

Chapter 4

0.1 Data and Methods

The dataset consisted of 502 observations, each an individual respondent to an online survey conducted through Amazon’s Mechanical Turk crowd labor service. The full text of the survey can be found in the appendix. Participants were asked a series of demographic and general political knowledge and opinion questions. Then, each was asked to read a set of two sample referendum ballot measures, and to answer follow-up questions with their personal preferences as if they were being asked to vote on the proposal in question. The survey software was programmed to display one of two versions of each sample to each participant. One version of each was the official language which actually appeared on the ballot in Oklahoma for the 2016 general election; the other I created for the purpose of this experiment.

I chose three of the five follow-up questions as dependent variables for this analysis; specifically, those which referred to *overall support* for the proposition, *salience* (whether the respondent would be willing to engage in activism either for or against the proposal), and *elected official support* (whether they would vote to re-elect someone who was in favor of the proposition).

0.1.1 Treatment language

For SQ 779, where the control group read

The article creates a limited purpose fund to increase funding for public education. It increases State sales and use taxes by one cent per dollar to provide revenue for the fund.

the treatment language replaced the foregoing with

The article creates a limited purpose fund to increase funding for public education. To provide revenue for the fund, it mandates a 22% increase in State sales and use taxes.

Similarly, for SQ 790, the control language was

This section has been interpreted by the courts as requiring the removal of a Ten Commandments monument from the grounds of the State Capitol. If this measure repealing this section is passed, the government would still be required to comply with the Establishment Clause of the United States Constitution, which is a similar constitutional provision that prevents the government from endorsing a religion or becoming overly involved with religion.

and the treatment language changed the above to

The purpose of the measure is to allow the use of school tuition vouchers provided as a benefit to low income families, and to permit those families to use those vouchers to send their children to the school of their choice, even if that school is affiliated with a religious institution or is religious in nature. The state government would still be bound by the Establishment Clause of the United States Constitution, which provides that states may not endorse an official religion, or give preference to one religion over another.

The treatments were randomized among the participants and across both questions, so that a roughly equivalent number of respondents viewed each version. Both versions of each proposal were timed to display for 90 seconds, and the respondents were not allowed to move past the ballot language until the timer had expired. In addition, I inserted a reading check question after each version so as to ensure that the respondent had actually read the treatment or control, before proceeding. The software was programmed to end the survey for a given respondent if they incorrectly answered the check question. Because of the way MTurk operates, individuals who failed a reading check were automatically excluded from the sample for not having completed the task (or “hit” in MTurk lingo) for which they signed up. Respondents who otherwise failed to complete the survey, or who gave incomplete responses, were removed from the dataset by listwise deletion. The latter category only resulted in 8 deletions out of an original sample of 510, leaving an N of 502 for analysis.

0.1.2 Demographics and Summary Statistics

It is well known that MTurk workers differ as a group from the general population, especially in relation to certain demographic variables (Krupnikov and Levine 2014). Generally speaking, any given sample of MTurk respondents will indicate as slightly left of center ideologically, with a concomitant lean toward Democratic party identification. They are predominantly white and middle class in relation to income. They tend to register somewhat higher than the median for education, and most are unmarried.

Nevertheless, this fact alone does not render the service useless as a source for convenience samples. When used for experimental rather than observational purposes, the effect on generalizability can be mitigated, if a small number of covariates are included when fitting models. The most important controls are party identification and ideology (Levay, Freese, and Druckman 2016; Mullinix et. al 2015).

Table 1: MTurk Sample Demographics

	mean	sd	median	min	max	range	se
Sex	1.49	0.50	1.00	1.00	2.00	1.00	0.02
Education	4.21	1.22	5.00	2.00	7.00	5.00	0.05
Race	1.49	1.23	1.00	1.00	7.00	6.00	0.05
Income	5.92	2.94	6.00	1.00	12.00	11.00	0.13
Marital	3.03	1.88	3.00	1.00	5.00	4.00	0.08
Ideology	2.55	1.23	2.00	1.00	5.00	4.00	0.05
Party	3.35	1.84	3.00	1.00	7.00	6.00	0.08
$N=502$							

Table 1 contains demographic sample statistics for all respondents. Figures 1 and 2 show the distribution of ideology and party ID through the entire sample. Ideology was measured on a 5-point Likert scale (1=Very Liberal, 5=Very Conservative), and party on a 7-point (1=Strong Democrat, 7=Strong Republican). Interestingly, this particular group of MTurk workers had a high number of self-identified independents, though the overall direction was toward the Democrats. Ideology roughly paralleled the norm for MTurk (Levay, Freese, and Druckman 2016). Considering that these two political demographics represent the primary controls needed when modeling from MTurk samples, the dataset obtained through the

survey is particularly well suited for this project.

