No Substitute for Competence

Online Appendix

November 17, 2019

Simon Lanz

Contents

4 Appendix: Empirical Framework

4.1 Party Issue Attention: CMP Coding Scheme

Table 4.1: CMP recoding scheme

Issue	CMP codes
External relations	per101; per102; per103; per106; per107; per108; per109; per110
Social policy	per503; per504; per505; per506; per507; per706
Services	per303
Economy	per401; per402; per403; per404; per405; per406; per407; per408; per409; per410; per411; per412; per413; per414; per415; per416; per701; per702; per703; per704
Immigration	per607; per608
Security	per104; per105; per605
Quality of live	per201; per202; per203; per204; per501; per502; per705
Other	per301; per302; per304; per305; per601; per602; per603; per604; per606

5 Appendix: The Sources of Issue Ownership

5.1 A Bayesian Framework

The requirements on the regression models used in this study are high since they have to simultaneously measure effects of party-specific and voter-specific variables across multiple countries. The Bayesian framework offers the most straight-forward solution to this challenge.

Bayesian inference is a genre of statistics where prior knowledge together with data yields posterior knowledge.[1] The Bayesian framework rests on Bayes's theorem, which specifies how to update beliefs in light of new data. Let $\mathbf{y}$ be the data and θ an unknown, continuous parameter. Such parameters follow the probability density function (pdf) denoted $p(\theta)$ for the prior pdf and $p(\theta|\mathbf{y})$ for the posterior pdf.[2] Bayes's theorem is,

$$p(\theta|\mathbf{y}) \propto p(\mathbf{y}|\theta)p(\theta), \tag{5.1}$$

With the constant of probability

$$\left[\int p(\mathbf{y}|\theta)p(\theta)d\theta\right]^{-1}$$

Where $p(\mathbf{y}|\theta)$ is the joint probability density of $\mathbf{y}$ indexed by θ. This density can be re-written as likelihood function $\mathcal{L}(\theta|\mathbf{y})$ (see Tanner 1996: 14).[3] In words, Equation 5.1 is what Jackman (2009: 14) calls the Bayesian mantra: "the posterior is proportional to the prior times the likelihood". Bayes's theorem is designed such that if we have no prior knowledge about θ, its posterior density is proportional to the likelihood function. Put differently, with uninformative priors, Bayesian and frequentist methods yield similar results (Jackman 2000: 377).[4]

For most statistical models, including those in this project, the posterior probability density is too complicated to compute analytically. Therefore, Bayesian analyses exploit the Monte Carlo principle, which states that we can learn about θ by sampling many times from its posterior density $p(\theta|\mathbf{y})$ (see Krauth 2006: Chapter 1).[5] All sampling in this project (and in most Bayesian analyses) is based on the Markov chain theory. These chains have the property that they visit a certain point in the parameter space with the same frequency as the probability of that point under the posterior pdf (Jackman 2009: 172). Markov generated samples are auto correlated. Hence, the point in the parameter space visited by the chain depends on the previous point. This imposes a level of inefficiency on the random-walk, which is usually balanced out by a large number of draws. The heart and soul of any Markov chain Monte Carlo (MCMC) are its jumping rules. These algorithms define how the chain travels through the parameter space and when samples are accepted or rejected. I refrain from describing different samplers. Jackman (2009: Chapter 5) and Kruschke (2014: Chapter 7) both provide an accessible introduction into the workhorses of MCMC, the Metropolis-Hasitngs algorithm and the Gibbs sampler.

I implement MCMC with the statistical software `JAGS` (Plummer 2015), which is written in `C++` and therefore runs on different computer-operating systems including MacOS and Windows.[6] `JAGS` stands for 'Just Another Gibbs Sampler', which is somewhat misleading since the chains are not necessarily estimated with the Gibbs algorithm. The program is designed to choose the most efficient sampler among those available. I use the package `rjags` to let the statistical software `R` interact with `JAGS` (Plummer 2016).[7]

A careful monitoring of the chains increases the confidence that the chains converged on a posterior pdf and that their runtime is sufficiently long for them to travel to all areas of $p(\theta|\mathbf{y})$. I rely on both visual inspection and numerical description of the chains. Convergence and run-length diagnostics are done with the package `coda` (Plummer, Best, Cowles, Vines, Sarkar, Bates, Almond and Magnusson 2016).[8] The `JAGS` code of each model is presented in the Appendix of the each empirical chapter.

