Online Appendix: Understanding People's Choice When They Have Two Votes

The 2013 German Election and Survey Methodology

The 2013 election in Germany gave the center-right Christian Democratic Union/Christian Social Union (hereafter CDU for short) a plurality of seats, for the third consecutive time. In terms of popular vote, the CDU received above 40% of the ballots in both election types, distancing the center-left Social Democratic Party (SPD) by some 10 percentage points.[1] Angela Merkel's party also secured a comfortable advance from the second-runner in terms of the seat distribution, obtaining slightly less than 50% of the seats compared to 30.5% for the SPD. On the other hand, the Christian Democrats' traditional coalition partner, the Free Democratic Party (FDP), did not garner enough list votes to meet the legal threshold of 5%, and as a result, was not allocated any seat. The two other minor parties having received seats (the Greens and the Left, with about 10% of the deputation each) being ideologically at odds with Merkel's party, this complicated the formation of a coalition controlling a majority of seats in the Bundestag. The two largest parties eventually formed an unlikely coalition government.

The Bavarian survey was conducted by Harris/Decima between September 16 and 21, 2013, with 4,762 respondents, and a post-election wave conducted between September 23 and 28, with 4,041 from the first-wave responding to the second wave questionnaire. The Lower Saxon survey was conducted by the same firm between September 12 and 19 with 1001 respondents. A post-election wave was held between September 23 and 30, with 789 respondents. Overall, the contact rate was 12% and the response rate 11.5%. In both cases, a stratified, quota based sampling approach was used, the quotas being established for age, gender, and education. The vote distributions in the sample closely match the observed vote distribution in the total population of voters, especially in the case of Bavaria. As a result, our multivariate analysis does not include sample weights. Our empirical models will contain a dummy variable called

[1] Official results are taken from the web site of the German Federal Returning Officer (www.bundeswahlleiter.de).

Bavaria, equaling one if a respondent is from Bavaria and zero if from Lower Saxony.[2] Table A1 provides descriptive statistics on all variables used in the models presented in the paper.

Table A1: Descriptive Statistics

Variable	Party	Mean	Std. Err.
Local Chances	CDU	0.816	0.191
	SPD	0.547	0.252
	Greens	0.338	0.253
	FDP	0.206	0.220
	Left	0.143	0.196
Local Ratings	CDU	0.212	0.409
	SPD	0.158	0.365
	Greens	0.015	0.122
	FDP	0.006	0.074
	Left	0.004	0.061
Party Ratings	CDU	0.633	0.296
	SPD	0.596	0.254
	Greens	0.481	0.287
	FDP	0.307	0.279
	Left	0.229	0.286
Leader Ratings	CDU	0.688	0.316
	SPD	0.520	0.305
	Greens	0.390	0.289
	FDP	0.296	0.258
	Left	0.331	0.306
Coalition Ratings		0.524	0.299
Party ID	CDU	0.320	0.467
	SPD	0.177	0.382
	Greens	0.068	0.252
	FDP	0.022	0.146
	Left	0.024	0.152
Age		0.428	0.199
Education		0.652	0.349
Gender (Female = 1)		0.438	0.496

The table reports descriptive statistics of our variables for the 2,694 respondents with non-missing observations. All variables are scaled between 0 and 1.

Party and leader ratings are based on questions asking respondents how much they like or dislike the various parties and leaders on a 0 to 10 scale (later rescaled from 0 to 1). Table A1 shows that the CDU was the most liked party while the Left was the most disliked. As for party leaders, Angela Merkel enjoyed an advantage with an average rating of 0.687 (about 7 out of 10), followed by Peer Steinbrück from the SPD. Overall, the ordering of average ratings in the sample is consistent with the support each party received at the time of the 2013 federal election.

The measurement of local candidate ratings differs from the previous two variables. We make use of responses to a survey question asking whether there is a candidate that the re-

[2] We tested whether our main results are affected by the combination of two Landers. The results presented below were replicated after including interaction terms with the Bavaria dummy variable. These interaction effects were for the most part insignificant.

spondent particularly likes in the constituency, and if yes, from which party. Only around 30% of those who voted mentioned a candidate, almost all of them referring to a CDU or SPD candidate. The Local Chances variable is the score given by respondents to the perceived chances of each party winning in their constituency, on a 0 to 10 scale (again rescaled to run from 0 to 1). Typically, CDU and SPD candidates were perceived to have the best chances of winning in the constituency.

