Online Appendix for "A behavioral theory of electoral structure"

1) Countries, dates, sample sizes and position in national electoral cycles

Table App-1 Countries, survey years, positions in national electoral cycles, and sample sizes

Countries (0-0.52)	Year	Cycle	Interviews	Countries (0.53-1)	Year	Cycle	Interviews
Netherlands	1994	0.025	968	Hungary	2004	0.534	1,198
Finland	1999	0.056	501	Finland	2009	0.543	998
Spain	2004	0.060	1,208	Estonia	2009	0.564	1,003
Greece	2004	0.074	481	*Germany*	2004	0.574	593
Italy	1994	0.097	984	Cyprus	2004	0.610	500
Romania	2009	0.127	991	Italy	1999	0.620	3,708
Lithuania	2009	0.151	989	Germany	1989	0.620	1,170
Austria	2009	0.171	993	Italy	2004	0.627	1,553
Slovenia	2009	0.175	987	Belgium-Flanders	2009	0.660	519
Germany	1999	0.176	1,000	Belgium-Wallonia	2009	0.660	448
Sweden	1999	0.181	505	Latvia	2009	0.667	999
France	1989	0.210	981	Portugal	1994	0.671	948
Greece	1994	0.224	937	Poland	2004	0.677	960
Netherlands	1999	0.272	1,001	Sweden	2009	0.677	1,002
Italy	2009	0.285	963	Netherlands	2009	0.714	998
France	1994	0.287	981	Belgium-Flanders	1994	0.728	560
Finland	2004	0.309	899	Belgium-Wallonia	1994	0.728	397
Spain	2009	0.310	996	Slovakia	2009	0.744	1,003
Malta	2009	0.310	991	Czech Republic	2009	0.754	1,002
Estonia	2004	0.319	1,604	Cyprus	2009	0.760	992
Denmark	1999	0.338	1,001	Portugal	2004	0.762	958
Ireland	1994	0.339	930	Greece	1999	0.765	500
Netherlands	2004	0.361	1,586	Great Britain	2004	0.770	1,498
Spain	1994	0.368	942	Hungary	2009	0.785	1,003
Belgium-Flanders	1989	0.381	539	Denmark	2004	0.793	1,317
Belgium-Wallonia	1989	0.381	457	Spain	1999	0.812	1,000
Denmark	2009	0.390	999	Great Britain	2009	0.816	978
France	2009	0.393	986	Greece	2009	0.837	986
France	2004	0.397	1,406	Spain	1989	0.889	916
Austria	2004	0.401	1,000	Germany	1994	0.909	2,082
France	1999	0.401	1,020	Portugal	1999	0.917	500
Poland	2009	0.405	992	Slovenia	2004	0.921	998
Ireland	1999	0.406	503	Germany	2009	0.922	992
Ireland	2004	0.412	1,133	Denmark	1994	0.925	979
Italy	1989	0.416	957	Netherlands	1989	0.931	948
Great Britain	1989	0.417	909	Portugal	2009	0.932	994
Latvia	2004	0.420	1,000	Bulgaria	2009	0.979	985
Denmark	1989	0.424	948	Belgium-Flanders	1999	1.000	274
Great Britain	1994	0.428	1,018	Belgium-Wallonia	1999	1.000	226
Sweden	2004	0.433	2,100	Greece	1989	1.000	940
Portugal	1989	0.453	956	Ireland	1989	1.000	916
Slovakia	2004	0.460	1,063	Luxembourg	1989	1.000	289
Czech Republic	2004	0.501	889	Luxembourg	1994	1.000	488
Austria	1999	0.502	501	Luxembourg	1999	1.000	301
Ireland	2009	0.508	978	Luxembourg	2004	1.000	1,335
Great Britain	1999	0.514	977	Luxembourg	2009	1.000	996

On each of the occasions listed in Table App-1 an average of some 1,000 respondents were interviewed in each of the countries that were, at the time, members of the European Union (EU) – European Community until 1993 – except for 2004 when no survey was fielded in Malta. This amounted to 12 countries in 1989 and 1994, 15 in 1999, 24 in 2004 (only 21 yielding usable data since all party variables were omitted in Belgium, Lithuania and Sweden), and 27 in 2009. Northern Irish respondents were excluded, being too few to do justice to their separate party system; Belgium was divided into two electoral contexts since Flanders and Wallonia have different party systems. So we investigate 92 electoral contexts, as listed. Note that Table App-1 contains not only countries and dates but also the position in the national electoral cycles of each country that each EP election occurred.

