Denis Cohen: *Between Strategy and Protest: How Policy Demand, Political Dissatisfaction and Strategic Incentives Matter for Far Right Voting*

ONLINE APPENDIX

Summary Statistics

Variable	*Mean*	*SD*	*Min*	*Max*	*Count*	*Unique Obs*	*% Missing*
Varying across H = 53586 Choices							
Probability to Vote Far Right (PTV)	0.18	0.29	0	1		49070	8.43
Normalized PTV	0.08	0.15	0	1		49070	8.43
Policy Distance	0.42	0.27	0	1		41856	21.89
Policy Distance (debiased)	0.41	0.27	0	1.02		40761	23.93
Left-Right Placement of Far Right	0.75	0.3	0	1		44118	17.67
Varying across N = 48404 Individuals							
Left-Right Self-Placement	0.52	0.24	0	1		42861	11.45
Political Dissatisfaction	0.43	0.29	0	1		46906	3.09
Age When Left Full-Time Education							
≤ 16	0.18				8483	46415	4.11
16-19	0.37				17291	46415	4.11
≥ 20	0.44				20641	46415	4.11
Male	0.49				23554	48403	0
Age (×.01)	0.48	0.17	0.15	0.99		48265	0.29
Age (×.01), squared	0.26	0.17	0.02	0.98		48265	0.29
Union Household	0.37				17440	47425	2.02
Attendance of Religious Services							
> Once a Week	0.03				1164	40111	17.13
Once a Week	0.12				4702	40111	17.13
> Few Times a Year	0.34				13487	40111	17.13
Less Often	0.21				8573	40111	17.13
Never	0.3				12185	40111	17.13
Varying across J = 52 Choice Situations							
Far Right NP Seat Share	0.06	0.07	0	0.22		52	0
Far Right NP Vote Share	0.08	0.06	0	0.22		52	0
Far Right Polling Average	0.08	0.07	0	0.26		52	0
Far Right EP Vote Share	0.08	0.07	0	0.27		52	0
Far Right Government Involvement	0.13				7	52	0

TABLE A.1 *Summary statistics (pre-imputation).*

Models and Estimation

Software and Computation

The initial data management was preformed using Stata 12. Multiple imputation of missing data was performed in R using Amelia II (Honaker, King, and Blackwell 2015). The interim data processing and final processing of the estimation results were also performed in R. All models were implemented in Stan (Stan Development Team 2016a) via the R package 'rstan' (Stan Development Team 2016b).

Imputation Model

I divide my data analysis into two parts. I first create multiply imputed data sets, across which I perform Bayesian inference in a second step. This comes with the benefit of a considerably leaner computational intensity and hence, enormous time savings, compared to fully Bayesian approaches to missing data handling. For the first step, I generate $M = 5$ imputed data sets using the Expectation-Maximization Bootstrap algorithm implemented in AMELIA II (Honaker, King, and Blackwell 2015). This procedure relies on the assumptions that the unobserved data are missing at random and that the complete data are distributed multivariate normal.

I include all information from both left and right-hand sides of the regression model: Individual's subjective probability of a future vote for a far right party, the ideological distance metric, political dissatisfaction, education, age (linear and squared), gender, whether individuals' are/live with union members and how frequently they attend religious services. Additionally, I include variables on respondents' left-right self-placement, their left-right perception of the far right party in question, a sum score across the probability of future vote items for all parties, individuals' partisanship, discrete future vote intention for the far right and their intention to abstain in the next general election. I account for the clustered nature of the data by specifying country-waves as a cross-sectional grouping factor.

Post-estimation, I account for the variability in the MCMC estimates ran on different imputations by pooling posterior draws from the Markov chains ran on the imputed data sets (Zhou and Reiter 2010). Posterior medians and quantiles of the estimated parameters and derived quantities of interest, then, directly reflect the uncertainty of the imputation procedure. Although Zhou and Reiter (2010) point out that this procedure tends to produce deflated uncertainty estimates when the number of imputations is small my analyses presented in the paper and Online Appendix rely on the minimum requirement for imputed data sets of $M = 5$. This is because the estimation procedure performed on each of the imputed data sets is highly time consuming and computationally intensive in terms of both RAM and CPU usage.

As a safeguard against risking overly confident inference, I rerun the main analysis presented in the paper with $M = 25$ imputations. The results are presented below in Fig. A.1. As the Figure shows, using $M = 25$ as opposed to $M = 5$ imputations yields visually indistinguishable estimates, which suggests that using a larger number of imputations hardly changes the uncertainty estimates of my analysis.

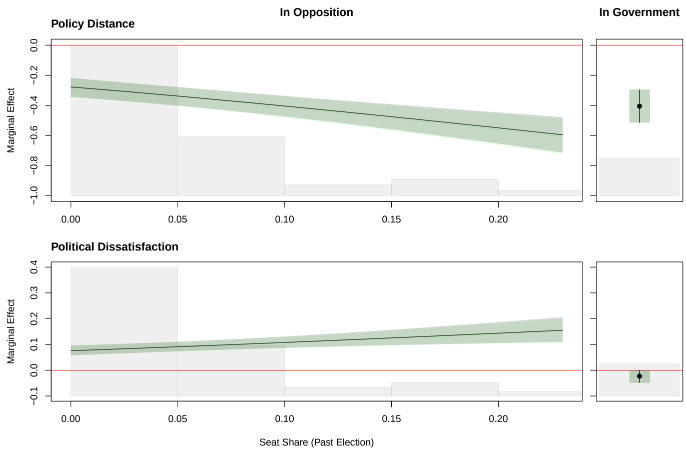


Figure A.1. *Replication of the main analysis, ran across $M = 25$ imputed data sets. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

Full Model Specifications

Regression Models. I specify a series of hierarchical regression models of individuals' probability to vote for the far right. These models feature intercepts, β_{0j}, which vary across context-specific choice situations. Furthermore, they feature slope coefficients β_c, $c = 1, ..., C$, multiplying C predictors x_{hc} (including transformed terms and interaction terms, but excluding a unit constant to multiply the intercept) included in the model. These coefficients do not vary and thus represent pooled effects across choice situations. Additionally, I include a random effect ν_i. When political contexts feature multiple far right parties, the analysis includes multiple choice calculi per individual. To account for the dependence among these observations, ν_i captures individual-specific idiosyncrasies for individuals facing multiple choices while assigning a joint intercept to all remaining individuals for whom only one choice calculus is observed.

In order to accommodate the zero-inflated distributional property of the dependent variable, I specify hierarchical tobit models. These take the general form of

$$y_h = 0 \text{ if } y_h^* \leq 0$$
$$y_h = y_h^* \text{ if } y_h^* > 0$$

where

$$y_h^* = \beta_{0jk} + \sum_{c=1}^{C} \beta_c x_{hc} + \nu_i + \epsilon_h$$

The varying intercepts β_{0j} are distributed univariate normal such that

$$\beta_{0j} = \mu_{\beta_0} + \psi_j, \psi \sim \mathrm{N}(0, \sigma_\psi)$$

Similarly, the random effect ν_i is distributed univariate: $\nu_i \sim \mathrm{N}(0, \sigma_\nu)$.

Prior Specifications. As I estimate these models in a fully Bayesian framework, it is necessary to specify prior distributions for all estimated parameters. I specify weakly informative normal priors or the intercept and slope coefficients, $\mu_0, \beta \sim \mathrm{N}(0, 10)$, and half-cauchy priors for the variance terms such that $\sigma_\epsilon, \sigma_\nu, \sigma_\psi \sim \mathrm{Cauchy}^+(0, 5)$.

Weighting. The estimation uses a weighting scheme which concurrently allows for disproportionate influence of individuals within country-waves due to different sampling probabilities and equalizes the disproportionate influence between country-waves and party-specific choice situations due to different cluster sample sizes. Toward that end, I employ the sampling or poststratification weights included in the EES and then weight all observations h clustered in a given choice situation j such that their summed weighted is equal across all choice situations: $\sum_{h_j=1}^{H_j} w_{hj} = \frac{N}{J}$ for all $j = 1, ..., J$.

Calculation of the Quantities of Interest

The primary quantities of interest throughout the main empirical section of the paper are *conditional expected values* and *conditional average marginal effects*. This section explicates how I obtain these quantities from the regression estimates.

Conditional Expected Values. The *expected value* of an observed (i.e., possibly censored) response after tobit estimation for a given observation i is defined as

$$\mathbb{E}(y_i|\mathbf{x}_i) = \Phi\left(\frac{\mathbf{x}_i'\beta}{\sigma_\epsilon}\right)(\mathbf{x}_i'\beta + \sigma_\epsilon \lambda_i)$$

where

$$\lambda_i = \frac{\phi(\mathbf{x}_i'\beta/\sigma_\epsilon)}{\Phi(\mathbf{x}_i'\beta/\sigma_\epsilon)}$$

and ϕ and Φ denote the probability density and cumulative distribution functions of the normal distribution, respectively (see Greene 2012, 848).

As my model involves multiple interaction effects, I am interested in the expected value of y_i conditional on the values of the interacted variables. Let u, v and w denote the interacted predictors. Furthermore, let $\mathbf{z}$ represent a vector of all background covariates not involved in the interaction. My quantity of interest is the expected value of y_i conditional on any desired values $\tilde{u}$, $\tilde{v}$ and $\tilde{w}$ while keeping the background covariates fixed: $\mathbb{E}(y_i|\tilde{u}, \tilde{v}, \tilde{w}, \mathbf{z}_i)$.