Coalition preferences were tapped using questions asking people how much they like or dislike (on a 0 to 10 scale) different government coalitions that could be formed after the election. For the purpose of this study, we focus on the two most plausible coalitions, those involving CDU with the FDP on the one hand and SPD with the Greens on the other hand. The actual turn of events leading to a Grand Coalition between the CDU and SPD was an unlikely outcome, which is why it would make little sense to explain vote choice using preferences over such an unusual coalition. To create our coalition ratings variable, we simply subtract the score given to the SPD–Greens coalition from the score given to the CDU–FDP coalition. The resulting variable is rescaled into the $[0, 1]$ range. The mean score is 0.523, suggesting that the CDU and FDP formed a slightly more popular coalition than did the SPD and Greens (0.5 indicates indifference between the coalitions).

In the last part of our empirical analysis, we reassessed our hypotheses after accounting for our respondents' level of sophistication. We measure sophistication using educational attainment. Since survey quotas were established in part on this variable, its distribution closely matches that of the actual German population, making it the most reliable indicator of sophistication at our disposal. This variable contains three categories that account for the specificity of the German education system, in which different types of high schools coexist. The first category contains respondents with lower secondary or incomplete secondary schooling (about 20% of our final sample), the second category contains those with standard secondary schooling or technical degrees (37% of the sample), while the third category contains respondents with high secondary degrees or college education (42% of our sample). We create interaction terms by multiplying this educational attainment measure with our party-specific variables. For reasons exposed in the paper, we are especially interested in testing for the existence of contamination effects conditional on the level of education.

Finally, the cross-tabulation in Table A2 shows the relationship between the two vote choices in the sample. As can be seen, most voters opt for a straight-line ticket, the main diagonal containing the largest proportions. Some proportion of Green and SPD voters were also keen on splitting their vote between these parties, which are usually expected to become coalition partners should the opportunity to form the government come about. Likewise, voters supporting the FDP list were somewhat likely to pick a CDU candidate in their local constituency, and vice-versa.

Table A2: Cross-Tabulation of Observed List and Candidate Votes

		List Vote				
		CDU	SPD	Greens	FDP	Left
Candidate Vote	CDU	87%	3%	1%	8%	1%
	SPD	4	78	14	1	4
	Greens	5	16	69	3	7
	FDP	18	3	0	79	0
	Left	3	10	0	0	87
Total (N = 2,694)		1,319	757	270	190	158

The table reports the percentage distribution of the list vote across the candidate vote choice in the survey sample. Percentages may not add up to 100 due to rounding. The bottom row reports the frequencies by list vote choice.

Convergence Diagnostics

For each of the two principal vote models, we computed three samples of 1,000,000 Markov chain Monte Carlo (MCMC) draws, using different sets of starting values each time. In both cases, a first MCMC sample is computed after setting the starting values of our parameters to zero. The next two samples use overdispersed starting values following the sequences $(-1, 1, -1, \ldots)$ and $(1, -1, 1, \ldots)$, respectively. This leaves us with a total of six million MCMC draws. To proceed with our empirical analysis, we make use of the last 500,000 draws from each of the three MCMC samples, once again for both the list vote and candidate vote equations. For each model, we used non-informative priors for the parameters, namely a multivariate normal distribution with mean zero and an identity covariance matrix $\boldsymbol{I}$. The priors for the covariance matrices are drawn from the inverse-Wishart distribution using the default values proposed by Imai and van Dyk (2005), the degrees of freedom being set to five—the number of alternatives—and the scale parameter to one.