As this table also shows, in our data 11 countries are represented five times, 2 countries four times, 3 countries three times, 8 countries twice, and 4 countries once. One country, Luxembourg, also has elections exactly every five years. For a single country to be synchronized in this way is not incompatible with random assignment. What might be of more concern is that Luxembourg holds national and EP elections concurrently, so that citizens participate in the EP ballot who would not have done so on separate days. However, our dependent variable (as explained in the Data section of the text) is the propensity of *ever voting* for a party, not reported EP vote, so that concurrent elections do not introduce conceptual difficulties (see also footnote 11 in the main text).

2) Explanation of the dependent variable (propensities to vote)

Party support is both about parties and about voters. It is also about the ways in which voters and parties match or fail to match: the affinity between them. Indeed, in our paper we refer to three types of variables familiar from discrete choice modeling. There are individual-specific variables, things about people; there are choice-specific variables, things about parties; and there are voter-party affinities, things that draw particular types of people to particular types of parties.

Individual-specific variables are familiar to those who study voter turnout (political interest, education, and so forth) but are seldom employed in studies of party support except as components in measures of voter-party affinity. Variables such as left-right location have effects that are “tuned” to the particular parties with which affinities are being measured, enabling us to produce measures such as proximity to each party on a left-right or issue scale, as explained in the main text of our paper. Choice-specific variables such as party size can be implemented directly: we assume that strategically-minded individuals are more likely to support a party the larger it is. Certain affinity variables can be handled almost as directly: party identification can be coded as the extent to which respondents identify with each party (in our case by using a simple 0/1 dummy variable) and the party best for addressing a respondent’s most important issue is handled in the same way. Demographic affinities are measured in a more elaborate manner detailed in a separate section of this appendix.

In order to move beyond a voter-centric approach and include in our analysis choice-specific variables and measures of voter-party affinity it is necessary to adopt a modeling strategy that encompasses all parties at once rather than focusing on one party at a time.[1] Restructuring (“stacking”) the data so that party-oriented information is organized into separate lower-level cases (one case for each party) nested within respondents (instead of as separate variables, as is conventional) allows us to think of party preferences in general (generic party preferences), rather than focusing on preferences for specific parties. An alternative approach more common in the literature is for scholars to move to the party level of analysis[2]; but this can focus attention on factors that play little part in the behavior of most voters if those factors are characteristic of small parties. This strategy also requires aggregation of individual-level information to the party level, losing much potentially important detail.

Generic party support as outcome of interest overcomes this problem and also makes possible a measure of the dependent variable on a quasi-interval scale, rather than the dummy “voted for this party or not” that is more common in electoral research. We employ a measure of

[1] Evidently, when we focus on one party at a time, effects of party-level variables cannot be estimated since, for just one party, they have no variance. Conditional logit makes such analyses possible, but customary uses of CL employ interactions between each input variable and indicators for each party, thus producing party-specific findings rather than findings relating to generic party support.

[2] e.g. Adams, James, Lawrence Ezrow, and Zeynep Somer Topcu. 2011. "Is Anybody Listening? Evidence that Voters Do not Respond to European Parties’ Policy Statements during Elections." *American Journal of Political Science* 55(2): 370-82.

De Vries, Catherine E., and Sara B. Hobolt. 2012. "When Dimensions Collide: The Electoral Success of Issue Entrepreneurs." *European Union Politics* 13(2): 246-68.

Propensity-to-Vote (PTV)[3] that follows a proven measurement and analysis strategy.[4] Respondents are asked to report separately for each party the likelihood that they would ever vote for that party, measured on a scale of 0-10 where 0 is labeled "would never vote for this party" and 10 is labeled "am certain to vote for this party at some time." Research has shown that the question is not interpreted absolutely literally by respondents[5] – for example, older respondents who realistically only have a few elections left in their lifetimes, do not give more "never vote" responses than younger respondents do. Thus the questions appear to function, as was intended, as measures of Downsean "utility",[6] although that word has acquired a somewhat different meaning in the context of rational choice theorizing – reason why they are no longer referred to by use of that term.

