Supplementary Information for: The Heightened Importance of Racism and Sexism in the 2018 U.S. Midterm Elections

Brian F. Schaffner

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Contents

1 Question wording for dependent variables

1.1 2018 House vote

Asked only of respondents who answered: "I definitely voted in the Midterm Election on November 6th."

For whom did you vote for U.S. House?

1. CANDIDATE NAME (CANDIDATE PARTY)
2. CANDIDATE NAME (CANDIDATE PARTY)
3. Other (text entry)
4. I did not vote in this race
5. Not sure

1.2 2016 Presidential vote

Asked only of respondents who answered "Yes" when asked: "Did you vote in the 2016 General Election?"

In the election for U.S. President, who did you vote for?

1. Donald Trump
2. Hillary Clinton
3. Someone else
4. I did not cast a vote for president
5. I don't recall

1.3 2016 House vote

For whom did you vote for U.S. House in 2016?

1. CANDIDATE NAME (CANDIDATE PARTY)
2. CANDIDATE NAME (CANDIDATE PARTY)
3. Other (text entry)
4. I did not vote in this race
5. I did not vote
6. Not sure

2 Accuracy of House Vote Recall

As noted in the paper, Rivers and Lauderdale (2016) find that voters are able to recall their presidential vote from four years prior with about 95% accuracy. However, this paper relies on the ability of voters to remember their vote choice in a previous House election. While there is little if any research on how well voters can recall who they voted for in previous House elections, the 2010-2014 CCES panel survey provides one way to gain some leverage on this question. Members of the 2010-2014 CCES panel were asked who they voted for in their House election just after (November 2010) the 2010 midterm elections. Then, during the 2014 wave of the survey, respondents were first asked if they had voted in 2010 and among those who said they did, a follow up question asked: "For whom did you vote for House of Representatives in 2010?" The response options were "The Democratic candidate," "The Republican candidate," "Other," and "Not sure."

Table SI.1 shows how people actually reported voting for House in 2010 based on who they recalled voting for in 2014. For example, 91.1% of people who recalled voting for a Democrat in the House election in 2010 did in fact say that they voted Democratic just after the 2010 election. 93% of those recalling a 2010 Republican vote in 2014 were accurate about that recollection. When respondents were inaccurate, those inaccuracies largely canceled out; that is, there is no significant partisan bias caused by these recollections. Indeed, the two-party House vote among the sample as reported immediately after the 2010 election was 57-43 in favor of the Republicans; if we relied on the 2014 recollections, the two-party 2010 House vote among the sample would be 56-44.

While the amount of error for recall even four years later is small and not biased in any particular direction, it is still important to understand whether relying on recall might affect inferences about the role of sexism and racial attitudes. While the 2010-2014 panel survey did not include items measuring sexism, it did include two racial resentment items. Table SI.2 shows the results from two models – one that models 2010 House vote using the question from the 2010 wave of the CCES panel study and the other that models 2010 House vote using the question about recall from 2014. Both models follow the approach from the paper by using a binary vote choice variable (0 = voted Democrat, 1 = voted Republican) and including only respondents who were validated voters. The models use the same set of respondents and all the covariates are measured in the 2014 wave in order to best mimic the

Table SI.1: Accuracy of 2010 House vote recall when asked in 2014

	2014 recall	
2010 vote report	Democratic candidate	Republican candidate
Democrat	91.1%	3.5%
Republican	4.7%	93.0%
Other	4.2%	3.5%
N	2,888	3,111

analysis of 2018 House vote presented in the paper.

While there are some differences in the coefficients for partisanship ($p = 0.04$) and ideology ($p = 0.02$), the key comparison for the purposes of the paper are the coefficients for racial resentment across the two models. In the model using the contemporaneous vote choice measure, the racial resentment coefficient is 3.214 while in the recall model it is 3.566. This difference is relatively small in magnitude and not close to being statistically significant ($p = 0.34$).

Overall, this analysis shows that voters are highly accurate when recalling their previous vote choices, even in House elections. Additionally, there is no evidence that relying on recall would significantly strengthen the coefficient for a measure of racial attitudes. Furthermore, there are two reasons to expect that the accuracy would be even higher for the analysis presented in the paper. First, whereas this analysis asks people to recall a House vote from four years prior, the analysis in the paper relies on people remembering their House vote from just two years ago. Second, the recall question asked in the panel study only provided respondents with the selection of a candidate's party, but in the 2018 survey analyzed in the paper, respondents were provided both candidate names and parties when asked to recall their 2016 vote. Providing this additional information likely improved the recall accuracy for respondents.