5.2 JAGS Code Full Models

This code is for a country with five parties (e.g. Austria, Canada, or Iceland). The second line of code loops over observations (i in 1:NOBS), the third line of code loops over choice alternatives (j in 1:5). ag (issue attention), pe (performance), di (positional distance), pi (partisanship) are the sources of competence ratings (varying over i and j). p[i,j] is the probability of voting for each party j and follows equation ??. The priors are fixed in the lines following #priors.

```
model{
     for(i in 1:NOBS){
      for(j in 1:5){
               mu[i,j]   <- beta[j,1]
                         + beta[j,2]*age[i]
                         + beta[j,3]*sex[i]
                         + beta[j,4]*educ[i]
                         + gamma[1]*ag[i,j]
                         + gamma[2]*pe[i,j]
                         + gamma[3]*di[i,j]
                         + gamma[4]*pi[i,j]
               emu[i,j] <- exp(mu[i,j])
               p[i,j] <- emu[i,j]/sum(emu[i,1:5])
          }
          y[i] ~ dcat(p[i,1:5])
     }

     # priors
     for(k in 1:4){
          beta[1,k] <- 0
     }
     for(j in 2:5){
          beta[j,1:4] ~ dmnorm(b0,B0)
     }
     for(h in 1:4){
          gamma[h] ~ dnorm(0,.01)
     }
}
```

5.3 Partial Models

These partial models take the following form:

$$V_{ij} = \beta_{j0} + \beta_{j1} \cdot age_i + \beta_{j2} \cdot sex_i + \beta_{j3} \cdot education_i + \gamma_1 \cdot source_{ij} \tag{5.2}$$

Where $source_{ij}$ corresponds to the four sources of issue ownership: issue emphasis, performance, party identification, and voter-party distance. The models are estimated with the following `JAGS`-code:

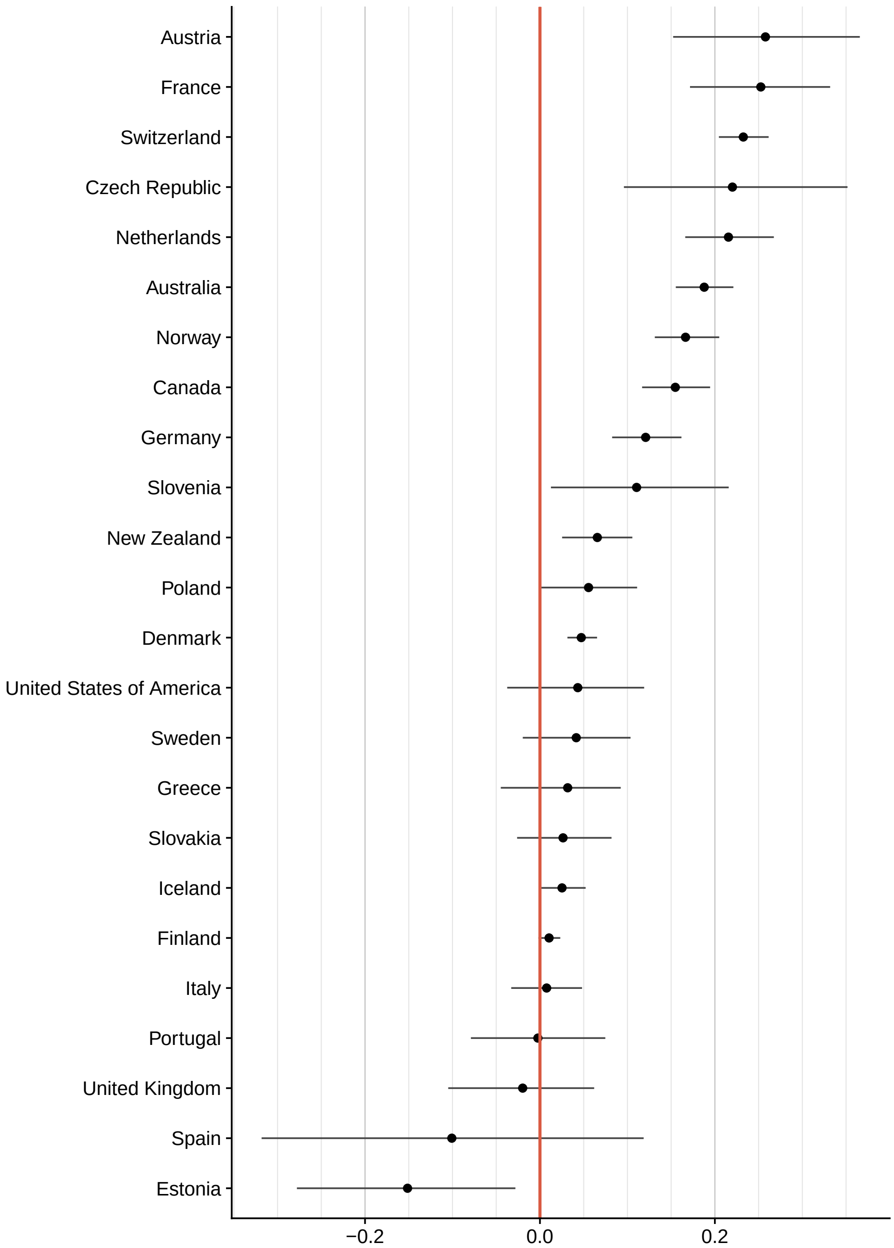
```
model{
     for(i in 1:NOBS){
          for(j in 1:5){
               mu[i,j]   <- beta[j,1]
                          + beta[j,2]*age[i]
                          + beta[j,3]*sex[i]
                          + beta[j,4]*educ[i]
                          + gamma*sou[i,j]
               emu[i,j] <- exp(mu[i,j])
               p[i,j] <- emu[i,j]/sum(emu[i,1:5])
          }
          y[i] ~ dcat(p[i,1:5])
     }

     # priors
     for(k in 1:4){
      beta[1,k] <- 0
     }
     for(j in 2:5){
          beta[j,1:4] ~ dmnorm(b0,B0)
     }
     gamma ~ dnorm(0,.01)
}
```