Conditional Marginal Effects. Suppose we are interested in the marginal effect of u conditional on any desired values $\tilde{w}$ while, keeping values of and v and the background covariates at their observed values. For each observation $i = 1...N$, the marginal effect of u conditional on $\tilde{w}$, v, and $\mathbf{z}_i$ can be retrieved by taking the difference in the conditional expected values of y_i when marginally incrementing u_i over the absolute value of the increment. Here, I calculate the conditional marginal effect of u when incrementing u_i around its observed value, i.e., when going from $u_i' = u_i - 0.005$ to $u_i'' = u_i + 0.005$. The sample average conditional marginal effect can then be retrieved by taking the expectation over all observations. As the sample averages might not be representative of the underlying populations, I compute weighted average conditional marginal effects, using the weighting scheme described above:[12]

$$\mathbb{E}\left(\text{weight}_i \times \frac{\mathbb{E}\left(y_i|u_i'', \tilde{w}, v, \mathbf{z}_i\right) - \mathbb{E}\left(y_i|u', \tilde{w}, v, \mathbf{z}_i\right)}{|u_i'' - u_i'|}\right)$$

Reporting uncertainty. As I estimate my models in a Bayesian framework, I retrieve S posterior draws for all model coefficients which are sampled from their respective posterior distributions. By repeating the calculation of the quantities of interest for each set of posterior draws, I directly obtain posterior distributions of these quantities. Uncertainty can then be straightforwardly reported in the form of quantiles (e.g., 95% intervals) or posterior standard deviations (Bayesian standard errors).

[12]Weighting does not substantially change the estimates. Thus, average conditional marginal effects and weighted average conditional marginal effects do not produce divergent findings.

Robustness Checks

Alternative Model Specifications

Hierarchical Linear Model. In order to test the robustness of my findings, I first re-estimate Eqs. (1) and (2) using a hierarchical linear specification. The model formula specifying the linear prediction, weighting scheme, and choice of priors remains the same as the one used in the main analysis.

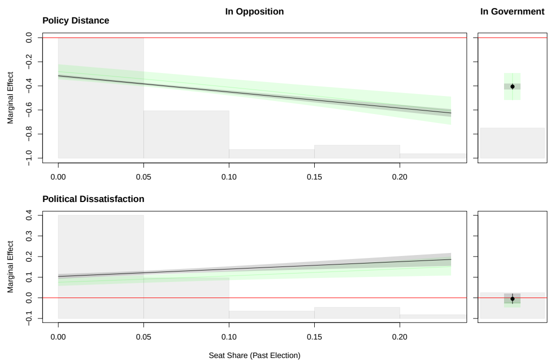


Figure A.2. Replication of the main analysis, using a hierarchical linear specification instead of a hierarchical tobit specification. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.

Hierarchical Hurdle Model. Additionally, I specify a hierarchical following Cragg (1971). This specification relaxes the assumption of the tobit model that the data generating processes governing the occurrence of zeroes and the variation in non-zero outcomes in the outcome variable can be summarized by the same set of parameters.

As Figs. A.2 and A.3 show, the prediction from these alternative analyses vastly overlap with those presented in the main analysis and yield the same substantive conclusions.

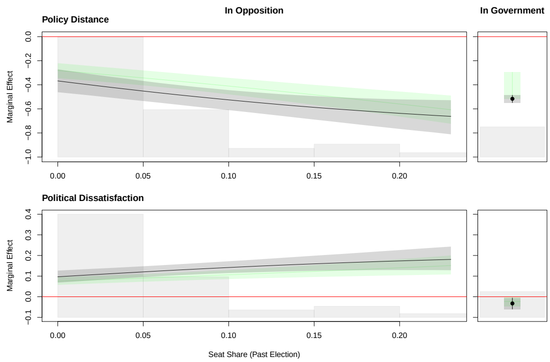


Figure A.3. *Replication of the main analysis, using a hierarchical two-part specification akin to Cragg (1971) instead of a hierarchical tobit specification. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

Unpooled Estimation and Subsets of Parties

For an intuitive visual understanding of how the magnitude of the effects of policy demand and political dissatisfaction is conditioned by contextual incentives, I pursue what Gelman and Hill (2007) call an unpooled estimation strategy. In all plots presented below, the ordering of parties in government along the x-axis follows the alphabetical order of the country names. It has no substantive meaning and is unrelated to the estimation procedure.

In a first step, I estimate regressions of vote probabilities on policy demand, political dissatisfaction, and the micro-level controls separately across clusters to retrieve cluster-specific estimates of average marginal effects under tobit, linear, and hurdle model specifications. In a second step, I then specify a macro-level model, regressing the first-step estimates on my contextual predictor, the share of seats in the past national election. In this second step, I account for the uncertainty of the first-stage estimates using the WLS-approach suggest by Lewis and Linzer (2005).

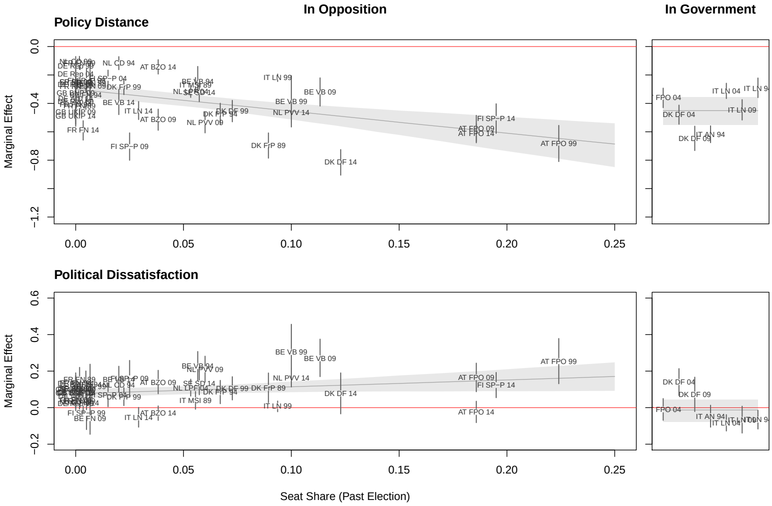


Figure A.4. Context-specific estimates using a tobit specification. Posterior medians and 95% posterior intervals.

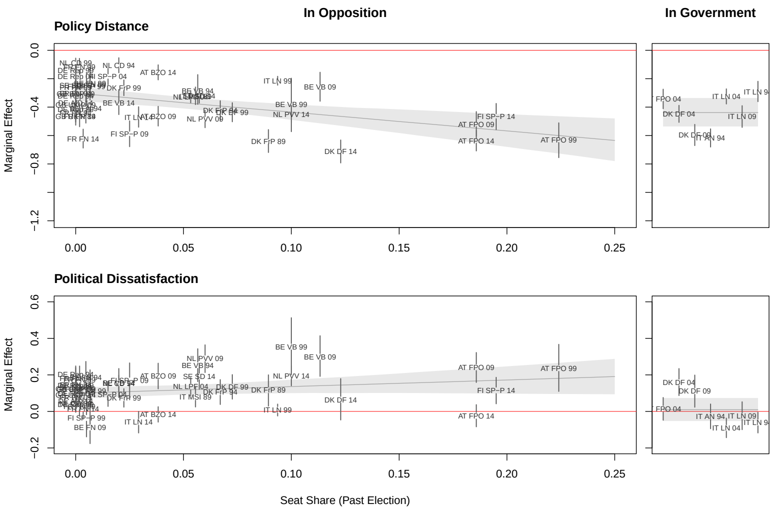


Figure A.5. Context-specific estimates using a linear specification. Posterior medians and 95% posterior intervals.

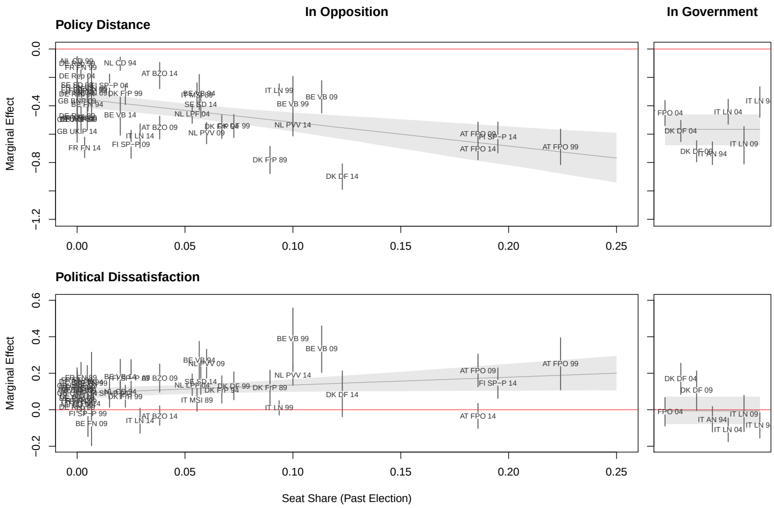


Figure A.6. Context-specific estimates using a two-part specification. Posterior medians and 95% posterior intervals.

Next, I replicate the above analyses to test whether the contextual moderation effects are robust to the exclusion of certain subsets of parties. First, I subset the sample to parties of the *populist radical right*, excluding parties of the *non-populist extreme right*. In particular, I exclude the Italian AN and British BNP as members of the 'old' far right as opposed to the 'new' radical right. These concurrently represent the only parties in the sample which are non-populist (Mudde 2007). Secondly, I subset the sample to *anti-immigration parties*. Therefore, I exclude the AN, UKIP (2009) and the AfD (2014) – parties for which the immigration issue played a subordinate role at the time of the respective surveys.

