POLITICAL CAMPAIGNS AND OPEN-MINDED THINKING

WEB APPENDIX

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OPEN-ENDED RESPONSES AND RATIONALIZATION (REFERENCED IN NOTE 8)

Another reply to the concern that these open-ended responses are rationalizations comes from Kelley (1983), who argues that, "Interviewers are strangers, and respondents are given anonymity. The likes and dislikes expressed are overwhelmingly those that one would expect to play a part in voting, and many voters express likes and dislikes that run counter to their choices, something that we usually do not do when trying to justify a decision already taken" (23).

Rationalization processes can serve a social function by demanding that voters canvass those reasons that are publicly defensible. Gutmann and Thompson (1996) point out that reason-giving prepares citizens to engage in dialogue with others: "If citizens publicly appeal to reasons that are shared, or could be shared, by their fellow citizens, and if they take into account these same kinds of reasons presented by similarly motivated citizens, then they are already engaged in a process that by its nature aims at a justifiable resolution of disagreement" (25). Intense campaigns may increase citizens' sense that they ought to canvass these reasons more thoroughly. Even if the responses that are given do not constitute the "real" reasons that drive judgment, the provision of open-ended responses still reflects motivation to *defend* a judgment, and this defense could take on an open-minded or biased flavor, depending on the citizen's motivation.

DETAILS ON NESTED MULTINOMIAL LOGIT (REFERENCED IN NOTE 9)

A nested multinomial logit (NMNL) specification allows us to model a selection process leading into a polychotomous outcome. The selection process is modeled as a function of a set of covariates, Z, and the polychotomous outcome process is modeled as a function of a set of covariates, X, conditional upon the selection outcome. The probability of "choosing" some alternative Y_{jk}, at initial level *j* and sequential level *k* is expressed as:

$$P_{jk} = \frac{e^{V_{jk}}}{\sum_{m=1}^{M}\sum_{n}^{N_m} e^{V_{mn}}}$$

Where $V_{jk} = \beta' X_{jk} + \alpha' Z_j$, and X_{jk} represents variables that predict choices in level *k* (i.e., variables that distinguish balanced, pro-Democrat, and pro-Republican respondents from each other) and Z_j represents variables that predict choices in level j (i.e., variables that predict opinionation about either candidate).

The nested logit coefficients are estimated using Full-Information Maximum Likelihood by maximizing the following log-likelihood (Greene 2003):

$$\ln L = \sum_{i=1}^{n} \ln[\Pr(k|j) * \mathrm{Prob}(j)]$$

For nested multinomial logit, each observation must appear ΣN_k times in the dataset. In this case, it means that each observation appears four times (when j=0 (nothing to say), N_k=1 (only one outcome: nothing); when j=1 (something to say), N_k = 3 (three outcomes: balanced, pro-Democrat bias, pro-Republican bias)). The nested logit is run using the original plus three "duplicate" observations as a group. A series of dummy variables is created, such that each dummy variable represents one of the ΣN_k possible outcomes (nothing, balanced, pro-Democrat bias, pro-Republican bias). In each group of observations, these dummies "dummy out" exactly one of the four observations. The dependent variable is equal to zero when the respondent's choice *k* does not match the observation's dummied outcome and is equal to one when the respondent's choice *k* does match the observation's dummied outcome. Additionally, a series of interaction terms is specified to indicate how each of the X_{jk} variables ought to predict the ΣN_k outcomes given that the respondent has something to say (given one suppressed reference category), and a series of interaction terms is specified to allow for estimation of how each of the Z_j variables predicts *j*.

OPEN-MINDED THINKING BY EDUCATION, SELECTION COEFFICIENTS

Predicting Open-Minded and Biased Thinking, by Education. Selection Coefficients.

	Factors predicting j=Nothing to Say High Education	**Factors predicting j=Nothing to Say Low Education**
Intensity	-0.816*	-0.667*
	(0.250)	(0.238)
Something to Like about	-0.847*	-1.080*
Sitting Senator	(0.116)	(0.111)
Something to Dislike	-1.143*	-1.341*
about Sitting Senator	(0.158)	(0.192)
Strength of Partisanship	-0.500*	-0.778*
	(0.177)	(0.162)
Black	0.486*	0.337*
	(0.200)	(0.171)
Female	0.119	0.329*
	(0.097)	(0.094)
Age	-1.680*	-1.315*
	(0.285)	(0.206)
Seniority	-1.029*	-0.011
	(0.309)	(0.286)
Open Race	-0.557*	0.257
	(0.254)	(0.234)

