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Supplemental Material: Countering Non-Ignorable Nonresponse in Survey Models with Randomized Response Instruments and Doubly Robust Estimation

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Appendix 1. Ethical review

The survey instrument used in this analysis was deemed to be exempt from review by the Institutional Review Board at my university on 9/21/2018 with the category of "research involving the use of educational tests (cognitive, diagnostic, aptitude, or achievement), survey procedures, interview procedures, or observation of public behavior."

Ipsos recruits their research panel to be representative of the entire United States population. Panel members are randomly recruited through probability-based sampling, and households are provided with access to the Internet and hardware if needed. Ipsos obtains consent via industry standard practices for recruiting people into panel surveys; they also provide all respondents with privacy and confidentiality protections. I had no access to personally identifiable information. There was a modest deception in the survey in that respondents were asked what they would like to discuss next. Their request was implemented (e.g., if they said sports, they were asked two questions about sports), but then they were asked political questions after that. There was no intervention in the political process over and above any effects answering a political survey may have on the respondents' attitudes.

I did not compensate survey respondents for their time and effort. This is standard practice for short surveys about politics (that should take no more than 15 minutes to answer). I have no way of knowing if any respondents were entered into the modest incentive program Ipsos uses to encourage participation and create member loyalty. This program enters selected individuals into sweepstakes with cash rewards and other prizes to be won; the expected value of these programs is minimal. There are minimal risks to the respondent in answering this survey. The questions are not typically considered sensitive and I had no way of identifying any of the respondents. There is no reason to believe that this survey or research differentially benefits or harms particular groups.

Appendix 2. Double robust estimation for MAR models

To provide a sense of how doubly robust estimation works in the MAR context, Figure 1 shows results from a series of simulations. Suppose that true models are

$$\begin{aligned} Pr(R=1|X) &= logit(\gamma_0 + \gamma_{X1}X1 + \gamma_{X2}X2) \\ Pr(Y=1|X) &= logit(\beta_0 + \beta_{X1}X1 + \beta_{X2}X2) \end{aligned}$$

and that we estimate not only the true specifications but also two misspecified models

$$\begin{aligned} Pr(R=1|X) &= logit(\gamma_0) \\ Pr(Y=1|X) &= logit(\beta_0) \end{aligned}$$

The misspecified models perform poorly. The misspecified response equation assumes everyone (whatever their X values) has the same probability of responding. The misspecified outcome equation assumes everyone (whatever their X values) has the same probability of having $Y = 1$.

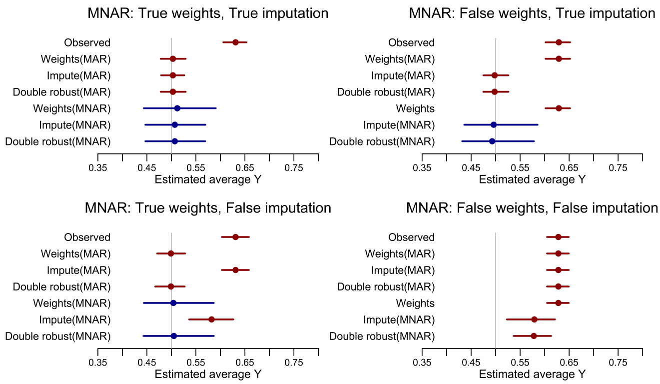

Figure 1. Simulation results for MAR data

The upper left of Appendix Figure 1 shows the observed mean in the data and the population estimates for IPW, imputation and doubly robust models if we use the correct specifications for both weighting and imputation. The bars indicate the 5th and 95 percentile results from 100 simulations. The MAR methods are on top and the MNAR methods are on the bottom. Because both the weighting and imputation specifications are correct, it is unsurprising that all models produce seemingly unbiased estimates. This is in contrast to Figure 1 in the main paper in which the MAR models perform poorly when the data generating process is MNAR. Notice, though, that the MNAR models have substantially higher variance. There is a bias-efficiency tradeoff as the MNAR model are always unbiased but produce less precise estimates. This results echos general bias-efficiency tradeoffs with two-stage least squares and other instrumental variable type models. The implication is that if one has no evidence of MNAR data generation, then one is better off using MAR-type models.