Table SI.2: Probit models estimating predictors of 2010 House vote as measured contemporaneously and by recall

	2010 vote measured in 2010	2010 vote measured in 2014
Racial resentment	3.214***	3.566***
	(0.485)	(0.512)
Ideology	2.504***	3.393***
	(0.313)	(0.406)
Partisanship	3.010***	3.516***
	(0.219)	(0.272)
Frequent church attendance	0.280*	0.229
	(0.123)	(0.141)
Infrequent church attendance	0.124	-0.0892
	(0.130)	(0.150)
Female	-0.162	-0.173
	(0.0984)	(0.106)
Age: 30-54	0.118	0.280
	(0.278)	(0.258)
Age: 55 and over	0.0120	0.0521
	(0.262)	(0.253)
College degree	0.0888	0.0125
	(0.0998)	(0.109)
Less than $40k	-0.327*	-0.496*
	(0.163)	(0.222)
$40k - $100k	-0.247	-0.327
	(0.161)	(0.212)
Over $100k	-0.0766	-0.0687
	(0.163)	(0.236)
White	-0.339*	-0.128
	(0.163)	(0.255)
Black	-0.587*	-1.177***
	(0.249)	(0.352)
Hispanic	-0.0665	-0.405
	(0.325)	(0.525)
Intercept	-4.125***	-5.096***
	(0.453)	(0.509)
N	5757	5757

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

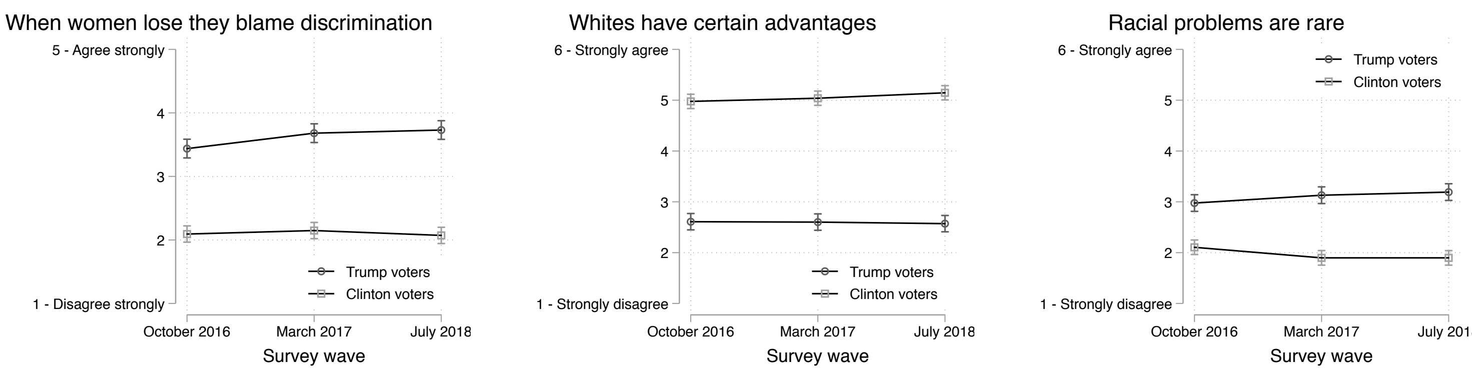
3 Stability of Hostile Sexism and Denial of Racism Items, 2016-2018

As noted in the paper, some recent studies have found that racial attitudes are shifting over time (Engelhardt, Forthcoming; Hopkins and Washington, Forthcoming). However, those studies apply to other measures of racial attitudes (specifically, racial resentment and stereotypes). Fortunately, YouGov fielded a panel survey that interviewed the same set of 731 respondents in October 2016, March 2017, and July/August 2018. This survey included the two items that I use in the paper for the denial of racism scale as well as one of the two hostile sexism items. Thus, we can use this panel survey to examine whether there were significant shifts in how Clinton or Trump voters responded to these items in subsequent waves.

Figure SI.1 plots the average responses to each of the three items among people who said they voted for Clinton and Trump in the first wave. There are some relatively minor shifts of note. For example, Trump voters moved about one-quarter of a point (on the five-point scale) in a more sexist direction on the item asking whether they agreed or disagreed that "when women lose to men in a fair competition, they typically complain about being discriminated against." This movement came between the first and the second wave, with little additional movement during the third wave. Clinton voters did undergo any notable (or statistically significant) shift on this item.