Table 5.1: Sources of competence: issue emphasis

Country	Emphasis, γ	γ HPD	Controls
Australia	0.06	[0.05, 0.07]	✓
Austria	0.09	[0.05, 0.12]	✓
Canada	0.05	[0.04, 0.07]	✓
Czech Republic	0.08	[0.03, 0.13]	✓
Denmark	0.02	[0.01, 0.03]	✓
Finland	0.01	[0.00, 0.01]	✓
France	0.10	[0.07, 0.13]	✓
Germany	0.04	[0.03, 0.06]	✓
Iceland	0.01	[0.00, 0.02]	✓
Netherlands	0.09	[0.07, 0.11]	✓
New Zealand	0.02	[0.01, 0.04]	✓
Norway	0.07	[0.06, 0.08]	✓
Poland	0.03	[0.01, 0.05]	✓
Switzerland	0.09	[0.08, 0.10]	✓
Greece	0.01	[-0.02, 0.04]	✓
Slovakia	0.01	[-0.01, 0.03]	✓
Slovenia	0.04	[-0.01, 0.08]	✓
Sweden	0.01	[-0.01, 0.04]	✓
United States	0.02	[-0.01, 0.05]	✓
Italy	-0.004	[-0.02, 0.01]	✓
Portugal	-0.017	[-0.05, 0.02]	✓
Spain	-0.014	[-0.08, 0.05]	✓
United Kingdom	-0.007	[-0.03, 0.02]	✓
Estonia	-0.06	[-0.11, -0.01]	✓

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 iterations after 50,000 iterations burn-in.



