	0.009	0.068	0.037	0.064
	(0.046)	(0.037)	(0.044)	(0.039)	(0.041)
Female	−0.088	0.156	0.229	0.272	0.120
	(0.306)	(0.237)	(0.327)	(0.242)	(0.318)
Constant	1.247	0.881	1.823*	1.096	0.068
	(0.789)	(0.608)	(0.824)	(0.619)	(0.412)
Observations	512	512	512	512	512
Log Likelihood		−336.458		−329.133	
Akaike Inf. Crit.		692.917		680.266	
Psuedo R^2	0.15		0.19		0.19
Note:					*p<0.05

Table A16: Full Results: Logistic Regression for Non-Veteran Amateur Republicans' Coverage of Veterans' Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Veterans' Issues in Campaign Platforms		
	(Model 1)		(Model 2)
Balancing Weights	✓	✗	✓
Presence of Military Veteran	0.230	0.242	0.250
	(0.294)	(0.234)	(0.290)
Open Race	0.247	0.385	0.307
	(0.315)	(0.263)	(0.319)
Rep. Presidential Vote	0.013	0.005	
	(0.011)	(0.009)	
Seat Safety: Democratic			0.123
(Reference: Competitive)			(0.334)
Seat Safety: Republican			0.322
(Reference: Competitive)			(0.347)
Primary Type: Open	−0.314	−0.252	−0.309
	(0.271)	(0.224)	(0.284)
2020	−0.062	0.026	−0.046
	(0.289)	(0.223)	(0.290)
District % Veteran Population	0.075	0.092	
	(0.347)	(0.280)	
Above Average Veteran Population			0.239
			(0.313)
# of Military Installations	−0.009	−0.014	−0.015
	(0.061)	(0.049)	(0.058)
Female	0.257	0.218	0.228
	(0.294)	(0.251)	(0.301)
Constant	−1.278*	−0.999*	−0.963*
	(0.602)	(0.463)	(0.439)
Observations	398	398	398
Log Likelihood		−252.334	
Akaike Inf. Crit.		522.668	
Psuedo R^2	0.0315		0.0299
Note:			*p<0.05

Table A17: Full Results: Logistic Regression for Non-Veteran Professional Democrats' Coverage of Veterans' Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Veterans' Issues in Campaign Platforms				
	(Model 1)		(Model 2)		(Model 3)
Balancing Weights	✓	✗	✓	✗	✓
Presence of Military Veteran	0.116	0.169	0.320	0.355	0.020
	(0.205)	(0.202)	(0.209)	(0.207)	(0.210)
Experience in Elected Office	0.465*	0.560*	−0.199	−0.117	0.476*
	(0.223)	(0.185)	(0.273)	(0.229)	(0.231)
Current Member of Congress			1.490*	1.385*	
			(0.277)	(0.249)	
Open Race	−0.547*	−0.711*	−0.125	−0.155	−0.575*
	(0.255)	(0.208)	(0.276)	(0.232)	(0.258)
Dem. Presidential Vote	−0.003	0.007	−0.013	−0.009	
	(0.008)	(0.007)	(0.009)	(0.008)	
Seat Safety: Democratic					−0.470
(Reference: Competitive)					(0.278)
Seat Safety: Republican					−0.593
(Reference: Competitive)					(0.304)
Primary Type: Open	0.238	0.106	0.210	0.148	0.246
	(0.224)	(0.169)	(0.229)	(0.173)	(0.228)
2020	−0.332	−0.179	−0.466*	−0.275	−0.311
	(0.210)	(0.165)	(0.219)	(0.171)	(0.212)
District % Veteran Population	0.319	0.670*	0.340	0.663*	
	(0.240)	(0.202)	(0.246)	(0.205)	
Above Average Veteran Population					0.090
					(0.230)
# of Military Installations	0.038	0.005	0.047	0.011	0.070
	(0.037)	(0.029)	(0.036)	(0.030)	(0.041)
Female	0.009	−0.180	0.257	−0.040	0.086
	(0.218)	(0.164)	(0.217)	(0.170)	(0.224)
Constant	−0.161	−0.562	−0.015	−0.125	−0.050
	(0.467)	(0.400)	(0.488)	(0.421)	(0.312)
Observations	668	668	668	668	668
Log Likelihood		−441.126		−426.447	
Akaike Inf. Crit.		902.252		874.894	
Psuedo R^2	0.06		0.12		0.08

Note: *p<0.05

Table A18: Full Results: Logistic Regression for Non-Veteran Amateur Democrats' Coverage of Veterans' Issues in Online Campaign Platforms, 2018-2020

	DV: Adopted Veterans' Issues in Campaign Platforms		
	(Model 1)		(Model 2)
Balancing Weights	✓	✗	✓
Presence of Military Veteran	0.026	0.099	−0.016
	(0.224)	(0.216)	(0.224)
Open Race	0.081	−0.034	0.111
	(0.247)	(0.218)	(0.237)
Dem. Presidential Vote	0.008	0.004	
	(0.009)	(0.007)	
Seat Safety: Democratic (Reference: Competitive)			−0.387
			(0.379)
Seat Safety: Republican (Reference: Competitive)			−0.266
			(0.330)
Primary Type: Open	−0.270	−0.337	−0.522*
	(0.268)	(0.209)	(0.246)
2020	−0.095	−0.059	0.035
	(0.228)	(0.189)	(0.221)
District % Veteran Population	0.603	0.770*	
	(0.319)	(0.245)	
Above Average Veteran Population			0.462
			(0.277)
# of Military Installations	0.049	0.007	0.070
	(0.047)	(0.038)	(0.041)
Female	0.086	0.171	0.036
	(0.220)	(0.193)	(0.225)
Constant	−0.933	−0.638	−0.490
	(0.555)	(0.427)	(0.369)
Observations	539	539	539
Log Likelihood		−342.523	
Akaike Inf. Crit.		703.047	
Psuedo R^2	0.04		0.06
Note:			*p<0.05