Using multiple chains allows us to compute the Gelman-Rubin potential scale reduction factors (PSRF) to assess whether they have converged to a stationary distribution (Gelman and Rubin 1992). Table A3 reports these statistics for the parameters of both vote equations. A value close to one indicates that convergence has been achieved. As can be seen, for both equations, all values fall well below the conventional benchmark of 1.1, suggesting that we have successfully reached convergence. The conclusion holds when considering the upper limit of the 97.5% credible interval for this statistic. Table A3 also reports the p-values from the Heidelberger and Welch (1983) convergence tests. In all cases, we obtain values larger than 0.05, supporting the (null) hypothesis of stationary distributions and strengthening the conclusion that we have successfully reached convergence.

We use the same specification for the models with interactions using the educational attainment variable, and diagnostic statistics also indicate successful convergence. The Gelman-Rubin multivariate PSRF statistic approximates to 1.01 for both models.

References

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Heidelberger, Philip, and Peter D. Welch. 1983. "Simulation Run Length Control in the Presence of an Initial Transient." *Operations Research* 31(6): 1109–1144.

Imai, Kosuke, and David A. van Dyk. 2005. "MNP: R Package for Fitting the Multinomial Probit Model." *Journal of Statistical Software* 14(3): 1–32.

Table A3: Convergence Diagnostic Statistics

		List Vote			Candidate Vote		
Party	Parameter	GR	GR (97.5%)	HW-p	GR	GR (97.5%)	HW-p
	Local Chances	1.0000	1.0000	0.98	1.0004	1.0012	0.54
	Local Ratings	1.0001	1.0003	0.20	1.0002	1.0004	0.58
	Party Ratings	1.0002	1.0002	0.84	1.0013	1.0019	0.40
	Leader Ratings	1.0001	1.0002	0.10	1.0001	1.0002	0.50
	Contamination Effects	1.0000	1.0000	0.72	1.0001	1.0005	0.30
	Party ID	1.0002	1.0007	0.54	1.0005	1.0013	0.17
SPD	Coalition Ratings	1.0004	1.0008	0.39	1.0014	1.0016	0.75
	Age	1.0001	1.0003	0.52	1.0001	1.0003	0.87
	Education	1.0000	1.0000	0.57	1.0000	1.0001	0.11
	Gender	1.0001	1.0003	0.67	1.0000	1.0001	0.73
	Bavaria	1.0001	1.0003	0.69	1.0000	1.0002	0.52
	Intercept	1.0002	1.0006	0.39	1.0002	1.0002	0.89
Greens	Coalition Ratings	1.0009	1.0028	0.20	1.0002	1.0008	0.57
	Age	1.0001	1.0005	0.63	1.0002	1.0007	0.87
	Education	1.0000	1.0000	0.92	1.0000	1.0000	0.83
	Gender	1.0002	1.0008	0.51	1.0000	1.0001	0.69
	Bavaria	1.0002	1.0007	0.17	1.0001	1.0004	0.67
	Intercept	1.0002	1.0007	0.09	1.0001	1.0001	0.74
FDP	Coalition Ratings	1.0003	1.0012	0.22	1.0006	1.0016	0.11
	Age	1.0001	1.0005	0.62	1.0001	1.0002	0.58
	Education	1.0000	1.0000	0.20	1.0008	1.0025	0.61
	Gender	1.0001	1.0002	0.31	1.0002	1.0006	0.87
	Bavaria	1.0001	1.0002	0.81	1.0000	1.0000	0.80
	Intercept	1.0002	1.0006	0.28	1.0004	1.0012	0.26
Left	Coalition Ratings	1.0005	1.0011	0.47	1.0004	1.0011	0.59
	Age	1.0004	1.0014	0.06	1.0002	1.0006	0.75
	Education	1.0000	1.0001	0.97	1.0009	1.0028	0.49
	Gender	1.0000	1.0001	0.89	1.0001	1.0003	0.67
	Bavaria	1.0001	1.0005	0.12	1.0002	1.0006	0.38
	Intercept	1.0003	1.0010	0.18	1.0004	1.0014	0.86
Cov. Matrix	SPD:Greens	1.0007	1.0014	0.53	1.0007	1.0025	0.45
	SPD:FDP	1.0014	1.0047	0.06	1.0005	1.0019	0.40
	SPD:Left	1.0010	1.0022	0.29	1.0012	1.0036	0.51
	Greens:Greens	1.0004	1.0014	0.66	1.0002	1.0006	0.52
	Greens:FDP	1.0019	1.0068	0.23	1.0011	1.0012	0.81
	Greens:Left	1.0010	1.0027	0.25	1.0014	1.0018	0.11
	FDP:FDP	1.0001	1.0004	0.84	1.0006	1.0010	0.44
	FDP:Left	1.0009	1.0031	0.09	1.0007	1.0009	0.23
	Left:Left	1.0004	1.0012	0.17	1.0005	1.0006	0.28
Multivariate PSRF			1.0062			1.0039	