The upper right of Appendix Figure 1 shows the estimates produced by the three models when the response equation is misspecified. The weighted estimate is far from the true value, but the imputation model is fine and – importantly – the doubly robust model essentially inherits the good properties of the properly specified imputation model. The lower left panel of Figure 1 shows the case when the response model is correctly specified and the imputation model is incorrectly specified. Here, the weights produce the correct estimate, while the imputation model produces an estimate that is far from the truth. The doubly robust inherits the good properties of the weighting model.

The lower right panel of Appendix Figure 1 shows the limits of the doubly robust estimator. If both specifications are incorrect, the doubly robust estimator is incorrect as well. In this case, the mis-specifications are rather severe so there is no improvement in the doubly robust model relative to the others. In other cases, the doubly robust estimator can show improvements if one of the mis-specified models is only weakly mis-specified (Robins and Rotnitzky 2001). In general, though, there is no result on relative performance of doubly robust estimators when both models are mis-specified (Kang and Schafer 2007).

Appendix 3. Weak Instrument

The precision of the estimates depends on the strength of the instrument. Appendix Figure 2 displays simulation results when $\gamma_Z = 0.75$, which is substantially smaller than the $\gamma_Z = 2.0$ in the simulations in the main paper. Simulation results for the $\gamma_Z = 2.0$ are shown in a lighter color for each of the MNAR estimators. The MNAR estimators all become less precise for the weaker instrument.

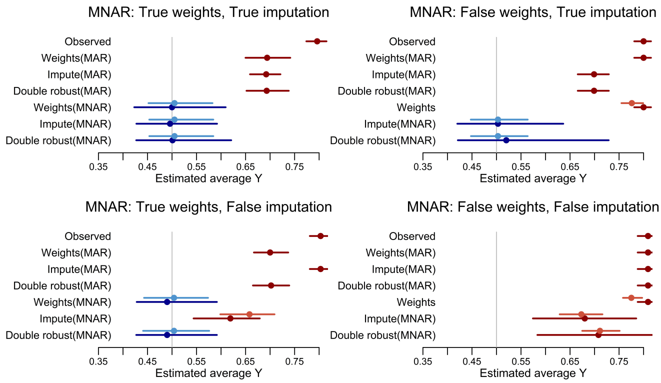

Figure 2. Simulation results with weak instrument

Appendix 4. Selection bias function

Equation 5 characterizes the selection bias function in Sun et al. (2018). For a logit function, $\eta(x, y, z) = \gamma_Y$ as can be seen by substituting the following into the $\eta(x, y, z)$ function:

$$
\begin{aligned}
Pr(R = 1|x, y, z) &= \frac{e^{\gamma_X X + \gamma_Y}}{1 + e^{\gamma_X X + \gamma_Y}} \\
Pr(R = 0|x, y, z) &= \frac{1}{1 + e^{\gamma_X X + \gamma_Y}} \\
Pr(R = 1|x, Y = 0, z) &= \frac{e^{\gamma_X X}}{1 + e^{\gamma_X X}} \\
Pr(R = 0|x, Y = 0, z) &= \frac{1}{1 + e^{\gamma_X X}}
\end{aligned}
$$

Appendix 5. Intuition of estimating equations for MNAR IPW

The MNAR IPW model uses estimating equations. A classic example of an estimating equation estimator is a method of moments estimator that estimates population moments with sample moments.

For simplicity, suppose there are no covariates and consider two separate data sets: one generated by a MAR process and one generated by a MNAR process. The left columns of Table A1 show that there are 1,000 people in the population for each of the four combinations of Z and Y. The next two columns display hypothetical observed data given a MAR data generation process. We assume that Z is a proper instrument so that it affects response, but is independent of Y in the full population. For each value of Y, there are 200 $Z = 0$ observations and 400 $Z = 1$ observations, reflecting the increase in responsiveness associated with Z. For each value of Z, there are the same number of $Y = 0$ and $Y = 1$ observations, reflecting the fact that Y has no influence on propensity to respond in a MAR data generation process.