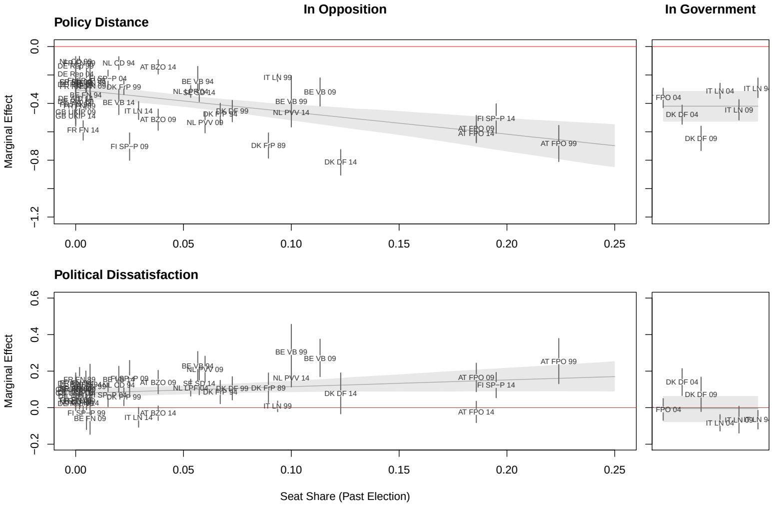


Figure A.7. *Context-specific estimates using a tobit specification. Does the exclusion of non-populist extreme right parties change the findings? No.*

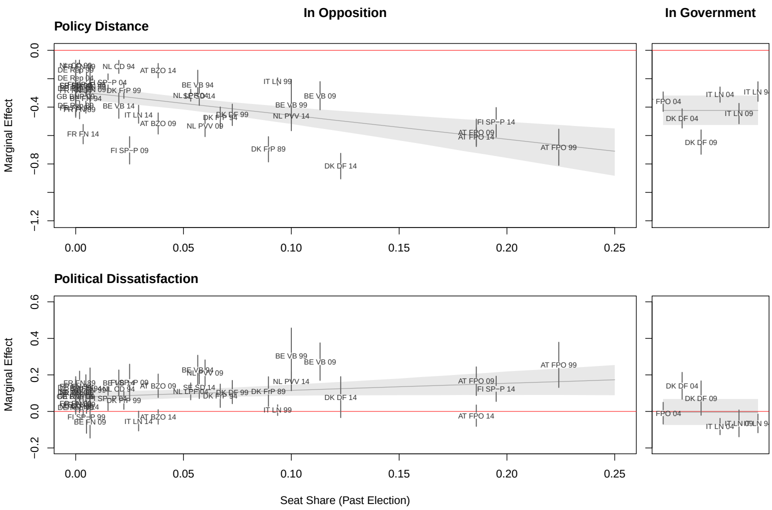


Figure A.8. *Context-specific estimates using a tobit specification. Does the exclusion of parties for whom immigration is not central change the findings? No.*

Lastly, Fig. A.9 replicates the analysis presented above in Fig. A.4 while testing whether the estimates of the average marginal effects of policy demand and political dissatisfaction vary by far right legislative strength (seat shares) for far right parties in both opposition and in government, i.e., on both the left-hand side and the right-hand side of the Figure.

Of note, variation in the seat shares of far right parties in government is limited and the number of unique observations ($J = 7$) of far right parties in government is small. Therefore, the uncertainty estimates for the moderation patterns among far right parties in government are very large. Even though it appears that the marginal effect of policy distance is decreasing (increasing in magnitude) in far right strength, the slope of the marginal effects plot is in fact positive roughly 16% of the time. The estimates also confirm that governing far right parties jeopardize their appeal to dissatisfied voters at all levels of legislative strength. Thus, in studying voting behavior for far right parties in government, there is substantively not much added value in conditioning the effects of policy demand and political dissatisfaction on legislative strength. Therefore, the findings concerning governing far right parties in the paper and in the other parts of the Online Appendix present unconditional effects.

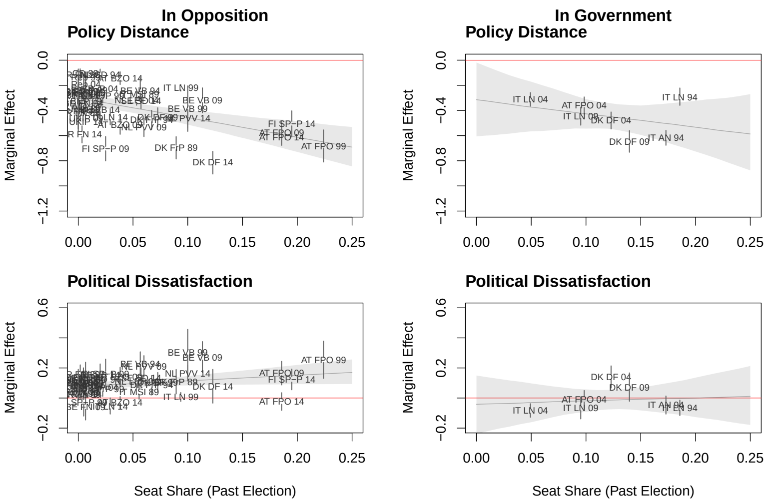


Figure A.9. Context-specific estimates using a tobit specification. Posterior medians and 95% posterior intervals.

Alternative Specifications of Micro-Level Measures

Outcome Variable: Normalized PTV Metric. Subjective party-specific probability to vote scores are a fruitful way to elicit how attractive individuals consider a given party beyond their post-hoc revealed vote choice. This is particularly valuable for the study of small parties which few respondents end up voting for (van der Eijk et al. 2006). A common criticism of PTV scores, however, is that numerical values representing subjective vote probabilities are not necessarily equivalent across individuals because individuals' reporting the same (unconditional) probability of voting for the far right may have highly different inclinations of actually doing so depending on the probabilities they assign to the other available alternatives.

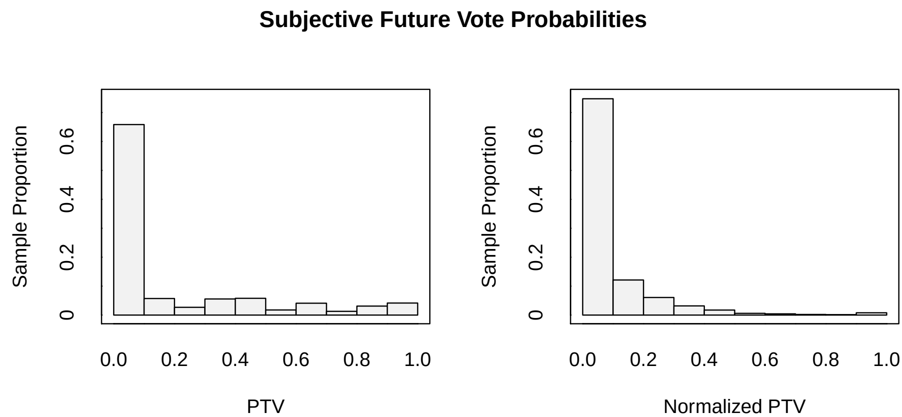


Figure A.10. Histograms of subjective vote probabilities, original and normalized versions.

To address this problem, I conduct a robustness check using a normalized version of the PTV metric. That is, I normalize the previous measure for each respondent by the sum of their subjective vote probabilities across all available parties. For every respondent with a non-zero subjective probability of turning out in future, this yields the probability of voting for a given far right party (as opposed to voting for any other party) – conditional on actually turning out. For example, an individual reporting a 0.5 probability and an individual reporting a 0.8 probability of voting far right while reporting zero probabilities of voting for all other parties both receive a normalized probability of 1, indicating that if they were to turn out, they would certainly vote for the far right. An individual reporting a 0.8 probability of voting for the far right along with a 0.5 probability of voting for the mainstream right and a 0.3 probability of voting or the mainstream left, in contrast, receives a normalized probability of 0.5, indicating that if they were to turn out, there are equal chances of voting for the far-right and voting for another party. I assign zeroes for those respondents who assign zero probabilities to all options in the choice set.

Figure A.10 compares the distributions of the unconditional and normalized subjective vote probabilities. Unsurprisingly, the normalized PTV metric is more skewed to the right than the original metric as reported individual vote probabilities for the far right are depressed by individuals' vote probabilities for other parties. Both metrics have a large point mass (> 60%) at zero, indicating that many respondents categorically negate the possibility of ever voting for the far right.

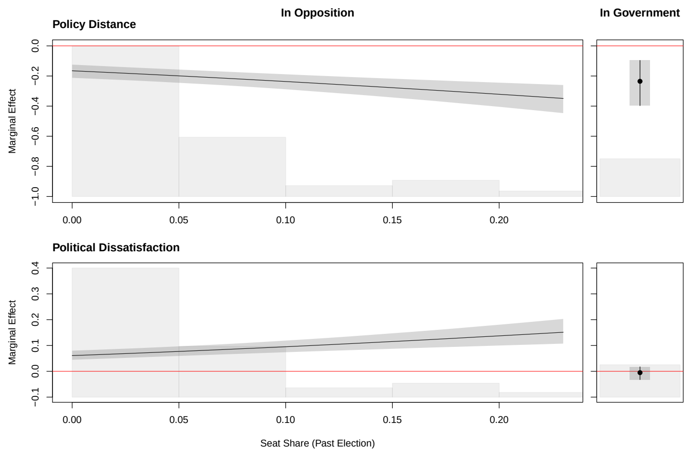


Figure A.11. Replication of the main analysis, using normalized subjective vote probabilities.