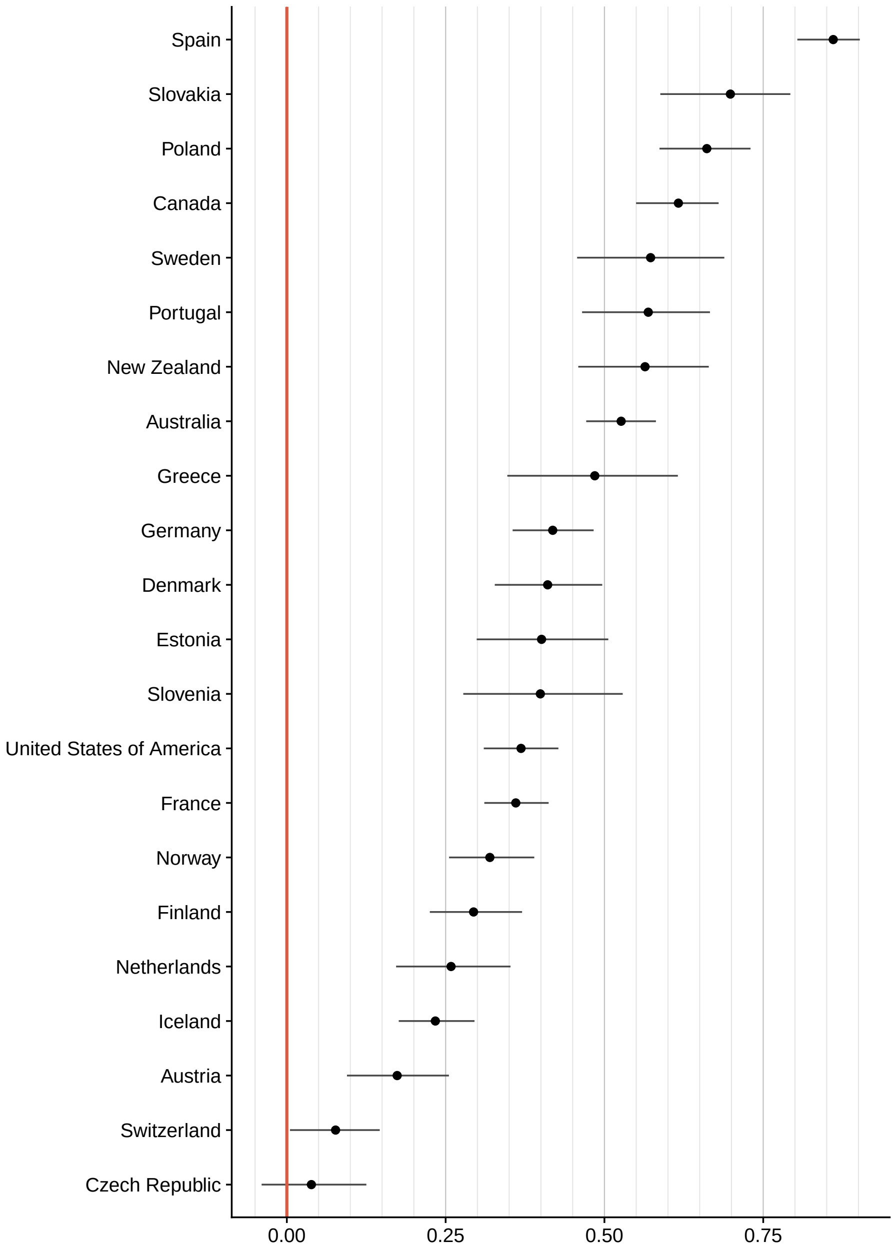
Note: FDs associated with changing party issue emphasis from 'low' (mean - 7.5) to 'high' (mean + 7.5). Orange line indicates no change in predicted probability.

Figure 5.1: FDs: party competence and issue emphasis (partial models)

Table 5.2: Sources of competence: performance

Country	Performance, γ	γ HPD	Controls
Australia	1.06	[0.95, 1.19]	✓
Austria	0.32	[0.17, 0.45]	✓
Canada	1.27	[1.12, 1.43]	✓
Denmark	0.82	[0.69, 0.97]	✓
Estonia	0.71	[0.53, 0.89]	✓
Finland	0.69	[0.56, 0.83]	✓
France	0.78	[0.67, 0.90]	✓
Germany	0.81	[0.68, 0.94]	✓
Greece	0.94	[0.74, 1.17]	✓
Iceland	0.51	[0.39, 0.64]	✓
Netherlands	0.55	[0.37, 0.73]	✓
New Zealand	1.39	[1.14, 1.67]	✓
Norway	0.87	[0.73, 1.02]	✓
Poland	1.43	[1.23, 1.67]	✓
Portugal	1.32	[1.06, 1.60]	✓
Slovakia	1.54	[1.26, 1.90]	✓
Slovenia	0.99	[0.71, 1.32]	✓
Spain	1.81	[1.56, 2.09]	✓
Sweden	1.20	[0.96, 1.48]	✓
United States	0.61	[0.52, 0.71]	✓
Czech Republic	0.07	[-0.09, 0.23]	✓
Switzerland	0.08	[-0.09, 0.24]	✓

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 iterations after 50,000 iterations burn-in.