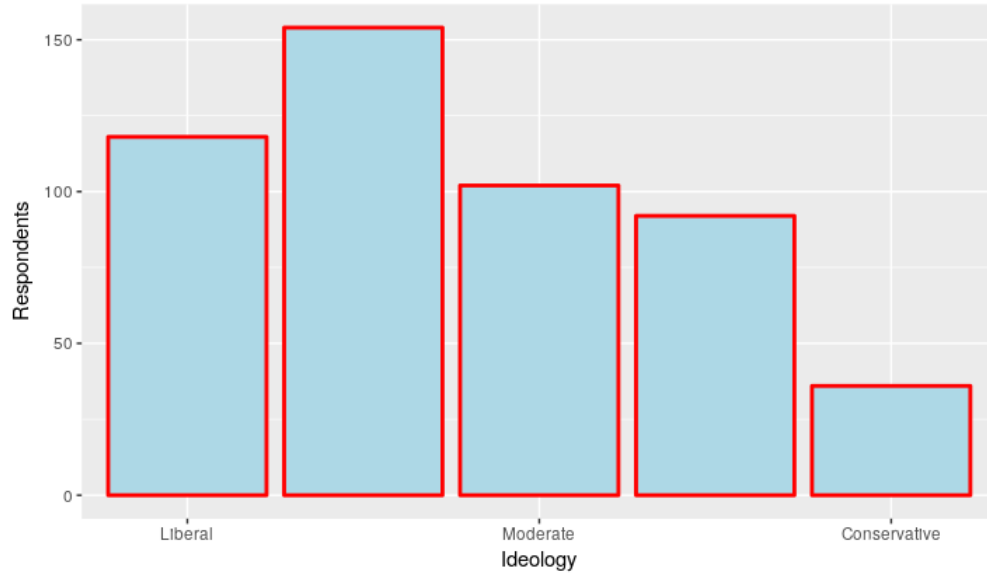


Figure 1: MTurk Sample – Ideological breakdown ($N = 502$)

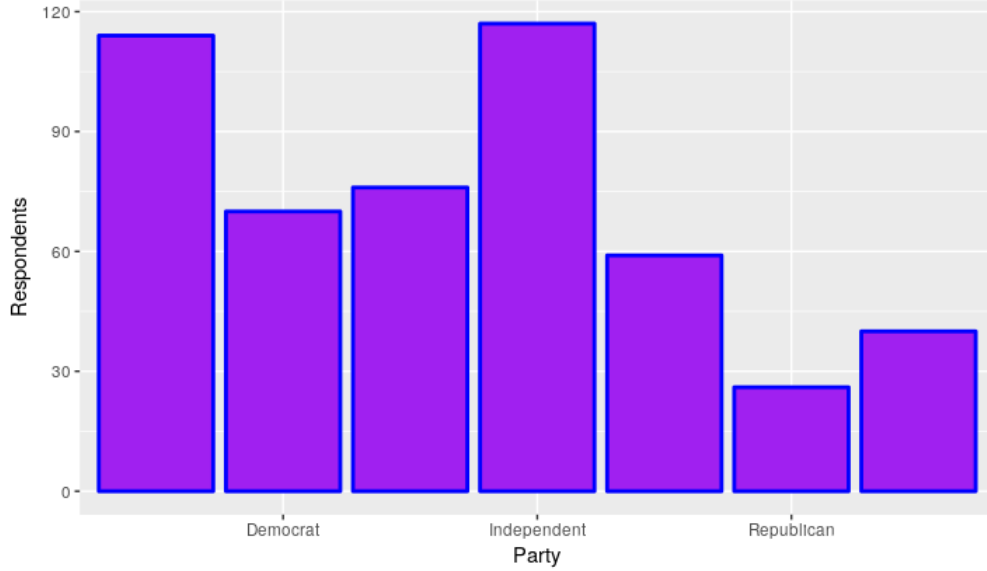


Figure 2: MTurk Sample – Party Identification ($N = 502$)

0.1.3 Model Specification

I first estimated the effects of the treatments themselves against each of the dependent variables using a Pearson’s Chi-squared test with Yates’ continuity correction. I then placed each treatment variable into a series of binomial logit models with interaction terms, containing the explanatory variables for voting habits. I also tested the inclusion of dummy variables for certain demographics, as a check for mediation. This method of statistical analysis is appropriate given that the dependent variables are dichotomous.