Since the normalization changes the distribution of the outcome variable considerably (see summary statistics in Table A.1), unlike in previous robustness checks, one cannot directly compare the magnitude of the findings reported in Fig. A.11 with those in the main analysis. The model produces weaker effects, an artifact of the normalization of the PTV metric which strongly lowered the mean and the variance of the outcome variable. This model also exhibits weightier effects of political dissatisfaction relative to those of policy demand, suggesting that political dissatisfaction plays an even greater role once we take into account if voters consider far right parties the primary or only options for their future vote choices. The increase in the relative importance of political dissatisfaction notwithstanding, the results confirm the substantive conclusions from the main analysis.

Accounting for Party Position Rationalization Bias. A well-known problem in using Euclidean distance metrics between voters' self-placement on the left-right scale and their subjective placement of parties on the same scale is party position rationalization bias. Rationalization of party position occurs when individuals locate parties they like, and tend toward electorally, closer to their own position while shifting parties they dislike farther away. This tainted perception of party positions results in upward-biased estimates of the effect of policy proximity/distance.

To account for this type of bias while maintaining that idiosyncratic perceptions of party positions are substantively meaningful and behaviorally relevant, I follow Weber's (2015) procedure to estimate and correct for party position rationalization. This approach rests on the comparison of the left-right placement of a given voter i for party p with the mean placement of party p among voters with the same ideological disposition on the left-right scale who have a neutral position towards party p. As these voters display neither a strong like of dislike for party p, their average placement of party p is assumed to be untainted, and thus a reliable measure for the parties' position. By matching on left-right self-placement, on the other hand, the approach acknowledges that variance in party placement resulting from individuals' ideological self-placements are meaningful and should not be discarded.

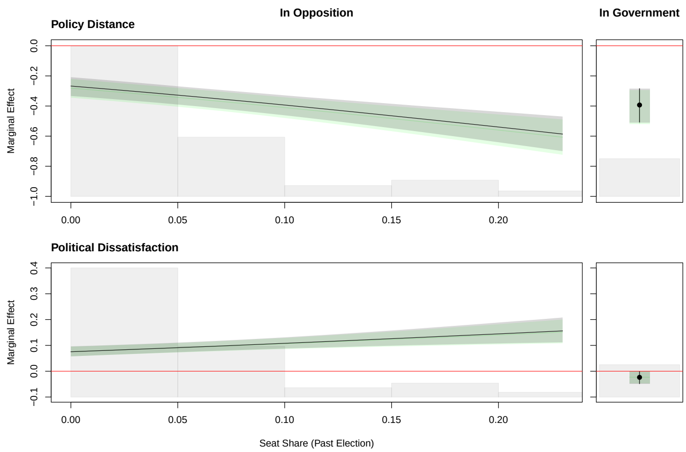


Figure A.12. Replication of the main analysis, correcting for party position rationalization bias in the policy distance metric. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.

The results, displayed in A.12, show a slight decrease in the magnitude of the effects of policy demand but do not change the substantive conclusions drawn from the main analysis.

Accounting for Potential Endogeneity of Political Dissatisfaction. This robustness check addresses the possibility that one predictor, political dissatisfaction, is endogenous to another – proximity to the radical right's policy platform. The risk of ignoring a possible (causal) relationship between policy demand and political dissatisfaction would be a bias in the effects of the former. Jointly included in an additive model with policy demand, political dissatisfaction would "block" the indirect effects of policy demand that unfold through political dissatisfaction. The result, presuming that the policy distance metric affects both dissatisfaction and PTVs negatively and that dissatisfaction affects PTVs positively, would be a depressed magnitude of the coefficient on the distance metric, representing only the remaining direct effect.

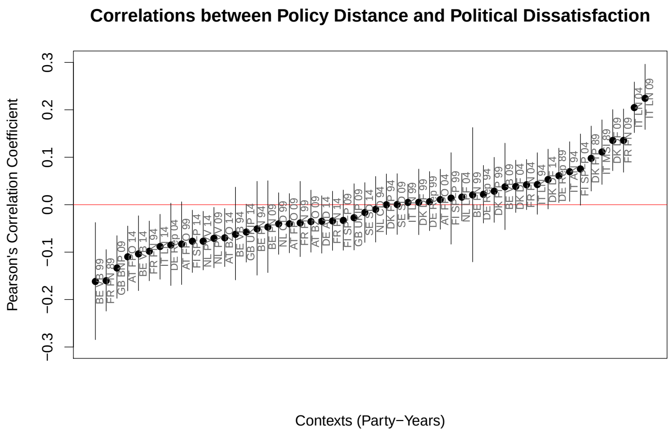


Figure A.13. Context-specific correlations between policy demand and political dissatisfaction. Posterior medians and 95% posterior intervals. Point estimates and 95% confidence intervals.

To scrutinize whether this problem materializes, I first analyze the bivariate relationship of the two predictors. Figure A.13 plots Pearson correlation coefficients for all 52 contexts included in the analysis. The insights are two-fold. First, ranging between roughly -.2 and .2, correlations between political dissatisfaction and individual's proximity to far right parties' policy platform are of limited magnitude, and in many instances, not significantly distinguishable from zero. Second, while in some contexts, the correlations are negative (indicating that those who agree *less* with the far right's policy platform are *more* satisfied), in others, they are positive (indicating that those who agree *less* with the far right's policy platform are *less* satisfied). We should therefore not presume that ideological compatibility with the far right's policy stances results in increased political dissatisfaction per se.

I conduct an additional robustness check, substituting the measure for political dissatisfaction with the residuals of a series of context-by-context regressions of political dissatisfaction on the policy distance metric. Under this specification, the residuals may be interpreted as the portion of political dissatisfaction that is not determined by policy demand. Moreover, under this specification, policy demand and the substitute measure of political dissatisfaction are orthogonal by construction – hence, the effect of policy demand will be unaffected by the inclusion of the substitute measure of dissatisfaction.

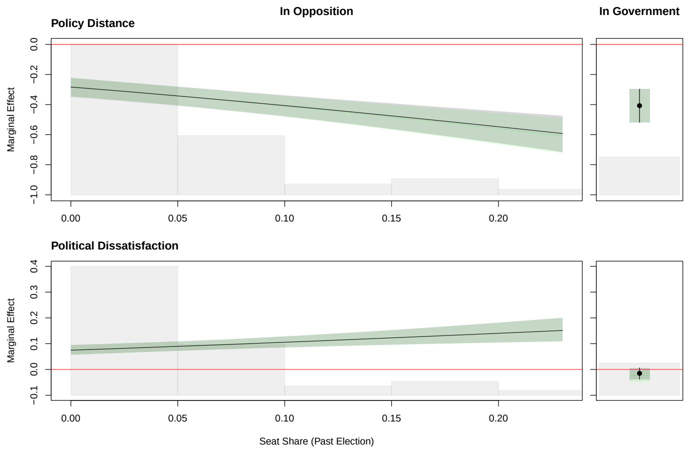


Figure A.14. Replication of the main analysis, correcting for potential endogeneity of political dissatisfaction. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.

The results, displayed in A.14, are fully in line with those presented in the main analysis. There is thus no indication that potential endogeneity of political dissatisfaction results in biased inferences.

Change in the Measure of Dissatisfaction: 1989-2009 Subset. Due to constraints of data availability, my analysis uses different measures of political dissatisfaction. For the 1989-2009 waves, I make use of an item prompting respondents to rate how satisfied they were with the way democracy worked in their country. In the 2014 wave, this item was replaced with an item asking whether respondents believed their voice counted in their country. Both items are measured on similar ordinal scales. Divergences between the 2014 item and the 1989-2009 item in terms of means, variances as well as bivariate and multivariate relationships with demographic, attitudinal and behavioral indicators are minor. More importantly, any of these divergences are consistently smaller than divergences over time across the five waves which featured the initial dissatisfaction item. Nonetheless, to ensure that the inconsistency in my operationalization does not critically drive my findings, I repeat the analysis on a 1989-2009 subsample.

The results show a slightly stronger increase in the marginal effect of political dissatisfaction as the seat share of oppositional far right parties increases than in the

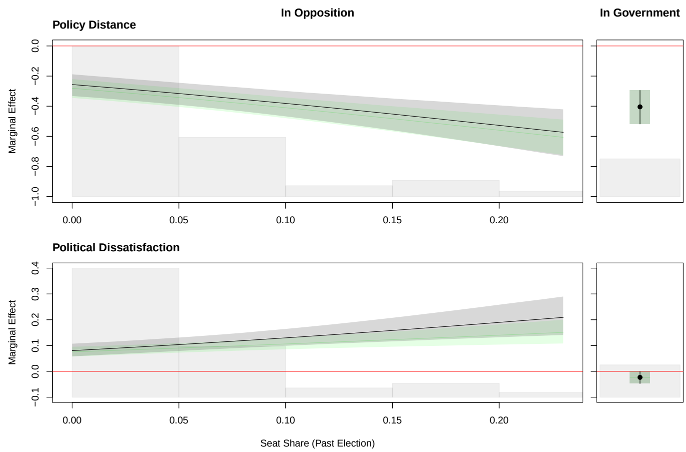


Figure A.15. Replication of the main analysis, subsetting the data to the 1989-2009 waves of the EES. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.

