Constrained Citizens? Ideological Structure and Conflict Extension in the American Electorate, 1980-2016

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July 30, 2021

Supplementary Appendix

Contents

A.1 Survey Items from the 1980-2016 American National Election Studies

Variable	1980	1984	1988	1992	1996	2000	2004	2008	2012	2016
`abortion` (4)	V800311	V840423	V880395	V923732	V960503	V000694	V045132	V085086	abortpre_4point	V161232
`gaydiscrim` (4)			V880853	V925924	V961194	V001481	V045156a	V083211x	gayrt_discstd_x	V161229x
`gayadopt` (2)						V000748	V045158	V083213	gayrt_adopt	V161230
`gayadopt` (4)				V925928						
`gaymarriage` (3)							V043210	V083214	gayrt_marry	V161231
`guncontrol` (2)					V961217					
`guncontrol` (3)								V083164	gun_control	V161187
`guncontrol` (5)						V000731	V043189			
`welfarespend` (3)				V923726	V960497	V000676	V043169	V083145	fedspend_welfare	V161209
`poorspend` (3)				V923817	V960565	V000680	V043172	V083148	fedspend_poor	V161211
`libcon` (7)	V800267	V840369	V880228	V923509	V960365	V000440	V043085	V083069	libcpre_self	V161126
`govtspend` (7)	V800291	V840375	V880302	V923701	V960450	V000545	V043136	V083105	spsrvpr_ssself	V161178
`guarjobs` (7)	V801110	V840414	V880323	V923718	V960483	V000615	V043152	V083128	guarpr_self	V161189
`healthins` (7)		V841058	V880318	V923716	V960479	V000609	V043150	V083119	inspre_self	V161184
`envjobs` (7)					V960523	V000708	V043182	V083154	envjob_self	V161201
`aidtoblacks` (7)	V801062	V840382	V880332	V923724	V960487	V000641	V043158	V083137	aidblack_self	V161198
`defspend` (7)	V800281	V840395	V880310	V923707	V960463	V000581	V043142	V083112	defsppr_self	V161181
`immigrationlevel` (5)				V926235	V961325	V000510	V045115	V085082	immigpo_level	V162157
`libcon.branch` (7)						V000446				
`govtspend.branch` (5)						V000549				
`guarjobs.branch` (5)						V000619				
`healthins.branch` (5)						V000613				
`envjobs.branch` (5)						V000712				
`aidtoblacks.branch` (7)						V000644				
`defspend.branch` (5)						V000586				
`govtspend.new` (7)								V083108x		
`univ.health` (7)								V083124x		
`defspend.new` (7)								V083115x		

Cells are shaded if the survey item is not available in the corresponding year. The number of response categories for each survey item listed in parentheses.

A.2 The Dynamic Ordinal Item Response Theory (DO-IRT) Model and JAGS Code

The DO-IRT model is identified by constraining the discrimination parameter of the guaranteed jobs and income issue scale to be positive and placing a standard normal prior on the ideal points (Bafumi et al., 2005). Priors for the DO-IRT model are specified in Equations 1–7:

$$\theta_i \sim N(0, 1) \tag{1}$$

$$\beta_{j1} \sim N(\mu_A, \tau_A) \tag{2}$$

$$\beta_{jt} \sim N(\beta_{j(t-1)}, \tau_B) \tag{3}$$

$$\alpha_{jc1} \sim N(\mu_B, \tau_C) \tag{4}$$

$$\alpha_{jct} \sim N(\alpha_{jc(t-1)}, \tau_D) \tag{5}$$

$$\mu_{A:B} \sim N(0, 1) \tag{6}$$

$$\tau_{A:D} \sim \text{Gamma}\,(1, 0.1) \tag{7}$$

Note that precision τ is equal to the inverse of variance σ^2, so that Equation 7 is equivalent to $\sigma^2_{A:D} \sim \text{Gamma}^{-1}\,(1, 0.1)$. Rather than set the precision terms on the random-walk priors to fixed values (which manually controls the degree of smoothing between time periods), I place hyperpriors on τ and estimate them from the data (Reuning, Kenwick and Fariss, 2019; Caughey and Warshaw, 2015). Results from experiments using set values of τ are available in Section A.4.

The JAGS code (Plummer, 2003) below is specific to modeling responses to a seven-point issue scale, but is modified accordingly for issue scales with different numbers of response categories.

```
model {

# SEVEN-POINT ISSUE SCALES
for (i in 1:n){
for (j in 1:p){
Y[i, j] ~ dcat(Pi[i, j, 1:7])
```

```
probit(Z[i, j, 1]) <- alpha[j, 1, time[i]] - beta[j, time[i]]*x[i]
probit(Z[i, j, 2]) <- alpha[j, 2, time[i]] - beta[j, time[i]]*x[i]
probit(Z[i, j, 3]) <- alpha[j, 3, time[i]] - beta[j, time[i]]*x[i]
probit(Z[i, j, 4]) <- alpha[j, 4, time[i]] - beta[j, time[i]]*x[i]
probit(Z[i, j, 5]) <- alpha[j, 5, time[i]] - beta[j, time[i]]*x[i]
probit(Z[i, j, 6]) <- alpha[j, 6, time[i]] - beta[j, time[i]]*x[i]

Pi[i, j, 1] <- Z[i, j, 1]
Pi[i, j, 2] <- Z[i, j, 2] - Z[i, j, 1]
Pi[i, j, 3] <- Z[i, j, 3] - Z[i, j, 2]
Pi[i, j, 4] <- Z[i, j, 4] - Z[i, j, 3]
Pi[i, j, 5] <- Z[i, j, 5] - Z[i, j, 4]
Pi[i, j, 6] <- Z[i, j, 6] - Z[i, j, 5]
Pi[i, j, 7] <- 1 - Z[i, j, 6]
}}

# PRIORS ON X
for (i in 1:n){
x[i] ~ dnorm(0, 1)
}

# PRIORS ON BETA
for(j in 1:p){
beta[j,1] ~ dnorm(mu.A, tau.A)
for(t in 2:T){
beta[j,t]~dnorm(beta[j, t-1], tau.B)
}}

# PRIORS ON ALPHA
for (j in 1:p){
for (c in 1:(K[j]-1)){
alphastar[j, c, 1] ~ dnorm(mu.B, tau.C)
}
alpha[j, 1:(K[j]-1), 1] <- sort(alphastar[j,1:(K[j]-1),1])
for (t in 2:T){
for (c in 1:(K[j]-1)){
alphastar[j, c, t] ~ dnorm(alphastar[j,c,(t-1)], tau.D)
}
alpha[j,1:(K[j]-1),t] <- sort(alphastar[j,1:(K[j]-1),t])
}}

# HYPER PRIORS ON MEAN AND PRECISION TERMS
mu.A ~ dnorm(0, 1)
mu.B ~ dnorm(0, 1)
tau.A ~ dgamma(1, 0.1)
```

```
tau.B ~ dgamma(1, 0.1)
tau.C ~ dgamma(1, 0.1)
tau.D ~ dgamma(1, 0.1)

}
```

A.3 Additional Information about the Estimation Procedure and Data

Starting values for the item (α_{jt}, β_{jt}) and subject (θ_i) DO-IRT model parameters are generated for each of the three MCMC chains as follows:

1. α_{jt} (the difficulty parameters): draws from a standard normal distribution that are sorted for each issue j and time period t to respect cutpoint orderings.

2. β_{jt} (the discrimination parameters): draws from truncated standard normal distributions that are strictly negative for issues $j \in 1, 12, 20$ at all time periods t, and strictly positive otherwise. This helps to identify the latent dimension such that higher values correspond to more conservative/right-wing positions.

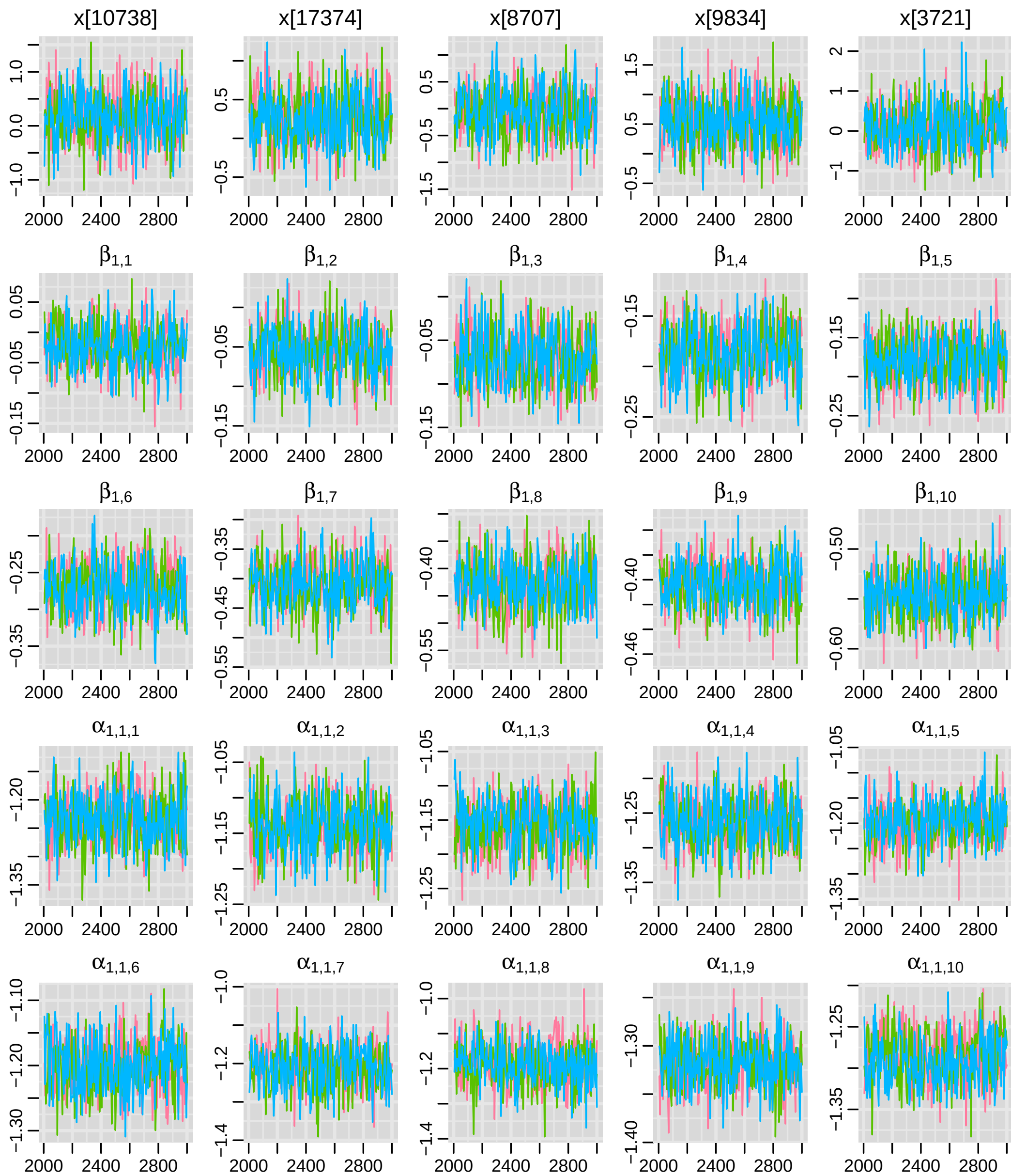
3. θ_i (the respondent ideal points): I use a method developed by Imai, Lo and Olmsted (2016) that quickly approximates IRT estimates using an expectation-maximization algorithm, adding a small amount of random noise ($\varepsilon \sim N(0, 0.05)$) to each ideal point estimate.[1]

These values are used to initialize three MCMC chains for `rjags` (Plummer, 2003). Each chain is run for 3,000 iterations, discarding the first 2,000 iterations as burn-in samples and thinning the remaining 1,000 iterations by five, leaving 600 samples (200 $\times$ three chains) to characterize each parameter's posterior density. Convergence of the chains is assessed through visual inspection of the trace, density, and autocorrelation; the Geweke diagnostic (Geweke, 1992); and the Gelman-Rubin diagnostic (Gelman and Rubin, 1992). For illustrative purposes, Figure A1 provides MCMC trace plots for five random respondent ideal points, the discrimination parameter for the first issue (abortion) across the ten time periods, and the first difficulty parameter for abortion across the ten time periods.

Pooling data from the 1980-2016 quadrennial ANES Time Series studies between yields 25,635 total respondents. Of these, 24,060 respondents provided answers to at least three issue scales;

[1] The procedure is implemented in the `emIRT` package in `R` (Imai, Lo and Olmsted, 2020). At present, the package accommodates ordinal scales with only three response categories. Hence, I collapse all larger issue scales into three-point scales. The method provides reasonable starting values nonetheless.

Figure A1: MCMC trace plots for selected parameters.



and all but one (i.e., 24,059) of these respondents also had at least one non-missing value on the three measures of political sophistication.[2] We use the final specification in our main analysis.

Figure A2 shows the distribution of issue scales responses in our final dataset. Most respondents provide a good deal more than the minimum of three responses. Specifically, 99% of the 24,059 respondents register at least four issue preferences, 98% at least five, 95% at least six,

[2]The variables for the sophistication measures are from the ANES Time Series cumulative data file: VCF0310 for interest, VCF0723 for involvement, and VCF0050a for knowledge. Cronbach's $\alpha = 0.63$.

and 90% at least seven. Estimating the DO-IRT model using minimum values of four, five, and six responses yields the results presented in Figures A3-A5, respectively. Each is virtually indistinguishable from Figure 1 in the main text.

Figure A2: Total number of valid issue responses by ANES respondents.