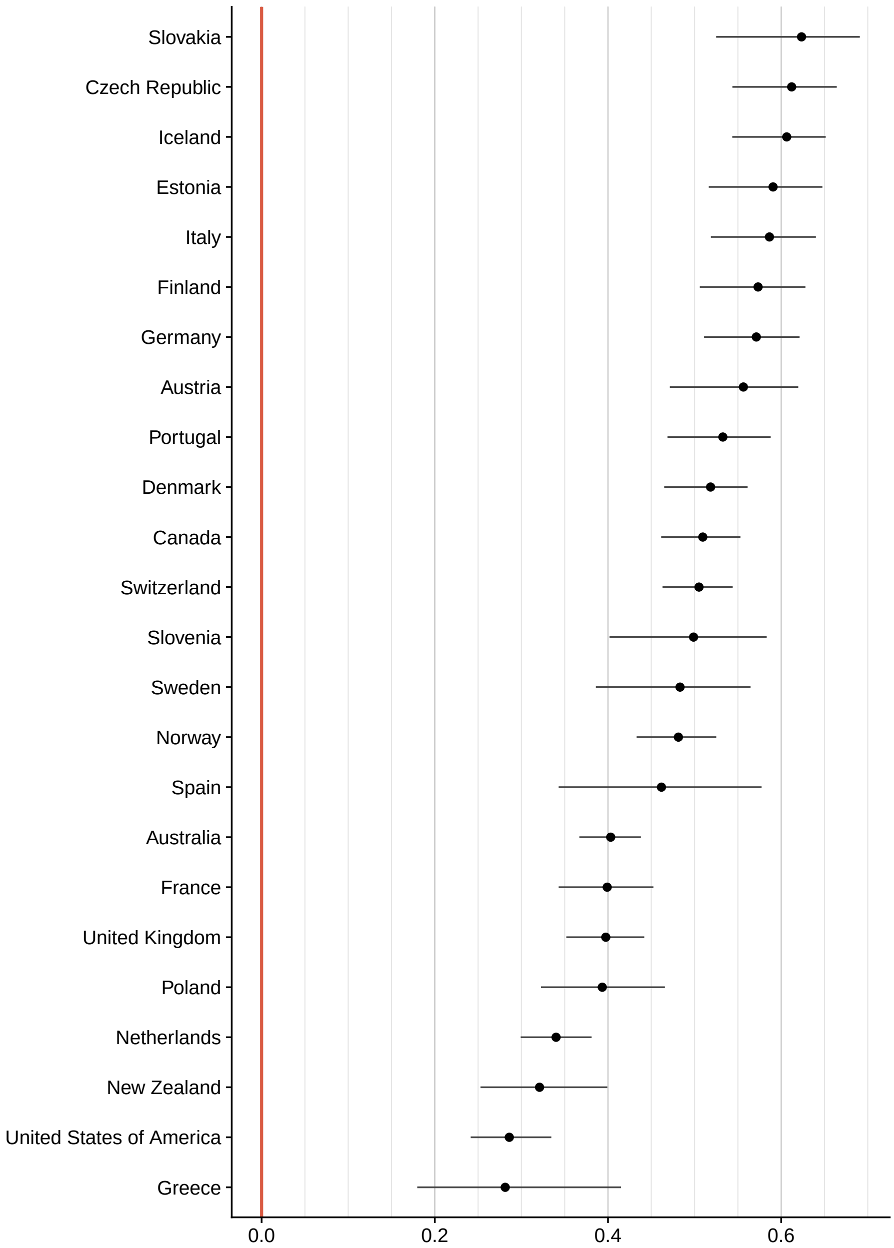
Note: FDs associated with changing evaluation of government performance from 'very bad' to 'very good'. Orange line indicates no change in predicted probability.