1989-2014 main analysis. However, the difference is not substantial and does not change the substantive conclusions drawn from the main analysis.

Replication Using Alternative Measures Based on ESS 1-8. The analysis presented in the main text relies on data from the European Election Studies, 1989-2014. This choice is motivated by a desire to maximize not only spatial but also temporal heterogeneity in the far right party family for my comparative inquiry into far right voting. Arguably, this choice comes at the cost of having to rely on rather unspecific measures to capture the key theoretical concepts of *policy demand* and *political dissatisfaction* (in terms of anti-establishment sentiment).

In order to scrutinize whether the results replicate using more refined measures, I replicate the analysis using data from rounds 1-8 of the European Social Survey (ESS 1-8 2018). While this considerably reduces the temporal scope to electoral contexts between 1999 and 2015, it increases the spatial scope by including Norway and Switzerland.[13] For

[13] I include the following parties and electoral contexts: *Austria:* BZO 06*, BZO 08, BZO 13, FPO 02*, FPO 06*, FPO 08, FPO 13; *Belgium-Wallonia:* FN 99, FN 03, FN 07, FN 10, FN 14; *Belgium-Flanders:* VB 99, VB 03, VB 07, VB 10, VB 14; *Switzerland:* SVP-UDC 99*, SVP-UDC 03*, SVP-UDC 07*, SVP-UDC 11*, SVP-UDC 15*; *Germany:* NPD 05, NPD 09, NPD 13, Rep 02, Rep 05, Rep 09, AfD 13; *Denmark:* FrP 01, FrP 05,

the key variables, I use vote choice in the previous national election (in place of PTVs), anti-immigration preferences, estimated as a latent trait per an ordinal item response model that accounts for differential item functioning (in place of policy demand),[14] and trust in politicians (in place of political dissatisfaction).[15] Trust in politicians, unlike trust in parties, has been consistently included in all ESS waves and is therefore used here. It also correlates extremely closely (> .8) with trust in parties and can therefore be considered a good proxy of anti-establishment sentiment. The contextual moderator, as in the main analysis, is the seat share of the far right in the national legislature at the time when respondents cast their ballot vote choice, i.e., the seat share determined in the previous election.

Figure A.16 reports the average marginal effect from hierarchical logistic regressions, conducted separtely for far right parties in opposition and far right parties in government, analogously to the main analysis. In presenting the findings, I asjusted the scales of the predictors such that the graphical display corresponds to that of the main analysis: Effects of immigration preferences (policy demand) are displayed in terms of pro-immigration preferences, and thus in terms of increasing distance to the anti-immigration platform that far right parties campaign on. These effects are therefore negative. Effects of trust in politicians (political dissatisfaction) are a function of increasing mistrust and thus positive. Furthermore, both measures are standardized such that they can be interpreted on the same

DF 01, DF 05*, DF 07*, DF 11*; *Finland:* SP-P 99, SP-P 03, SP-P 07, SP-P 11, SP-P 15; *France:* MNR 02, FN 02, FN 07, FN 12; *United Kingdom:* BNP 05, UKIP 10, UKIP 15; *Italy:* LN 01, LN 06*, LN 13; *Netherlands:* LPF 02, LPF 03*, LPF 06, PVV 06, PVV 10, PVV 12*; *Norway:* Fr 01, Fr 05, Fr 09, Fr 13; *Sweden:* SD 10, SD 14. Party-years marked with an asterisk* indicate instances with far right government involvement in the legislative period preceding the election.

[14]The latent trait is estimated from three items: (1) "To what extent do you think [country] should allow people of the same race or ethnic group as most [country] people to come and live here?", (2) "How about people of a different race or ethnic group from most [country] people?", and (3) "How about people from the poorer countries outside Europe?". Response categories for all questions are allow many, allow some, allow a few, allow none. The measurement model is $\mathrm{y}_{ik} = \mathrm{logit}^{-1}(\tau_{ck} - \lambda_k \eta_i - \theta_{jk}$, where y_{ik} is respondent i's response to item k, τ_{ck} are item-specific thresholds, λ_k are item-specific loadings, and η_i is the latent measure of anti-immigration preferences for respondent i. θ_{jk} is a contextual random effect with item-specific scale that controls for differential item functioning (see Stegmueller 2011). I retrieve posterior medians of η_i and use these as the measure of policy demand in my analysis.

[15]The item is "Please tell me on a score of 0-10 how much you personally trust each of the institutions I read out. 0 means you do not trust an institution at all, and 10 means you have complete trust."

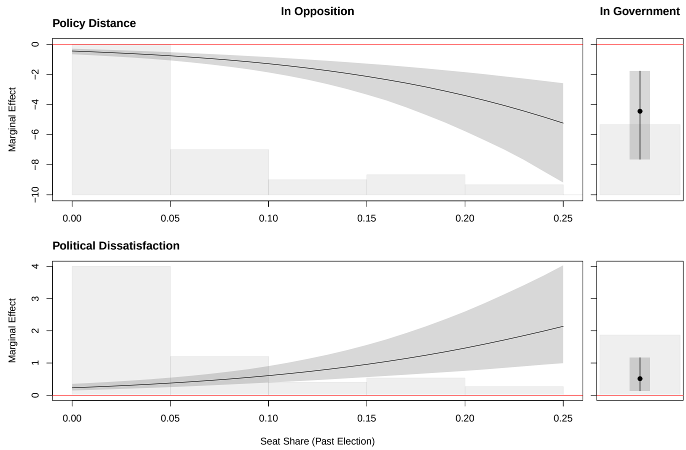


Figure A.16. Replication of the main analysis, using alternative measures and data from ESS Rounds 1-8.

scale. The average marginal effects thus present the change in the predicted probability of voting for a far right party (in percentage points) for a standard deviation increase in each of the predictors.

Despite using a different outcome measure and a vastly different sample of spatio-temporal contexts, the results support the substantive conclusions drawn from the main analysis. Substantive demand for anti-immigration policies is relatively more important than mistrust in politicians. Furthermore, among far right parties in opposition, the effect of substantive demand is increasing decisively in the far right's prior legislative strength; the effect of mistrust in politicians is also increasing, yet more mildly so. Far right parties in government can attract voters by substantive demand at similar levels to strong far right parties in opposition. In slight contrast to the main analysis, far right parties in government weakly attract voters on dissatisfaction/mistrust. The effect is, however, substantively very small and, as hypothesized, much smaller than among strong oppositional far right parties. This supports the argument that government involvement widely reduces the credibility of far right parties' anti-establishment appeal.

Alternative Specifications of the Contextual Moderator

Vote Shares in the Past National Election. In general elections held under disproportional electoral rules, electorally strong far right parties with little parliamentary presence might provide similar strategic incentives to potential voters as far right parties with pronounced legislative strength, e.g. by setting the political agenda and influencing mainstream parties during electoral campaigns. Therefore, I rerun my analysis using far right parties' vote share in the most recent general election in place of their seat share in the current legislature as the contextual moderator.

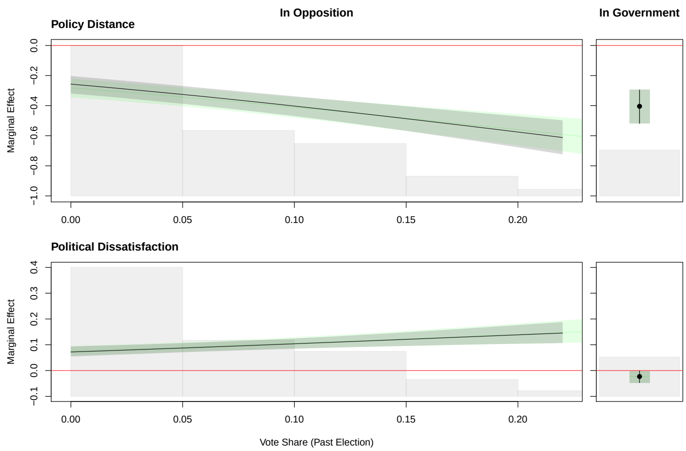


Figure A.17. Replication of the main analysis, using vote shares in the previous national election as the contextual moderator. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference. The range of the predictions on the left hand side corresponds to the range of the alternative contextual moderator and may therefore differ from the range of the prediction from the main analysis.

The results presented in Fig. A.17 show that the discrepancy between vote and seat shares in rather disproportional electoral systems (France, United Kingdom) does not critically drive the findings reported in the main text.

Votes Shares in EP Elections. Given that the field time of the European Election Studies is in the weeks following elections to the European Parliament, we may expected that voters' decision calculi are more heavily influenced by the impact far right parties made in these election rather than by their presence in, or absence from, national parliament in the months or years before the survey.