These measures bring several advantages over more conventional measures of party support. Such measures (1) being quasi-interval, permit use of modeling strategies (regression analysis) that yield meaningful effect parameters; (2) differentiate between parties not voted for according to their different degrees of attractiveness to voters; and (3) provide information about respondents who did not actually vote, differentiating between them on the basis of how likely they would be to support each party if they did vote. In consequence of (3) these questions give rise to very little missing data – and missing data that does not necessarily vary with the extent of turnout. At the same time these questions provide for a direct translation into party choice for those who did vote: it has been shown that, of those giving their highest score to a particular party, some 90% actually vote for that party (and, of those who do not, most have scores that are tied with a different party or they are respondents who did not vote).[7] So these variables contain the same information as party choice variables, but in the context of far more detailed and nuanced information about support for all parties.

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[3] The questions were first asked in Dutch election studies in the early 1980s and have been asked in studies of elections to the European Parliament since 1989. In recent years they have found their way into increasing numbers of national election studies in addition to the Dutch ones, notably the Austrian, British, German, Irish, Italian, Portuguese and Spanish studies.

[4] Eijk, Cees van der, and Mark N. Franklin (eds.). 1996. *Choosing Europe? The European Electorate and National Politics in the Face of Union*. Ann Arbor: University of Michigan Press.

Eijk, Cees van der. 2002. "Design Issues in Electoral Research: Taking Care of the (Core) Business." *Electoral Studies* 21(2): 189-206.

Eijk, Cees van der, Wouter van der Brug, Martin Kroh, and Mark N. Franklin. 2006. "Rethinking the Dependent Variable in Voting Behavior: On the Measurement and Analysis of Electoral Utilities." *Electoral Studies* 25(3): 424-47.

Brug, Wouter van der, Cees van der Eijk, and Mark N. Franklin. 2007. *The Economy and the Vote: Economic Conditions and Elections in Fifteen Countries*. Cambridge: Cambridge University Press.

[5] Tillie, Jean. 1995. *Party Utility and Voting Behavior*. Amsterdam: Het Spinhuis.

[6] Eijk, Cees van der, Wouter van der Brug, Martin Kroh, and Mark N. Franklin. 2006. "Rethinking the Dependent Variable in Voting Behavior: On the Measurement and Analysis of Electoral Utilities." *Electoral Studies* 25(3): 424-47.

[7] Tillie, Jean. 1995. *Party Utility and Voting Behavior*. Amsterdam: Het Spinhuis.

Eijk, Cees van der, and Michael Marsh. 2011. "Comparing Non-ipsative Measures of Party Support." Paper presented at the First European Conference on Comparative Electoral Research, 1-3 Dec 2011, University of National and World Economy, Sofia, Bulgaria.

3) Measurement of objective and subjective concerns: the case of social structure

As explained in the main text, our objective in this paper is to observe the effects of first-order-ness on the objective and subjective bases for party support. In the vocabulary of discrete choice modeling, objective bases for party support are either choice-specific (if they relate to objective party characteristics) or individual-specific (if they relate to objective voter characteristics). Subjective concerns originate as individual-specific, but they involve party-specific features (for example giving rise to a measure of proximity), as described in the main text.

It might be thought that the same would be the case for social structure and, indeed, a common, inductive method of operationalizing social structure to predict party support across countries is to use y-hats from a party-by-party analysis predicting the dependent variable.[8] But, as a more deductive alternative that allows for more straightforward interpretation, social structure can be measured in quasi-objective terms if we derive a latent variable that is a one-dimensional summary of the multi-dimensional space in which the demographic variables it summarizes are located. Such a latent variable could be derived using factor analysis but, with most of the social structure variables being categorical, a more appropriate technique is Joint Correspondence Analysis (JCA), which produces scores for each case along a "principal axis," analogous to a factor.[9] If the support scores for different parties are arrayed in the same multidimensional space as the hierarchy axis, they will either be orthogonal to that axis or they will be related to it, positively or negatively. To the extent that support for a party is related, either positively or negatively, to the social hierarchy axis, scores on the hierarchy axis will contribute to determining the extent of support for that party.