For the analyses below, I used the following standard logit model:

$$Pr(y_i = 1) = \text{logit}^{-1}(\beta_0 + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + x_1x_2\beta_{x_1x_2} + x_1x_3\beta_{x_1x_3}) \quad (1)$$

In each case, the probability of $y=1$ is expressed as an inverse logit function of the linear predictors. The treatment variable, x_1 , is binary and has the value $x_1 = 1$ if the individual received the treatment language as opposed to the control. Variables x_2 and x_3 are ordered categorical (treated as continuous) and refer to the number of times the individual voted in state/national and local elections, respectively. Figures 3 and 4 show the counts for each of these independent variables. Finally, the interaction terms combine the treatment variable with one or the other of the voting variables, in order to assess the effect of increased habitual voting on the framing effect of the alternative treatment.

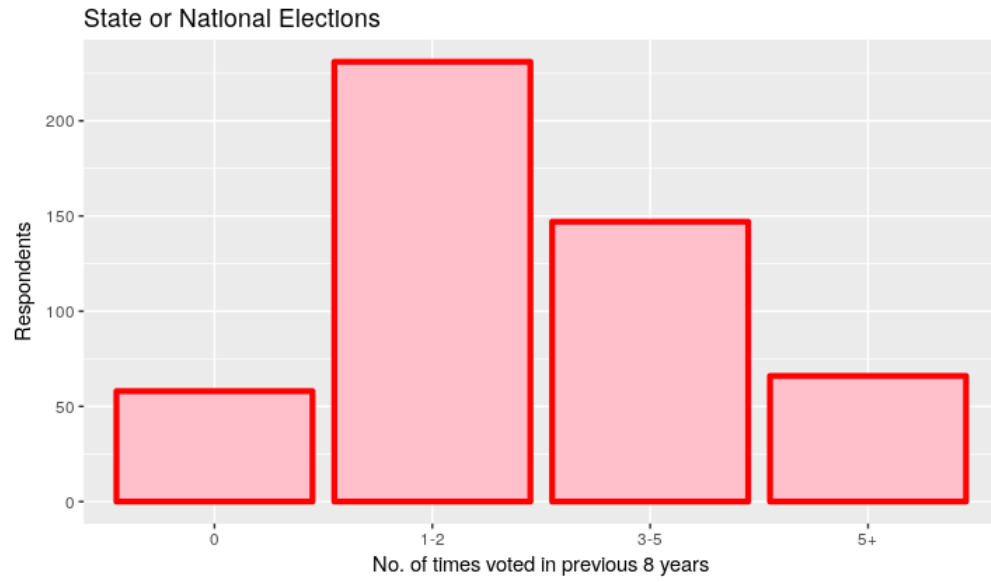


Figure 3: MTurk Sample – National Voting Habits ($N = 502$)