The rightmost two columns display hypothetical observed data given a MNAR data generation process. As in the MAR process, there are more $Z = 1$ observations for each value of Y. Unlike the MAR process, there are also more $Y = 1$ observations for each value of Y, which satisfies the

Table A1. Hypothetical population and sample values

	Population		Observed			
			MAR		MNAR	
	Y = 0	Y = 1	Y = 0	Y = 1	Y = 0	Y = 1
Z = 0	n_{00} = 1000	n_{01} = 1000	n_{00} = 200	n_{01} = 200	n_{00} = 100	n_{01} = 250
Z = 1	n_{10} = 1000	n_{11} = 1000	n_{10} = 400	n_{11} = 400	n_{10} = 250	n_{11} = 500

MNAR definition that responsiveness depends on Y conditional on covariates (which is only Z in this example).

Equation h[4] in the estimating equations for the MNAR weighted model imposes the condition that Z minus its expected value is independent of Y in the full population, which we estimate with weighted values of Y. This condition is $\sum \frac{R_i Y_i}{\hat{\pi}_i}(Z_i - \hat{Z}_i) = 0$. The fraction on the left limits the calculation to observations with $R_i = 1$ and $Y_i = 1$. Given that there are no X covariates in this simple example, the expected value of Z is simply its average. Suppose that the average of Z is 0.5, then $(Z_i - \hat{Z}_i) = 0.5$ for $Z_i = 1$ and $(Z_i - \hat{Z}_i) = -0.5$ for $Z_i = 0$, implying

$$\sum \frac{R_i Y_i}{\hat{\pi}_i}(Z_i - \hat{Z}_i) = 0 \quad (1)$$

$$\frac{n_{R=1,Y=1,Z=1}}{Pr(R = 1|Y = 1, Z = 1)} = \frac{n_{R=1,Y=1,Z=0}}{Pr(R = 1|Y = 1, Z = 0)} \quad (2)$$

$$\frac{n_{11}}{\pi(\gamma_0 + \gamma_Z + \gamma_Y)} = \frac{n_{01}}{\pi(\gamma_0 + \gamma_Y)} \quad (3)$$

Assuming Z is valid instrument, $n_{11} > n_{01}$ and therefore it is necessary that $\gamma_Z > 0$ in order to satisfy the equality.

The second estimating equation (h[2]) implies that $\frac{n_{10}}{\pi(\gamma_0+\gamma_Z)} + \frac{n_{11}}{\pi(\gamma_0+\gamma_Z+\gamma_Y)} = \sum Z$.

For MAR, these quantities will be the same in expectation. Setting $\gamma_Y = 0$ will satisfy this condition in our example; in our example, $Pr(R = 1|Z = 1, Y) = 0.4$.

For the MNAR case, there are disproportionately many observations with both $Z = 1$ and $Y = 1$; setting $\gamma_Y > 0$ will lower the weight on the disproportionately high n_{11} group.

For completeness, note that h[1] implies that the sum of weights (which are the inverse of the probabilities) totals N: $\frac{n_0}{\pi(\gamma_0)} + \frac{n_{01}}{\pi(\gamma_0+\gamma_Y)} + \frac{n_{10}}{\pi(\gamma_0+\gamma_Z)} + \frac{n_{11}}{\pi(\gamma_0+\gamma_Z+\gamma_Y)} = N$.

Appendix 6. Complete results

Tables A2 through A15 present the full results for the results discussed in Figures 3 through 7 in the main text. The doubly robust estimation procedure produces three sets of parameters. The left column in each table is labeled "Z: Pr(Z|X)"; it displays the coefficients on the X covariates in a model explaining Z. Because Z is randomly assigned, these are generally insignificant and uninteresting.

It is possible to add additional interactions in the imputation models (e.g., cross-terms among the X variables) as well, although I do not do so for simplicity.