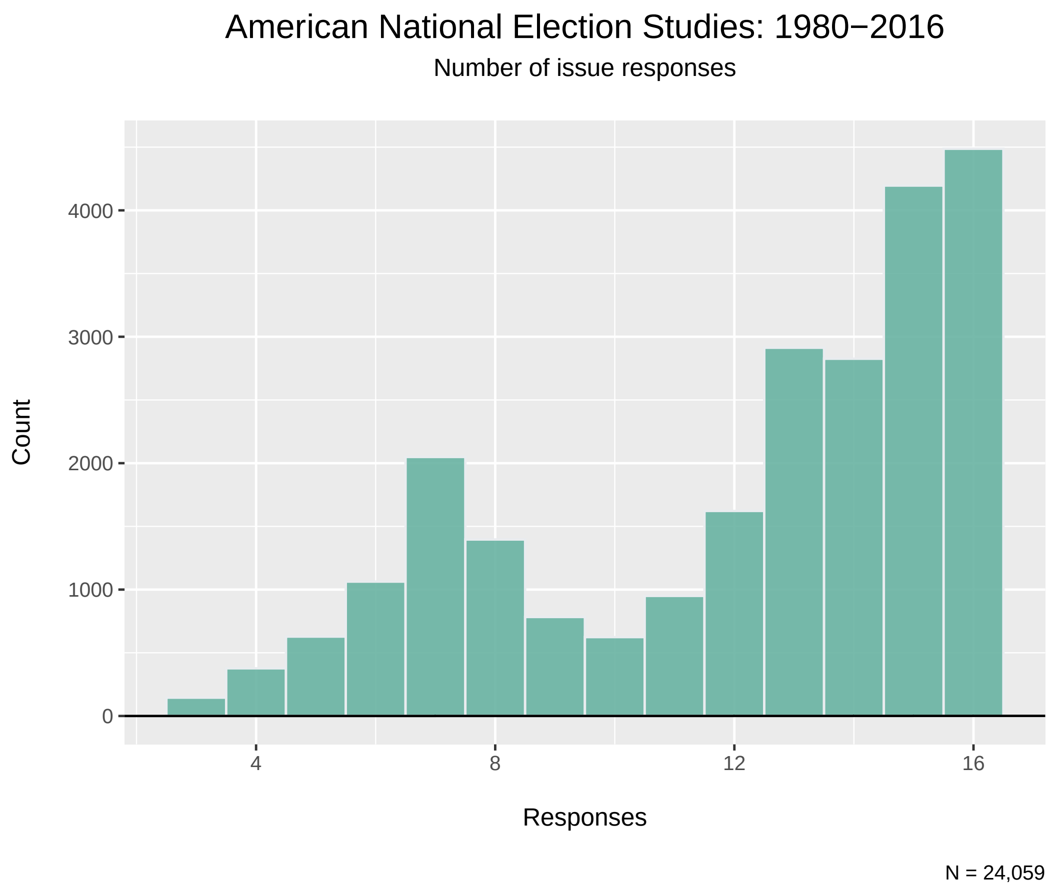


Figure A3: Issue discrimination parameters (β_{jt}) from the Bayesian dynamic ordinal IRT (DO-IRT) model using respondents who provided at least four issue positions.

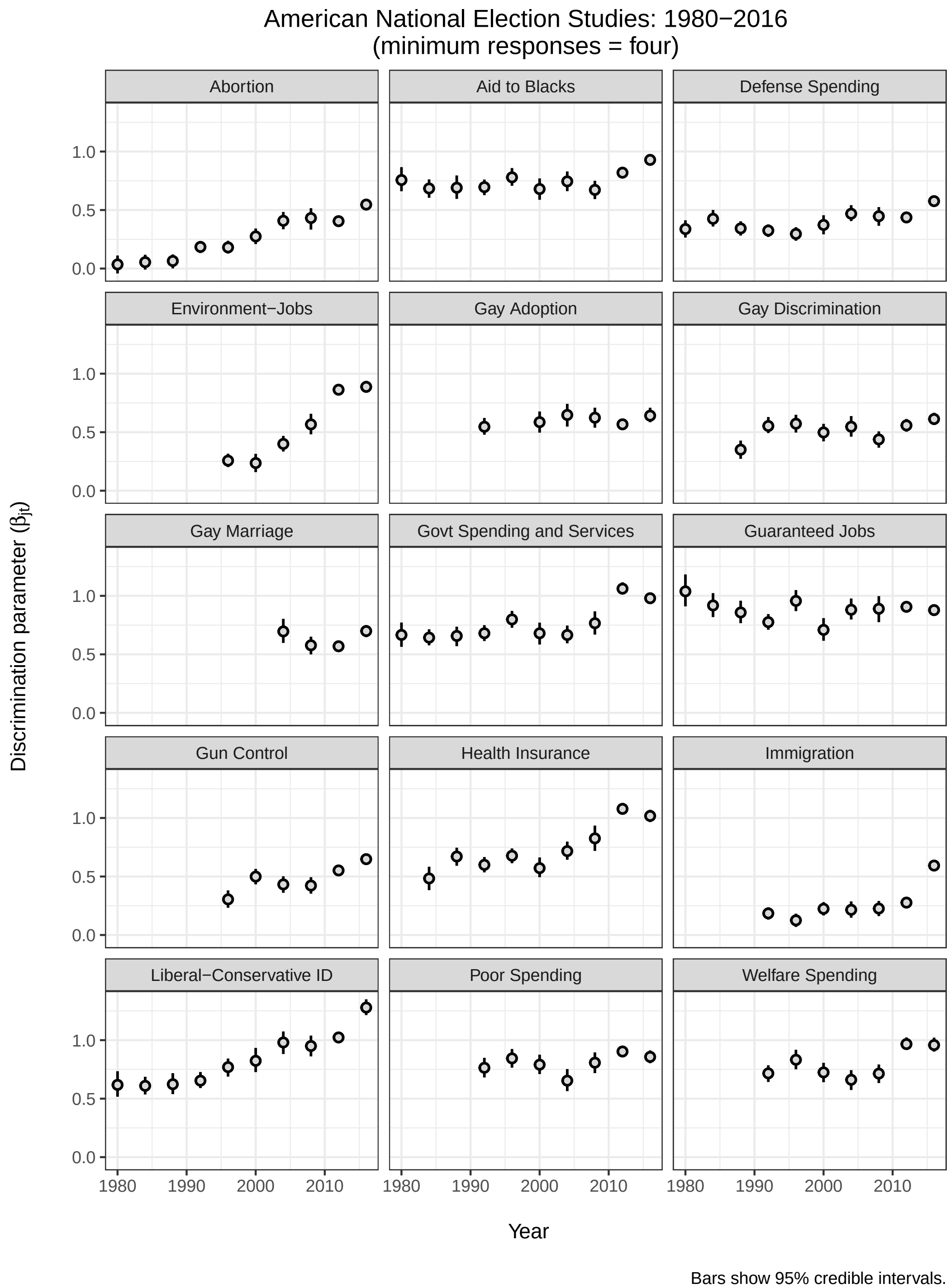


Figure A4: Issue discrimination parameters (β_{jt}) from the Bayesian dynamic ordinal IRT (DO-IRT) model using respondents who provided at least five issue positions.

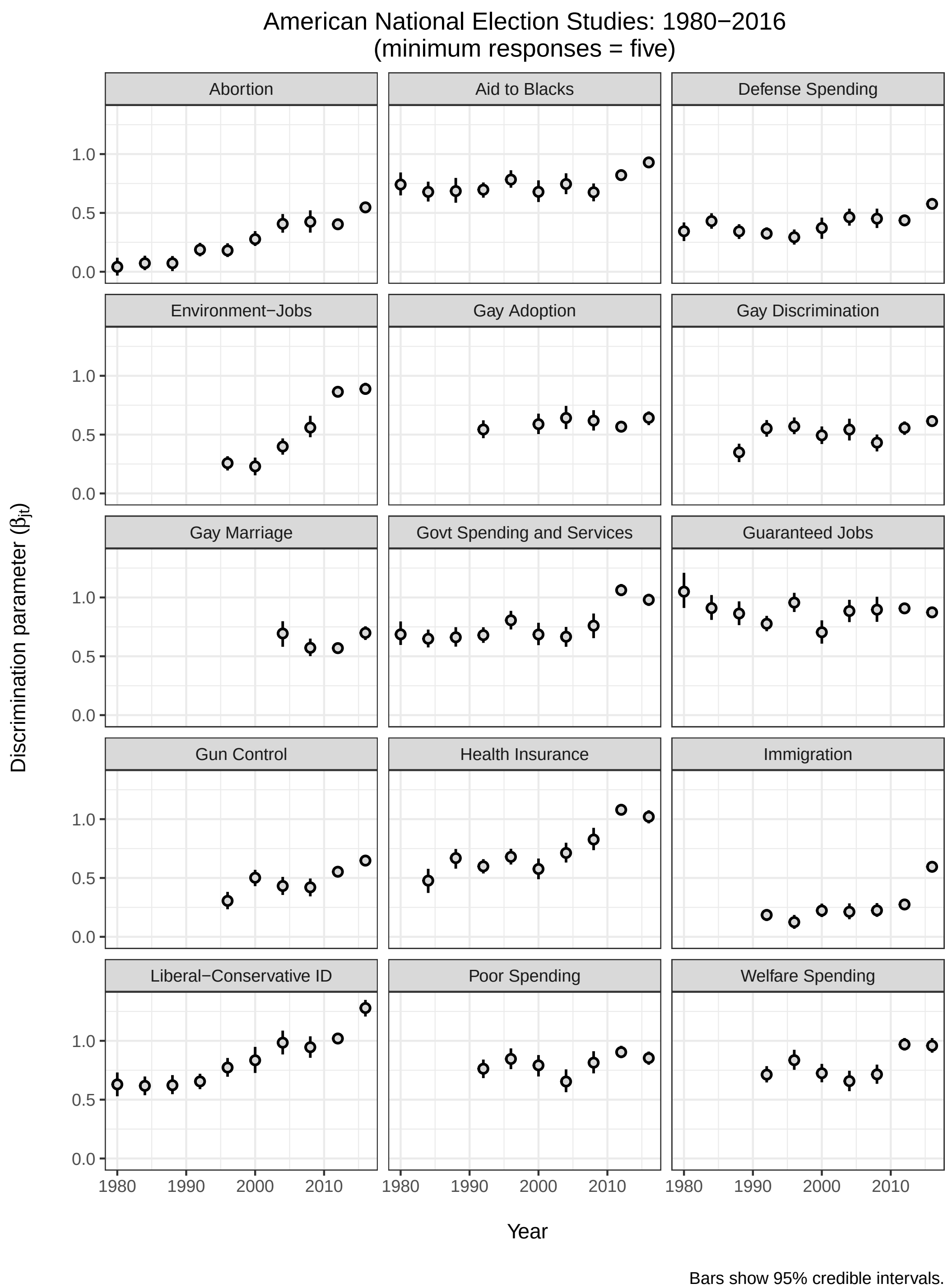
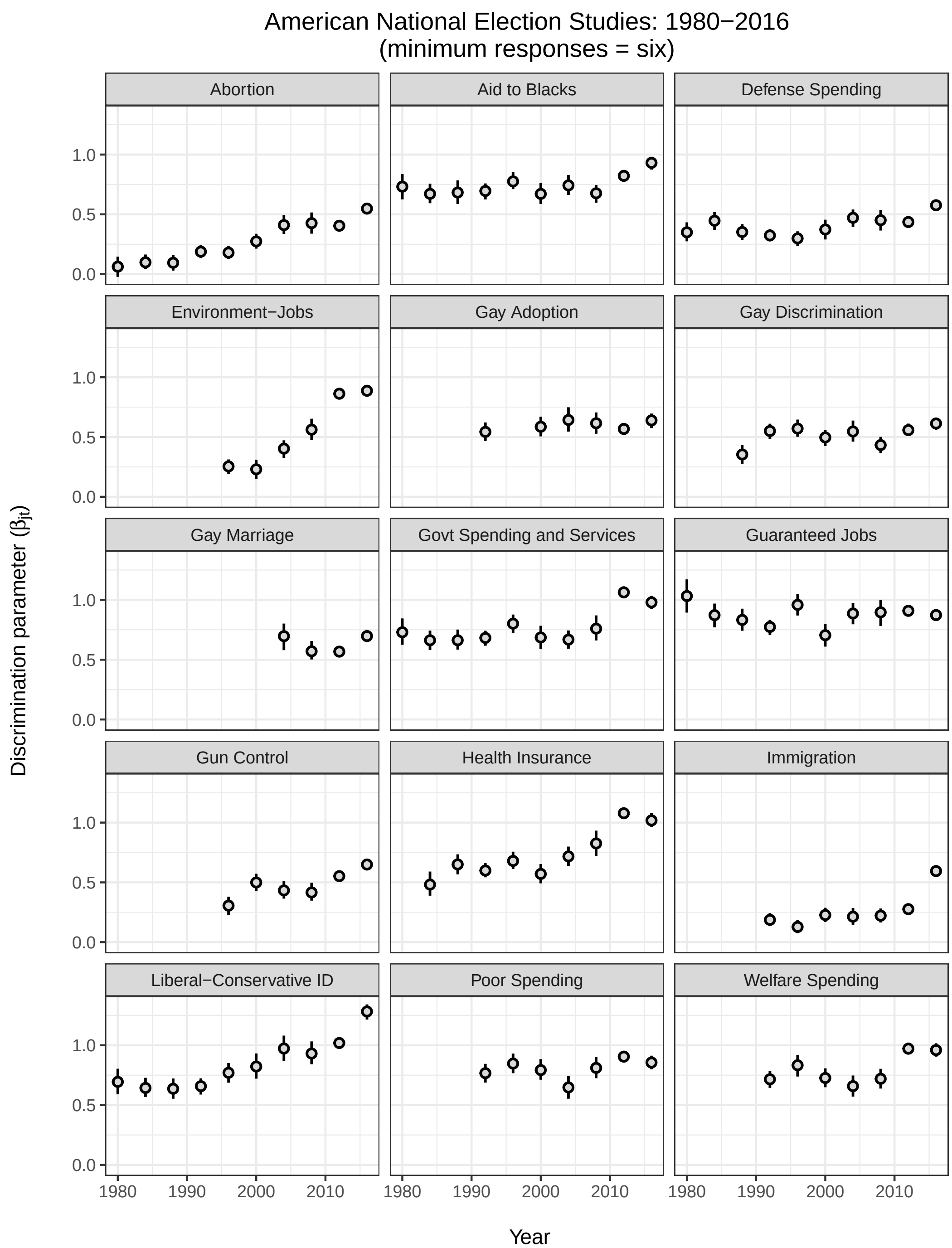


Figure A5: Issue discrimination parameters (β_{jt}) from the Bayesian dynamic ordinal IRT (DO-IRT) model using respondents who provided at least six issue positions.



Bars show 95% credible intervals.

A.4 Results Using Alternate Specifications of the Random-Walk Priors

The Bayesian DO-IRT model developed in this paper (Section A.2) places a random-walk prior on the difficulty (α_{jct}) and discrimination (β_{jt}) parameters (not the respondent ideal points θ_i, as in most applications of the dynamic IRT model) to facilitate exchangeability between time periods. Specifically, normal priors are placed on α_{jct} and β_{jt} with precision terms τ that themselves have prior distributions (hyperpriors). At $t = 1$, μ follows a standard normal distribution and the precision τ is distributed Gamma with shape and scale parameters 1 and 0.1, respectively. For $t > 1$, μ is equal to the parameter's value in the previous period $t - 1$ (i.e., $\alpha_{jc(t-1)}$ or $\beta_{j(t-1)}$) while τ, as before, has a Gamma prior with shape and scale parameters 1 and 0.1, respectively.