Figure App-1 seeks to represent support for two different political parties, along with position on the social hierarchy axis, in a three-dimensional space. The figure uses conventions from dimensional analysis in which arrows are related to the extent that they move in the same direction (indeed, conventionally the correlation between two arrows is given by the cosine of the angle between them). The origin for this space is in the centre of the depicted box. The social hierarchy axis is represented as running through this origin from a point on the lower left front wall to a point on the upper right back wall of the box. It runs through the origin because, as a JCA axis (just like a set of factor scores), it has a negative as well as a positive pole. The two party support arrows both start at the origin. They have no negative poles, because PTVs measure the likelihood of ever voting for a party, which cannot be less than zero.[10] In this case PTV1 runs

[8] Eijk, Cees van der, and Mark N. Franklin, eds. 1996. *Choosing Europe? The European Electorate and National Politics in the Face of Union*. Ann Arbor: University of Michigan Press.

[9] Greenacre, Michael. 2006. "From Simple to Multiple Correspondence Analysis." In *Correspondence Analysis and Related Methods*, ed. Michael Greenacre and Joerg Blasius. Boca Raton: Chapman & Hall/CRC, p. 41-76.

[10] Note that the PTVs are not part of the JCA itself, but they are related to the dimension produced by the JCA (the hierarchy axis in Figure App-1). Also note once again that in a stacked data matrix PTV scores have been generalized – though they relate to particular parties those parties are different in each country – and effects on those PTVs are similarly generalized, being best interpreted not as "effects on Party A" but as "effects on a party."

from the origin to the right front wall while PTV2 runs from the origin to the bottom front wall. Though each arrow is depicted in a different dimension, the two party support arrows subtend non-zero angles with the hierarchy axis. The angles are labeled by curved lines whose lengths depict the sizes of the angles (20º and 60º). PTV1 is more strongly correlated with social hierarchy because its line subtends a smaller angle with the social hierarchy arrow than does PTV2. Moreover, PTV1 is positively related to social hierarchy (the two arrows are moving in the same general direction) while PTV2 is negatively related.

Since those relationships are non-zero, social structure has the opportunity to affect support for those two parties, as it does for any other parties whose support dimensions are not orthogonal to the hierarchy axis. A measure that contains no choice-specific component does in this way have the opportunity to influence the extent to which different parties receive support.