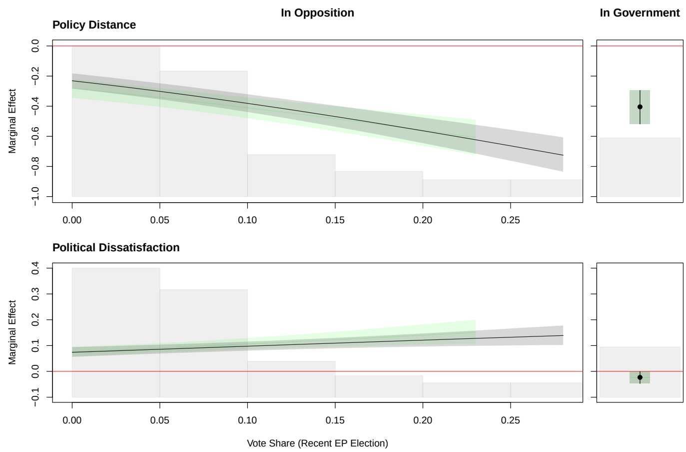


Figure A.18. *Replication of the main analysis, using vote shares in the most recent election to the European Parliament as the contextual moderator. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference. The range of the predictions on the left hand side corresponds to the range of the alternative contextual moderator and may therefore differ from the range of the prediction from the main analysis.*

In order to scrutinize if my arguments on the repercussions of contextual incentives holds given far right parties' performance in EP elections, I replicate the main analysis using far right vote shares in the most recent EP election as the contextual moderator. Since EP election are, and have been, vastly proportional, I focus on vote shares in the following test. The results, displayed in Figure A.18, are in line with the results presented in the main analysis but display a marginally stronger increase in the marginal effect of policy demand as EP vote shares of oppositional far right parties. This can likely be attributed to the few but notable instances in which far right parties' performance in EP elections was far better than their performance in the preceding national election. This indicates that voters are attentive to these incentives and update their expectation on the far right's credibility.

Pre-Survey Public Opinion Polls. Following this logic, we may expect that voters to respond to public opinion polls. Therefore, I replicate the analysis using party-specific polling averages in the two month prior to the survey. I use data made available by Jennings and Wlezien (2016) and updated by Mark Kayser, Matthias Orlowski and Jochen Rehmert as part of their ongoing research. Where national polling data was unavailable, I used weighted proportions of vote intentions (excluding prospective non-voters) from the most recent Eurobarometer waves prior to the EES field time. For small parties that were subsumed under 'Others' in polls and the EB vote intention question, I set the value to zero.

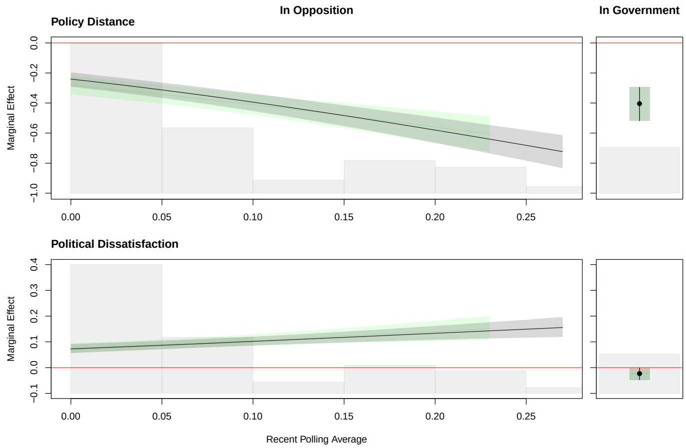


Figure A.19. *Replication of the main analysis, using parties' polling averages in the two months prior to the survey as the contextual moderator. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference. The range of the predictions on the left hand side corresponds to the range of the alternative contextual moderator and may therefore differ from the range of the prediction from the main analysis.*

As one can see in Fig. A.19, the results are in line with those presented in the main analysis and those presented in the preceding robustness check. Altogether, then, the robustness checks lend further credibility to the argument presented in the paper: The substantive conclusions hold across varying conceptualizations and operationalizations of contextual incentives.

Robustness to Contextual Variables

This section tests the robustness of the proposed micro-macro interactions to competitive configurations in the national party landspace. Since the primary effect(s) of interest are the interaction effects of legislative strength on the one hand and policy demand and political dissatisfaction, respectively, on the other, an effective control variable strategy requires that alternative contextual variables that may account for variation in the effects of the two micro-level predictors be interacted with them as well. Therefore, the model from Eq. (1) in the main text extends to

$$
\begin{aligned}
\text{ptv}_h^* =& \beta_{0jk} + \beta_1 \text{dist}_h + \beta_2 \text{dissatisfact}_i + \beta_3 \text{seat share}_j \\
&+ \beta_4 \text{dist}_h \times \text{seat share}_j + \beta_5 \text{dissatisfact}_i \times \text{seat share}_j + \beta_6 \text{control}_j \\
&+ \beta_7 \text{dist}_h \times \text{control}_j + \beta_8 \text{dissatisfact}_i \times \text{control}_j \\
&+ \mathbf{x}_i' \gamma + \nu_i + \epsilon_h
\end{aligned}
\tag{3}
$$

As even the inclusion of a single contextual control variable thus requires the inclusion of multiple interaction terms per model, I check the robustness of my findings to contextual variables one at a time.

Toughness of Mainstream Competitor. First, I test whether the results hold when taking into account alternative options for voters with strongly right-leaning voters. I control for the position of the right-most mainstream competitor of the far right, a variable coined ‘toughness’ by Arzheimer (2009). For this purpose, I use data from the CMP/MARPOR project (Volkens et al. 2017). I focus on members of the conservative, christian democratic, liberal, and social democratic party families which hold at least 5% of the seats in the national legislature.

For every electoral context, I identify the rightmost position out of this subset of the far right’s competitors. I do so using two alternative CMP measures as ratio scales: (1) the standard left-right (*rile*) measure and (2) a measure of the far right’s core issues of national identity, $natident_{p_t} = \frac{per601_{p_t}+per608_{p_t}-(per602_{p_t}+per607_{p_t})}{per601_{p_t}+per602_{p_t}+per607_{p_t}+per608_{p_t}}$, constructed from items *per601* (National way of life: positive), *per602* (National way of life: negative), *per607* (Multicultarilism: positive) and *per608* (Multiculturalism: negative).

As one can see in Figs. A.20 and A.21, the results displayed in the main analysis are robust to the inclusion of either version of measuring the ‘toughness’ of the far right’s mainstream competitors.

Presence of Other Anti-Establishment Parties. Second, I test whether the results hold when taking into account alternative options for politically dissatisfied voters. I control for the availability of other anti-establishment parties, defined by the presence (=1) or absence (=0) of such parties in national parliaments at the time of the survey. I do so

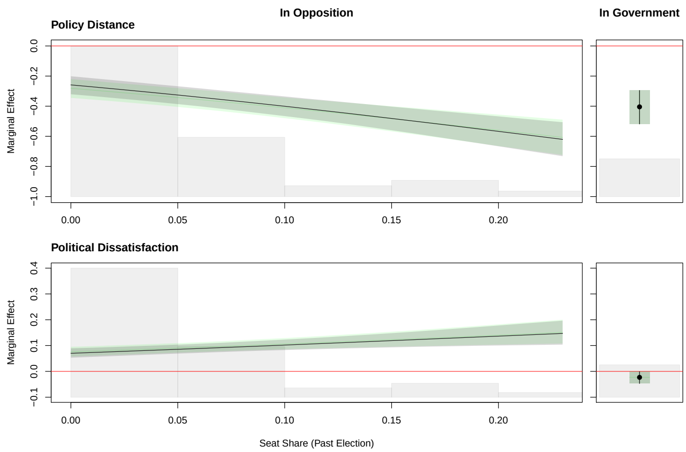


Figure A.20. *Replication of the main analysis, controlling for 'toughness' of the right-most mainstream competitor (left-right). Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

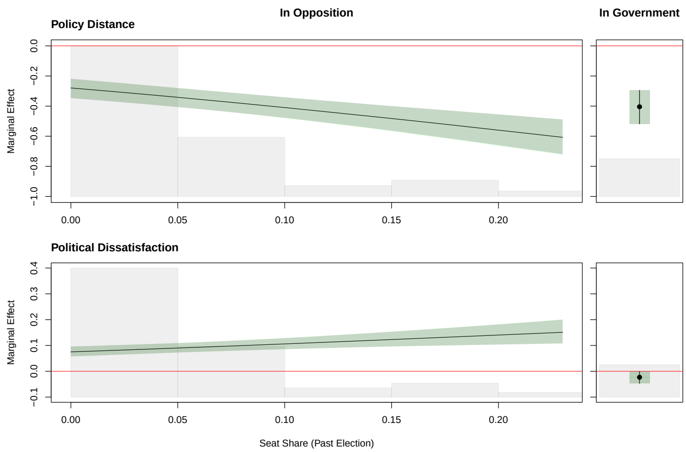


Figure A.21. *Replication of the main analysis, controlling for 'toughness' of the right-most mainstream competitor (national identity). Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

indiscriminately of the core ideology of other anti-establishment competitors. This results in the following instances in which far right parties competed with other anti-establishment parties:

Country	Year(s)	Party	Anti-Establishment Competitor(s)
AT	09-14	FPO	BZO, TS (14)
		BZO	FPO, TS (14)
BE-F	09	VB	LDD
DE	94-04	REP	PDS/LEFT
	14	AfD	PDS/LEFT
DK	99	DF	FrP
		FrP	DF
IT	94	AN	LN, FI
	94-14	LN	AN (94), FI, M5S (14)
NL	94-99	CD	SP[16]

TABLE A.2 *Anti-establishment competitors of far right parties with representation in the national legislature at the time of the survey.*

As one can see in Fig. A.22, the results displayed in the main analysis hold when controlling for the presence or absence of other anti-establishment parties.