The variances of the random walk priors are known as "innovation variances" (or sometimes "evolution variances") because they control the amount of temporal smoothing for the associated parameters (see, e.g., Martin and Quinn, 2002; Caughey and Warshaw, 2015; Reuning, Kenwick and Fariss, 2019). Larger innovation variances (equivalently, smaller innovation precisions, since $\sigma^2 = \tau^{-1}$) produce less smoothing (i.e., temporally independent estimates). Smaller innovation variances (larger innovation precisions) produce greater smoothing (i..e, temporal dependence), with an innovation variance of 0 producing a constant model with no over-time variation. Placing hyperpriors on the innovation precision terms allows them to be estimated from the data.

In order to test the sensitivity of the results to different values of the innovation precisions, I replace τ on the random walk priors (Equation 7 in Section A.2) with three fixed values: 0.01, 1, and 100. I then estimate those models using the same MCMC simulation procedure as the original model and present the estimated discrimination parameters in Figures A6-A8.

Each specification shows similar increases in mass conflict extension, though of course featuring different levels of smoothing. The result from the original model (Figure 1 in the main text) falls between the bumpier, more idiosyncratic estimates in Figure A6 and the heavily smoothed estimates in Figure A8. Though all of these configurations yield similar substantive conclusions, the use of hyperpriors in the original model facilitates the flow of information between time periods (i.e., exchangeability) and hence produces more precise estimates of the item parameters.

Figure A6: Issue discrimination parameters (β_{jt}) from a Bayesian dynamic ordinal IRT (DO-IRT) model with a large evolution variance parameter on the item random-walk priors ($\sigma^2 = 100$, $\tau = 0.01$). This parameterization induces less smoothing.

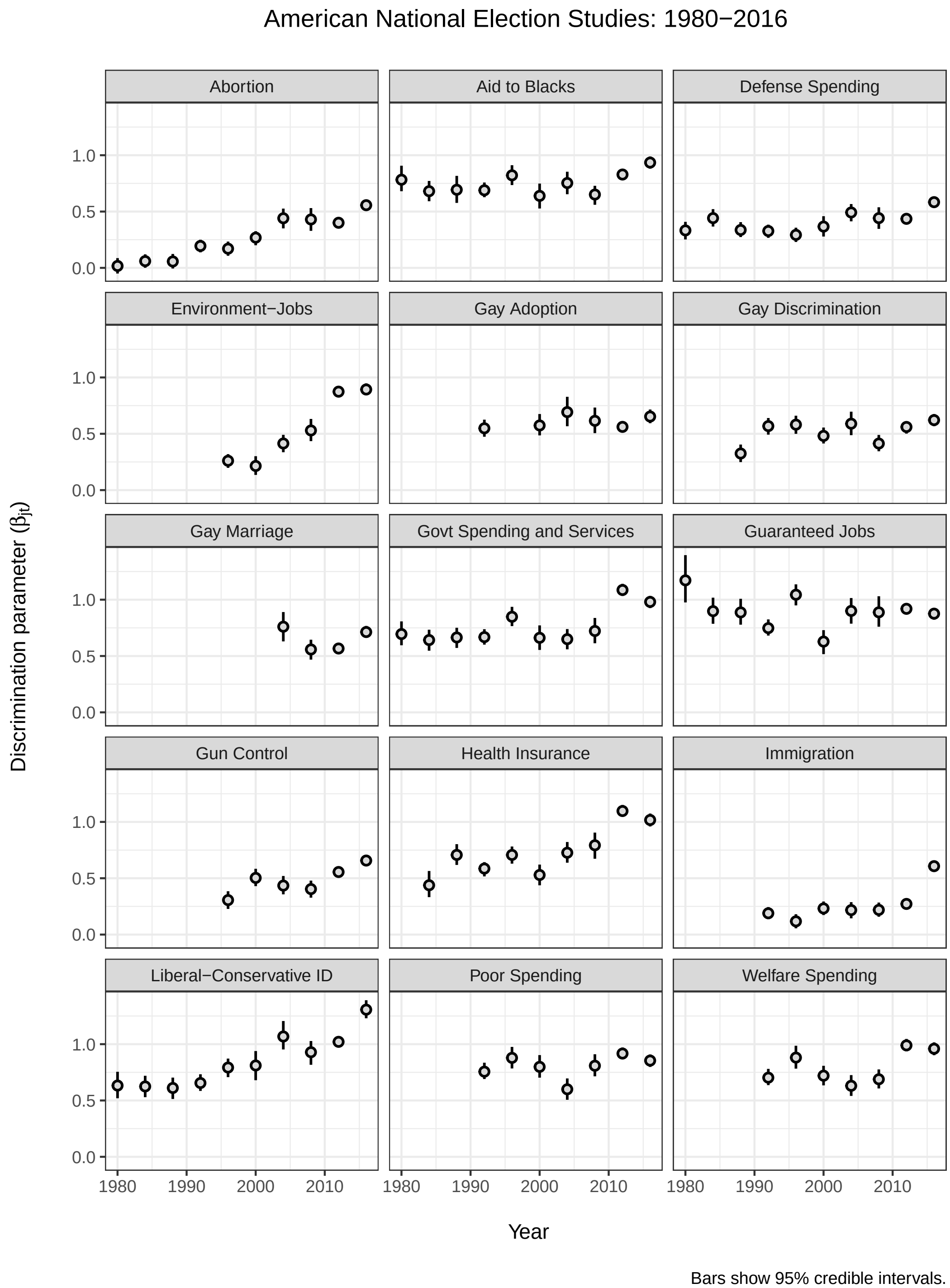


Figure A7: Issue discrimination parameters (β_{jt}) from a Bayesian dynamic ordinal IRT (DO-IRT) model with a medium evolution variance parameter on the item random-walk priors ($\sigma^2 = 1$, $\tau = 1$). This parameterization induces moderate smoothing.

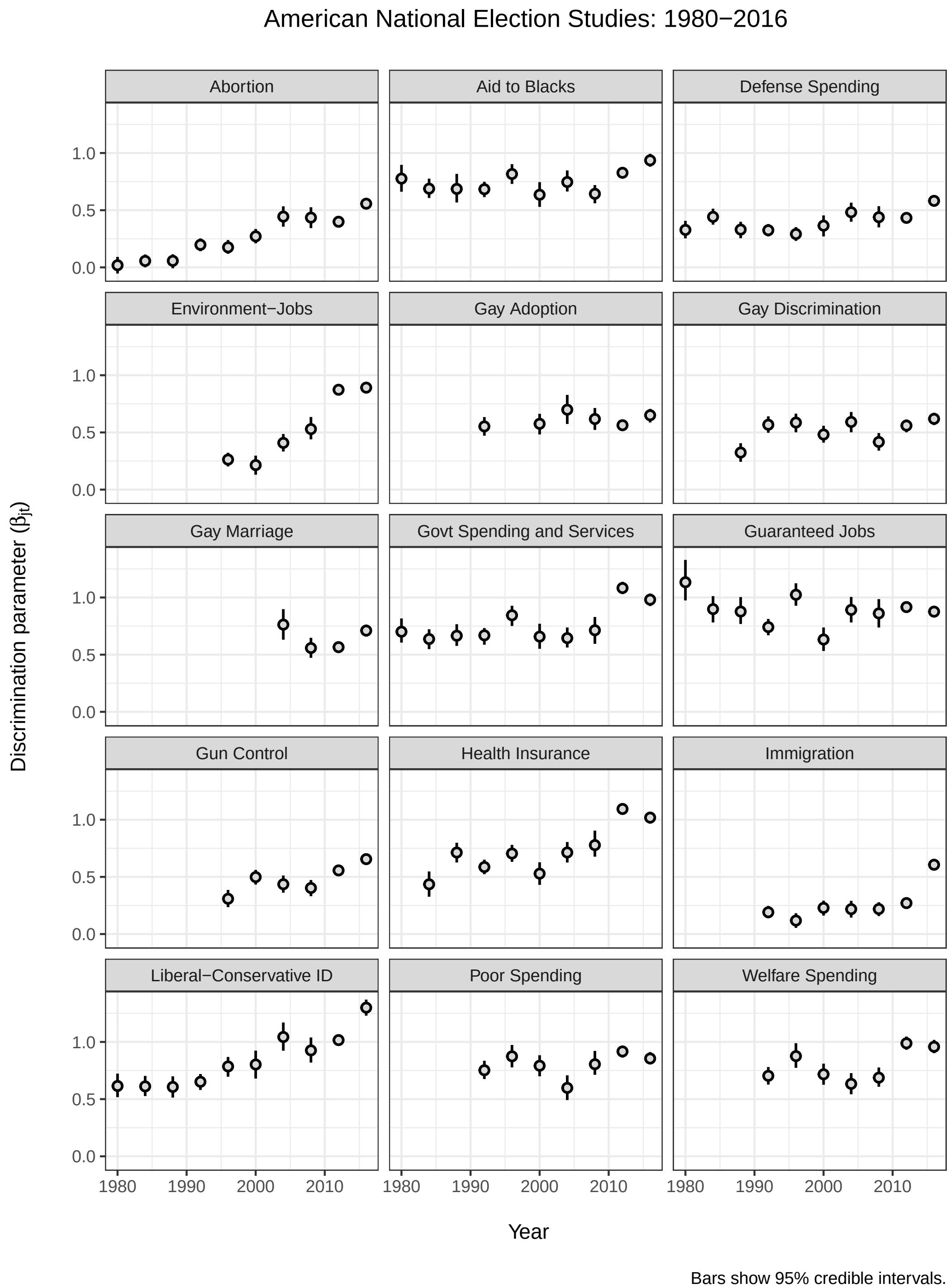
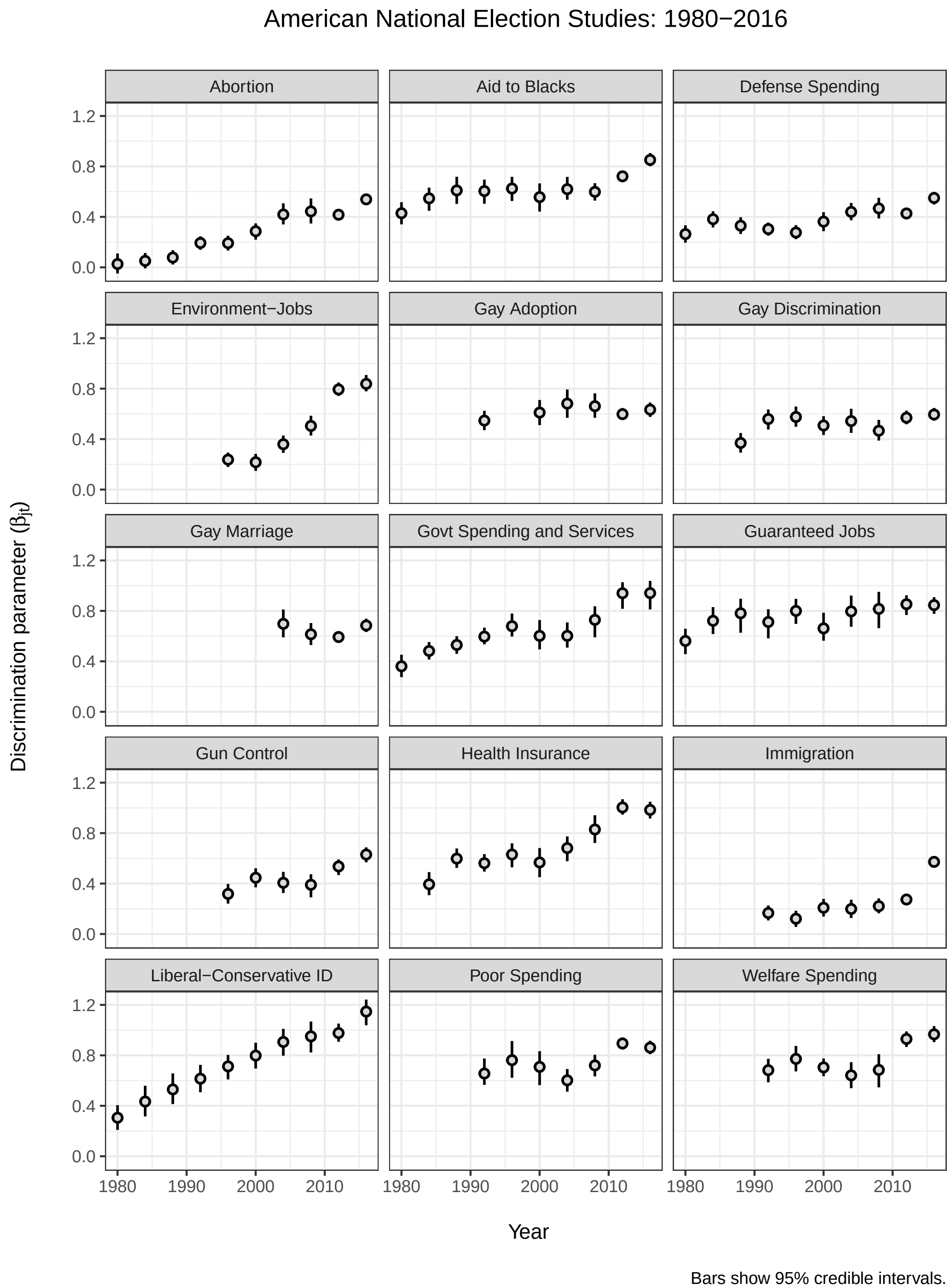