The middle column in each table is labeled "Response: Pr(R|Z, Y, X)." It reports the coefficients for the model explaining response, which is based on the weighting equation used in MNAR IPW models The two most important parameters are in the two top rows. First is the coefficient on Z, which reflects the effect of the randomized response instrument on the probability of response. If this coefficient is not large, the model will be underpowered. Notice that the coefficient is always more than 6 times the size of the standard error and often much larger. Second is the coefficient on

Y, which reflects the effect of Y on response. This is the variable associated with non-ignorable non-response. If it is large relative to its standard error, we have evidence of non-ignorable non-response. This coefficient and associated standard errors are plotted in the smaller panels on the left of each of Figures 3 through 7 in the main text.

The right column in each table is labeled "Y: Pr(Y, Z, R=1)." It displays the coefficients in the model predicting Y as a function of Z and X given $R = 1$. Note that this is a reduced-form model. In the full population, Y is independent of Z by construction (via the randomization of Z). Given that Z affects response, however, it may be associated with Y in the observed sample. In DAG-terminology, conditioning on response opens a pathway for Z to be associated with Y. This reduced-form model is used in Equation 6 in the main text, the model that guides the imputation of Y given $R = 0$ based on Y given $R = 1$ and the γ_Y parameter that reflects the degree of non-ignorable non-response. Because this is a reduced-form model, the coefficients are not directly interpretable in the sense that coefficients on a similar-looking model for a full population would be.

The results in Table A2 are robust to changing the coding of turnout. If I code the turnout variable to equal 1 for respondents who were either "very" or "absolutely" certain to turnout, 86% of respondents said they would turn out. Using the doubly robust estimator leads to an estimate of 57% turnout by this standard, with $\gamma_Y = 2.79$ with a standard error of 0.75. For both turnout standards, the MNAR-weighting and MNAR imputation results are quite similar to the doubly robust estimates.

The models by subgroups (e.g., Midwest, Democrats, Republicans) are limited to white individuals. Similar to maximum likelihood models, the MNAR estimation process cannot estimate parameters for groups that are unanimous with regard to their value of Y. A probit model, for example, cannot estimate a coefficient on college-educated if $Y = 1$ for every college-educated person (because an essentially infinite value of the coefficient would produce such a pattern in the data). Such issues are more likely to arise for smaller data sets and for variables that strongly predict the outcome of interest. In this case, the dichotomous variable for African Americans in the Midwest is perfectly predictive of Trump support: all 18 Midwestern African Americans in the sample did not approve of Trump. Therefore, I limit the data to white people in the Midwest model. This also happens to be the group commonly associated with possible Trump-related non-ignorable nonresponse.

I needed to omit African-American individuals from all party-based models due to perfect predictability. In this case, the perfect predictability was associated with the interaction with the instrument used in the imputation model. For example, among African-American Democrats, 95 did not approve of Trump and 5 did approve, which does not cause perfect predictability. Among African-American Democrats in the $Z = 1$ treatment group, however, all 13 did not approve of Trump.

Table A11 provides results not directly presented in the main text. Because only around 11 percent of Democrats approved of the Trump tax cuts, there was limited variation on the dependent variable and, hence, limited statistical power. This table changes the dependent variable to equal 1 for Democrats who did not disapprove of the tax cuts. Similar to what we saw with Trump approval for Democrats, we see stronger signs of non-ignorable non-response with the more variable dependent variable.

Table A2. Turnout: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.42	0.18	0.34	0.69
Y	NA	NA	1.91	0.43	NA	NA
(Intercept)	0.04	0.12	-0.8	0.24	-1.07	0.33
Female	-0.01	0.07	-0.68	0.15	0	0.19
Black	-0.08	0.11	-1.17	0.21	0.47	0.44
Hispanic	0	0.1	-0.18	0.22	0.2	0.28
SomeCollege	0.06	0.08	-0.01	0.18	0.62	0.23
College	0.07	0.09	0.39	0.2	1.1	0.28
Grad	-0.18	0.11	0.27	0.2	1.23	0.33
Age	0	0	0.02	0	0.03	0.01
Z*Female	NA	NA	NA	NA	0.61	0.42
Z*Black	NA	NA	NA	NA	-0.34	1.03
Z*Hispanic	NA	NA	NA	NA	-0.13	0.58
Z*SomeCollege	NA	NA	NA	NA	-0.04	0.53
Z*College	NA	NA	NA	NA	-0.26	0.53
Z*Grad	NA	NA	NA	NA	-0.44	0.64
Z*Age	NA	NA	NA	NA	0.01	0.01
Observations	3,573		1,501		1,501	