Convergence statistics for the main models reported in Table 2 of the main paper. The first two columns for each equation report the Gelman-Rubin (GR) potential scale reduction factor (PSRF) statistics along with the 97.5% upper bound of their credible interval. The third column reports the p-value of the Heidelberger-Welch (HW) diagnostic test of stationary distributions. Values larger than 0.05 indicate that the test is passed, supporting the conclusion of a stationary distribution. The tests are performed on a combined sample of 1,500,000 MCMC draws for each vote model.

Additional Results

Table 2 from the main text reports the mean and the 95% credible intervals of the posterior distributions for our parameters of interest. The left section of the table reports statistics for the list vote equation, whereas the right section reports candidate vote estimates. The values can be interpreted in a similar fashion to frequentist statistical models, in the sense that a result is considered significant when the entire credible interval is either positive or negative. The main text provides a discussion of the substantive findings.

To illustrate the size of contamination effects, we compute changes in the predicted probability of choosing a local candidate (or party list), without and with an anterior decision to support the list (or local candidate) of that party. Table A4 reports these values. In each case, the posterior predicted probabilities are computed after setting all other variables at their sample means. As can be seen in the upper portion of Table A4, a voter having made a prior decision to support the CDU list is more likely to vote for a CDU local candidate. The marginal effect is reported in the upper-left cell of Table A4, and corresponds to approximately +11 percentage points. Obviously, this implies that the same voter is less likely to support candidates from the other parties. The size of the contamination effect is similar for a voter having decided to support the SPD list. On the other hand, the spillovers are weaker for smaller parties. The bottom part of the table reports the change in predicted probabilities associated with contamination effects in the opposite direction. As anticipated from the results discussed in the main text, those effects are smaller in magnitude.

Since vote decisions are the combination of multiple factors, we cannot easily interpret any individual vote as being a spillover. However, we can infer the overall proportion of votes affected by contamination based on the models' parameters. To do this, we first compute the predicted vote choices of sample respondents by constraining the contamination effects to zero and assigning a vote to the alternative with the highest posterior predictive probability. Next, we compare this choice with the one based on the posterior predictive probability computed with actual sample values. We performed these comparisons using a random sample of 5,000 MCMC draws for each election, and using the mean predicted probabilities to infer vote choices. For the plurality component, the estimated proportion of votes cast differently when constraining the contamination effects to zero is about 2.2%, which is the number reported in the text, compared to 1.2% for the PR component. Using a model with effects conditional on education and replicating this calculation by constraining the education variable to its lowest level (see below for details on this alternative specification), the proportions are 5% and 2.4%, respectively for the local candidate vote and list vote. Again, these results suggest that contamination effects have a limited aggregate impact on mixed systems, with the balance of these effects flowing from the PR to the plurality component.

Table A4: Estimated Size of Contamination Effects

	List → Candidate				
	Change in Candidate Vote Probability				
List Vote	CDU	SPD	Greens	FDP	Left
CDU	0.112				
SPD		0.117			
Greens			0.043		
FDP				0.011	
Left					0.009

	Candidate → List				
	Change in List Vote Probability				
Candidate Vote	CDU	SPD	Greens	FDP	Left
CDU	0.077				
SPD		0.079			
Greens			0.030		
FDP				0.021	
Left					0.009

Marginal effects representing the change in the out-of-sample posterior predictive probability of choosing a party given that a voter previously made a decision to vote for the party indicated in the row header in the other election type. Probabilities are computed after setting all other explanatory variables of the models at their mean values.