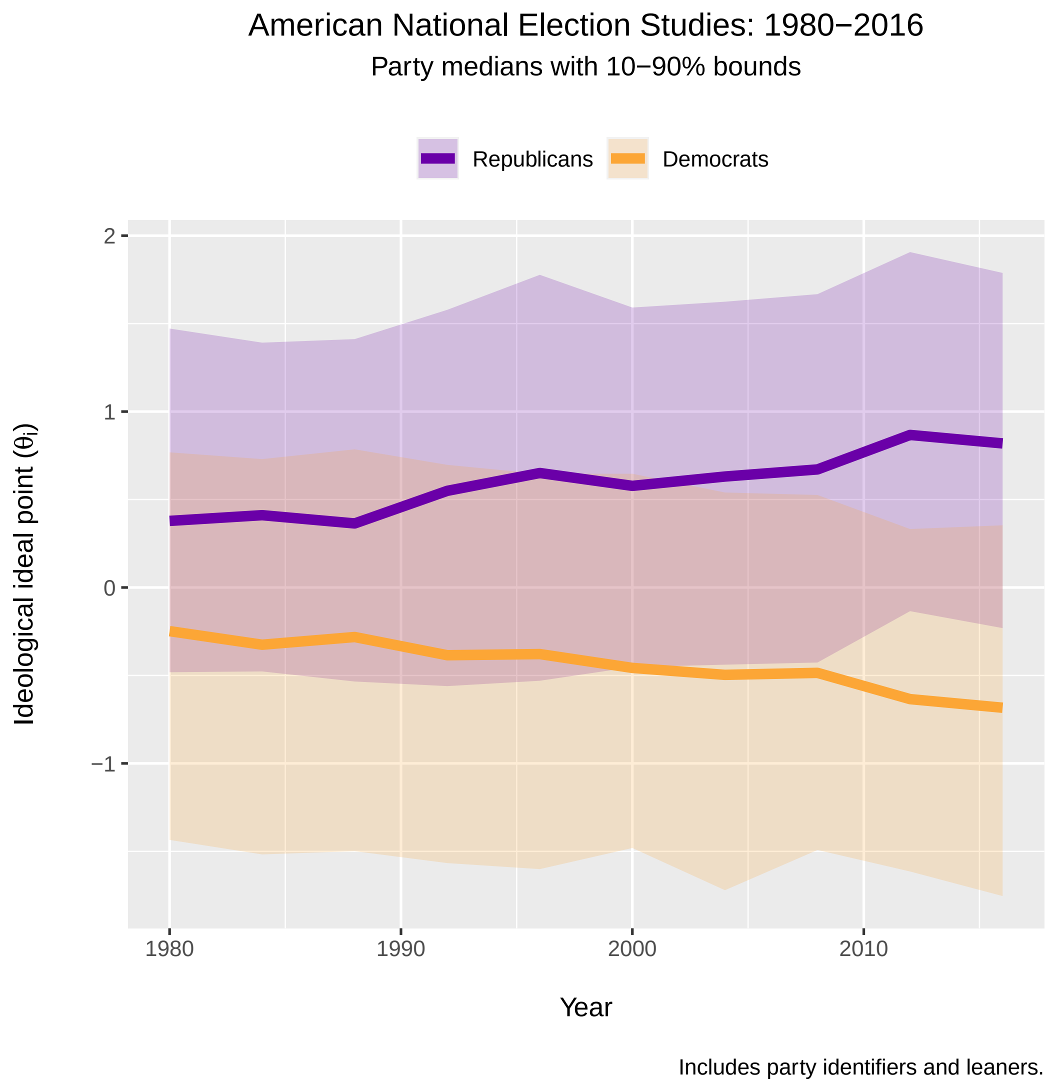
Figure A8: Issue discrimination parameters (β_{jt}) from a Bayesian dynamic ordinal IRT (DO-IRT) model with a small evolution variance parameter on the item random-walk priors ($\sigma^2 = 0.01$, $\tau = 100$). This parameterization induces greater smoothing.



A.5 Estimates of Mass Ideological Polarization

Figure A9 plots the median ideal point estimates θ_i for Democratic and Republican party identifiers (including leaners) over time. The ideological locations of the middle 80% of respondents in each party are shown in the shaded regions.

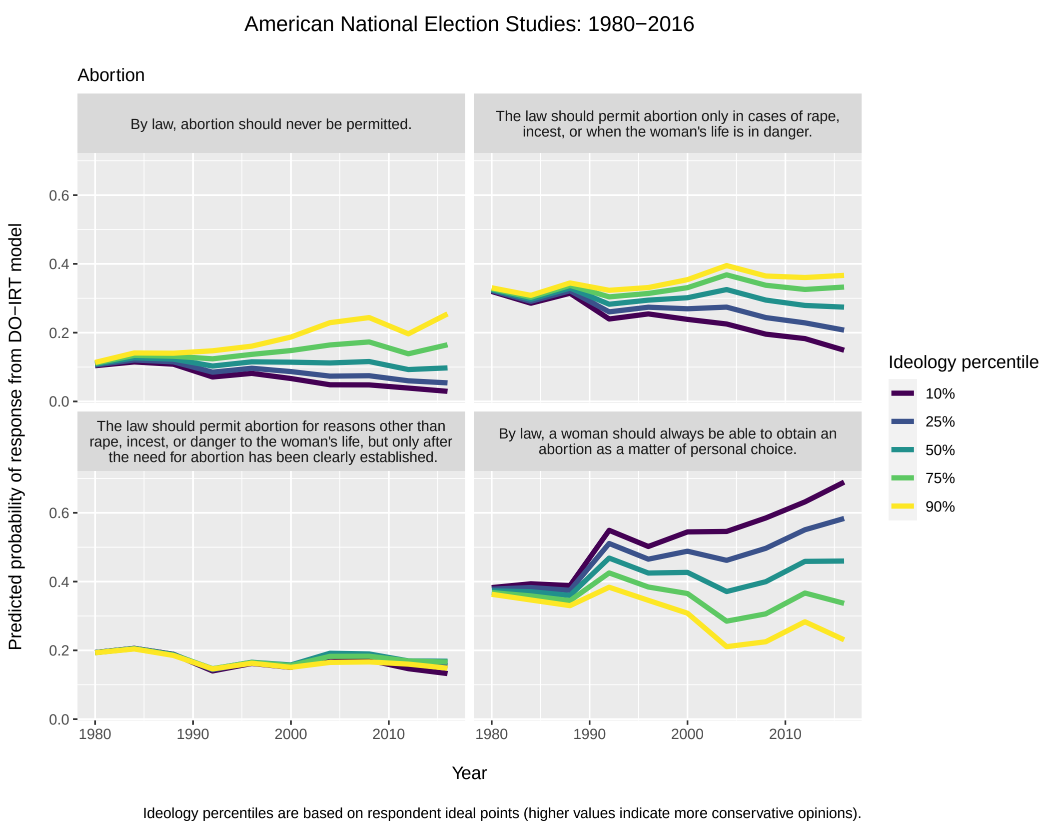
Figure A9: Tracking changes in ideal point estimates (θ_i) by partisanship.



A.6 Over-time Issue Response Probabilities from the DO-IRT Model

To give a sense of the substantive meaning of the observed changes in the issue discrimination parameters, Figures A10-A22 show the predicted probabilities of item responses over time.[3] The probabilities are calculated by plugging in the mean values of the corresponding item (discrimination and difficulty) parameters for five respondent ideal point values: those at the 10th, 25th, 50th, 75th, and 90th percentiles.[4] For instance, from Figure A10 below we see that regardless of ideal point, respondents are virtually equally likely to answer that "by law, a woman should always be able to obtain an abortion as a matter of personal choice" on the abortion item. By 2016, respondents in the 10th ideological percentile have a 69% probability of providing the same response compared to 23% for respondents in the (90th) percentile.

Figure A10: Predicted abortion responses over time by ideal point percentile.



[3] I thank an anonymous review for this suggestion. This section estimates responses for the thirteen issues that are included in at least six consecutive periods.

[4] That is, voters who are more conservative (have larger ideal point estimates θ_i) than 10, 25, 50, 75, and 90% of respondents. The corresponding ideal point values are -1.10, -0.59, -0.01, 0.57, and 1.15, respectively.

Figure A11: Predicted aid to blacks and minorities responses over time by ideal point percentile.

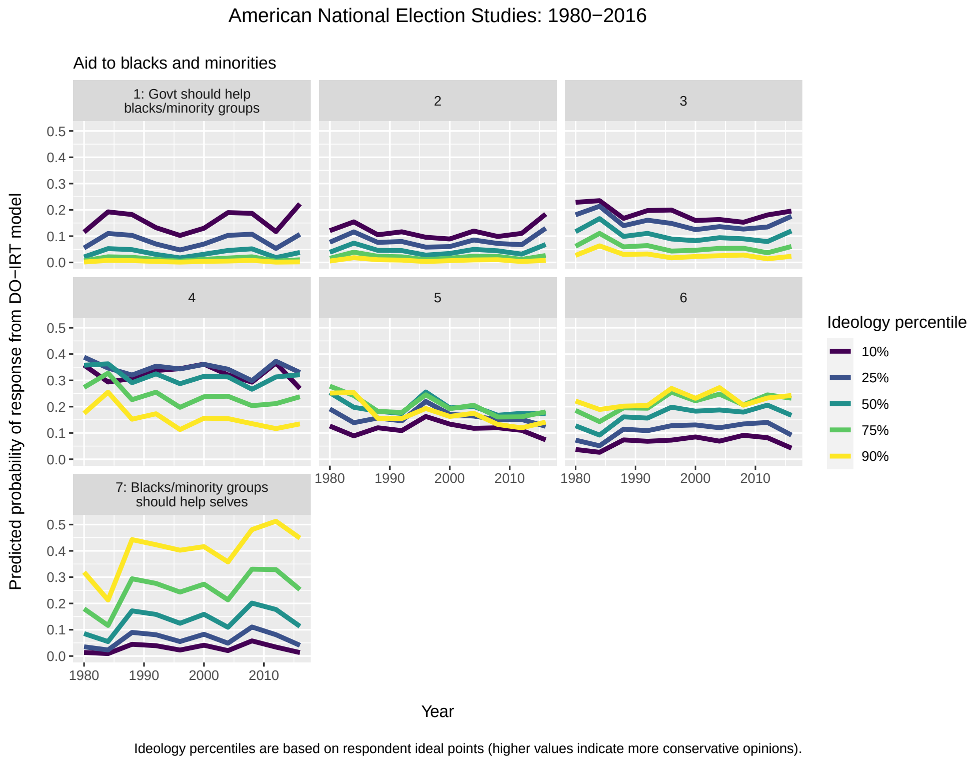


Figure A12: Predicted defense spending responses over time by ideal point percentile.

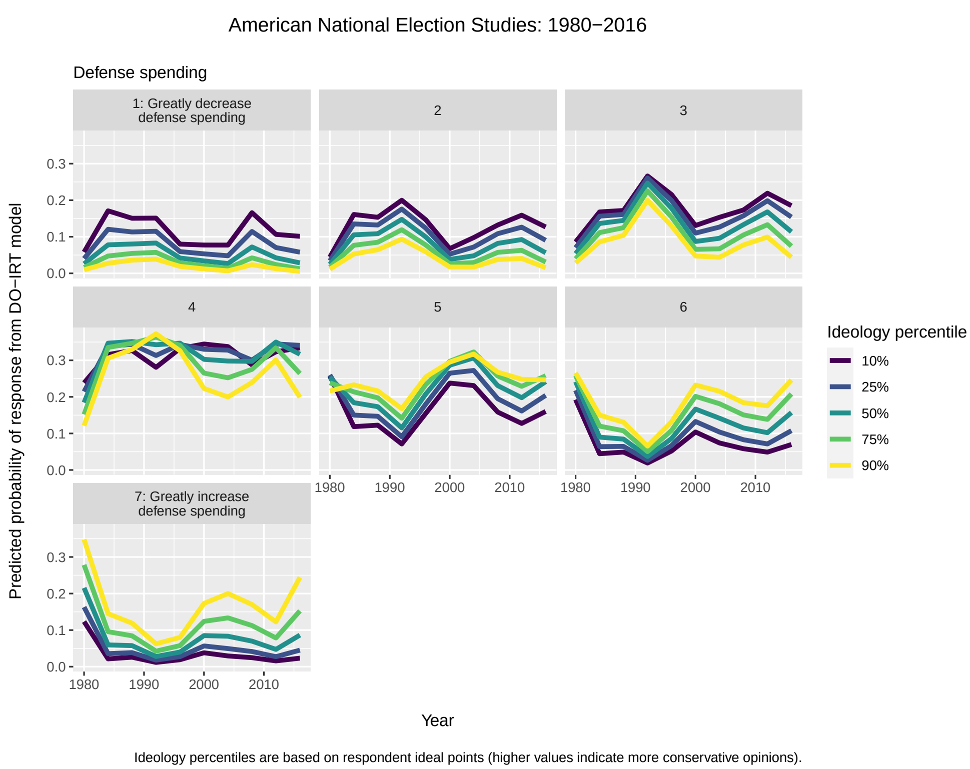


Figure A13: Predicted environment-jobs responses over time by ideal point percentile.

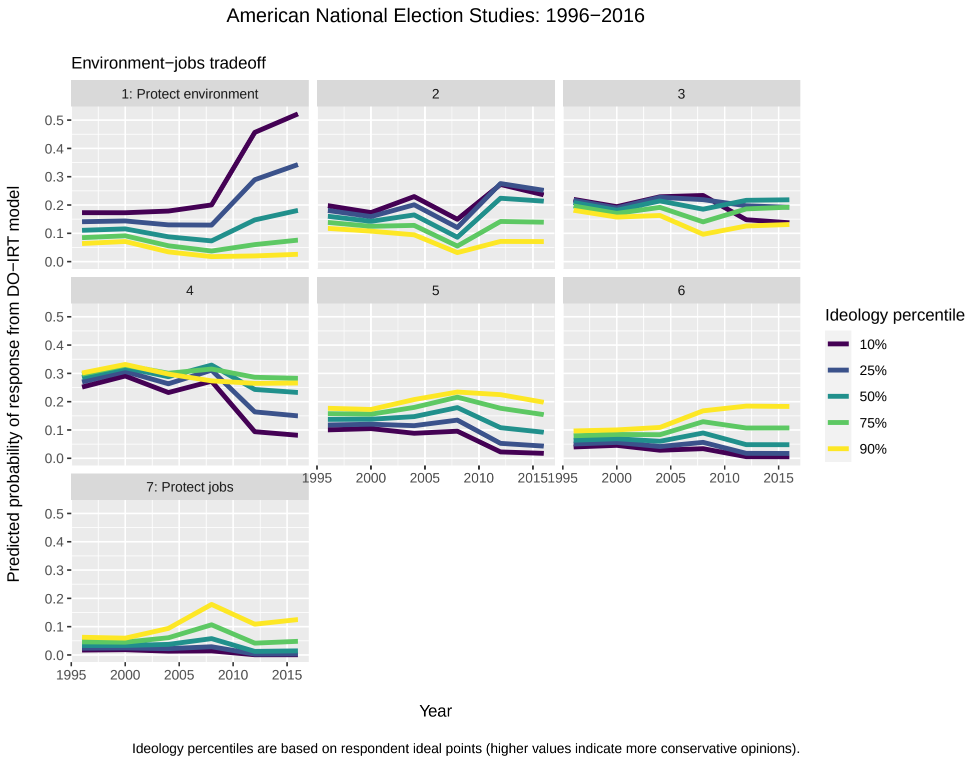


Figure A14: Predicted gay discrimination responses over time by ideal point percentile.