On the item asking whether "white people in the U.S. have certain advantages because of the color of their skin," neither Trump not Clinton voters showed any significant shifts in their responses across the three waves. Finally, on the item asking whether respondents agreed that "racial problems in the U.S. are rare, isolated situations," both Trump and Clinton voters showed some modest (but statistically significant movement). Specifically, Democrats moved about one-fifth of a point toward more disagreement with this item, whereas Republicans moved about one-fifth of a point toward more agreement.

Figure SI.1: Average responses across three waves of panel survey



Note: N = 605 respondents interviewed in 2016, 2017, and 2018. Vertical lines represent 95% confidence intervals.

4 Bivariate Probit Models for 2016 House and Presidential vote choice

In Table SI.3 I present the results from a bivariate probit model predicting vote choices for president and House from 2016 using respondents to the 2018 CCES competitive districts study. This is the model use to produce Figure 2 in the paper. In order to ensure that the findings from this model are not affected by the fact that respondents are being asked to recall vote choices from two years earlier, I re-estimated the same model using data from the 2016 CCES. The results from that model are shown in Figure SI.4 and the same patterns persist (with sexism and denial of racism being stronger predictors of the 2016 presidential vote than they were for the 2016 House vote).

Table SI.3: Bivariate probit model estimating predictors of 2016 House and Presidential Vote

	2016 House Vote	2016 Presidential Vote
Hostile sexism	0.777***	1.697***
	(0.211)	(0.300)
Denial of racism	1.142***	1.841***
	(0.212)	(0.268)
Change in income	0.607*	1.140***
	(0.246)	(0.328)
Ideology	1.710***	1.617***
	(0.240)	(0.290)
Partisanship	2.844***	3.191***
	(0.187)	(0.218)
Frequent church attendance	-0.0876	0.0620
	(0.128)	(0.157)
Infrequent church attendance	-0.0679	-0.123
	(0.131)	(0.154)
Female	0.167	-0.141
	(0.108)	(0.112)
Age: 30-54	0.181	-0.0452
	(0.166)	(0.206)
Age: 55 and over	0.424*	0.255
	(0.169)	(0.210)
College degree	0.0819	-0.157
	(0.117)	(0.126)
Less than $40k	-0.0783	0.0230
	(0.186)	(0.198)
$40k - $100k	-0.0119	0.229
	(0.162)	(0.175)
Over $100k	0.0245	0.187
	(0.190)	(0.192)
White	-0.0832	0.316
	(0.187)	(0.231)
Black	-0.744*	-0.247
	(0.317)	(0.395)
Hispanic	-0.391	0.175
	(0.224)	(0.276)
Intercept	-3.590***	-4.951***
	(0.345)	(0.529)
N	6,277	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table SI.4: Bivariate probit model estimating predictors of 2016 House and Presidential Vote

	2016 House Vote	2016 Presidential Vote
Hostile sexism	0.958***	1.698***
	(0.280)	(0.357)
Denial of racism	2.053***	2.915***
	(0.312)	(0.438)
Change in income	-0.411	-1.027**
	(0.271)	(0.348)
Ideology	0.643*	1.040*
	(0.315)	(0.446)
Partisanship	2.590***	2.989***
	(0.248)	(0.283)
Frequent church attendance	0.109	-0.199
	(0.161)	(0.186)
Infrequent church attendance	0.293*	0.127
	(0.138)	(0.178)
Female	-0.333*	-0.0771
	(0.131)	(0.156)
Age: 30-54	0.00215	0.432
	(0.255)	(0.370)
Age: 55 and over	-0.154	0.517
	(0.246)	(0.362)
College degree	0.0167	0.00900
	(0.143)	(0.136)
Less than $40k	0.171	-0.156
	(0.224)	(0.239)
$40k - $100k	-0.0423	-0.396
	(0.221)	(0.218)
Over $100k	-0.0300	-0.238
	(0.252)	(0.233)
White	0.213	0.247
	(0.217)	(0.313)
Black	-0.464	-0.0924
	(0.364)	(0.480)
Hispanic	-0.892*	0.131
	(0.443)	(0.408)
Intercept	-2.614***	-3.838***
	(0.457)	(0.541)
N	1,207	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Multivariate probit model for 2016 House and Presidential vote choice and 2018 House vote choice

Here I estimate a multi-variate probit model, which allows me to simultaneously estimate three vote choice models at once – 2016 House vote, 2016 presidential vote, and 2018 House vote. The patterns from this model are consistent with those described from two separate bivariate probit models in the paper. Specifically, the coefficients for hostile sexism and denial of racism are much smaller in the 2016 House vote model than they are in both the 2016 presidential vote choice model and the 2018 House vote model. Notably, there are only small differences (which are not statistically significant) between the coefficients in the 2016 presidential vote choice model and the 2018 House vote. Thus, this model shows clearly that in 2018, the House vote came to be influenced by sexism and denial of racism in a way that was much more like the 2016 presidential vote.