Table A3. Trump approval, full population: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-1.9	0.1	0.08	0.65
Y	NA	NA	0.07	0.39	NA	NA
(Intercept)	0.04	0.12	-0.93	0.21	-0.5	0.27
Female	-0.01	0.07	-0.48	0.1	-0.25	0.15
Black	-0.08	0.11	-0.71	0.23	-2.25	0.6
Hispanic	0	0.1	-0.17	0.17	-0.9	0.25
SomeCollege	0.06	0.08	0.26	0.12	-0.05	0.18
College	0.07	0.09	0.82	0.14	-0.42	0.22
Grad	-0.18	0.11	0.79	0.15	-0.58	0.24
Age	0	0	0.03	0	0.01	0
Z*Female	NA	NA	NA	NA	0.11	0.33
Z*Black	NA	NA	NA	NA	-0.32	1.24
Z*Hispanic	NA	NA	NA	NA	-0.22	0.51
Z*SomeCollege	NA	NA	NA	NA	-0.13	0.47
Z*College	NA	NA	NA	NA	-0.17	0.46
Z*Grad	NA	NA	NA	NA	-0.34	0.5
Z*Age	NA	NA	NA	NA	0	0.01
Observations	3,573		1,449		1,449	

Table A4. Trump approval, Midwest: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.07	0.29	-0.01	2.06
Y	NA	NA	-1.34	0.78	NA	NA
(Intercept)	-0.70	0.29	-0.69	0.58	-0.81	0.66
Female	0.13	0.16	-0.19	0.25	-0.17	0.37
SomeCollege	0.41	0.21	-0.04	0.31	0.31	0.43
College	0.17	0.23	0.05	0.37	-0.22	0.52
Grad	-0.14	0.25	0.54	0.39	-0.32	0.57
Age	0.01	0.00	0.05	0.01	0.02	0.01
Z*Female	NA	NA	NA	NA	0.07	0.88
Z*SomeCollege	NA	NA	NA	NA	-0.89	1.04
Z*College	NA	NA	NA	NA	-0.86	1.31
Z*Grad	NA	NA	NA	NA	-0.25	1.28
Z*Age	NA	NA	NA	NA	0.00	0.03
Observations	606		272		272	

Table A5. Trump approval, Democrats: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
temp Z	NA	NA	-1.85	0.15	1.90	6.58
Y	NA	NA	-0.46	1.29	NA	NA
(Intercept)	-0.05	0.20	-0.50	0.37	-2.44	1.35
Female	-0.06	0.11	-0.32	0.15	-0.17	0.85
Hispanic	0.10	0.13	-0.17	0.19	0.06	0.85
SomeCollege	0.08	0.14	0.30	0.21	0.19	0.74
College	0.11	0.15	0.82	0.26	-1.03	2.03
Grad	0.02	0.16	0.55	0.27	-1.33	2.50
Age	0.00	0.00	0.02	0.00	0.01	0.02
Z*Female	NA	NA	NA	NA	0.47	3.38
Z*Hispanic	NA	NA	NA	NA	-0.41	4.08
Z*SomeCollege	NA	NA	NA	NA	-1.26	4.08
Z*College	NA	NA	NA	NA	-0.46	4.96
Z*Grad	NA	NA	NA	NA	-0.41	7.50
Z*Age	NA	NA	NA	NA	-0.04	0.11
Observations	632		1,392		632	