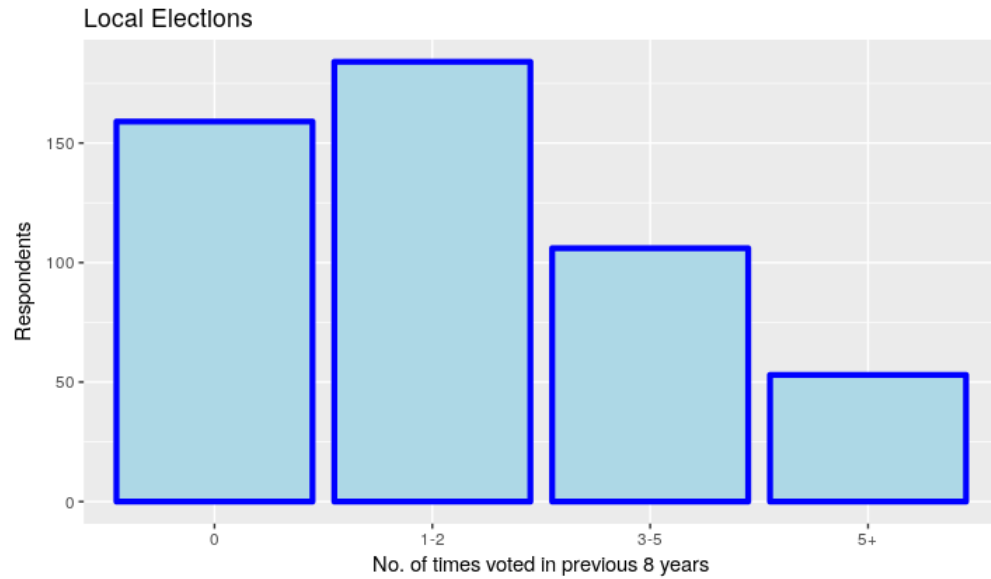


Figure 4: MTurk Sample – Local Voting Habits ($N = 502$)

0.2 Results

Based on the prior studies discussed above, the expectation would be that if framing effects are present, they should be mitigated by the level of experience of the individual voter. Stated differently, the interaction terms contained in the models should indicate significant coefficients in the *opposite* direction from that of the treatment effect. If it is indeed the case that individuals develop experiential cognitive benefits from repeated voting behavior, the evidence of this reduction of the framing effect should consistently appear across all models.

Below I discuss specific findings from each of the two state question treatments. In each case, I begin with the percentage change in support based purely on exposure to the treatment language, and then provide the regression models both with and without demographics. In addition, I include separation plots for certain models. These visualizations of goodness of fit are designed to show the predictive power of any given model with binary outcomes (Greenhill et al. 2011).

In a separation plot, the fitted values from each of the logit models are re-ordered from lowest to highest probability, and then compared against the actual outcomes from the dataset. The comparison is then displayed as a sequence of light and dark lines from left (lowest) to right (highest), with the dark color representing the occurrence of the event in question, and the light color representing a non-event. Thus, a model with good predictive power will have more dark colored lines farther to the right of the plot (where the probabilities are highest), and fewer dark lines toward

the left side.

0.2.1 Treatment Set 1

The results from the Education Sales Tax question are shown in Table 2. The *taxation* frame appears to have had a marked negative effect on support for the measure. The total number of YES votes dropped by approximately 27 percentage points from the control group to the treatment group. In other words, the alternative ballot language seems to have contributed to roughly a 45% drop in support for the sales tax proposal. The difference is highly significant; more importantly, it maintains its character as the explanatory variables and interactions are added to the mix.

Table 2: Results – Education Sales Tax

	% YES Vote	% Activism	% Re-Elect
Control	60	15	52
<i>Taxation</i>	33	16	33
Difference	-27%***	1%	-19%***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ using a two-tailed test

When the outcome is placed into the logit models containing data on respondents' voting habits, it quickly becomes apparent that no mitigation effects are present (Table 3). Neither of the interaction terms shows any significance for any of the three dependent variables. This is not to say that some other latent interaction is not taking place; however, it seems more likely that the framing effects are strong enough to overwhelm any experiential advantage from habitual voting.

Table 3: Logistic Regression – Education Sales Tax

	YES Vote	Activism	Re-Elect
(Intercept)	0.92*	−2.04***	0.53
	(0.39)	(0.54)	(0.38)
<i>Taxation</i> frame	−1.17*	−0.49	−0.83
	(0.56)	(0.77)	(0.56)
Voted State/National	−0.04	−0.21	−0.11
	(0.23)	(0.32)	(0.22)
Voted Local	−0.20	0.36	−0.08
	(0.19)	(0.27)	(0.19)
<i>Taxation</i> x Voted S/N	−0.32	0.01	−0.19
	(0.34)	(0.46)	(0.33)
<i>Taxation</i> x Voted Local	0.39	0.26	0.23
	(0.30)	(0.41)	(0.30)
AIC	662.54	432.56	673.86
BIC	687.85	457.87	699.17
Log Likelihood	−325.27	−210.28	−330.93
Deviance	650.54	420.56	661.86
Num. obs.	502	502	502

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Regression coefficients with standard errors in parentheses.