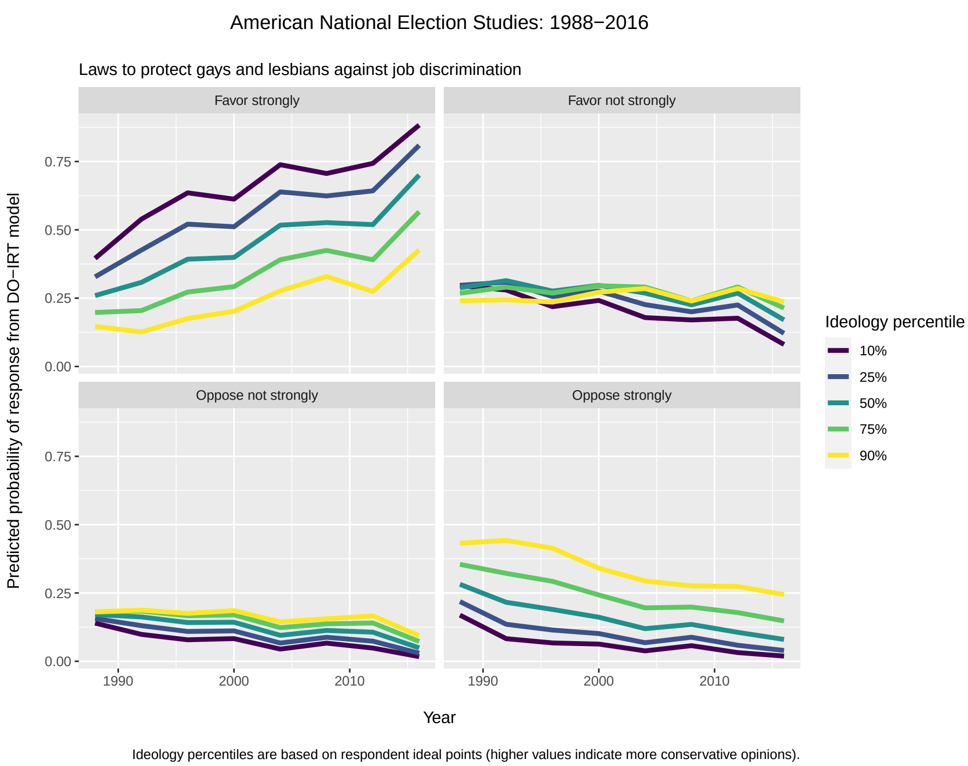


Figure A15: Predicted government spending and services responses over time by ideal point percentile.

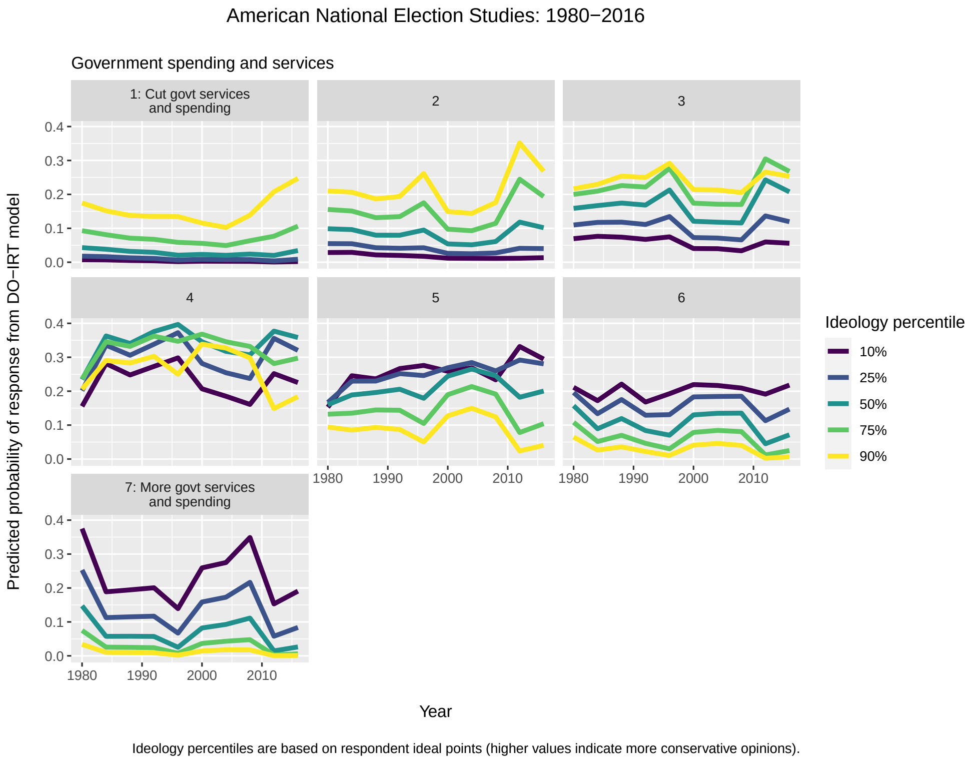


Figure A16: Predicted guaranteed jobs responses over time by ideal point percentile.

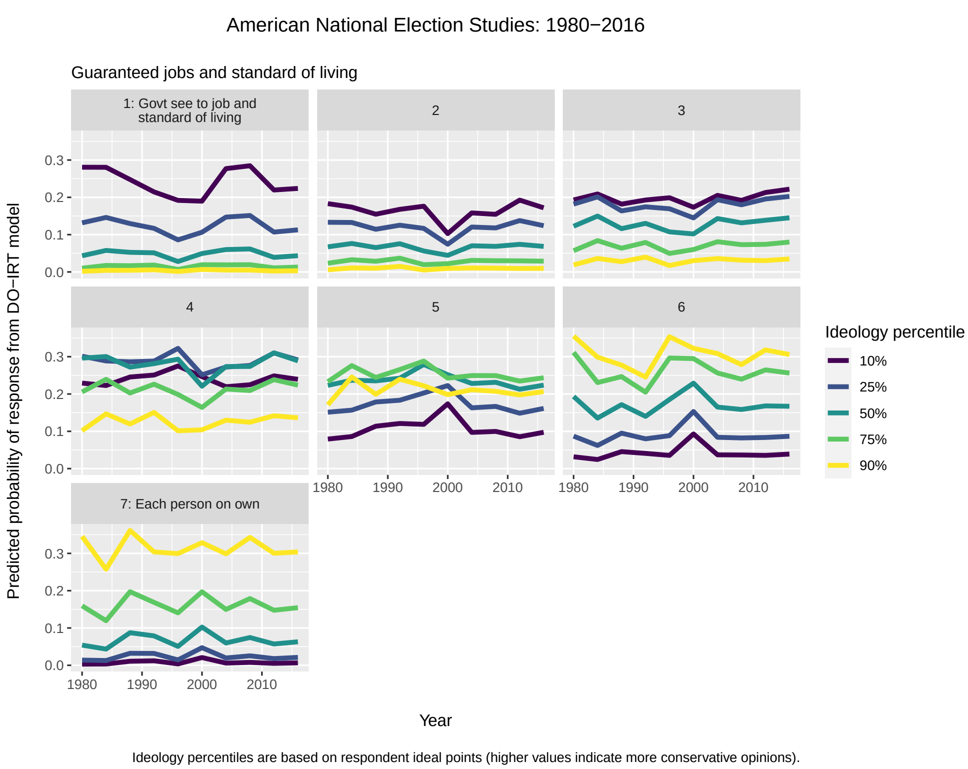
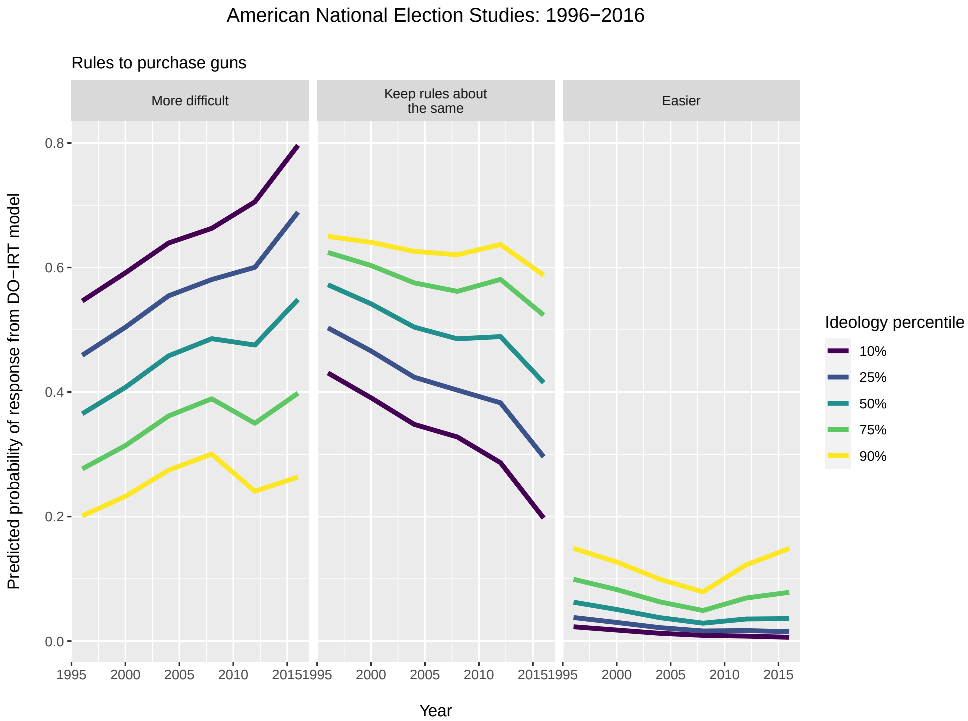
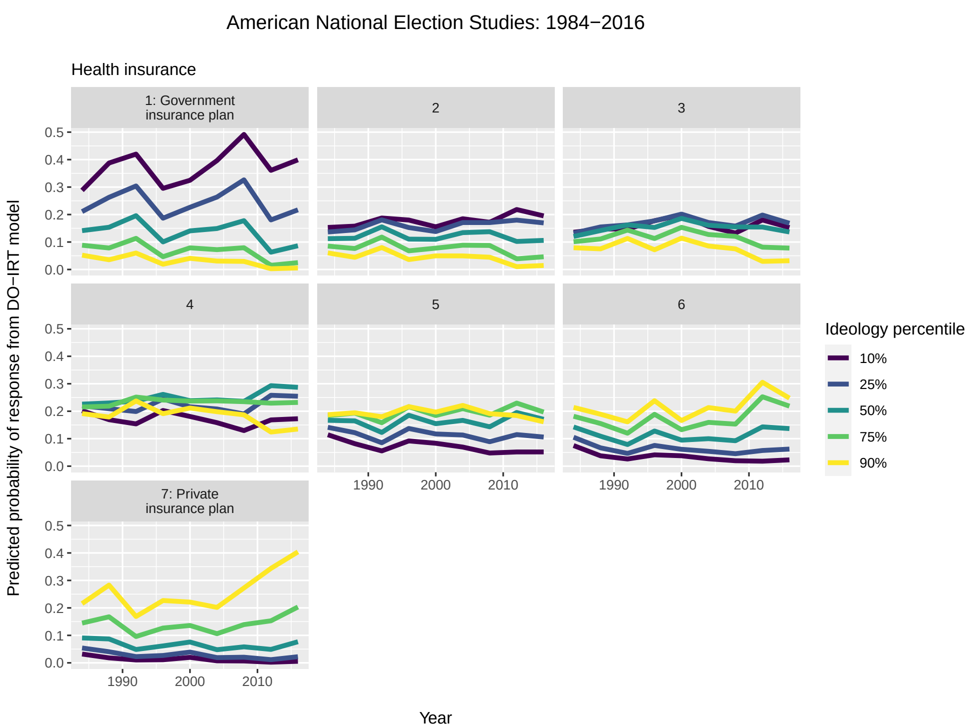


Figure A17: Predicted gun control responses over time by ideal point percentile.



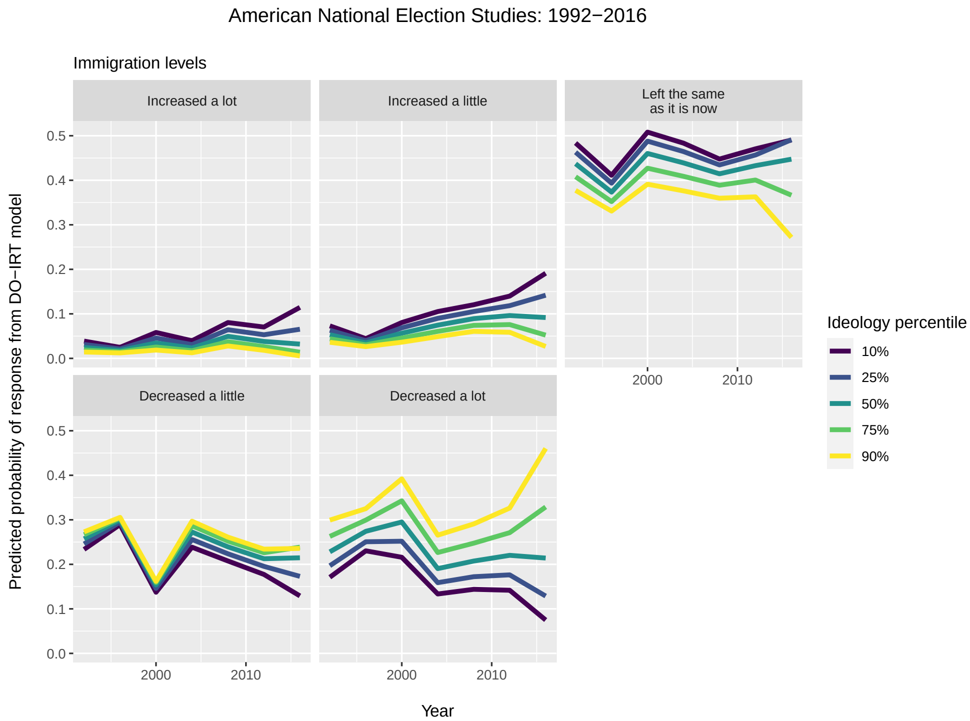
Ideology percentiles are based on respondent ideal points (higher values indicate more conservative opinions).

Figure A18: Predicted health insurance responses over time by ideal point percentile.