Figure 5.2: FDs: party competence and performance (partial models)

Table 5.3: Sources of competence: partisanship

Country	P. ident., γ	γ HPD	Controls
Australia	1.97	[1.83, 2.12]	✓
Austria	2.82	[2.56, 3.09]	✓
Canada	2.65	[2.46, 2.84]	✓
Czech Republic	3.20	[2.91, 3.52]	✓
Denmark	2.51	[2.35, 2.67]	✓
Estonia	3.01	[2.67, 3.37]	✓
Finland	3.19	[2.97, 3.43]	✓
France	2.29	[2.09, 2.49]	✓
Germany	3.19	[2.98, 3.41]	✓
Greece	4.09	[3.36, 4.96]	✓
Iceland	3.10	[2.85, 3.36]	✓
Italy	2.17	[1.96, 2.40]	✓
Netherlands	1.81	[1.67, 1.95]	✓
New Zealand	2.48	[2.13, 2.86]	✓
Norway	2.29	[2.12, 2.47]	✓
Poland	3.42	[3.09, 3.79]	✓
Portugal	2.76	[2.42, 3.12]	✓
Slovakia	3.66	[3.33, 4.03]	✓
Slovenia	2.42	[1.96, 2.90]	✓
Spain	3.86	[3.32, 4.50]	✓
Sweden	3.17	[2.88, 3.48]	✓
Switzerland	2.65	[2.46, 2.85]	✓
United Kingdom	2.17	[1.96, 2.40]	✓
United States	2.17	[1.96, 2.40]	✓

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 iterations after 50,000 iterations burn-in.



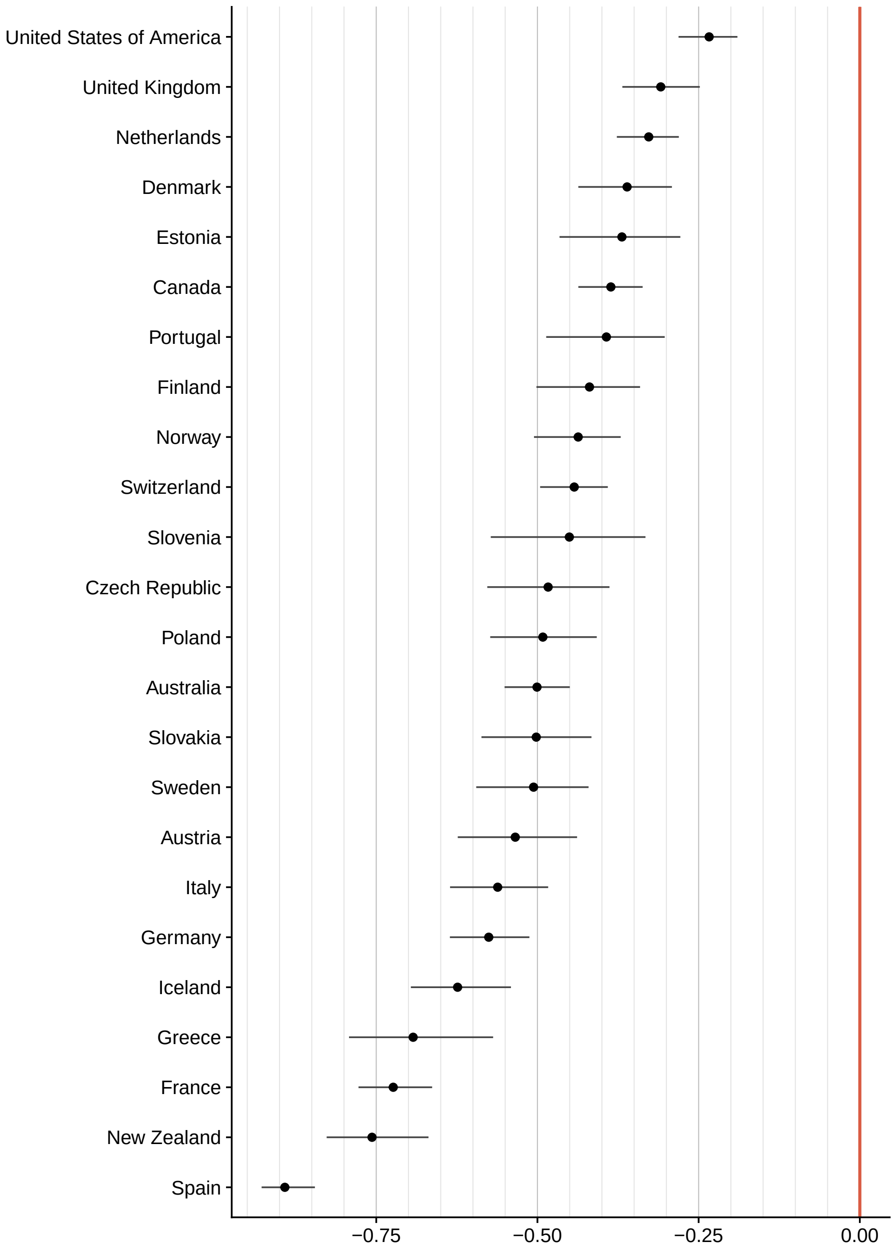
Note: FDs associated with changing party identification from 'no' to 'yes'. Orange line indicates no change in predicted probability.