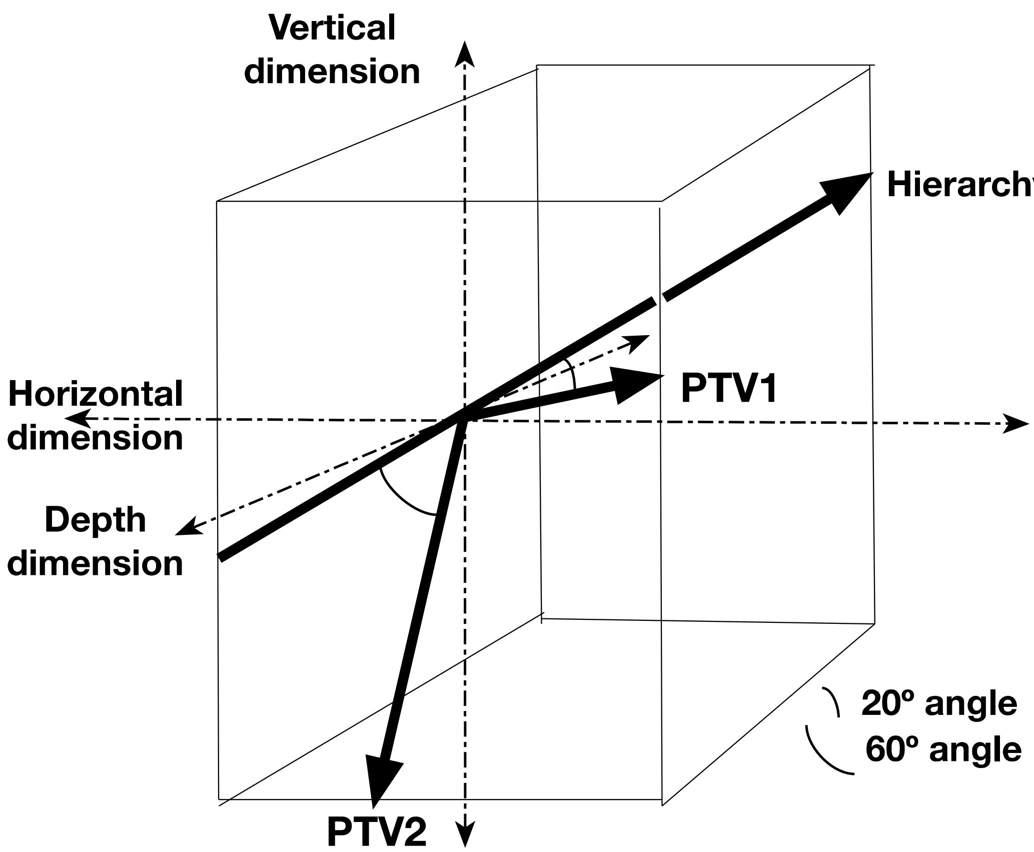

Figure App-1 Extent of correspondence between support for two parties and social hierarchy

The first dimension of our JCA analysis reflects a clear pattern of social hierarchy: The characteristics that load on one side are young/middle-aged, male, upper/middle class, educated, urban, not religious, working/studying, unionized. Their opposites load on the other end. This axis explains 23.8 percent of the inertia in the variables that it summarizes (approximately the same percentage of the summarized variance[11]). This is fully satisfactory given that the explicit

[11] Greenacre, Michael. 2010. *Correspondence Analysis in Practice*. Boca Raton: Chapman & Hall/CRC, p. 148.

aim of the JCA is to produce a theoretically meaningful measure of social hierarchy (rather than to maximize variance explained by absorbing just any sociodemographic differences).

The proportions of the common variance contributed by each of the summarized variables are shown in Table App-2 (which sums the effects of each variable's different categories whose individual contributions are of no particular interest). The largest contribution is that of region, actually the country-year elsewhere described as the electoral context. We expect the structure of social characteristics to vary over space and time, and failing to take account of these differences would result in misestimating the effects of social structure (reason why region is conventionally viewed as a social structural variable). In practice, 89 percent of the variance between contexts is explained by country, so the largest proportion of these differences are due to country differences in social structure. Still, these differences, while large, contribute less than a third to the common variance. Religiosity contributes more as do class and education taken together.

Table App-2 Contribution of social structure variables to common variance

Social structural variable	Specific contribution	Group contribution
Age	0.028	
Gender	0.008	
Personal characteristics		0.036
Occupational class	0.024	
Work category*	0.088	
Trade union membership	0.086	
Traditional social class		0.198
Education	0.118	0.118
Religion	0.233	
Church attendance	0.108	
Religiosity		0.341
Urban/rural	0.012	
Region (country-year)	0.291	
Geography		0.303
Total**	0.996	0.996

* Student / unemployed / housewife / retired.
** Total is less than 1.0 because of rounding.

From the JCA analysis, values for each respondent can be assigned (predicted) on a basis that effectively amounts to an estimate of each respondent's coordinate on the axis. Because the orientation of the JCA factor is arbitrary in relation to party orientations on the social structure dimension, those values are then given signs consistent with the polarity of each party's support in relation to the axis. More precisely, we re-oriented the factor based on separate regressions that sought to predict support (PTV) for each party from respondents' JCA coordinates (along with the other five independent variables of the standard model in Table 1). For those parties for which the coefficient of the JCA factor turned out positive, the coordinates were left unchanged; if it turned out negative, the coordinates were multiplied by -1, ensuring a positive effect of social structure on PTVs for all parties. Just as, for example, ideological proximity is always positive no matter whether a party is right, center or left, our JCA procedure constructs an equivalent variable from a large demographic vector. In this way, an entirely objective measure of social hierarchy becomes an independent variable in our main analysis, as called for by our theoretical expectations.

Importantly, the measure of hierarchy cannot explain structural specifics of the social basis of politics in individual countries, and it should not be evaluated against this criterion. Its comprehensive design rather follows our interest in cyclical dynamics. A generalized summary measure allows us to model short-term change in the effect of social structure independently of time-invariant differences between contexts.