Table A5 reports the results for models including an interaction between alternative-specific variables and the level of educational attainment of respondents, used as an indicator of voter sophistication. The lower panel of the table is produced by adding the MCMC draws for the coefficients of each variable and those of their respective interactions with education. Notice that, for simplicity, we only report the summary of posterior distributions for variables with interactions. As can be seen by comparing the two panels of Table A5, contamination effects are essentially driven by voters with lower levels of education, a result that we emphasized in the main manuscript.

Finally, Table A6 reproduces Table 3 from the main text using the model with education interactions, using two different approaches to hypothesis testing. As can be seen, contamination effects arise for voters with a lower level of educational attainment. In contrast, our other hypotheses about the determinants of each separate decision are more strongly supported when considering highly educated voters. These findings are consistent with the view that sophisticated voters rely on distinct selection criteria for each vote.

Table A5: Bayesian Multinomial Probit Models with Education Interactions

	List Vote		Candidate Vote	
Variable	Mean	[Credible Interval]	Mean	[Credible Interval]
		Low Education (Education = 0)		
Local Chances	0.452	[−0.062, 0.975]	0.504	[0.002, 1.022]
Local Ratings	0.244	[−0.040, 0.530]	0.300	[0.025, 0.583]
Party Ratings	2.253	[1.612, 2.921]	1.981	[1.354, 2.612]
Leader Ratings	1.516	[0.967, 2.082]	1.202	[0.679, 1.743]
Candidate → List	0.364	[0.102, 0.632]		
List → Candidate			0.987	[0.584, 1.409]
Party ID	0.516	[0.252, 0.789]	0.515	[0.247, 0.791]
		High Education		
Local Chances	−0.212	[−0.541, 0.116]	0.566	[0.269, 0.869]
Local Ratings	0.083	[−0.132, 0.296]	0.511	[0.303, 0.724]
Party Ratings	3.766	[3.106, 4.447]	2.840	[2.226, 3.435]
Leader Ratings	1.141	[0.745, 1.555]	0.636	[0.285, 0.997]
Candidate → List	0.139	[−0.049, 0.334]		
List → Candidate			0.099	[−0.094, 0.302]
Party ID	0.935	[0.737, 1.152]	0.560	[0.369, 0.756]
% Correctly Predicted		84.1%		84.6%
Observations		2,694		2,694
Monte Carlo Draws		1,500,000		1,500,000

Summary statistics of the posterior predictive distributions of parameters from the list and candidate vote equations, estimated with Bayesian multinomial probit models after including interaction variables between Education and each of the party-specific covariates. Only estimates for party-specific covariates are reported for simplicity, but the models include the same controls as in Table **??**. The 95% credible intervals are reported between brackets. The Gelman-Rubin multivariate PSRF statistic approximates to 1.01 for both models.

Table A6: Hypothesis Testing by Level of Education

	Method 1		Method 2	
Hypothesis	Probability	2log(B_{10})	Probability	2log(B_{10})
		Low Education (Education = 0)		
Local Chances	0.576	0.613	0.554	0.437
Local Ratings	0.653	1.265	0.609	0.886
Party Ratings	0.793	2.685	0.720	1.888
Leader Ratings	0.868	3.772	0.788	2.627
Contamination	0.999	13.218	0.994	10.192
		High Education (Education = 1)		
Local Chances	1.000	N/A	1.000	15.941
Local Ratings	1.000	16.282	0.997	11.863
Party Ratings	0.996	10.841	0.979	7.648
Leader Ratings	0.994	10.328	0.967	6.771
Contamination	0.346	−1.274	0.388	−0.914

Bayesian hypothesis tests based on the models reported in Table A5. Integrals are computed numerically using the MCMC draws. Method 1 compares the posterior distribution of the parameter of a vote model against the most credible value of the parameter in the other vote model (the median). Method 2 uses the difference between MCMC draws across vote models, restricting the correlation of coefficients to zero. B_{10} denotes Bayes factors. In all cases, we use non-informative prior probabilities $P(H_0) = 0.5$ and $P(H_1) = 0.5$.