The separation plot displayed in Figure 5 shows a relatively good fit for the Support and Re-Elect models. The darker shaded events increase to the right as the probability predictions of the model increase. The Activism model shows widely scattered results and it is readily apparent that no effects are discernible. As shown in Table 4, the inclusion of demographics does not appreciably alter the foregoing analysis. As one might expect, the ideology and party identification variables indicate that the more conservative and stronger Republican individuals tended to show lower support for both the tax increase itself, and for any public official who might be inclined to favor it. Yet the framing effect of the treatment remains, and

though significant, the contribution of the political variables to the overall result is rather small. None of the other demographics showed any statistical significance, which is consistent with ideology and party being the most important controls for an MTurk sample.

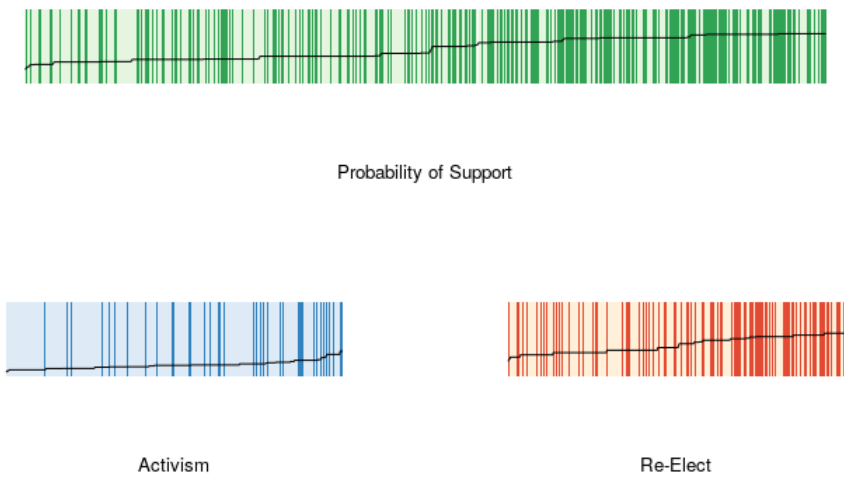


Figure 5: Separation Plot for *taxation* frame models

Table 4: Logistic Regression with Covariates– Education Sales Tax

	YES Vote	Activism	Re-Elect
(Intercept)	1.69** (0.57)	−2.38** (0.74)	0.79 (0.55)
<i>Taxation</i> frame	−1.17* (0.59)	−0.54 (0.78)	−0.75 (0.58)
Voted State/National	0.04 (0.24)	−0.24 (0.32)	−0.05 (0.23)
Voted Local	−0.26 (0.21)	0.34 (0.28)	−0.13 (0.20)
Conservative	−0.30* (0.14)	0.20 (0.18)	−0.38** (0.14)
Republican	−0.19* (0.09)	−0.15 (0.12)	−0.03 (0.09)
Education	0.10 (0.09)	−0.01 (0.11)	0.17* (0.08)
Income	0.03 (0.04)	0.08 (0.04)	0.01 (0.03)
<i>Taxation</i> frame x Voted S/N	−0.44 (0.36)	0.03 (0.46)	−0.26 (0.35)
<i>Taxation</i> frame x Voted Local	0.45 (0.32)	0.24 (0.41)	0.24 (0.31)
AIC	621.22	435.59	647.30
BIC	663.40	477.77	689.49
Log Likelihood	−300.61	−207.79	−313.65
Deviance	601.22	415.59	627.30
Num. obs.	502	502	502

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Regression coefficients with standard errors in parentheses.

0.2.2 Treatment Set 2

A somewhat murkier picture is painted by the results of the Religious Entanglement proposition. As can be seen from Table 5, the only significant framing effect is related to the Activism variable. It is interesting that the

religious charity frame produced a slight, but nevertheless visible, reduction in salience. There was no discernible difference in the level of support for the measure between the control and treatment groups.

Table 5: Results – Use of State Property for Religious Purposes

	% YES Vote	% Activism	% Re-Elect
Control	38	25	31
<i>Religious charity</i>	43	17	40
Difference	5%	-8%*	9%

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ using a two-tailed test

Table 6 indicates a slight difference from the regressions in Treatment Set 1, that being the significance of habitual local voting in relation to the Re-Elect variable. In this set of models where framing effects are present, voting habits show no significance as an explanatory variable; and where they do, there is no framing effect present. Again, the interactions produce a null result. Demographically, in this case it is level of education that shows some explanatory power, except with regard to the Activism model.