Table App-3 Descriptive statistics and coding details

Variable	Coding	Mean	SD
Propensity to vote (PTV)	Self-assessed propensity to ever vote for party (1=not at all probable … 11=very probable)	3.56	2.99
Party size	Share of seats party holds in national legislature (0=none … 1=all)	0.13	0.15
Social structure	JCA score (see Appendix section 2)	0.53	0.25
Partisanship	Whether respondent identifies with party (0=no; 1=yes)	0.07	0.25
Left-right proximity	Inverted distance between respondent and party on 11-point left-right scale (0=same position … 1=maximum distance)	0.68	0.26
Issue competence	Whether repondent thinks party is most competent to deal with "most important problem" (0=no; 1=yes)	0.07	0.26
EU proximity	Inverted distance between respondent and party on 11-point EU integration scale (0=same position … 1=maximum distance)	0.69	0.26
Cycle	Relative position of EP election in national electoral cycle (0=right after a national election … 1=right before a national election)	0.54	0.26
Two-party dominance (TPD)	Combined seat share of the largest two parties in the national parliament (0=none … 1=all)	0.65	0.17

N (response) = 681,200; N (respondents) = 88,700; N (context) = 92.

Table App-4 Estimation results for the effects displayed in Figure 3

Dependent:	ANOVA R-squared of party identification	ANOVA R-squared of issue competence	ANOVA R-squared of left-right proximity	ANOVA R-squared of EU proximity
Cycle	-0.144	-0.248	-0.155	-0.040
	(0.042)	(0.012)	(0.013)	(0.188)
Cycle-squared	0.126	0.220	0.163	0.032
	(0.025)	(0.016)	(0.005)	(0.179)
Constant	0.109	0.142	0.093	0.034
	(0.000)	(0.000)	(0.000)	(0.008)
p>F	0.039	0.038	0.013	0.323
R-squared	0.065	0.090	0.091	0.008

OLS coefficients with one-tailed p-values in parentheses.
N=92. p-values clustered by country (N=28).

Table App-5 Estimation results for the effects displayed in Figure 4

Dependent: Party Support (PTV)	*For party size*		*For social structure*	
Coefficients of fixed effects (with one-tailed p-values in parentheses)				
	Coef.	p-value	Coef.	p-value
Party size	11.01	(0.001)	2.64	(0.000)
Social structure	0.76	(0.000)	2.33	(0.007)
Cycle	3.83	(0.171)	1.32	(0.388)
Cycle-squared	-2.46	(0.237)	-0.06	(0.494)
Two-party dominance (TPD)	1.17	(0.219)	0.34	(0.424)
Cycle*TPD	-4.69	(0.204)	-1.13	(0.436)
Cycle-squared*TPD	3.36	(0.237)	0.01	(0.500)
Party size*TPD	-9.25	(0.014)		
Cycle*Party size	-29.50	(0.015)		
Cycle-squared*Party size	27.74	(0.023)		
Cycle*Party size*TPD	28.79	(0.044)		
Cycle-squared*Party size*TPD	-27.81	(0.050)		
Social structure*TPD			-1.84	(0.097)
Cycle*Social structure			-6.75	(0.034)
Cycle-squared*Social structure			6.74	(0.019)
Cycle* Social structure*TPD			7.94	(0.077)
Cycle-squared*Social structure*TPD			-8.07	(0.051)
Partisanship	3.68	(0.000)	3.67	(0.000)
Left-right proximity	3.06	(0.000)	3.01	(0.000)
Issue competence	2.04	(0.000)	2.00	(0.000)
EU proximity	0.64	(0.000)	0.63	(0.000)
Constant	-1.13	(0.142)	-0.54	(0.325)
Standard deviations of random effects (with standard errors in parentheses)				
Level 3 (context, N=92)	s.d.	s.e.	s.d.	s.e.
Intercept	0.77	(0.071)	0.82	(0.063)
Slope for Party size			2.31	(0.180)
Slope for Social structure	0.66	(0.054)	0.57	(0.047)
Slope for Partisanship	0.58	(0.042)	0.56	(0.044)
Slope for Left-right proximity	0.93	(0.074)	0.94	(0.071)
Slope for Issue competence	0.67	(0.056)	0.69	(0.053)
Slope for EU proximity	0.54	(0.042)	0.52	(0.041)
Level 2 (respondent, N=88,700)				
Intercept	0.92	(0.028)	0.92	(0.005)
Level 1 (party stack, N=681,200)				
Residual	2.16	(0.021)	2.15	(0.002)
Log likelihood	-1530468		-1527085	

Note: The first model has robust standard errors clustered by context to compensate for the random slope of party size, which had to be omitted as the interaction of size, cycle and TPD, none of which is an individual-level variable, would impede estimation. The cross-level interactions of the controls are also omitted as they are fully absorbed by their random slopes.