Table SI.5: Multivariate probit model estimating predictors of 2016 House and Presidential vote and 2018 House vote

	2016 House vote	2016 Presidential vote	2018 House vote
Hostile sexism	0.885***	1.609***	1.419***
	(0.242)	(0.312)	(0.248)
Denial of racism	1.204***	2.202***	2.066***
	(0.244)	(0.346)	(0.278)
Change in income	0.566*	1.156***	0.838**
	(0.276)	(0.342)	(0.311)
Ideology	1.858***	1.884***	1.769***
	(0.273)	(0.356)	(0.367)
Partisanship	2.874***	3.301***	2.881***
	(0.219)	(0.249)	(0.246)
Frequent church attendance	-0.0172	-0.163	0.140
	(0.146)	(0.180)	(0.148)
Infrequent church attendance	-0.0518	-0.301	-0.0961
	(0.144)	(0.192)	(0.181)
Female	0.252*	-0.00289	0.163
	(0.121)	(0.129)	(0.134)
Age: 30-54	0.163	0.191	-0.0581
	(0.206)	(0.187)	(0.262)
Age: 55 and over	0.284	0.606***	0.142
	(0.210)	(0.181)	(0.256)
College degree	0.0488	-0.120	-0.143
	(0.125)	(0.148)	(0.127)
Less than $40k	-0.120	0.0866	0.0258
	(0.190)	(0.230)	(0.206)
$40k - $100k	0.0122	0.184	-0.0979
	(0.162)	(0.210)	(0.166)
Over $100k	0.100	0.147	0.148
	(0.191)	(0.225)	(0.188)
White	0.412	-0.122	0.113
	(0.248)	(0.337)	(0.331)
Black	0.202	-0.0486	0.259
	(0.172)	(0.220)	(0.269)
Hispanic	-0.394	-0.147	-0.497
	(0.362)	(0.365)	(0.444)
Intercept	-4.039***	-5.246***	-4.776***
	(0.366)	(0.509)	(0.494)
N		5,606	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Mediation analysis with presidential approval

In the paper, I describe results from a model of vote choice in 2018 where I explore the extent to which the effects of racial attitudes and sexism on vote choice may be mediated by a voter's evaluation of Donald Trump. To estimate this effect, I conducted a mediation analysis using the `mediation` package in Stata (Hicks and Tingley, 2011; Imai, Keele, and Tingley, 2010; Imai, Keele, and Yamamoto, 2010). While such an analysis cannot make strong causal claims, it can provide suggestive evidence about whether part of the role that racial attitudes and sexism played in 2018 were mediated by how those factors affected one's approval (or disapproval) of Trump.

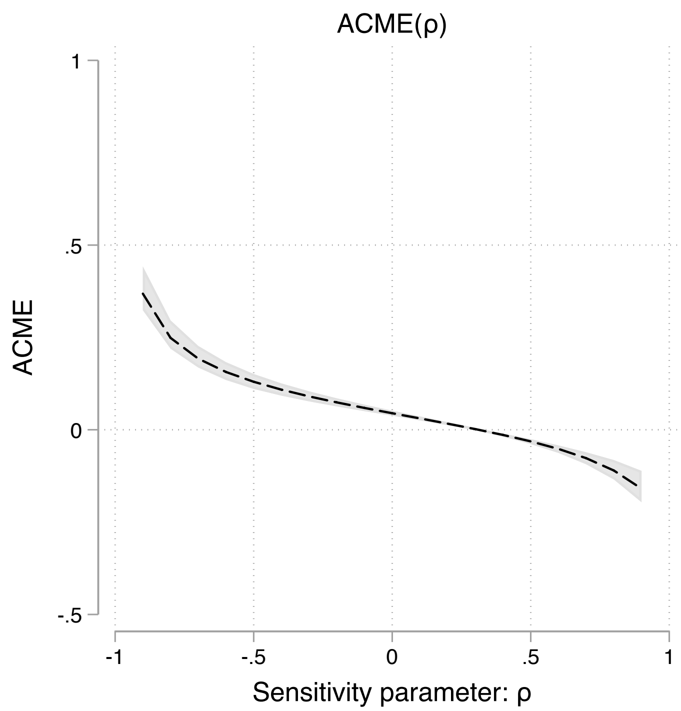
Table SI.6 shows the Average Causal Mediation Effect (ACME), the total direct effect, the total effect, and the percent of the total effect that is mediated for each variable. About 38% of the effect of hostile sexism is mediated by presidential approval, while about one-third of the effect of denial of racism is mediated by approval. To demonstrate the sensitivity of these estimates to the sequential ignorability assumption, the table also shows the estimate of the ρ at which the AMCE would be zero (.3). This is a relatively high threshold suggesting that these findings are fairly robust. Figure SI.2 plots the AMCE across values of ρ to provide additional details about sensitivity to the sequential ignorability assumption.