Replication with Joint Conditional Logits

Tables A7 to A9 replicate the main models presented in the paper using a frequentist approach and multinomial logit models (also called conditional logit models when they include alternative-specific variables). We fit a joint model in a fashion similar to seemingly unrelated regressions, using the *suest* pre-built command in the Stata software package. The simultaneous model is fitted internally by duplicating and stacking the dataset, using interaction terms with all parameters of one model, and then fitting the full model user standard errors clustered by respondent. We cannot reproduce exactly the models we used in the main paper for testing the role of voter sophistication, but we rely on split samples to fit the joint model for respondents with lower and higher levels of education. We test differences across models using Wald tests and report the p-values in Table A9. Most of the key findings mentioned in the paper are substantively the same when computed with this alternative approach. For instance, we also find a stronger contamination effect from the list vote to the candidate vote, yet only among the less sophisticated voters.

Table A7: Joint Multinomial Logistic Models of List and Candidate Votes

		List Vote		Candidate Vote	
Party	Variable	Estimate	Confidence Interval	Estimate	Confidence Interval
	Local Chances	−0.206	[−0.634, 0.223]	1.114	[0.621, 1.606]
	Local Ratings	0.253	[−0.002, 0.508]	0.840	[0.536, 1.144]
	Party Ratings	5.383	[4.588, 6.178]	4.947	[4.199, 5.694]
	Leader Ratings	2.055	[1.493, 2.617]	1.521	[0.979, 2.062]
	Candidate → List	0.206	[−0.041, 0.453]		
	List → Candidate			0.406	[0.051, 0.761]
	Party ID	1.233	[1.028, 1.437]	0.838	[0.627, 1.049]
SPD	Coalition Ratings	−4.225	[−5.478, −2.972]	−4.324	[−5.460, −3.188]
	Age	−0.089	[−0.981, 0.804]	0.369	[−0.464, 1.203]
	Education	−0.500	[−1.028, 0.027]	0.405	[−0.071, 0.880]
	Gender	0.039	[−0.323, 0.400]	0.055	[−0.273, 0.382]
	Bavaria	−0.159	[−0.643, 0.324]	0.613	[0.144, 1.081]
	Intercept	2.456	[1.448, 3.465]	1.226	[0.299, 2.153]
Greens	Coalition Ratings	−4.032	[−5.433, −2.630]	−2.464	[−3.828, −1.100]
	Age	−0.877	[−2.089, 0.334]	0.105	[−1.052, 1.261]
	Education	0.298	[−0.420, 1.017]	0.512	[−0.171, 1.196]
	Gender	0.059	[−0.382, 0.500]	0.277	[−0.172, 0.726]
	Bavaria	0.247	[−0.316, 0.810]	0.353	[−0.202, 0.908]
	Intercept	1.239	[0.037, 2.442]	−0.139	[−1.301, 1.023]
FDP	Coalition Ratings	2.805	[1.544, 4.066]	0.236	[−1.621, 2.094]
	Age	−0.582	[−1.604, 0.439]	−3.000	[−4.881, −1.118]
	Education	0.154	[−0.457, 0.765]	−0.119	[−1.007, 0.768]
	Gender	−0.194	[−0.630, 0.242]	−0.225	[−0.835, 0.385]
	Bavaria	1.018	[0.260, 1.775]	1.465	[0.188, 2.742]
	Intercept	−2.229	[−3.538, −0.920]	−0.916	[−3.073, 1.241]
Left	Coalition Ratings	−3.326	[−5.053, −1.598]	−3.035	[−4.963, −1.106]
	Age	−0.696	[−2.382, 0.989]	0.440	[−1.148, 2.029]
	Education	−1.110	[−1.917, −0.304]	−0.156	[−0.959, 0.647]
	Gender	0.128	[−0.432, 0.689]	0.507	[−0.107, 1.122]
	Bavaria	−0.291	[−0.941, 0.360]	0.287	[−0.436, 1.011]
	Intercept	2.300	[0.901, 3.699]	0.210	[−1.161, 1.582]
	Observations	2,694		2,694	

Joint estimation of frequentist, multinomial logistic models using a stacked dataset and an interaction variable for each election. The joint model is computed using clustered standard errors by respondent. 95% confidence intervals are reported between brackets.

