Supplemental Material
The Fall of Trump: Mobilization and Vote Switching in the 2020 Presidential Election

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A Variable Coding

A.1 Control variables:

- **Political awareness**: varies from 1 if the respondent reported that they hardly at all follow any news about politics to 4 if they follow political news most of the time.
- **Party ID**: is a categorical variable coded 1 for no party affiliate, 2 for Democrat, and 3 for Republican voters. No party affiliate are the baseline category.
- **Ideology**: varies from 1 if the respondent reported to be very liberal to 5 very conservative. Respondents who provided a "not sure" answer are recoded as moderates, coded as the middle category in this scale.
- **Age**: is a continuous variable varying from 18 to 95 years old.
- **Female**: is a dummy, coded 0 for male and 1 for female respondents.
- **Race**: is a categorical variable coded 0 for white, 1 for Black, 2 for Hispanic, 3 for voters of other races. White is the baseline category in all estimations.
- **Education**: is a dummy variable coded 0 for high school of less education, and 1 for some college or more education.
- **Income**: is a continuous variable varying from less than $10,000 to $500,000 or more
- **First time voter**: is a dummy variable coded 1 for those respondents who were not of voting age in 2016 and 0 otherwise. (We control for this variable only in models shown in Table 4)

A.2 Healthcare policy scale questions:

To create the healthcare scale variable, first we recode the following questions where a value of 1 means the respondent has a liberal stance of the issue and 0 a conservative position.

- Thinking now about health care policy, would you support or oppose each of the following proposals?
  1. Medicare to a single comprehensive public health care coverage program that would cover all Americans. (1 = support; 0 = oppose)
  2. Allow the government to negotiate with drug companies to get a lower price on prescription drugs that would apply to both Medicare and private insurance. Maximum negotiated price could not exceed 120% of the average prices in 6 other countries. (1 = support; 0 = oppose)
  3. Lower the eligibility age for Medicare from 65 to 50. (1 = support; 0 = oppose)
  4. Repeal the entire Affordable Care Act. (1 = oppose; 0 = support)

Then we aggregated them into a scale with five categories (0 if the respondent scored 0 in all four questions, to 4 if the respondent scored a 1 in all four questions), which we have rescaled to vary from 0 to 1.

Table 1: Healthcare Scale Distribution

Categories	0	0.25	0.5	0.75	1
Num. obs.	1,862	11,190	9,290	16,596	21,726

A.3 Immigration policy scale questions:

To create the immigration scale variable, first we recode the following questions where a value of 1 means the respondent has a liberal stance of the issue and 0 a conservative position.

- What do you think the U.S. government should do about immigration? Do you support or oppose each of the following?
  1. Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes. (1 = supports; 0 = oppose)
  2. Increase the number of border patrols on the US-Mexican border. (1 = oppose; 0 = support)
  3. Withhold federal funds from any local police department that does not report to the federal government anyone they identify as an illegal immigrant. (1 = oppose; 0 = support)
  4. Reduce *legal* immigration by 50 percent over the next 10 years by eliminating the visa lottery and ending family-based migration. (1 = oppose; 0 = support)
  5. Increase spending on border security by $25 billion, including building a wall between the U.S. and Mexico. (1 = oppose; 0 = support)

Then we aggregated them into a scale with six categories (0 if the respondent scored 0 in all five questions, to 5 if the respondent scored a 1 in all five questions), which we have rescaled to vary from 0 to 1.

Table 2: Immigration Scale Distribution

Categories	0	0.2	0.4	0.6	0.8	1
Num. obs.	8,568	9,383	6,550	7,092	10,978	18,243

B Descriptive Statistics

Table 3: Summary Statistics

		min.	mean	max.	st.dev
Outcome variables					
	Non voter 2016 → Biden voter 2020	0	0.62	1	0.49
	Third party voter 2016 → Trump voter 2020	0	0.50	1	0.50
	Third party voter 2016 → Biden voter 2020	0	0.69	1	0.46
	Trump voter 2016 → Biden voter 2020	0	0.04	1	0.20
	Clinton voter 2016 → Trump voter 2020	0	0.02	1	0.15
Policy issues					
	Experience with COVID-19	0	0.54	1	0.50
	Police	0	0.23	1	0.42
	RBG's replacement	0	0.59	1	0.49
	Pocketbook economy	0	0.54	1	0.23
	Sociotropic economy	0	0.72	1	0.33
	Healthcare policy	0	0.69	1	0.30
	Immigration policy	0	0.59	1	0.37
Controls					
	Political awareness	1	3.29	4	0.93
	Party ID	1	1.97	3	0.77
	Ideology	1	2.95	5	1.16
	Age	18	48.39	95	17.66
	Female	0	0.58	1	0.49
	Race	1	1.52	4	0.94
	Education	0	0.70	1	0.46
	Income	1	6.39	16	3.52
	First time voter	0	0.05	1	0.22