Table SI.6: Summary of effects of racial attitudes and hostile sexism via presidential approval

Variable	ACME	Direct effect	Total effect	% mediated	ρ at which AMCE=0
Hostile sexism	0.045	0.076	.121	37.6	0.30
	(.038, .053)	(.043, .111)	(.083, .162)	(28.0, 54.5)	
Denial of racism	0.083	0.169	.252	33.2	0.30
	(.073, .096)	(.130, .214)	(.209, .307)	(27.0, 39.7)	

Note: N = 7,771. 95% confidence intervals in parentheses. Models estimated including all control variables.

Figure SI.2: Average causal mediation effect as a function of degree of violation of sequential ignorability assumption



7 Effect of sexism and denial of racism conditional on candidate sex and race

One possibility for the increased importance of sexism and denial of racism in 2018 may be tied to the fact that more women and candidates of color ran for office in the 2018 midterm elections. To test this possibility, Table SI.7 shows the results from a bivariate probit model of House vote choice in 2016 and 2018. This model expands on the main model in the paper (Table 1) by adding indicators for the gender and race of the candidates competing in each House race. The candidate gender variable categorizes races in 2016 and 2018 based on whether two men were running against each other, whether two women were running against each other, whether a Republican man was running against a Democratic woman, or if a Republican woman was running against a Democratic man. Most respondents lived in districts with two male House candidates running against each other (62% in 2016 and 56% in 2018) while a significant share also lived in districts featuring a male Republican against a female Democrat (28% in 2016 and 29% in 2018).

The candidate race variable categorizes races in 2016 and 2018 based on whether two white candidates were running against each other, whether two non-white candidates were running against each other, whether a white Republican was running against a non-white Democrat, or whether a non-white Republican was running against a white Democrat. Candidates were classified as non-white if they identified as African American, Latinx, or Asian American. Most respondents lived in districts with two white House candidates running against each other (83% in 2016 and 77% in 2018) while a significant share also lived in districts featuring a white Republican against a non-white Democrat (12% in 2016 and 13% in 2018).

The model then also includes interaction terms–one between the candidate sex indicators and the hostile sexism variable and the other between the candidate race indicators and the denial of racism measure. This provides a test of whether whether the influence of sexism was stronger (or weaker) in races featuring a woman candidate and whether the influence of racism denial was stronger (or weaker) in contests featuring non-white candidates.

Table SI.7 presents the results from this model (the estimates for the control variables are hidden to allow the table to appear on a single page). Notably, only one of the interaction terms is statistically significant in the model–that is the interaction term conditioning the effect of denial of racism on contests where a non-white Republican was running against a white Democrat. The magnitude and direction of the coefficient effectively mutes the relationship between denial of racism and supporting Republican candidates when those candidates are minorities running against white Democrats. However, it is important to note that this condition is relatively rare – only 6% of respondents voted in a district that featured such a configuration of candidates.