Table A8: Joint Multinomial Logistic Models of List and Candidate Votes

	List Vote		Candidate Vote	
Variable	Estimate	[Confidence Interval]	Estimate	[Confidence Interval]
		LOW EDUCATION (Sub-Sample with Education < 1)		
Local Chances	−0.031	[−0.613, 0.552]	0.784	[0.036, 1.532]
Local Ratings	0.329	[0.004, 0.654]	0.665	[0.276, 1.055]
Party Ratings	4.852	[3.951, 5.754]	4.519	[3.588, 5.449]
Leader Ratings	2.415	[1.726, 3.104]	1.866	[1.148, 2.583]
Candidate → List	0.322	[0.020, 0.623]		
List → Candidate			1.067	[0.515, 1.618]
Party ID	0.989	[0.704, 1.274]	0.906	[0.607, 1.205]
		HIGH EDUCATION (Sub-Sample with Education = 1)		
Local Chances	−0.592	[−1.220, 0.036]	1.116	[0.451, 1.782]
Local Ratings	0.169	[−0.255, 0.594]	1.110	[0.597, 1.624]
Party Ratings	6.242	[4.742, 7.741]	5.622	[4.340, 6.903]
Leader Ratings	1.590	[0.664, 2.515]	1.216	[0.371, 2.060]
Candidate → List	0.117	[−0.306, 0.540]		
List → Candidate			−0.038	[−0.532, 0.456]
Party ID	1.427	[1.120, 1.734]	0.875	[0.550, 1.201]
Observations	2,694		2,694	

Joint estimation of frequentist, multinomial logistic models using a stacked dataset and an interaction variable for each election, on two different subsamples (low and high education). The joint model is computed using clustered standard errors by respondent. 95% confidence intervals are reported between brackets.

Table A9: Hypothesis Testing, Frequentist Models

Hypothesis	H_1	H_0	p-value
	Full Sample		
Local Chances	$\beta^1 \neq \alpha^1$	$\beta^1 = \alpha^1$	0.0000
Local Ratings	$\beta^2 \neq \alpha^2$	$\beta^2 = \alpha^2$	0.0008
Party Ratings	$\alpha^3 \neq \beta^3$	$\alpha^3 = \beta^3$	0.2929
Leader Ratings	$\alpha^4 \neq \beta^4$	$\alpha^4 = \beta^4$	0.0742
Contamination	$\theta_{LC} \neq \theta_{CL}$	$\theta_{LC} = \theta_{CL}$	0.2826
	Low Education (Sub-Sample with Education < 1)		
Local Chances	$\beta^1 \neq \alpha^1$	$\beta^1 = \alpha^1$	0.0271
Local Ratings	$\beta^2 \neq \alpha^2$	$\beta^2 = \alpha^2$	0.1338
Party Ratings	$\alpha^3 \neq \beta^3$	$\alpha^3 = \beta^3$	0.4990
Leader Ratings	$\alpha^4 \neq \beta^4$	$\alpha^4 = \beta^4$	0.1396
Contamination	$\theta_{LC} \neq \theta_{CL}$	$\theta_{LC} = \theta_{CL}$	0.0079
	High Education (Sub-Sample with Education = 1)		
Local Chances	$\beta^1 \neq \alpha^1$	$\beta^1 = \alpha^1$	0.0000
Local Ratings	$\beta^2 \neq \alpha^2$	$\beta^2 = \alpha^2$	0.0011
Party Ratings	$\alpha^3 \neq \beta^3$	$\alpha^3 = \beta^3$	0.4172
Leader Ratings	$\alpha^4 \neq \beta^4$	$\alpha^4 = \beta^4$	0.4692
Contamination	$\theta_{LC} \neq \theta_{CL}$	$\theta_{LC} = \theta_{CL}$	0.5727

Wald tests of the null of equal coefficients, using estimates from the joint multinomial logistic regression models reported in Tables A7 and A8.