Lack of Knowledge about Smaller Parties. Smaller parties are often less well-known than larger parties. This makes it harder for voters to determine how much they like or dislike the party and to which extent they agree or disagree with its policy platform. This raises the question whether the moderation patterns presented in the main analysis should be attributed to far right parties' legislative strength (captured by party size) or whether they are, at least partly, artifacts of voters lack of knowledge about smaller parties.

I conduct a corresponding robustness check, controlling for the percentage of voters who neither report a PTV for a given party nor know how to place it in the survey. The corresponding findings are reported in Fig. A.23 and yield the same substantive conclusions as the main analysis presented in the manuscript.

[16]Following van Kessel (2015), I only treat the SP as a populist (and thereby, anti-establishment) party in the 1990s.

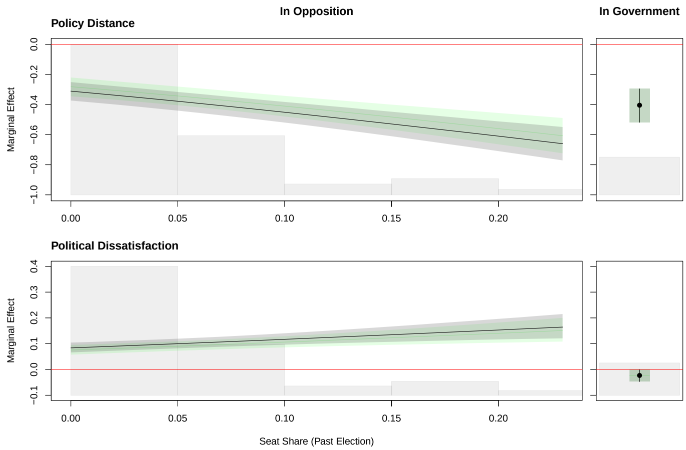


Figure A.22. *Replication of the main analysis, controlling for the presence of other anti-establishment parties in the national legislature. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

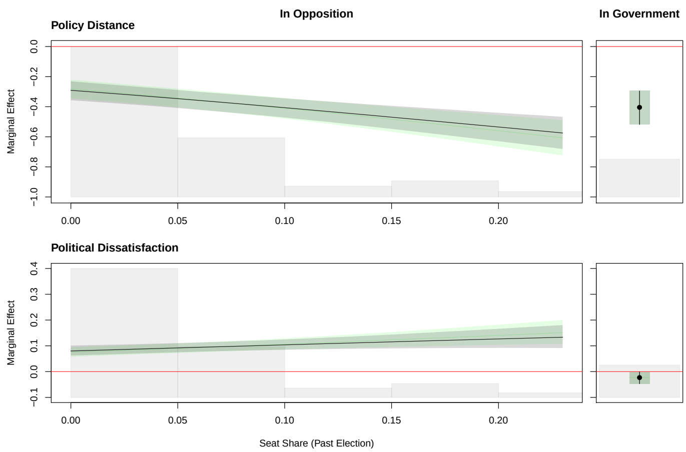


Figure A.23. *Replication of the main analysis, controlling for respondents' lack of knowledge about far right parties. Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

Alternative Procedure for Statistical Control (van der Eijk et al. 2006)

The control variable strategy presented in the preceding analyses follows common hierarchical modeling practice, i.e., it relies on pooled effect estimates for all background covariates. Assuming that the effects of individual-level control variables are invariant across clusters, however, may be a problematic assumption to make (e.g. Heisig, Schaeffer, and Giesecke 2017).

A possible alternative is presented in van der Eijk et al. (2006), who propose a procedure for statistical control especially suited for comparative analyses of PTV scores in multiparty contexts. The procedure aims to capture as much variation explained by voter-specific predictors as possible. This is based on the rationale that certain variables specific to voters but invariant across the parties they face (e.g., gender) may be differently or even divergently associated with voting behavior for different parties and across different electoral contexts.

The authors suggest (1) retrieving predicted values from election- and party-specific OLS regressions for each individual-specific predictor (y-hats), (2) demeaning the predicted values within party-elections, and (3) adding the demeaned predictions as transformed predictors to a pooled model. While the procedure is not well-suited for the study of substantive effects (as the transformed variables and their corresponding coefficients have no straightforward interpretation), I provide a robustness check applying the suggested transformation to all individual-specific background covariates whose effects are not of substantive interest (e.g., gender, age, education, attendance of religious services, and union membership).

The results are reported below in Fig. A.24. As one can see, the results yield the same substantive conclusions as the main analysis presented in the manuscript.

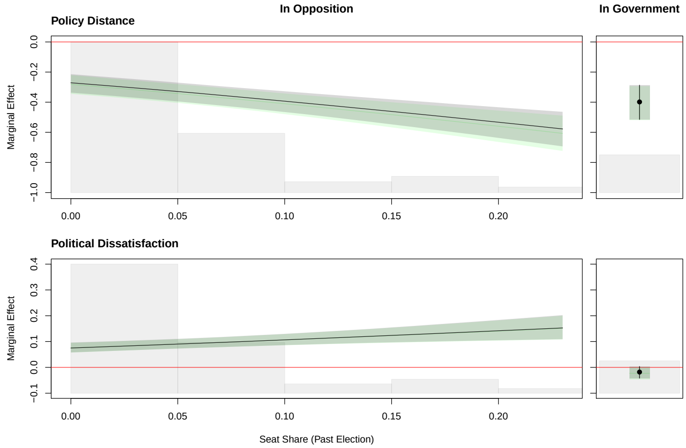


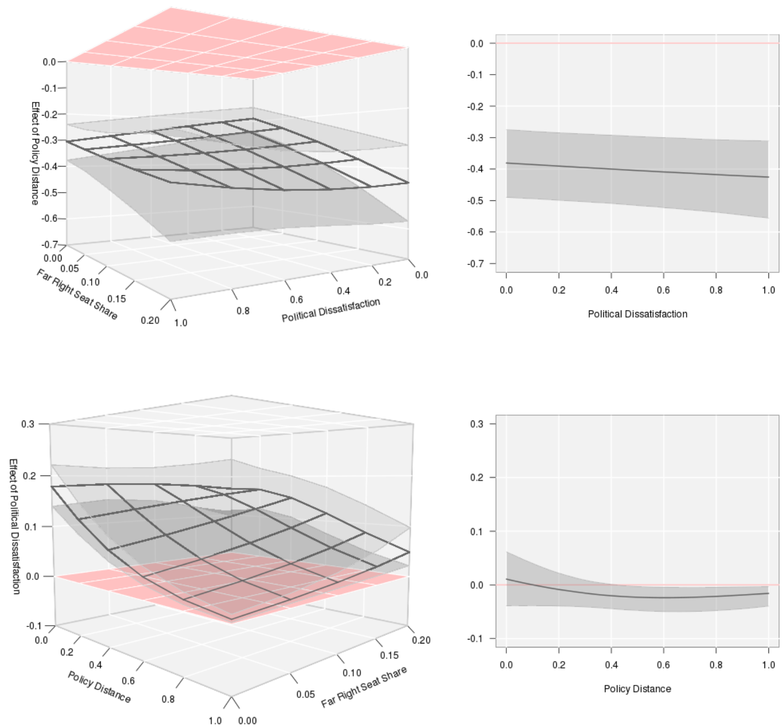
Figure A.24. *Replication of the main analysis, using the procedure for statistical control suggested in van der Eijk et al. (2006). Posterior medians and 95% posterior intervals. The prediction from the main analysis in Fig. 1 is displayed in green for reference.*

Micro-Level Mechanism with Three-Way Interaction

In order to provide a more nuanced understanding how and why contextually induced strategic incentives condition the relevance of policy demand and political dissatisfaction for micro-level voting behavior, I extend the anaylisis presented in the main paper to include a micro-level interaction between policy demand and political dissatisfaction. This allows us to scrutinize whether different strategic incentives condition the effects of policy demand and political dissatisfaction uniformly, or whether voters for whom high policy demand and high political dissatisfaction coincide respond differently than voters for whom the two electoral motives diverge.

The upper left of Figure A.25 shows that the importance of policy demand for far right voting increases both in political dissatisfaction and in the far right's legislative strength. When far right seat shares increase from 0% to 20%, the marginal effect of policy distance changes from -0.19 [-0.25, -0.13] to -0.45 [-0.57, -0.32] among politically satisfied voters and from -0.31 [-0.38, -0.24] to -0.42 [-0.56, -0.29] among politically dissatisfied voters. This also shows that legislative strength boosts the effect of policy demand more strongly among satisfied voters than among dissatisfied voters. Conversely, political dissatisfaction conditions the effect of policy demand more strongly when far right parties are weak than when they are strong.

The marginal effect of political dissatisfaction, displayed in the lower left of Figure A.25, increases primarily as a function of proximity of individuals' policy preferences



	Marginal Effect of Policy Distance		
	0% Seats	20% Seats	Government
Min. Dissatisfaction	-0.19 [-0.25, -0.13]	-0.45 [-0.57, -0.32]	-0.38 [-0.49, -0.27]
Max. Dissatisfaction	-0.31 [-0.38, -0.24]	-0.42 [-0.56, -0.29]	-0.43 [-0.56, -0.31]
	Marginal Effect of Political Dissatisfaction		
	0% Seats	20% Seats	Government
Min. Policy Distance	0.18 [0.14, 0.22]	0.17 [0.10, 0.25]	0.01 [-0.04, 0.06]
Max. Policy Distance	0.01 [0.00, 0.01]	0.05 [0.02, 0.10]	-0.02 [-0.04, 0.00]

Figure A.25. Replication of the main analysis, allowing for interdependent effects of policy demand and political dissatisfaction. Posterior medians and 95% posterior intervals.

to the far right's platform and less as a function of the far right's legislative strength. Among individuals who hold policy preferences congruous to the far right's platform, for instance, the effect magnitude remains nearly constant, going from 0.18 [0.14, 0.22] where far right parties are weak to 0.17 [0.10, 0.25] where they are strong. The main contrast between contexts of low and high far right legislative strength shows among individuals around the center of the policy distance scale: Here, the effect of political dissatisfaction is considerably stronger in contexts featuring strong far right parties.