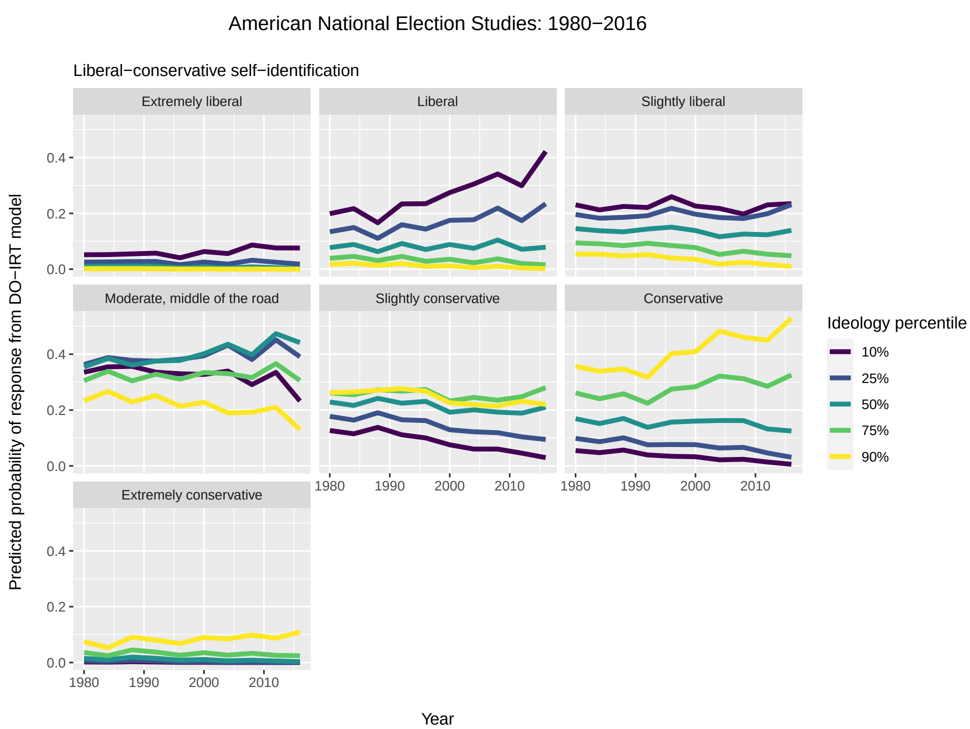
Ideology percentiles are based on respondent ideal points (higher values indicate more conservative opinions).

Figure A19: Predicted immigration responses over time by ideal point percentile.



Ideology percentiles are based on respondent ideal points (higher values indicate more conservative opinions).

Figure A20: Predicted ideological self-identification over time by ideal point percentile.



Ideology percentiles are based on respondent ideal points (higher values indicate more conservative opinions).

Figure A21: Predicted spending on the poor responses over time by ideal point percentile.

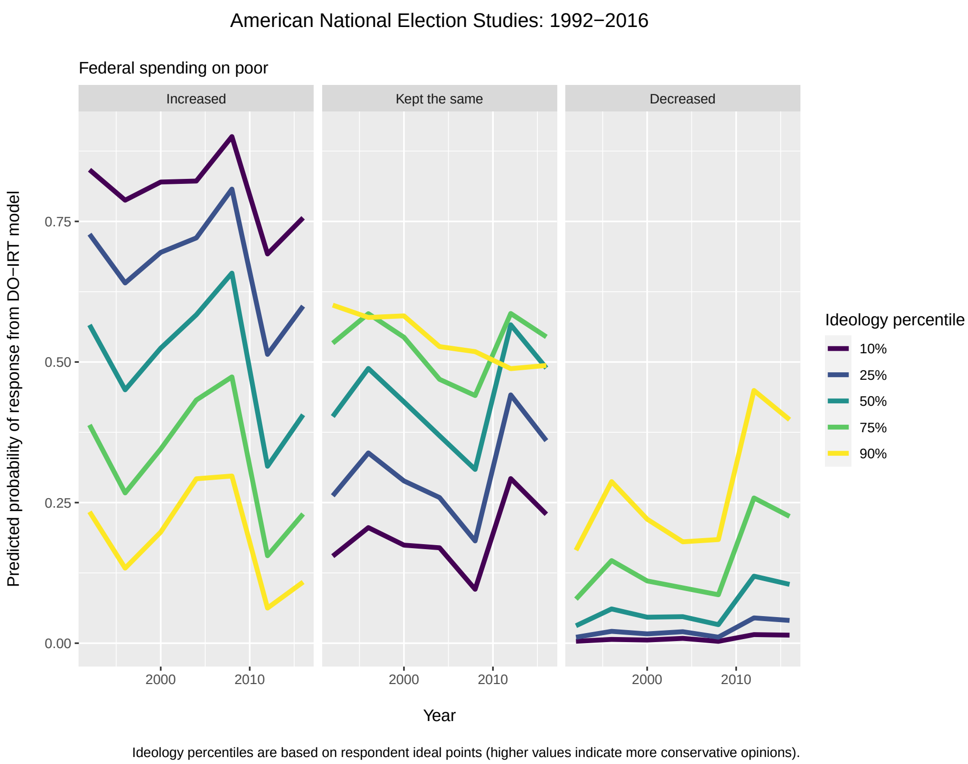
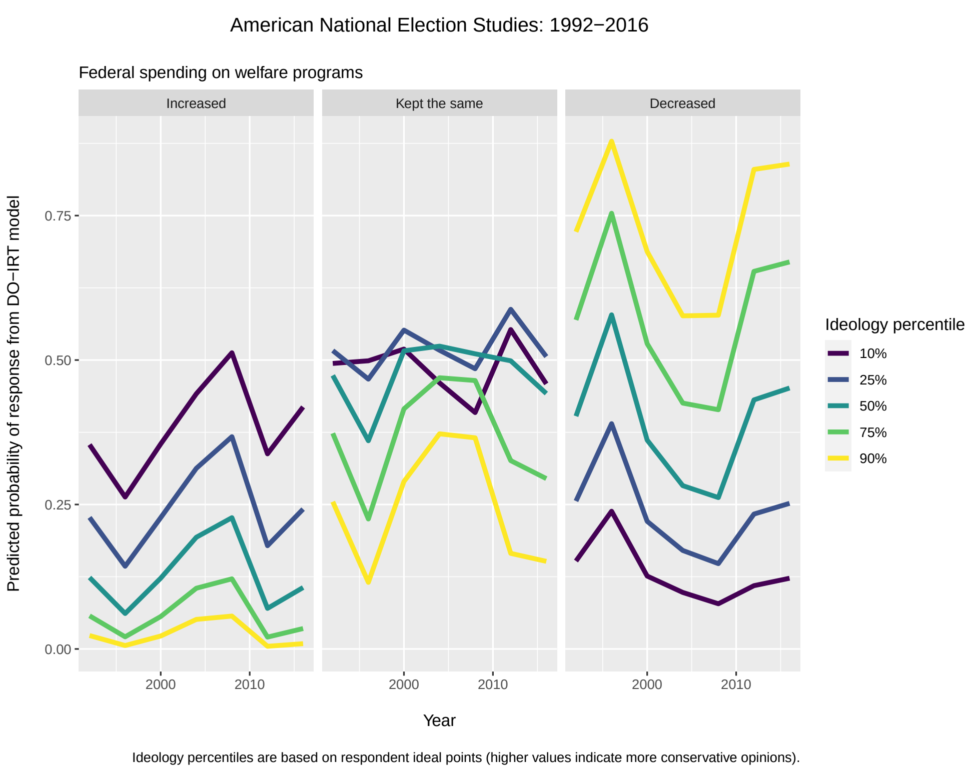


Figure A22: Predicted welfare spending responses over time by ideal point percentile.



A.7 Regression Models of the Effects of Core Values and Partisanship of Respondent Ideal Point Estimates

Table A1 provides the output of the linear regression models presented in Figure 5 in the main text. These results use the posterior means of the respondent ideal points. We can also evaluate the role of uncertainty in the respondent ideal points by using their full posterior densities.[5] Specifically, I estimate separate regression models for each of the 600 sets of sampled values (200 samples from each of the three MCMC chains) from the 24,059 posterior densities corresponding to each respondent's ideal point. This provides a distribution of (600) regression coefficients for the intercept term and each X variable (party identification, economic egalitarianism, and moral traditionalism) that can be characterized in terms of its mean and 95% highest posterior density (HPD) region or credible interval.

Figure A23 compares both sets of linear regression coefficients: the original estimates based only on the posterior means of the respondent ideal points, and the estimates based on the full set of samples from the ideal point posterior densities. The posterior mean-based coefficients are nearly always larger in magnitude, as would be expected given that any single slice of the posterior space will include extreme samples (creating measurement error) for some of the parameters. However, in virtually every case the uncertainty bounds on the two sets of coefficient estimates overlap. Hence, the results appear to be robust to the level of uncertainty in the respondent ideal points.

Table A1: Determinants of ideological scores (θ_i) by level of political sophistication (American National Election Study, 1988-2016).

	1988	1992	1996	2000	2004	2008	2012	2016
Low sophistication								
Party identification	0.18^*	0.15^*	0.22^*	0.22^*	0.23^*	0.21^*	0.32^*	0.36^*
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)	(0.02)
Egalitarianism	0.30^*	0.32^*	0.41^*	0.33^*	0.18^*	0.29^*	0.34^*	0.20^*
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)	(0.02)
Moral traditionalism	0.17^*	0.23^*	0.11^*	0.16^*	0.24^*	0.24^*	0.25^*	0.28^*

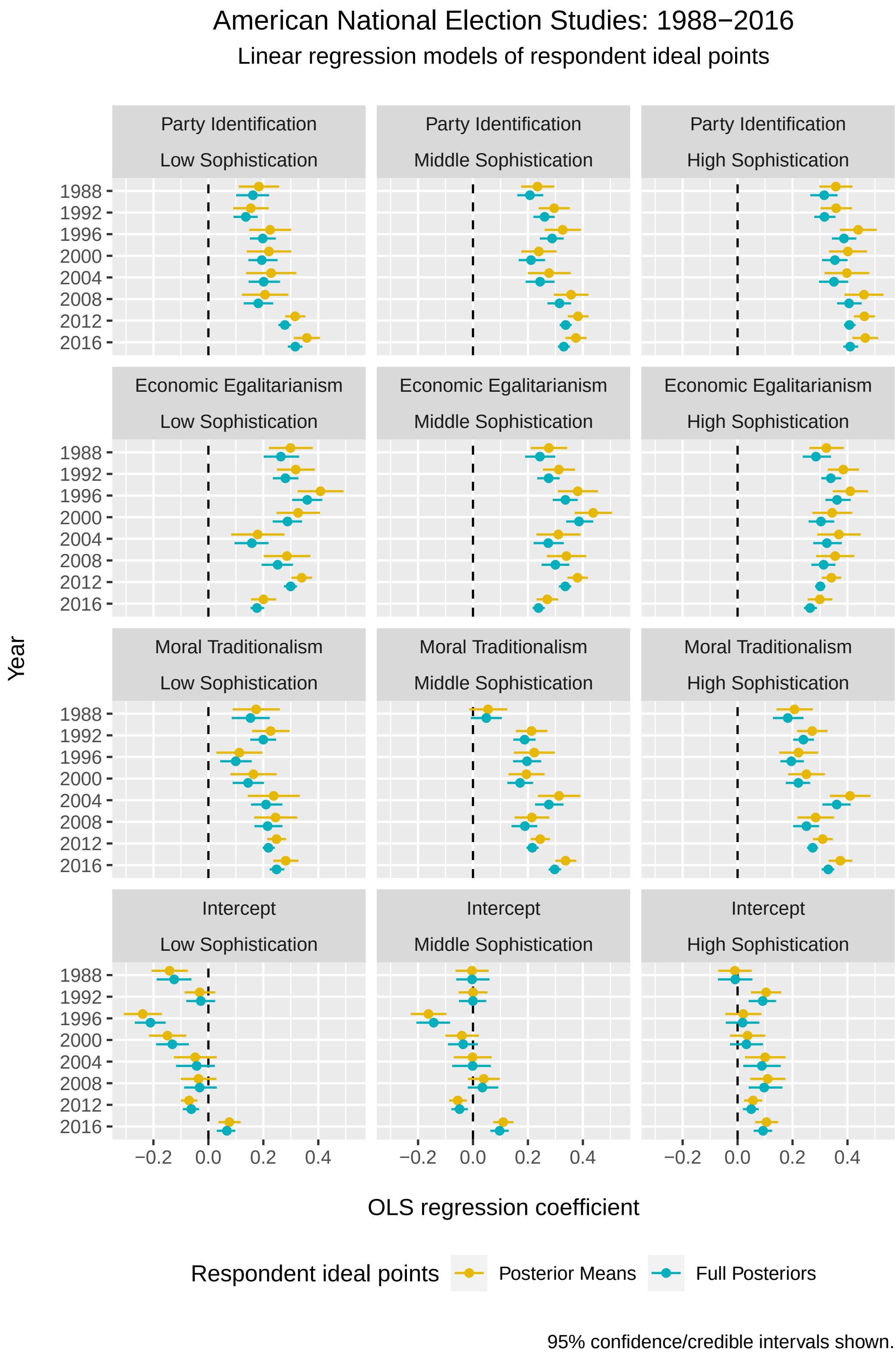
[5] I thank an anonymous reviewer for this suggestion.

	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)	(0.02)
Intercept	-0.14^*	-0.03	-0.24^*	-0.15^*	-0.05	-0.04	-0.07^*	0.08^*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
N	524	715	489	478	320	462	1672	1107
R^2	0.19	0.23	0.28	0.24	0.20	0.23	0.49	0.42
adj. R^2	0.19	0.23	0.27	0.24	0.19	0.22	0.49	0.42
Resid. sd	0.75	0.75	0.72	0.73	0.69	0.68	0.60	0.64
Middle sophistication								
Party identification	0.24^*	0.30^*	0.33^*	0.24^*	0.28^*	0.36^*	0.38^*	0.37^*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Egalitarianism	0.28^*	0.31^*	0.38^*	0.44^*	0.31^*	0.34^*	0.38^*	0.27^*
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.02)	(0.02)
Moral traditionalism	0.06	0.21^*	0.22^*	0.19^*	0.31^*	0.21^*	0.24^*	0.34^*
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Intercept	-0.00	-0.00	-0.16^*	-0.04	-0.00	0.04	-0.06^*	0.11^*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
N	595	748	514	508	365	530	1596	1378
R^2	0.24	0.38	0.46	0.46	0.49	0.48	0.61	0.61
adj. R^2	0.23	0.38	0.46	0.46	0.48	0.48	0.61	0.61
Resid. sd	0.72	0.71	0.68	0.68	0.65	0.67	0.63	0.64
High sophistication								
Party identification	0.36^*	0.36^*	0.44^*	0.40^*	0.40^*	0.46^*	0.46^*	0.46^*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.02)	(0.02)
Egalitarianism	0.32^*	0.38^*	0.41^*	0.34^*	0.37^*	0.36^*	0.34^*	0.30^*
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)
Moral traditionalism	0.21^*	0.27^*	0.22^*	0.25^*	0.41^*	0.28^*	0.31^*	0.37^*
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Intercept	-0.01	0.10^*	0.02	0.04	0.10^*	0.11^*	0.06^*	0.11^*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
N	599	742	510	537	364	495	1619	1132
R^2	0.48	0.59	0.67	0.59	0.73	0.67	0.73	0.74
adj. R^2	0.47	0.59	0.67	0.59	0.73	0.67	0.73	0.74
Resid. sd	0.72	0.72	0.70	0.72	0.68	0.71	0.66	0.67