C Full Models

Table 4: Logistic Regression Models for *New Voters* Voting for Biden in the 2020 Presidential Election

		DV: Non Voter 2016 → Biden Voter 2020			
		(1)	(2)	(3)	(4)
Short term	Experience with COVID-19	0.571***	0.546*	0.180	0.269
		(0.148)	(0.219)	(0.179)	(0.257)
	Police [not safe]	1.801***	1.091**	0.999***	0.631
		(0.233)	(0.333)	(0.266)	(0.379)
	RBG Replacement [after election]	4.584***	4.038***	2.975***	2.898***
		(0.150)	(0.247)	(0.181)	(0.268)
Medium term	Pocketbook Economy [worse]			0.137	0.902
				(0.437)	(0.595)
	Sociotropic Economy [worse]			2.096***	1.446**
				(0.344)	(0.493)
Long term	Healthcare [gov't involvement]			3.056***	1.997***
				(0.378)	(0.523)
	Immigration [supportive]			3.470***	3.587***
				(0.307)	(0.470)
	Political awareness		0.164		0.156
			(0.126)		(0.135)
	Democrat		2.561***		2.267***
			(0.348)		(0.328)
	Republican		−1.895***		−1.422***
			(0.269)		(0.303)
	Ideology		−0.852***		−0.563**
			(0.167)		(0.177)
	Age		0.013		0.027**
			(0.008)		(0.010)
	First time voter		−0.134		−0.096
			(0.472)		(0.474)
	Female		0.365		−0.161
			(0.239)		(0.272)
	Black		1.662***		2.169***
			(0.455)		(0.519)
	Hispanic		0.222		−0.027
			(0.390)		(0.429)
	Other race		0.112		0.310
			(0.418)		(0.522)
	College degree		0.417		0.362
			(0.243)		(0.262)
	Income		0.028		0.045
			(0.034)		(0.038)
	(Intercept)	−2.503***	−1.566	−6.886***	−6.854***
		(0.133)	(0.838)	(0.404)	(0.981)
	N	2,594	2,165	2,475	2,077

Notes: The dependent variable in models (1)-(4) is coded as one if a voter voted for Biden in 2020 Presidential election and zero for Trump. All models include an intercept. Logistic regression models (1)-(4) are estimated using maximum likelihood. The reported robust standard errors in parentheses are clustered by state. *** $p < .001$, ** $p < .01$, * $p < .05$

Table 5: Logistic Regression Models for Switchers to Major Party in 2020 Presidential election.

		DV: Third Party Voter 2016 → Trump Voter 2020				DV: Third Party Voter 2016→Biden Voter 2020			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short term	Experience with COVID-19	−0.370*	−0.102	−0.118	0.073	0.276	0.398	0.212	0.346
		(0.186)	(0.252)	(0.210)	(0.271)	(0.163)	(0.207)	(0.172)	(0.221)
	Police [not safe]	−2.139***	−1.427***	−1.516***	−1.028*	−0.831***	−0.525*	−1.197***	−0.727**
		(0.292)	(0.411)	(0.328)	(0.470)	(0.164)	(0.219)	(0.178)	(0.236)
	RBG Replacement [after election]	−2.504***	−2.585***	−1.476***	−1.684***	3.201***	2.991***	2.395***	2.405***
		(0.284)	(0.362)	(0.346)	(0.386)	(0.202)	(0.258)	(0.237)	(0.288)
Medium term	Pocketbook Economy [worse]			−0.822	−1.314			−0.628	−0.358
				(0.496)	(0.716)			(0.351)	(0.444)
	Sociotropic Economy [worse]			−1.018**	−0.778			1.092*	1.721**
				(0.352)	(0.453)			(0.475)	(0.627)
Long term	Healthcare [gov't involvement]			0.010	−0.580			2.460***	2.639***
				(0.373)	(0.520)			(0.327)	(0.477)
	Immigration [supportive]			−2.627***	−2.113***			0.058	0.328
				(0.345)	(0.491)			(0.335)	(0.449)
	Political awareness		0.037		−0.066		−0.017		−0.143
			(0.176)		(0.188)		(0.157)		(0.167)
	Democrat		0.188		0.389		1.588***		1.530***
			(0.567)		(0.722)		(0.285)		(0.285)
	Republican		0.565		0.575		−0.344		−0.064
			(0.318)		(0.327)		(0.385)		(0.421)
	Ideology		0.571***		0.276		0.144		0.386**
			(0.162)		(0.185)		(0.124)		(0.145)
	Age		0.021*		0.016		0.005		0.007
			(0.010)		(0.011)		(0.007)		(0.007)
	Female		0.966***		1.004**		0.364		0.319
			(0.288)		(0.333)		(0.205)		(0.216)
	Black		0.742		−0.128		1.010		0.973
			(0.780)		(0.813)		(0.563)		(0.630)
	Hispanic		0.912		1.024		−0.226		−0.031
			(0.608)		(0.647)		(0.345)		(0.352)
	Other race		0.625		0.491		−0.684*		−0.671
			(0.392)		(0.416)		(0.333)		(0.358)
	College degree		−0.300		−0.386		−0.321		−0.241
			(0.401)		(0.388)		(0.362)		(0.383)
	Income		−0.027		−0.053		0.039		0.050
			(0.036)		(0.039)		(0.030)		(0.031)
	(Intercept)	1.183***	−2.002	3.001***	1.928	−1.397***	−2.127**	−3.109***	−5.612***
		(0.156)	(1.117)	(0.346)	(1.343)	(0.207)	(0.806)	(0.448)	(1.026)
	N	7, 36	515	709	496	1, 211	925	1, 192	910