Table A6. Trump not strong disapproval, Democrats: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.11	0.28	0.59	1.36
Y	NA	NA	-1.79	0.89	NA	NA
(Intercept)	-0.05	0.20	0.68	0.77	-0.76	0.81
Female	-0.06	0.11	-0.27	0.17	-0.27	0.54
Hispanic	0.10	0.13	-0.13	0.25	-0.47	0.66
SomeCollege	0.08	0.14	0.07	0.29	-0.20	0.50
College	0.11	0.15	0.40	0.33	-1.28	1.04
Grad	0.02	0.16	0.05	0.39	-1.87	1.66
Age	0.00	0.00	0.02	0.01	0.00	0.01
Z*Female	NA	NA	NA	NA	0.37	0.83
Z*Hispanic	NA	NA	NA	NA	0.30	1.08
Z*SomeCollege	NA	NA	NA	NA	-0.71	0.99
Z*College	NA	NA	NA	NA	-0.03	1.32
Z*Grad	NA	NA	NA	NA	-0.09	2.12
Z*Age	NA	NA	NA	NA	-0.03	0.02
Observations	1,392		632		632	

Table A7. Trump approval, Republicans: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-1.85	0.16	-0.90	2.20
Y	NA	NA	0.74	0.82	NA	NA
(Intercept)	-0.12	0.20	-1.17	0.46	0.74	0.58
Female	0.05	0.11	-0.68	0.17	0.20	0.31
Hispanic	0.05	0.20	-0.39	0.28	-0.26	0.52
SomeCollege	0.18	0.14	-0.09	0.23	-0.08	0.47
College	0.05	0.15	0.65	0.23	-0.62	0.39
Grad	-0.37	0.18	0.74	0.26	-0.77	0.39
Age	0.00	0.00	0.03	0.01	0.02	0.01
Z*Female	NA	NA	NA	NA	-0.52	1.38
Z*Hispanic	NA	NA	NA	NA	-0.77	1.79
Z*SomeCollege	NA	NA	NA	NA	0.76	2.19
Z*College	NA	NA	NA	NA	0.79	1.62
Z*Grad	NA	NA	NA	NA	0.52	1.69
Z*Age	NA	NA	NA	NA	0.02	0.04
Observations	1,334		598		598	

Table A8. Trump strong approval, Republicans: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.13	0.20	0.68	1.11
Y	NA	NA	1.75	0.45	NA	NA
(Intercept)	-0.12	0.20	-1.08	0.33	-0.48	0.41
Female	0.05	0.11	-0.78	0.20	0.08	0.21
Hispanic	0.05	0.20	-0.60	0.27	-0.40	0.40
SomeCollege	0.18	0.14	-0.02	0.24	-0.17	0.27
College	0.05	0.15	0.78	0.26	-0.12	0.28
Grad	-0.37	0.18	0.82	0.28	-0.50	0.34
Age	0.00	0.00	0.03	0.01	0.01	0.01
Z*Female	NA	NA	NA	NA	0.14	0.60
Z*Hispanic	NA	NA	NA	NA	0.86	1.43
Z*SomeCollege	NA	NA	NA	NA	0.07	0.81
Z*College	NA	NA	NA	NA	-0.37	0.76
Z*Grad	NA	NA	NA	NA	-0.06	0.86
Z*Age	NA	NA	NA	NA	0.00	0.02
Observations	1,334		598		598	

Table A9. Tax cut approval, all: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.08	0.11	0.66	0.73
Y	NA	NA	0.75	0.32	NA	NA
(Intercept)	0.04	0.12	-0.82	0.18	-1.20	0.28
Female	-0.01	0.07	-0.46	0.10	-0.47	0.16
Black	-0.08	0.11	-0.68	0.17	-1.68	0.52
Hispanic	0.00	0.10	-0.16	0.16	-0.37	0.25
SomeCollege	0.06	0.08	0.22	0.13	0.23	0.19
College	0.07	0.09	0.77	0.14	0.21	0.22
Grad	-0.18	0.11	0.66	0.15	0.22	0.23
Age	0.00	0.00	0.03	0.00	0.01	0.00
Z*Female	NA	NA	NA	NA	0.19	0.38
Z*Black	NA	NA	NA	NA	0.88	1.26
Z*Hispanic	NA	NA	NA	NA	-0.55	0.77
Z*SomeCollege	NA	NA	NA	NA	-0.35	0.49
Z*College	NA	NA	NA	NA	-0.45	0.50
Z*Grad	NA	NA	NA	NA	-0.52	0.55
Z*Age	NA	NA	NA	NA	0.00	0.01
Observations	3,573		1,490		1,490	