CONGRESSIONAL RACES: DIFFERENCES IN MODEL SPECIFICATION (REFERENCED IN NOTE 17)

Congressional elections are generally far less competitive, less publicized, and less engaging to citizens. Campaign intensity is thus operationalized as a dichotomous indicator for whether or not *Congressional Quarterly* identified the race as one in which partisan turnover might occur. This covers 91 of the 435 congressional races and applies to 25% of the respondents in the 2000 NES. Analysis with a finer-grained measure that distinguishes between favored, leaning, and clear tossups yielded similar, though statistically less precise, results. The sample size in the NES 2000 is less favorable; the pooled Senate Election Studies yields over 6,000 respondents across 94 senate races. The NES 2000 yields only about 1,700 respondents across 373 congressional races. To accommodate the smaller sample size and the different instrumentation, I specify more parsimonious models. The selection model substitutes a measure of lack of opinionation on ten policy questions (number of Don't Knows) for opinionation on the sitting senator. It also omits the measure of seniority and open races. The outcome equation excludes the seniority measure, the interactions between partisanship and education (since these were inconclusive in the senate analysis), open race indicators, and the "verbosity" measure, since inclusion of them in the senate analysis did not change the substantive interpretation of the coefficient on campaign intensity.

REGRESSION ANALYSIS: ENGAGEMENT AND TURNOUT (REFERENCED IN NOTE 19)

Ordered probit coefficients with robust standard errors, adjusted for year-state clustering.

	Dependent variable: Interest in Campaign	Dependent variable: Voted in Senate Election
Nothing to say	-0.783*	-0.747*
	(0.050)	(0.057)
Biased towards Democrat or Republican	-0.209*	-0.107*
	(0.039)	(0.053)
Intensity	-0.252*	0.107
	(0.080)	(0.115)
Education	1.017*	1.146*
	(0.070)	(0.094)
Strength of partisanship	0.556*	0.512*
	(0.050)	(0.063)
Female	0.005	-0.003
	(0.031)	(0.038)
Age	1.239*	3.675*
	(0.302)	(0.362)
Age, squared	-0.595	-2.994*
	(0.375)	(0.418)
Black	0.025	-0.055
	(0.077)	(0.080)
1988 dummy	0.181*	0.222*
	(0.041)	(0.061)
1992 dummy	0.618*	0.238*
	(0.046)	(0.060)
τ_1	-0.156	1.041*
	(0.110)	(0.125)
τ_2	1.220	
	(0.112)	
pseudo lnL	-5014.32	-2870.11
N	5462	5459
Wald χ^2 (12)	1037.40	732.55
p> χ^2	0.000	0.000

*p<0.05, two-tailed
All variables scaled 0-1.
For the group of variables indicating nothing to say and biased towards candidates, the suppressed reference group consists of open-minded thinkers.

REGRESSION ANALYSIS: EXTREMITY OF PREFERENCE (REFERENCED IN NOTE 21)

Heckman coefficients with robust standard errors, adjusted for year-state clustering.

	Selection Coefficients Willingness to rate both candidates		Outcome Coefficients Extremity of Preference
Intensity	3.048* (0.220)	Nothing to say	-0.079* (0.012)
Something to like about sitting senator	0.337* (0.046)	Biased towards Democrat or Republican	0.104* (0.011)
Something to dislike about sitting senator	0.286* (0.067)	Intensity	-0.061 (0.034)
Education	0.638* (0.086)	Education	0.0004 (0.0127)
Strength of partisanship	0.222* (0.058)	Strength of partisanship	0.089* (0.128)
Female	-0.114* (0.042)	Female	0.017* (0.008)
Age	0.908* (0.375)	Age	0.233* (0.089)
Age, squared	-1.613* (0.471)	Age, squared	-0.193 (0.109)
Black	-0.158 (0.083)	Black	-0.037 (0.022)
Seniority	0.662* (0.326)	1988 dummy	-0.001 (0.013)
Open race	0.352 (0.246)	1992 dummy	0.005 (0.014)
Intercept	-2.400* (0.338)	Intercept	0.227* (0.036)
ρ	-0.219 (0.048)		
σ	0.243 (0.004)		
λ	-0.053 (0.012)		
pseudo lnL	-2763.95	Test of independence	
N (censored)	5484 (1693)	of equations (ρ=0)	
Wald χ^2 (11)	528.00	Wald χ^2 (1)	19.79
p> χ^2	0.000	p> χ^2	0.000

*p<0.05, two-tailed
All variables scaled 0-1.