Standard errors in parentheses

* indicates significance at $p < 0.05$

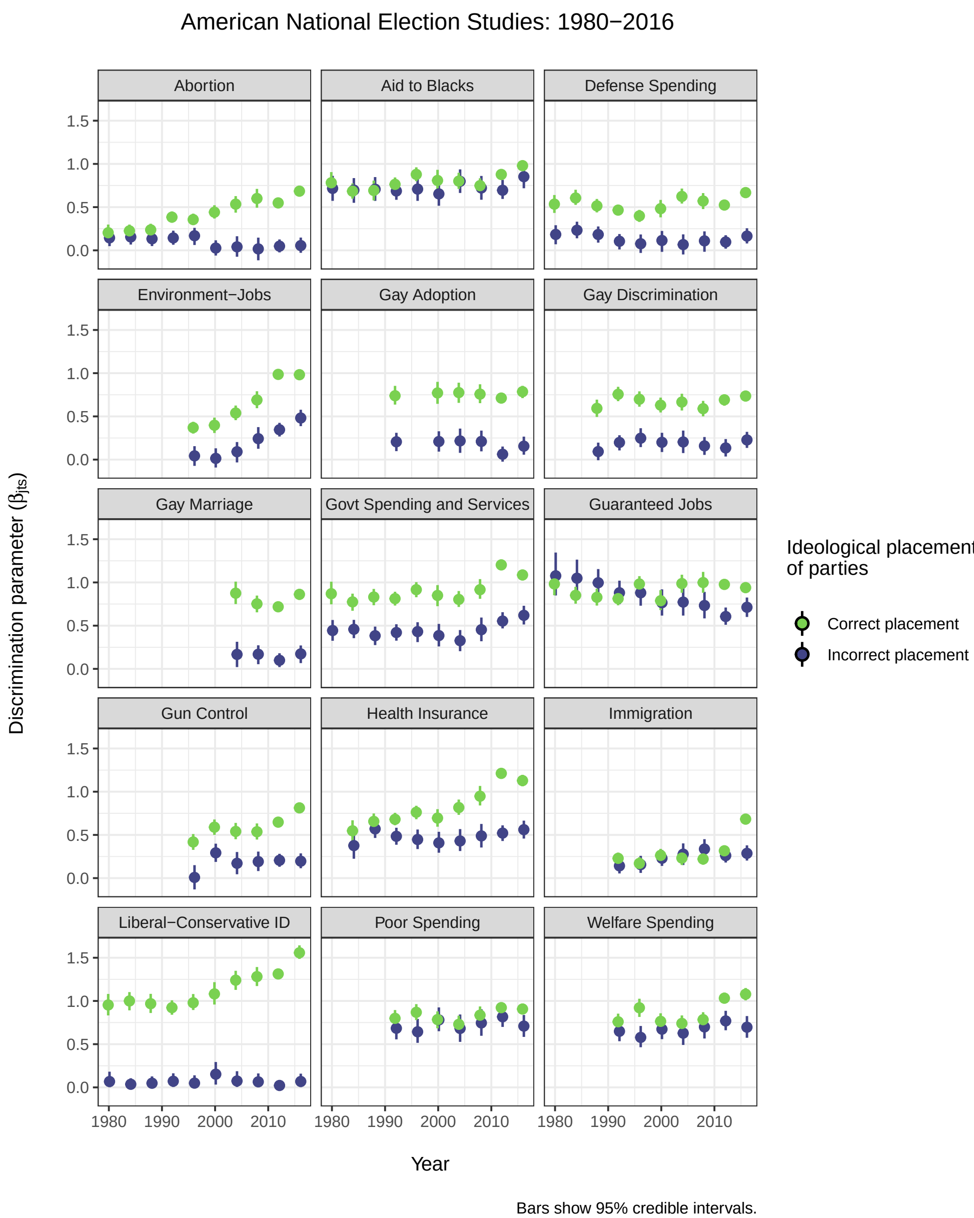
Figure A23: Comparing regression coefficients from alternate parameterizations of posterior information for the respondent ideal points.



A.8 Alternate Version of Figure 3 Using Party Ideological Placements to Measure Political Sophistication

Figure A24 shows the estimated issue discrimination parameters for respondents who correctly and incorrectly identified the relative ideological positions of the two major parties (that is, placed the Democratic Party to the left of the Republican Party on the liberal-conservative scale.)

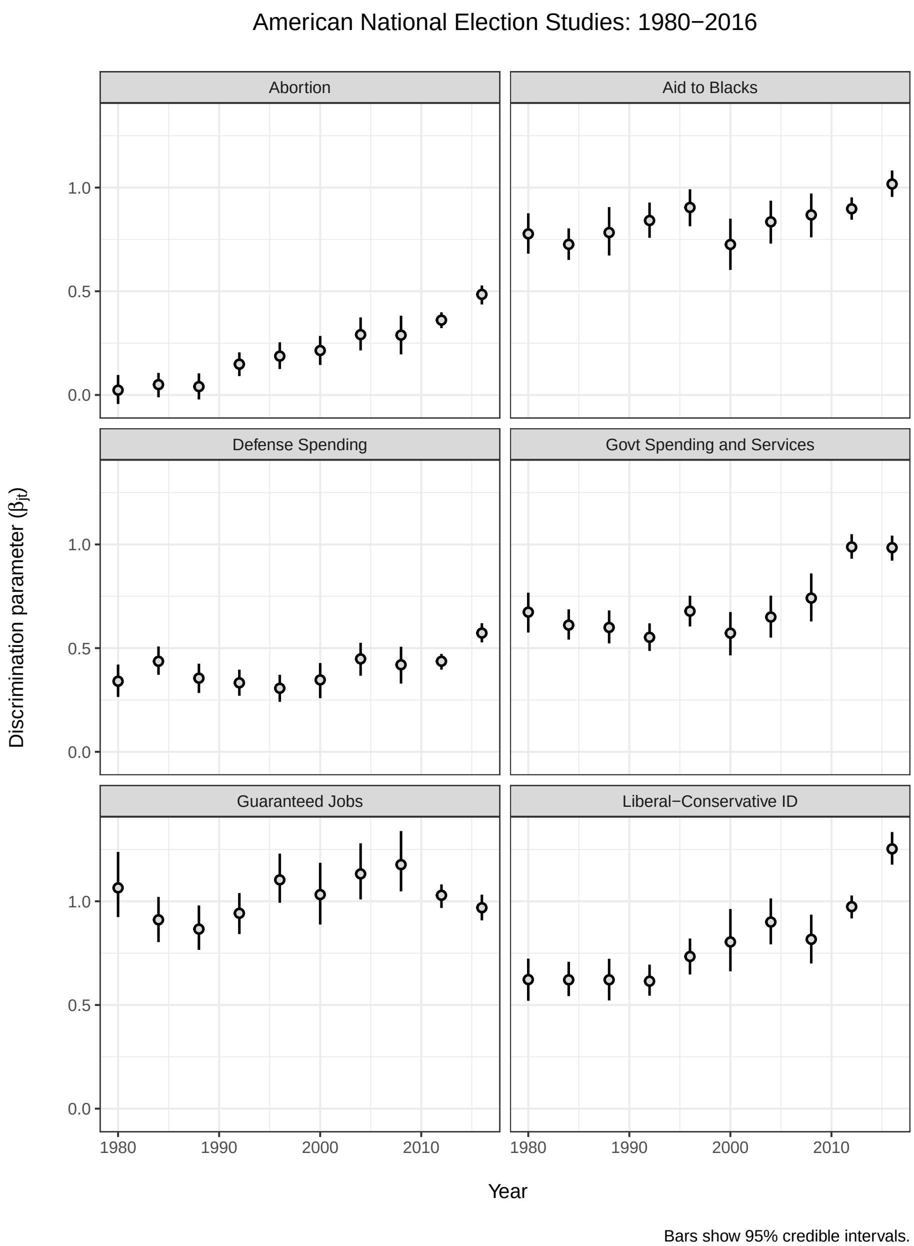
Figure A24: Issue discrimination parameters (β_{jts}) from the Bayesian dynamic ordinal IRT (DO-IRT) model by correct/incorrect ideological placement of the parties.



A.9 Alternate Version of Figure 1 Using Only Common Issue Scales to Estimate DO-IRT Model

Figure A25 shows the estimated issue discrimination parameters from a DO-IRT model that includes only the six issue scales common across all ten survey periods (1980-2016).

Figure A25: Issue discrimination parameters (β_{jts}) from the Bayesian dynamic ordinal IRT (DO-IRT) model using six common issue scales.



A.10 Bivariate Correlations between Issue Responses in the American National Election Studies, 1980-2016

Figures A26-A29 provide the bivariate Pearson correlations between issue responses in the 1980-2016 ANES Time Series studies.[6] The trends in interissue correlation are generally positive (indicating an increase in mass constraint), although measurement error associated with individual items (e.g., Jacoby, 1991; Ansolabehere, Rodden and Snyder, 2008) and the multiplicity of pairwise comparisons blur the extent to which Americans' policy attitudes have become increasingly coupled in a unidimensional ideological space.

[6]Figures A26-A29 plot the absolute values of the interissue correlations to accomodate reverse-coded items. Lowess smoothers with corresponding 95% confidence intervals included.

Figure A26: Interissue correlations in the mass public, 1980-2016 (1/4).

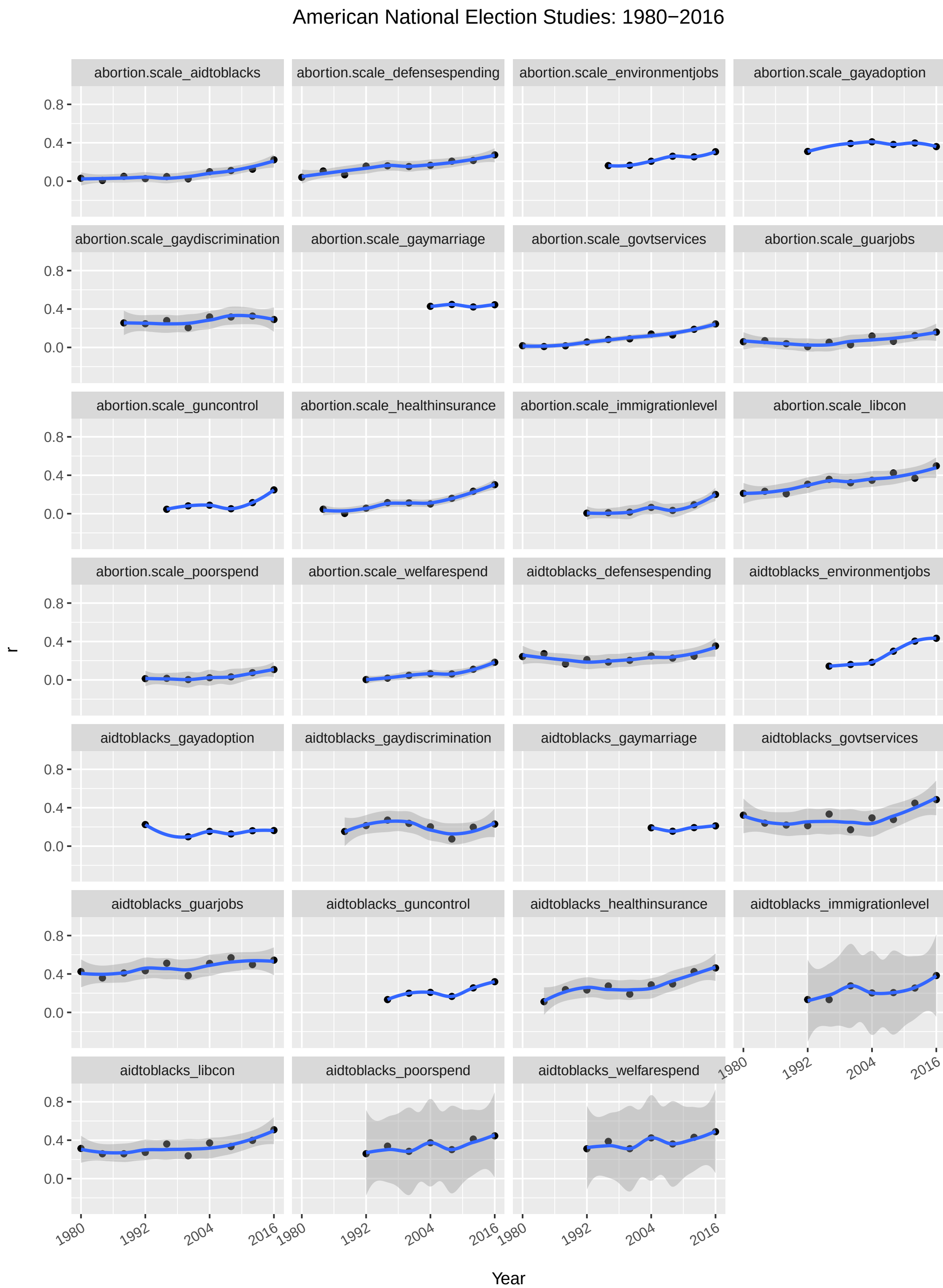


Figure A27: Interissue correlations in the mass public, 1980-2016 (2/4).