Table A10. Tax cut approval, Democrats: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-1.90	0.15	0.39	3.61
Y	NA	NA	-0.62	0.97	NA	NA
(Intercept)	-0.05	0.20	-0.29	0.37	-2.14	1.02
Female	-0.06	0.11	-0.37	0.15	-0.29	0.60
Hispanic	0.10	0.13	-0.19	0.19	0.49	0.60
SomeCollege	0.08	0.14	0.26	0.20	0.13	0.64
College	0.11	0.15	0.76	0.24	-0.47	1.11
Grad	0.02	0.16	0.52	0.23	-0.31	0.97
Age	0.00	0.00	0.02	0.00	0.01	0.02
Z*Female	NA	NA	NA	NA	0.32	1.96
Z*Hispanic	NA	NA	NA	NA	0.31	1.78
Z*SomeCollege	NA	NA	NA	NA	-0.33	2.40
Z*College	NA	NA	NA	NA	0.06	2.73
Z*Grad	NA	NA	NA	NA	0.00	2.93
Z*Age	NA	NA	NA	NA	-0.02	0.06
Observations	1,392		638		638	

Table A11. Tax cut not disapprove, Democrats: Doubly robust coefficient results (Note: these results are not plotted in the main text figures)

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.37	0.22	-1.70	1.11
Y	NA	NA	-2.24	0.42	NA	NA
(Intercept)	-0.05	0.20	1.47	0.50	1.00	0.50
Female	-0.06	0.11	-0.16	0.20	0.42	0.30
Hispanic	0.10	0.13	0.11	0.26	0.16	0.34
SomeCollege	0.08	0.14	0.00	0.27	-0.65	0.33
College	0.11	0.15	0.42	0.28	-1.44	0.48
Grad	0.02	0.16	0.07	0.29	-1.22	0.44
Age	0.00	0.00	0.02	0.01	-0.02	0.01
Z*Female	NA	NA	NA	NA	0.08	0.54
Z*Hispanic	NA	NA	NA	NA	0.75	0.66
Z*SomeCollege	NA	NA	NA	NA	0.03	0.72
Z*College	NA	NA	NA	NA	0.81	0.78
Z*Grad	NA	NA	NA	NA	0.27	0.81
Z*Age	NA	NA	NA	NA	0.00	0.02
Observations	1,392		638		638	

Table A12. Tax cut approval, Republicans: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.23	0.21	0.12	1.08
Y	NA	NA	1.74	0.49	NA	NA
(Intercept)	-0.12	0.20	-0.69	0.32	-0.67	0.39
Female	0.05	0.11	-0.54	0.20	-0.49	0.21
Hispanic	0.05	0.20	-0.21	0.34	-0.18	0.40
SomeCollege	0.18	0.14	-0.14	0.25	0.62	0.27
College	0.05	0.15	0.29	0.27	0.65	0.28
Grad	-0.37	0.18	-0.04	0.30	0.78	0.32
Age	0.00	0.00	0.02	0.01	0.02	0.01
Z*Female	NA	NA	NA	NA	0.00	0.56
Z*Hispanic	NA	NA	NA	NA	-1.03	0.98
Z*SomeCollege	NA	NA	NA	NA	-0.43	0.65
Z*College	NA	NA	NA	NA	0.11	0.72
Z*Grad	NA	NA	NA	NA	1.47	1.21
Z*Age	NA	NA	NA	NA	0.01	0.02
Observations	1,334		632		632	

Table A13. Racial conservativism, all: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.01	0.10	0.19	0.65
Y	NA	NA	-0.31	0.38	NA	NA
(Intercept)	0.04	0.12	-0.69	0.22	-0.93	0.26
Female	-0.01	0.07	-0.49	0.10	-0.28	0.15
Black	-0.08	0.11	-0.82	0.25	-2.34	0.51
Hispanic	0.00	0.10	-0.31	0.18	-0.91	0.24
SomeCollege	0.06	0.08	0.24	0.12	-0.03	0.18
College	0.07	0.09	0.75	0.14	-0.20	0.21
Grad	-0.18	0.11	0.70	0.15	-0.53	0.23
Age	0.00	0.00	0.03	0.00	0.03	0.00
Z*Female	NA	NA	NA	NA	0.20	0.33
Z*Black	NA	NA	NA	NA	-0.32	1.20
Z*Hispanic	NA	NA	NA	NA	-0.17	0.51
Z*SomeCollege	NA	NA	NA	NA	-0.20	0.47
Z*College	NA	NA	NA	NA	-0.35	0.47
Z*Grad	NA	NA	NA	NA	-0.30	0.50
Z*Age	NA	NA	NA	NA	0.00	0.01
Observations	3,573		1,493		1,493	