Figure 5.3: FDs: party competence and partisanship (partial models)

Table 5.4: Sources of competence: voter-party distance

Country	Distance, γ	γ HPD	Controls
Australia	-0.37	[-0.41, -0.33]	✓
Austria	-0.41	[-0.48, -0.34]	✓
Canada	-0.37	[-0.42, -0.32]	✓
Czech Republic	-0.56	[-0.64, -0.49]	✓
Denmark	-0.42	[-0.47, -0.38]	✓
Estonia	-0.33	[-0.40, -0.25]	✓
Finland	-0.49	[-0.55, -0.42]	✓
France	-0.67	[-0.75, -0.60]	✓
Germany	-0.75	[-0.82, -0.68]	✓
Greece	-0.66	[-0.80, -0.53]	✓
Iceland	-0.54	[-0.61, -0.48]	✓
Italy	-0.53	[-0.61, -0.46]	✓
Netherlands	-0.33	[-0.37, -0.29]	✓
New Zealand	-0.70	[-0.85, -0.58]	✓
Norway	-0.49	[-0.54, -0.45]	✓
Poland	-0.44	[-0.52, -0.37]	✓
Portugal	-0.33	[-0.41, -0.25]	✓
Slovakia	-0.50	[-0.58, -0.42]	✓
Slovenia	-0.48	[-0.60, -0.36]	✓
Spain	-1.25	[-1.47, -1.06]	✓
Sweden	-0.46	[-0.53, -0.39]	✓
Switzerland	-0.53	[-0.58, -0.48]	✓
United Kingdom	-0.20	[-0.25, -0.16]	✓
United States	-0.22	[-0.26, -0.18]	✓