To make it easier to understand the patterns in Table SI.7, Figure SI.3 shows the relationship between hostile sexism/denial of racism and vote choice in both 2016 and 2018 broken out by the traits of the candidates. The confidence intervals are not included in these plots because of they overlap so much that it obscures the slopes. Overall, these plots show

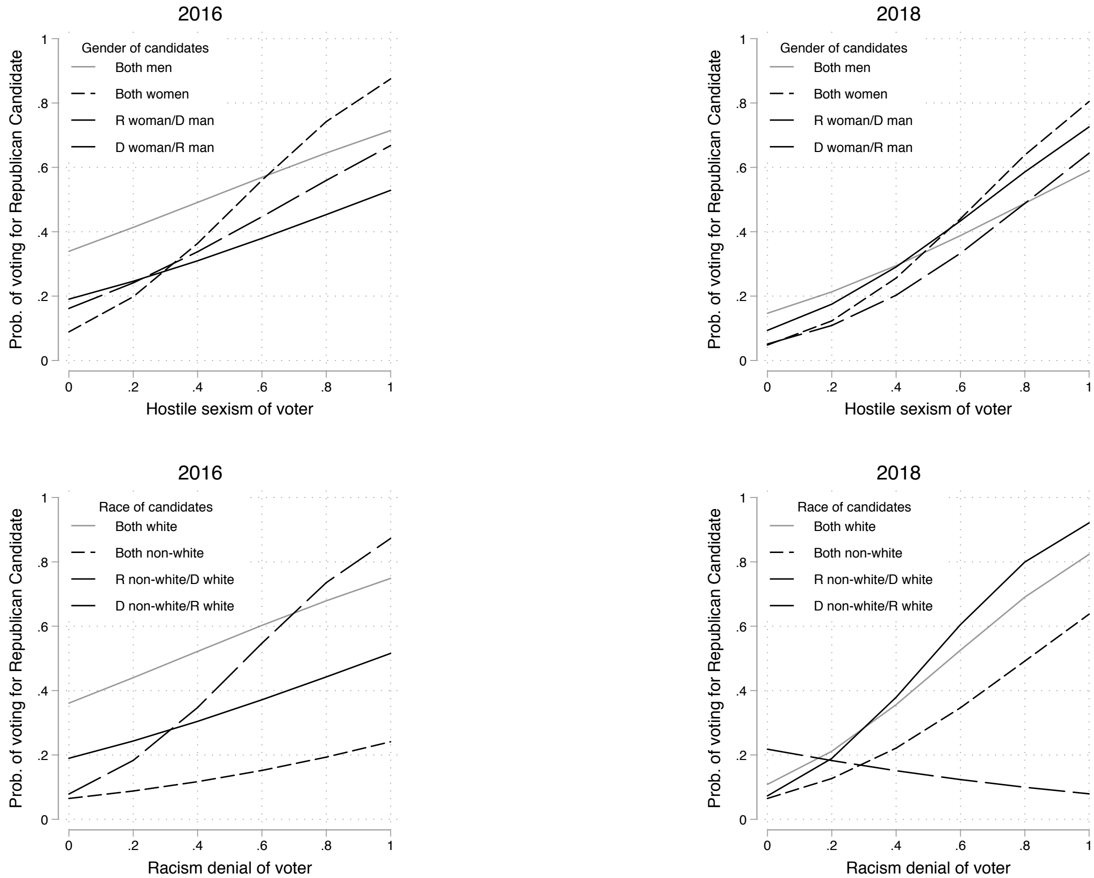
Table SI.7: Bivariate probit model estimating predictors of 2016 and 2018 House vote with interactions for candidate gender and race

Variable	2016 House vote	2018 House vote
Hostile sexism	0.981***	1.277***
	(0.297)	(0.310)
Both women	-0.872*	-0.817
	(0.390)	(0.456)
R woman/D man	-0.440	-0.441
	(0.309)	(0.507)
R man/D woman	-0.204	-0.312
	(0.237)	(0.270)
Both women x Hostile sexism	1.517	1.245
	(0.878)	(0.799)
R woman/D man x Hostile sexism	0.440	0.727
	(0.638)	(0.861)
R man/D woman x Hostile sexism	-0.033	0.642
	(0.437)	(0.474)
Denial of racism	1.026***	2.163***
	(0.266)	(0.328)
Both minorities	-0.124	0.596
	(0.555)	(0.358)
R minority/D white	-0.218	1.132**
	(0.385)	(0.360)
R white/D minority	-0.121	-0.188
	(0.231)	(0.361)
Both minorities x Denial fo racism	-0.215	-0.296
	(1.058)	(0.740)
R minority/D white x Denial of racism	1.528	-2.794***
	(0.944)	(0.800)
R white/ D minority x Denial of racism	-0.108	0.704
	(0.495)	(0.720)
Estimates for control variables not shown		
Intercept	-3.893***	-5.058***
	(0.382)	(0.454)
N	5,989	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure SI.3: Relationship between hostile sexism/denial of racism and predicted probability of voting Republican in 2016 and 2018, by traits of competing candidates



Note: Predicted probabilities generated from model in Table SI.7 holding all other variables at their mean values.

that the relationship between these attitudes and vote choice are mostly the same regardless of candidate traits.