The implications of these findings are threefold. First, the legislative strength of far right parties in opposition systematically incentivizes policy-directed considerations. Second, legislative strength does not undermine the far right's appeal to dissatisfied voters – to the contrary, strong far right parties attract dissatisfied voters more broadly than weak parties. Third, while policy demand and political dissatisfaction matter at all levels of legislative strength, the degree for their mutual reinforcement decreases as legislative strength increases. Whereas weak far right parties primarily attract a hard core of voters for whom far right policy demand and political dissatisfaction coincide, strong far right parties attract voters both via policy demand (at all levels of political dissatisfaction) and via political dissatisfaction (as long as voters do not diametrically oppose their policies).

For far right parties in government, voter evaluations are markedly driven by policy-directed considerations, and independently so of voters' political dissatisfaction. As displayed in the upper right of Figure 1, the marginal effect of policy demand ranges from -0.38 [-0.49, -0.27] to -0.43 [-0.56, -0.31] – comparable in magnitude to contexts with strong oppositional far right parties and indicating no signinificant variation along voters' political dissatisfaction. The bottom right of Figure 1, in line with my expectation, shows that political dissatisfaction does not substantially drive voters' choice calculus for far right parties in government. The effect is indistinguishable from zero among voters who agree with the far right's policy platform and turns slightly negative as individuals perceive the far right's platform farther from their own policy preferences. Far right parties in government thus fail to mobilize on political dissatisfaction. In evaluating these parties, voters rely exclusively on policy-directed considerations.

Tables for Main Models

TABLE A.3 *Posterior medians and 95% intervals from Bayesian hierarchical models, Eq.* (1).

	Models							
	Tobit		Linear		Hurdle			
					$\Pr(y > 0)$		$\mathbb{E}(y \mid y > 0)$	
Intercept	0.19	[0.07, 0.31]	0.28	[0.23, 0.33]	1.15	[0.57, 1.68]	0.09	[-0.05, 0.24]
Policy Distance	-0.81	[-0.84,-0.78]	-0.31	[-0.32,-0.30]	-2.83	[-2.96,-2.69]	-0.73	[-0.80,-0.67]
Dissatisfaction	0.22	[0.19, 0.24]	0.10	[0.09, 0.11]	0.64	[0.53, 0.75]	0.26	[0.22, 0.30]
Seat Share	1.64	[0.94, 2.33]	1.01	[0.70, 1.33]	6.91	[3.61,10.05]	1.04	[0.23, 1.83]
Distance × Seat Share	-1.12	[-1.50,-0.76]	-1.32	[-1.48,-1.16]	-6.74	[-8.64,-4.72]	0.47	[-0.17, 1.10]
Dissatisfaction × Seat Share	0.21	[-0.11, 0.54]	0.35	[0.20, 0.51]	1.90	[0.34, 3.47]	-0.24	[-0.70, 0.21]
Age When Left Full-Time Education (ref.: ≤ 15)								
16 – 19	-0.04	[-0.06,-0.02]	-0.01	[-0.02,-0.01]	-0.20	[-0.27,-0.13]	0.00	[-0.04, 0.02]
≥ 20	-0.14	[-0.16,-0.13]	-0.05	[-0.06,-0.05]	-0.65	[-0.73,-0.58]	-0.03	[-0.07,-0.01]
Male	0.05	[0.04, 0.06]	0.02	[0.02, 0.03]	0.16	[0.11, 0.21]	0.04	[0.03, 0.06]
Age	-0.43	[-0.59,-0.26]	-0.13	[-0.20,-0.05]	-2.63	[-3.34,-1.93]	0.28	[0.04, 0.52]
Age (squared)	0.21	[0.03, 0.38]	0.04	[-0.05, 0.11]	1.67	[0.93, 2.39]	-0.36	[-0.63,-0.10]
Union Household	0.02	[0.01, 0.03]	0.02	[0.01, 0.02]	0.01	[-0.05, 0.06]	0.06	[0.04, 0.08]
Religious Services (ref.: >Once a Week)								
Once a Week	-0.01	[-0.05, 0.04]	0.00	[-0.02, 0.02]	-0.04	[-0.24, 0.15]	0.01	[-0.05, 0.07]
A Few Times a Year	0.06	[0.01, 0.10]	0.03	[0.01, 0.04]	0.21	[0.02, 0.38]	0.05	[-0.01, 0.10]
Less Often	0.06	[0.01, 0.10]	0.03	[0.01, 0.05]	0.20	[-0.01, 0.38]	0.08	[0.02, 0.14]
Never	0.04	[0.00, 0.08]	0.03	[0.01, 0.05]	0.06	[-0.12, 0.23]	0.11	[0.05, 0.16]
Observations	45572		45572		45572		45572	
Individuals	41457		41457		41457		41457	
Choice Situations	45		45		45		45	
σ^2_ϵ	0.2		0.06		1 (fixed)		0.14	
σ^2_ψ	0.02		0.48		0		0	

TABLE A.4 *Posterior medians and 95% intervals, based on three different model specifications for far right parties in government, Eq.* (2).

	Models							
	Tobit		Linear		Hurdle			
					$\Pr(y > 0)$		$\mathbb{E}(y \mid y > 0)$	
Intercept	0.57	[0.46, 0.68]	0.43	[0.37, 0.50]	3.01	[2.55, 3.48]	0.10	[-0.14, 0.32]
Policy Distance	-0.86	[-0.92,-0.80]	-0.45	[-0.48,-0.42]	-2.89	[-3.18,-2.63]	-1.11	[-1.24,-0.99]
Dissatisfaction	-0.05	[-0.10, 0.00]	-0.01	[-0.03, 0.02]	-0.36	[-0.57,-0.16]	0.01	[-0.08, 0.10]
Age When Left Full-Time Education (ref.: ≤ 15)								
hspace1em 16 – 19	-0.06	[-0.09,-0.02]	-0.02	[-0.04, 0.00]	-0.41	[-0.56,-0.26]	0.04	[-0.02, 0.11]
≥ 20	-0.11	[-0.15,-0.07]	-0.04	[-0.06,-0.01]	-0.69	[-0.86,-0.52]	0.05	[-0.02, 0.12]
Male	0.05	[0.02, 0.07]	0.03	[0.02, 0.04]	0.15	[0.04, 0.25]	0.05	[0.01, 0.10]
Age	-0.49	[-0.87,-0.10]	-0.12	[-0.34, 0.10]	-3.77	[-5.39,-2.15]	0.69	[0.01, 1.47]
Age (squared)	0.44	[0.04, 0.84]	0.12	[-0.11, 0.34]	3.42	[1.75, 5.11]	-0.62	[-1.45, 0.10]
Union Household	-0.01	[-0.04, 0.02]	0.00	[-0.02, 0.01]	-0.02	[-0.14, 0.10]	-0.01	[-0.06, 0.05]
Religious Services (ref.: >Once a Week)								
Once a Week	0.13	[0.07, 0.20]	0.07	[0.04, 0.11]	0.56	[0.29, 0.82]	0.17	[0.05, 0.30]
A Few Times a Year	0.12	[0.06, 0.18]	0.07	[0.04, 0.10]	0.42	[0.15, 0.68]	0.20	[0.08, 0.33]
Less Often	0.16	[0.09, 0.23]	0.09	[0.05, 0.13]	0.59	[0.30, 0.87]	0.22	[0.09, 0.37]
Never	0.15	[0.08, 0.21]	0.10	[0.07, 0.14]	0.39	[0.11, 0.68]	0.32	[0.18, 0.47]
AT FPO 04	-0.23	[-0.49, 0.03]	-0.13	[-0.32, 0.06]	-1.10	[-1.31,-0.88]	-0.14	[-0.22,-0.05]
DK DF 04	-0.22	[-0.48, 0.04]	-0.11	[-0.30, 0.08]	-1.20	[-1.45,-0.95]	-0.05	[-0.15, 0.05]
IT LN 04	-0.25	[-0.51, 0.02]	-0.14	[-0.34, 0.04]	-1.01	[-1.22,-0.81]	-0.30	[-0.40,-0.21]
DK DF 09	-0.09	[-0.36, 0.17]	-0.02	[-0.22, 0.17]	-0.96	[-1.22,-0.71]	0.16	[0.06, 0.25]
IT LN 09	-0.11	[-0.37, 0.16]	-0.07	[-0.26, 0.12]	-0.44	[-0.65,-0.24]	-0.14	[-0.22,-0.06]
IT AN 94	-0.22	[-0.26,-0.18]	-0.14	[-0.16,-0.11]	-0.76	[-0.96,-0.56]	-0.32	[-0.40,-0.24]
Observations	8014		8014		8014		8014	
Individuals	6947		6947		6947		6947	
Choice Situations	7		7		7		7	
σ_ϵ^2	0.19		0.08		1 (fixed)		0.19	

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