Table 6: Logistic Regression – Use of State Property for Religious Purposes

	YES Vote	Activism	Re-Elect
(Intercept)	−0.09 (0.39)	−1.17** (0.44)	−0.62 (0.41)
<i>Religious charity</i> frame	0.37 (0.55)	−1.70* (0.71)	0.70 (0.57)
Voted State/National	−0.38 (0.24)	−0.07 (0.27)	−0.46 (0.26)
Voted Local	0.24 (0.21)	0.11 (0.23)	0.44* (0.23)
<i>Religious charity</i> frame x Voted S/N	−0.19 (0.34)	0.67 (0.40)	−0.21 (0.35)
<i>Religious charity</i> frame x Voted Local	0.14 (0.30)	−0.23 (0.35)	0.08 (0.31)
AIC	678.84	520.37	648.33
BIC	704.15	545.68	673.64
Log Likelihood	−333.42	−254.19	−318.17
Deviance	666.84	508.37	636.33
Num. obs.	502	502	502

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Regression coefficients with standard errors in parentheses.

Figure 6 contains the separation plots for the three models in Table 6. All show little if any predictive power. Although the Activism model does show significance at $p < 0.05$, its separation plot does not render as we might expect. This apparent disparity provides an illustration of a caveat of using these plots: when the overall number of events is small, the separation plot becomes less helpful. With regard to both treatments, the number of respondents answering "yes" to the activism question hovered around 20% of the total (roughly 50 individuals). So, while the drop in activism calculated as statistically significant, the graphical representation is more agnostic.

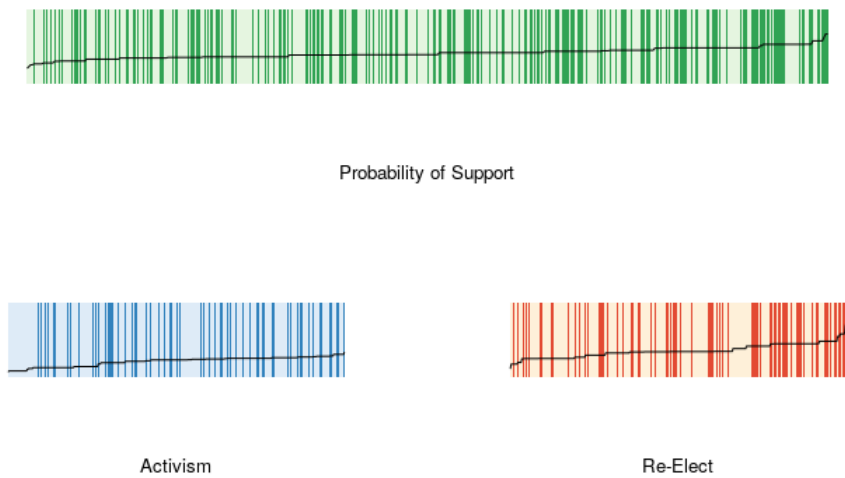


Figure 6: Separation Plot for *religious charity* frame models

Table 7: Logistic Regression with Covariates – Use of State Property for Religious Purposes

	YES Vote	Activism	Re-Elect
(Intercept)	−1.07*	−1.57*	−1.82**
	(0.53)	(0.62)	(0.56)
<i>Religious charity</i> frame	0.34	−1.64*	0.70
	(0.56)	(0.72)	(0.58)
Voted State/National	−0.41	−0.02	−0.48
	(0.25)	(0.27)	(0.26)
Voted Local	0.19	0.03	0.36
	(0.21)	(0.23)	(0.23)
Conservative	0.09	0.12	0.13
	(0.13)	(0.16)	(0.14)
Republican	0.06	−0.19	0.01
	(0.09)	(0.11)	(0.09)
Education	0.17*	0.12	0.24**
	(0.08)	(0.10)	(0.09)
Income	0.00	0.04	0.01
	(0.03)	(0.04)	(0.03)
<i>Religious charity</i> frame x Voted S/N	−0.19	0.57	−0.25
	(0.34)	(0.40)	(0.36)
<i>Religious charity</i> frame x Voted Local	0.15	−0.16	0.13
	(0.30)	(0.35)	(0.32)
AIC	677.61	519.61	645.06
BIC	719.80	561.80	687.24
Log Likelihood	−328.81	−249.81	−312.53
Deviance	657.61	499.61	625.06
Num. obs.	502	502	502

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Regression coefficients with standard errors in parentheses.