Table SI.8 presents predicted probabilities generated from the bivariate probit model. There are many ways one can structure this comparison, but one useful approach is to, for example, take voters who cast ballots in races featuring two white candidates in 2016 and then split that group into those who also voted in a race featuring two white candidates in 2018 and compare that group to those who voted in a race featuring a white Republican running against a non-white Democrat in 2018. This is what the top half of Table SI.8 shows. Among voters with a relatively low value on the denial of racism scale, the predicted probability of being a Republican to Democrat switcher was about .235 if their 2018 election featured a white Democrat and .297 for those with a non-white Democrat running. By contrast, among those with high levels of denial of racism, the predicted probability of being

Table SI.8: Predicted probability of being a switcher

Condition	Predicted probability R → D		Predicted probability D → R	
	Low denial	High denial	Low denial	High denial
Both white in '16 and '18	0.235	0.133	0.020	0.080
	(.170, .301)	(.089, .176)	(.004, .036)	(.047, .113)
Both white in '16, D non-white vs. R white in '18	0.297	0.069	0.018	0.097
	(.140, .453)	(.018, .121)	(.000, .046)	(.046, .148)
	Low sexism	High sexism	Low sexism	High sexism
Both men in '16 and '18	0.192	0.188	0.040	0.048
	(.136, .247)	(.142, .235)	(.015, .064)	(.023, .073)
Both men in '16, D woman vs. R man in '18	0.255	0.212	0.057	0.041
	(.166, .345)	(.141, .282)	(.003, .048)	(.016, .065)

Note: Predicted probabilities generated from model in Table SI.7 while holding all other variables at their mean values. For low sexism or denial of racism, value was set to .3; high values on these scales were set to .7. 95% confidence intervals presented in parentheses.

a Democrat to Republican switcher was .133 when the voter was in a district featuring white candidates in both elections, but just .069 when the Democratic candidate in 2018 was non-white. However, note that the confidence intervals for these predictions are highly overlappings.

The next two rows show a similar comparison, but this time comparing voters based on their levels of sexism and the gender composition of the candidates competing in each election. Low sexism voters who had elections with only male candidates in both 2016 and 2018 had a predicted probability of being a Republican to Democrat switcher of .192. However, low sexist voters in districts where the Democrat was a woman in 2018 had a predicted probability of .255 of switching their vote from Republican to Democrat. Thus, there is some indication that low sexism voters were more likely to become Democratic voters in 2018 when a woman was running in their district. However, the confidence intervals for these predictions overlap, meaning we cannot be confident there is a difference among the population of voters.

Finally, the columns on the right side of the table show predicted probabilities of being a voter who switched from supporting a Democrat in 2016 to a Republican in 2018. On this side of the table, the predicted probabilities are generally much smaller and there appears to be little difference based on the race or gender of the candidates running.

8 Additional robustness checks for main results

In this section I present a series of models which are robustness checks on the main bivariate probit model presented in the paper. First, Table SI.9 shows a model that includes an interaction term between hostile sexism and denial of racism. Note that this interaction term is not statistically significant in for either of the models.

Second, Table SI.10 shows the results from a model that only includes respondents living in the 52 competitive districts that were oversampled for the survey. Given that these respondents lived in districts that were subjected to the most intense campaign, it is notable that same patterns of the increasing importance of sexism and denial of racism persist for these individuals.

Finally, Table SI.11 presents results from a model that uses racial resentment as the measure of racial attitudes rather than denial of racism. Once again, the main patterns are consistent in this model. The coefficient for racial resentment is significantly larger in the 2018 House vote equation than it is for the 2016 House vote (p = .0162).