Notes: The dependent variable in models (1)-(8) is coded as one if voted for a third party candidate in 2016 but switched to Biden (Trump) in 2020 Presidential election, and zero for third party standpatters. All models include an intercept. Logistic regression models (1)-(8) are estimated using maximum likelihood. The reported robust standard errors in parentheses are clustered by state. *** $p < .001$, ** $p < .01$, * $p < .05$

Table 6: Logistic Regression Models for *Switchers* Voting for Biden (Trump) in the 2020 Presidential Election

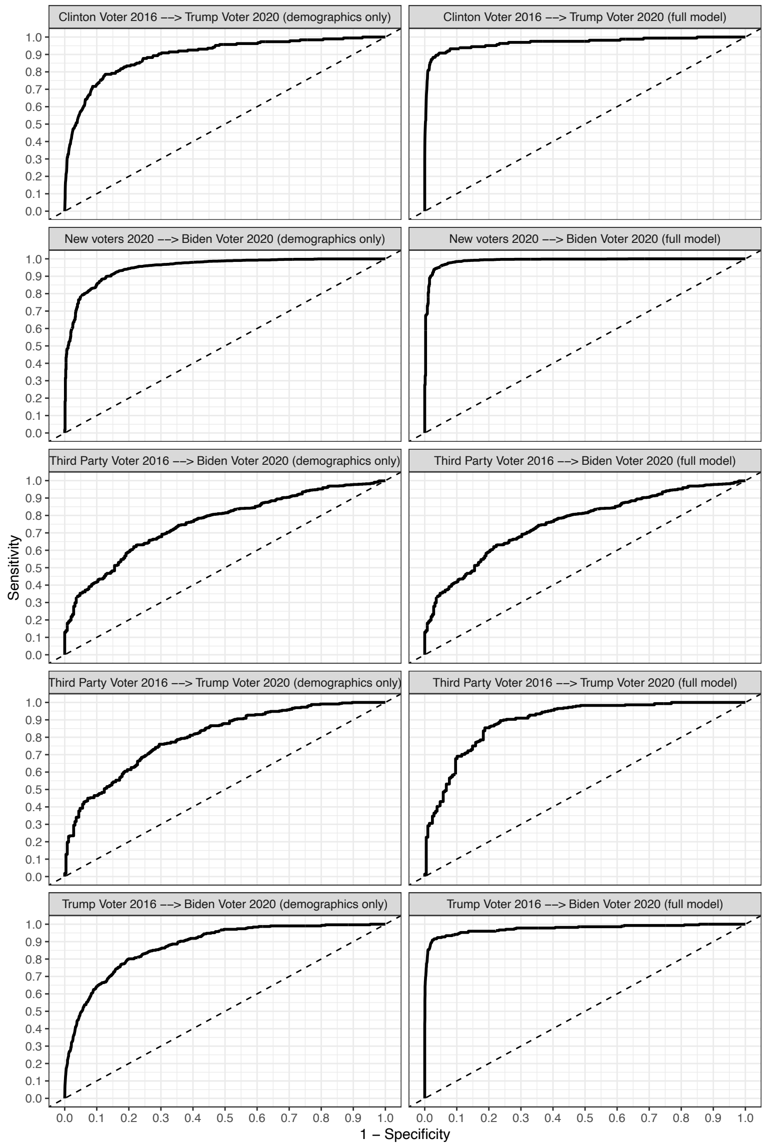
		DV: Trump Voter 2016 → Biden Voter 2020				DV: Clinton Voter 2016 → Trump Voter 2020			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short term	Experience with COVID-19	0.295	0.178	0.027	−0.013	−0.691***	−0.898***	−0.504*	−0.763***
		(0.167)	(0.207)	(0.193)	(0.232)	(0.177)	(0.214)	(0.212)	(0.232)
	Police [not safe]	0.820*	0.700	0.223	0.262	−1.784***	−1.051**	−1.487***	−0.742
		(0.344)	(0.377)	(0.415)	(0.428)	(0.359)	(0.371)	(0.409)	(0.438)
	RBG Replacement [after election]	5.459***	5.469***	3.651***	3.938***	−4.702***	−4.115***	−3.308***	−3.114***
		(0.186)	(0.274)	(0.210)	(0.273)	(0.188)	(0.245)	(0.235)	(0.274)
Medium term	Pocketbook Economy [worse]			−0.263	−0.093			0.872	0.542
				(0.505)	(0.567)			(0.512)	(0.612)
	Sociotropic Economy [worse]			2.926***	2.422***			−1.660***	−1.964***
				(0.446)	(0.540)			(0.398)	(0.505)
Long term	Healthcare [gov't involvement]			3.138***	3.495***			−2.381***	−1.830***
				(0.409)	(0.464)			(0.455)	(0.518)
	Immigration [supportive]			2.712***	2.724***			−3.041***	−2.925***
				(0.338)	(0.445)			(0.353)	(0.412)
	Political awareness		0.165		0.216		−0.345*		−0.473**
			(0.157)		(0.170)		(0.142)		(0.142)
	Democrat		0.715*		0.219		−1.402***		−1.642***
			(0.301)		(0.313)		(0.270)		(0.296)
	Republican		−0.936***		−0.886***		0.894**		0.275
			(0.228)		(0.257)		(0.316)		(0.368)
	Ideology		−0.877***		−0.541***		0.778***		0.376*
			(0.117)		(0.144)		(0.141)		(0.158)
	Age		0.028***		0.039***		−0.008		−0.007
			(0.008)		(0.009)		(0.008)		(0.009)
	Female		0.149		0.074		−0.174		0.029
			(0.204)		(0.244)		(0.234)		(0.258)
	Black		−0.501		−0.720		−0.909*		−1.187**
			(0.838)		(0.838)		(0.410)		(0.432)