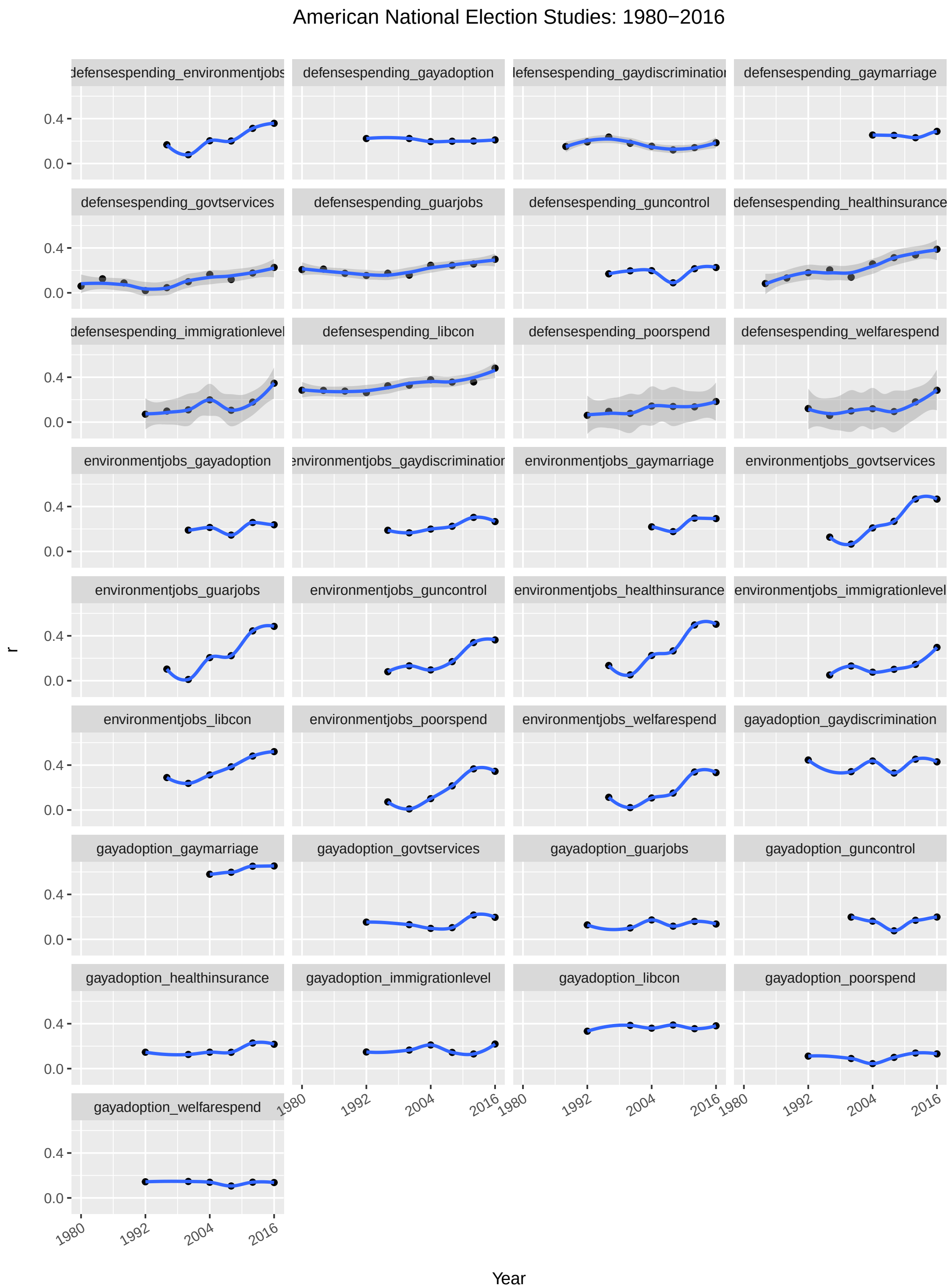


Figure A28: Interissue correlations in the mass public, 1980-2016 (3/4).

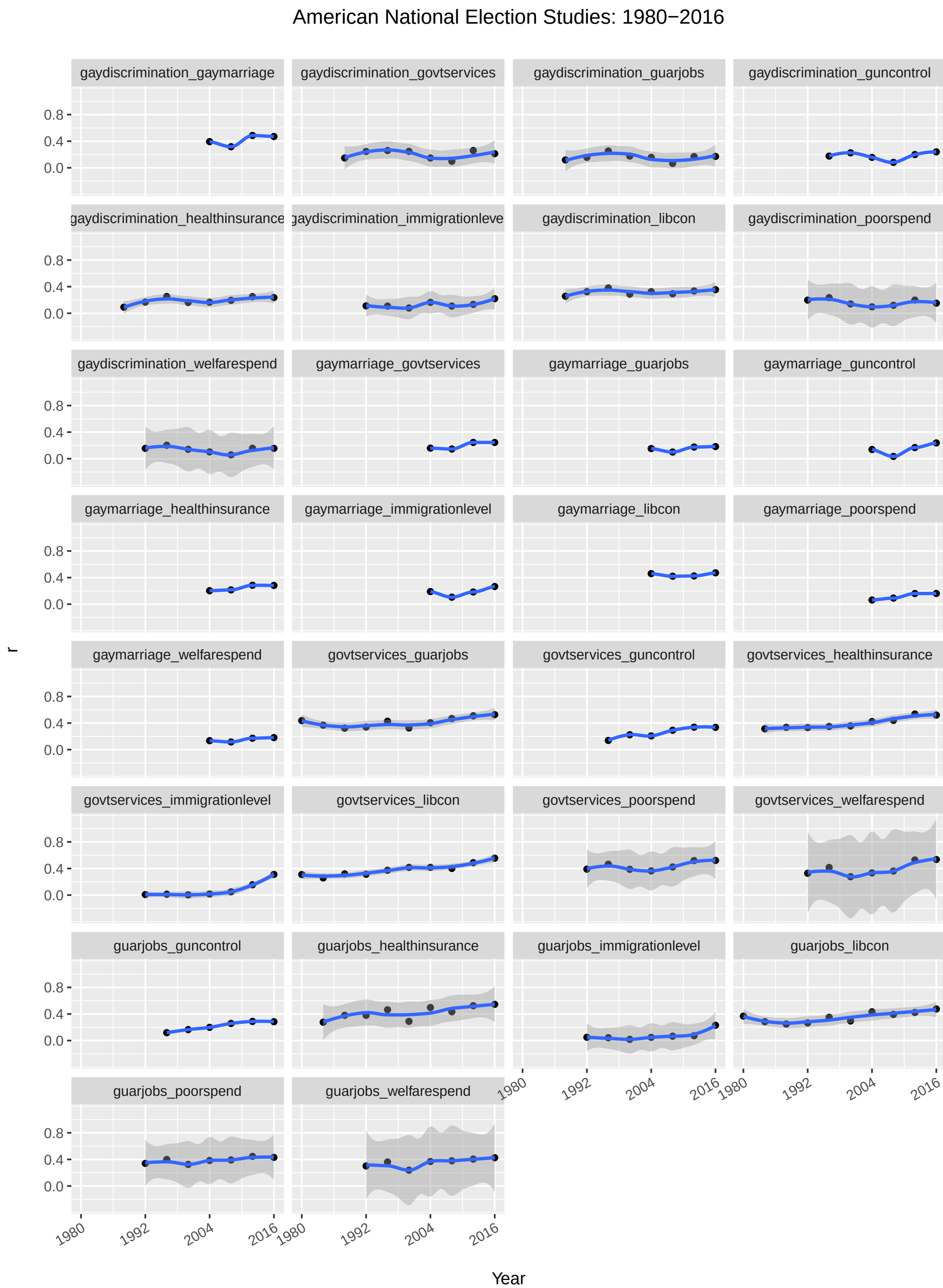
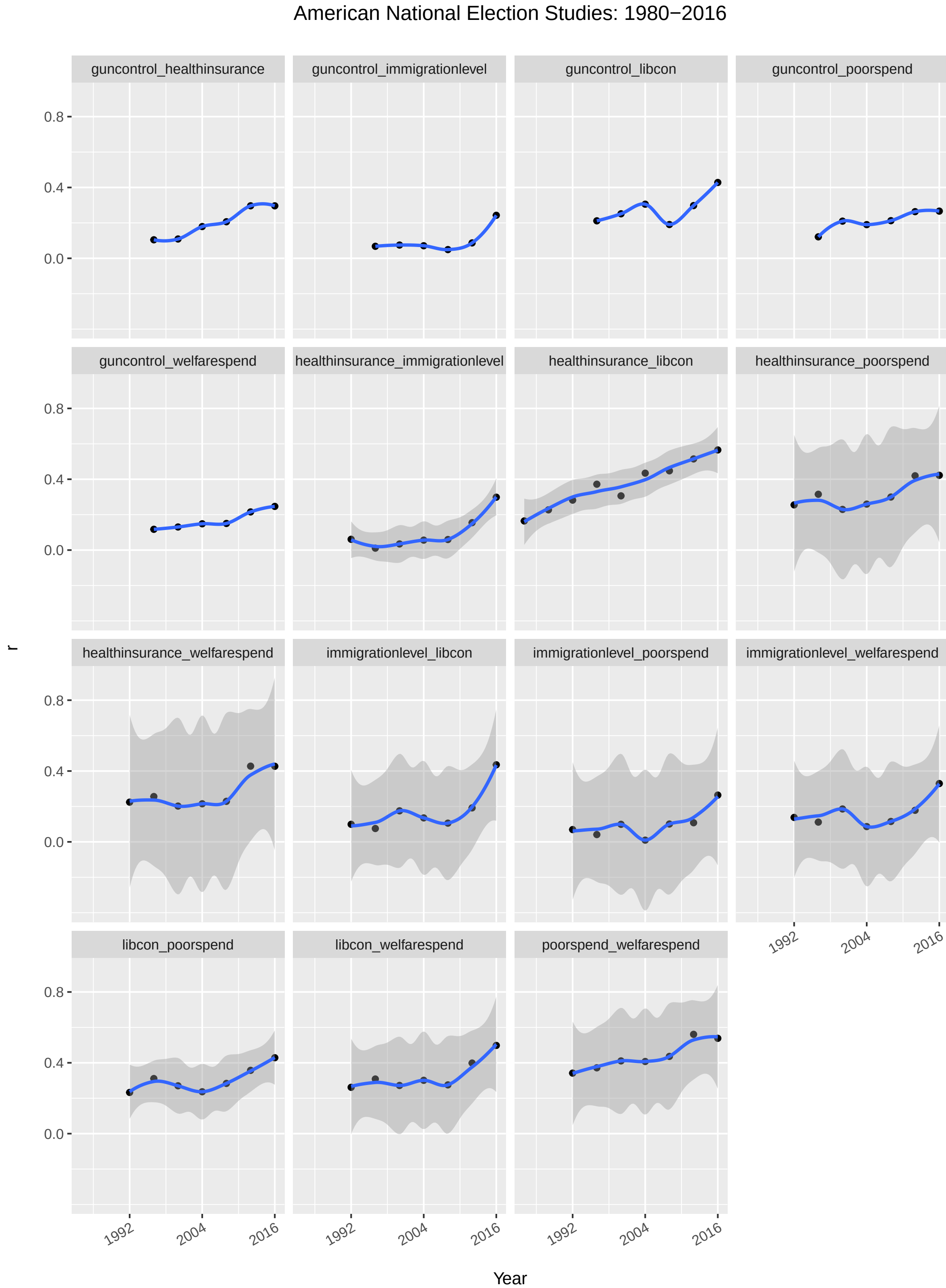


Figure A29: Interissue correlations in the mass public, 1980-2016 (4/4).



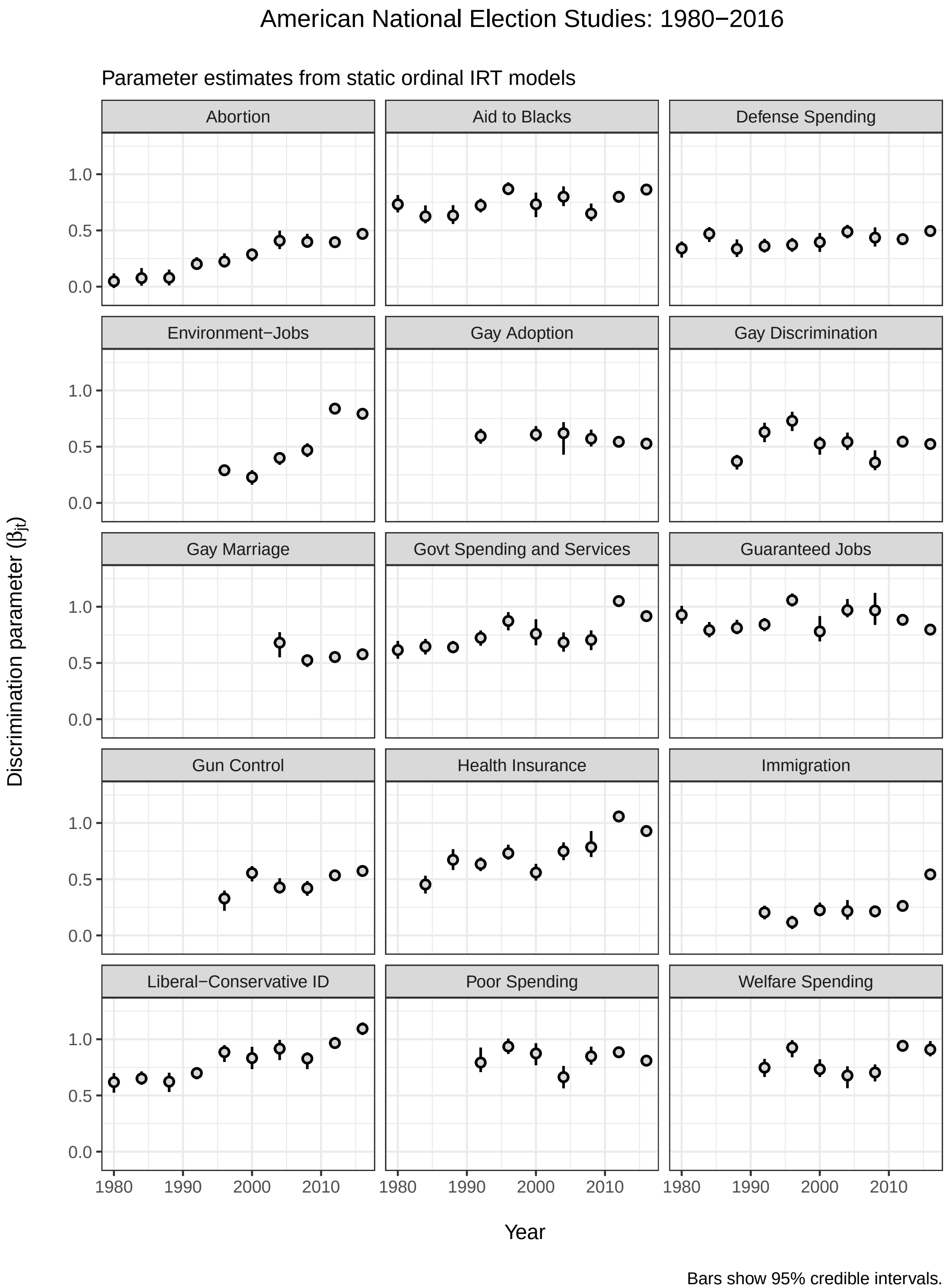
A.11 Discrimination Parameter Estimates from a Static Ordinal Item Response Theory (O-IRT) Model

As a robustness check on the main results, I also estimate a series of static ordinal item response theory (O-IRT) models in which a single set of item parameters are estimated for all issues but one (z_{-j}). The omitted issue j is divided into separate items corresponding to responses in each of the ten time periods ($z_{j1}, z_{j2}, \ldots, z_{j10}$). The static O-IRT model is then simultaneously estimated on the new data matrix z, with the process repeated for each issue j ($j = 1, \ldots, p$) following the same Bayesian approach as the dynamic model.[7]

The estimated discrimination parameters from the static O-IRT models are presented in Figure A30. Though this strategy assumes that all of the other issues have ideological mappings that are constant across time, the results reveal similar trends as the dynamic model towards greater conflict extension in American public opinion over this period.

[7] I thank an anonymous reviewer for this clever suggestion.

Figure A30: Issue discrimination parameters (β_{jt}) from a series of Bayesian static ordinal IRT (O-IRT) models.



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