8.1 Incorporating an interaction term between hostile sexism and denial of racism

Table SI.9: Bivariate probit model estimating predictors of 2016 and 2018 House vote, with interaction term between hostile sexism and denial of racism

	2016 House Vote	2018 House Vote
Hostile sexism	0.881*	2.073***
	(0.373)	(0.494)
Denial of racism	0.942*	2.610***
	(0.459)	(0.656)
Hostile sexism x Denial of racism	0.338	-1.103
	(0.758)	(1.126)
Change in income	0.528*	0.938**
	(0.260)	(0.296)
Ideology	1.882***	1.949***
	(0.248)	(0.330)
Partisanship	2.908***	2.817***
	(0.207)	(0.220)
Frequent church attendance	0.148	0.0605
	(0.135)	(0.139)
Infrequent church attendance	0.0391	-0.0931
	(0.135)	(0.160)
Female	0.311**	0.240*
	(0.113)	(0.119)
Age: 30-54	0.257	-0.236
	(0.186)	(0.228)
Age: 55 and over	0.374*	0.0862
	(0.187)	(0.218)
College degree	0.0358	-0.0530
	(0.115)	(0.122)
Less than $40k	0.0873	0.158
	(0.177)	(0.191)
$40k - $100k	0.180	-0.119
	(0.151)	(0.155)
Over $100k	0.273	0.241
	(0.179)	(0.186)
White	-0.162	0.233
	(0.206)	(0.206)
Black	-0.754*	-0.717
	(0.369)	(0.396)
Hispanic	-0.432	-0.106
	(0.237)	(0.323)
Intercept	-4.011***	-5.252***
	(0.394)	(0.464)
N	6,076	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8.2 Re-estimating main model only in competitive House districts

Table SI.10: Bivariate probit model estimating predictors of 2016 and 2018 House vote (only in 52 oversampled competitive House districts)

	2016 House Vote	2018 House Vote
Hostile sexism	0.782***	1.327***
	(0.145)	(0.183)
Denial of racism	1.111***	2.024***
	(0.151)	(0.193)
Change in income	1.032***	1.380***
	(0.174)	(0.186)
Ideology	1.841***	1.832***
	(0.159)	(0.213)
Partisanship	2.644***	2.673***
	(0.129)	(0.137)
Frequent church attendance	0.228**	0.189*
	(0.0865)	(0.0921)
Infrequent church attendance	0.185*	0.0837
	(0.0799)	(0.0912)
Female	0.100	-0.0151
	(0.0673)	(0.0741)
Age: 30-54	0.245	0.384*
	(0.131)	(0.188)
Age: 55 and over	0.300*	0.564**
	(0.131)	(0.180)
College degree	0.0407	-0.00635
	(0.0677)	(0.0775)
Less than $40k	0.0705	0.0245
	(0.125)	(0.130)
$40k - $100k	0.133	-0.0142
	(0.109)	(0.118)
Over $100k	0.222	0.129
	(0.116)	(0.125)
White	-0.0211	-0.295
	(0.127)	(0.200)
Black	-0.279	-0.937**
	(0.243)	(0.332)
Hispanic	-0.179	-0.445
	(0.195)	(0.274)
Intercept	-4.064***	-5.023***
	(0.249)	(0.341)
N	5,005	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8.3 Re-estimating main model using racial resentment instead of denial of racism

Table SI.11: Bivariate probit model estimating predictors of 2016 and 2018 House vote (using racial resentment instead of denial of racism

	2016 House Vote	2018 House Vote
Hostile sexism	0.784**	1.345***
	(0.238)	(0.274)
Racial resentment	1.546***	2.344***
	(0.264)	(0.344)
Change in income	0.569*	1.057***
	(0.254)	(0.300)
Ideology	1.738***	1.697***
	(0.245)	(0.328)
Partisanship	2.878***	2.829***
	(0.207)	(0.220)
Frequent church attendance	0.222	0.198
	(0.136)	(0.135)
Infrequent church attendance	0.0314	-0.0680
	(0.137)	(0.158)
Female	0.298**	0.188
	(0.112)	(0.118)
Age: 30-54	0.213	-0.318
	(0.196)	(0.228)
Age: 55 and over	0.295	-0.0433
	(0.197)	(0.218)
College degree	0.0935	0.0124
	(0.117)	(0.119)
Less than $40k	0.103	0.201
	(0.178)	(0.189)
$40k - $100k	0.171	-0.135
	(0.153)	(0.142)
Over $100k	0.271	0.219
	(0.183)	(0.170)
White	-0.114	0.348
	(0.201)	(0.224)
Black	-0.644	-0.539
	(0.361)	(0.431)
Hispanic	-0.422	-0.0684
	(0.235)	(0.332)
Intercept	-4.307***	-5.343***
	(0.364)	(0.455)
N	6,076	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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