	Hispanic		−0.449		−0.024		0.104		0.203
			(0.492)		(0.504)		(0.342)		(0.393)
	Other race		0.516		0.690		0.211		−0.360
			(0.436)		(0.433)		(0.427)		(0.478)
	College degree		0.979***		1.180***		0.310		0.501
			(0.226)		(0.273)		(0.318)		(0.344)
	Income		0.023		0.031		−0.038		−0.030
			(0.031)		(0.036)		(0.032)		(0.037)
	(Intercept)	−5.272***	−4.757***	−8.811***	−10.432***	0.083	−0.001	3.582***	5.125***
		(0.172)	(0.854)	(0.458)	(1.185)	(0.141)	(0.800)	(0.399)	(0.973)
	N	7,901	6,636	7,610	6,414	8,876	7,923	8,673	7,762

Notes: The dependent variable in models (1)-(8) is coded as one if a voter voted for Trump (Clinton) in 2016 but switched to Biden (Trump) in 2020 Presidential election, and zero for major party standpatters. All models include an intercept. Logistic regression models (1)-(8) are estimated using maximum likelihood. The reported robust standard errors in parentheses are clustered by state. *** $p < .001$, ** $p < .01$, * $p < .05$

D Model Performance

In Figure 1 we show the performance of each of our full policy logistic regressions. We plot the ROC curves and report the AUC scores. (Robin et al. 2011) This performance measure technique helps to not choose an arbitrary decision threshold when classifying predicted probabilities. The AUC score represents the area under the curve and measures the performance of our logistic regression classifier. As shown in the figure our classifier performs very well in predicting our binary response variables.

Figure 1: Model Fit Assessment



Notes: The figure shows the ROC curves for models controlling for demographics only and full policy and demographics models estimated in Table 4 column (4), Table 5 columns (4, 8), and Table 6 columns (4,8). The ROC curve captures the relationship of sensitivity (true positive rate) as a function of the (1-specificity) false positive rate. The AUC score, which represents the area under the curve, for each fitted model starting from the top left hand corner are: $AUC = 0.89$ vs. $AUC = 0.97$, $AUC = 0.95$, $AUC = 0.99$, $AUC = 0.7$, $AUC = 0.7$, $AUC = 0.8$, $AUC = 0.89$, $AUC = 0.86$, and $AUC = 0.97$ respectively. All AUC scores are very high which shows that the predictive performance of all our models is high.