Table A14. Racial conservativism, Democrats: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.26	0.30	-1.36	1.18
Y	NA	NA	-2.09	0.75	NA	NA
(Intercept)	-0.05	0.20	-0.05	0.41	-1.70	0.72
Female	-0.06	0.11	-0.49	0.19	-0.09	0.44
Hispanic	0.10	0.13	-0.26	0.24	-0.54	0.60
SomeCollege	0.08	0.14	-0.07	0.26	-0.63	0.48
College	0.11	0.15	0.49	0.28	-0.79	0.58
Grad	0.02	0.16	0.28	0.34	-1.78	1.05
Age	0.00	0.00	0.04	0.01	0.02	0.01
Z*Female	NA	NA	NA	NA	-0.06	0.66
Z*Hispanic	NA	NA	NA	NA	0.77	0.91
Z*SomeCollege	NA	NA	NA	NA	-0.03	0.81
Z*College	NA	NA	NA	NA	-0.06	0.86
Z*Grad	NA	NA	NA	NA	0.65	1.28
Z*Age	NA	NA	NA	NA	0.01	0.02
Observations	1,392		638		638	

Table A15. Racial conservativism, Republicans: Doubly robust coefficient results

	Z: Pr(Z|X)		Response: Pr(R|Z, Y, X)		Y: Pr(Y|Z, X, R=1)	
Variable	Coefficient	s.e.	Coefficient	s.e.	Coefficient	s.e.
Z	NA	NA	-2.08	0.18	0.35	0.99
Y	NA	NA	0.86	0.60	NA	NA
(Intercept)	-0.12	0.20	-0.97	0.31	-0.51	0.49
Female	0.05	0.11	-0.70	0.17	-0.20	0.27
Hispanic	0.05	0.20	-0.27	0.34	-0.76	0.41
SomeCollege	0.18	0.14	-0.03	0.20	0.59	0.40
College	0.05	0.15	0.54	0.22	0.39	0.35
Grad	-0.37	0.18	0.73	0.26	0.18	0.35
Age	0.00	0.00	0.03	0.01	0.03	0.01
Z*Female	NA	NA	NA	NA	0.42	0.55
Z*Hispanic	NA	NA	NA	NA	-0.65	1.04
Z*SomeCollege	NA	NA	NA	NA	-0.35	0.74
Z*College	NA	NA	NA	NA	0.03	0.73
Z*Grad	NA	NA	NA	NA	-0.29	0.80
Z*Age	NA	NA	NA	NA	0.00	0.02
Observations	1,334		614		614	

Appendix 7. Descriptive statistics

Table A16. Descriptive statistics: Averages and sample sizes

	All	Democrats	Republicans
Average Treatment	0.49	0.5	0.5
Average Response	0.42	0.44	0.46
Average Response|T=1	0.22	0.24	0.25
Average Response|T=0	0.61	0.64	0.67
Average Female	0.52	0.56	0.48
Average Black	0.11	0.17	0.02
Average Hispanic	0.15	0.20	0.08
Average Some college	0.28	0.28	0.29
Average College	0.20	0.20	0.22
Average Grad	0.15	0.17	0.13
Average Turnout	0.78	0.79	0.78
N Turnout	1,501	745	631
Average Trump approval	0.4	0.07	0.8
N Trump approval	1,449	732	607
Average Tax cut approval	0.36	0.11	0.66
N Tax cut approval	1,490	740	625
Average Race and flag (conservative)	0.45	0.19	0.78
N Race and flag (conservative)	1,493	742	627