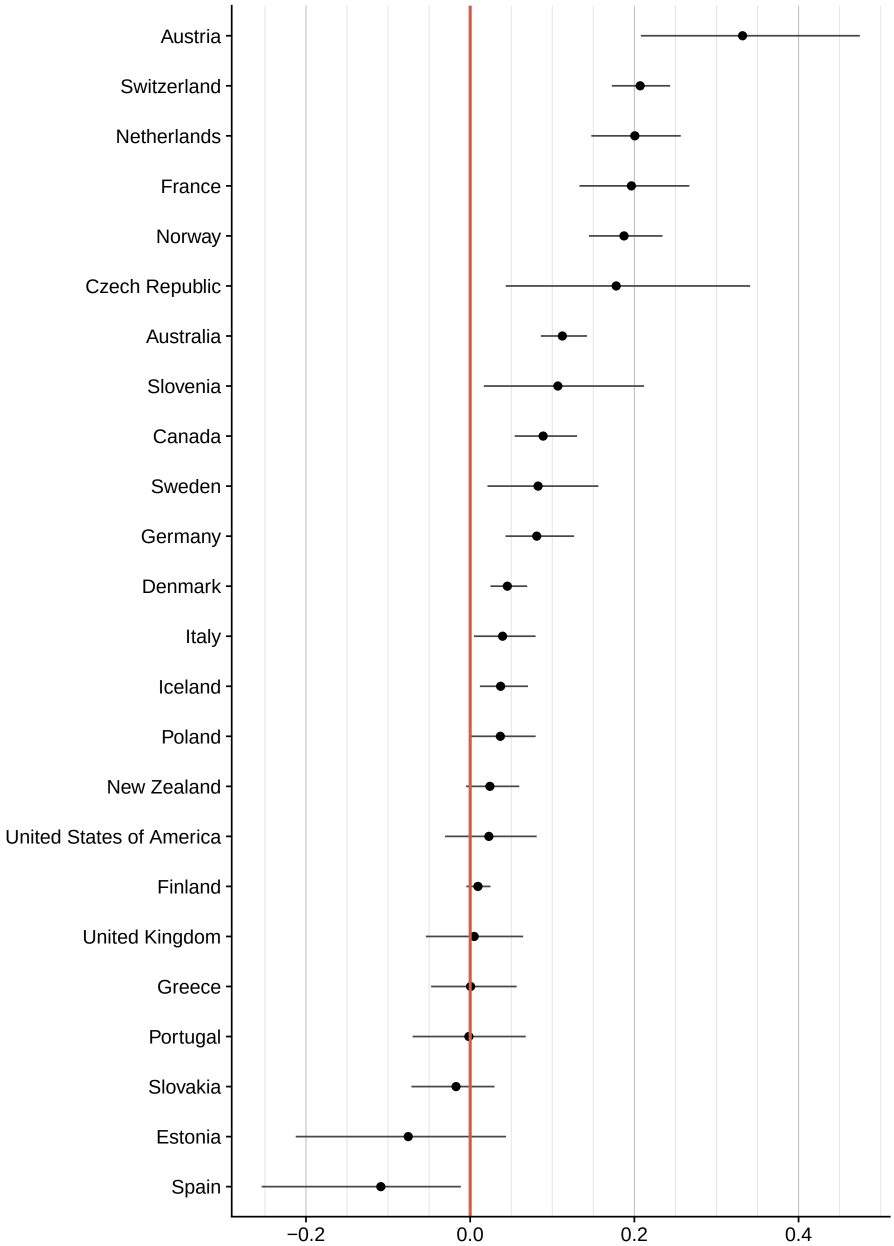
Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 iterations after 50,000 iterations burn-in.



Note: FDs associated with changing voter-party distance from 0 to 7. Orange line indicates no change in predicted probability.

Figure 5.4: FDs: party competence and voter-party distance (partial models)

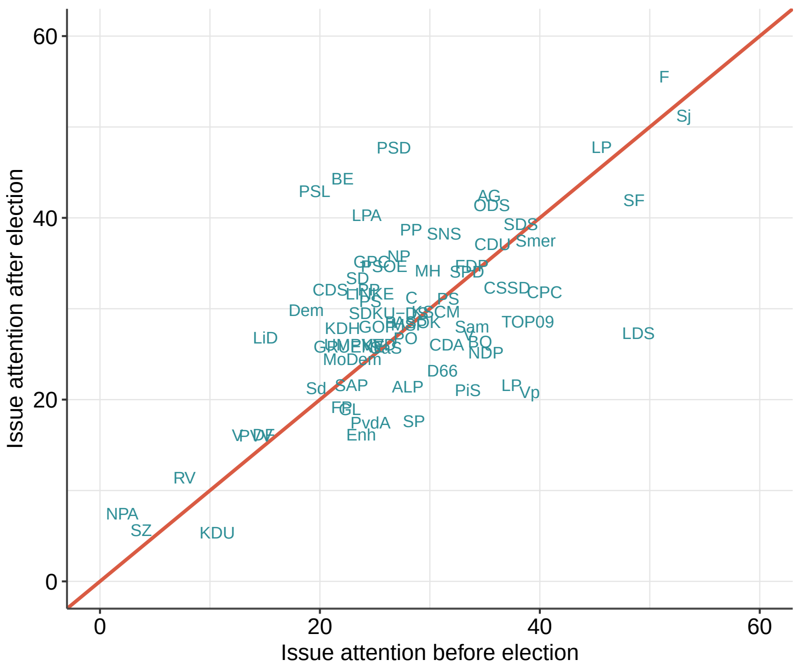
5.4 Party Issue Attention: First Differences



Note: FDs associated with changing party issue emphasis from 'low' (mean - 7.5) to 'high' (mean + 7.5). Orange line indicates no change in predicted probability.

Figure 5.5: FDs: party competence and issue emphasis

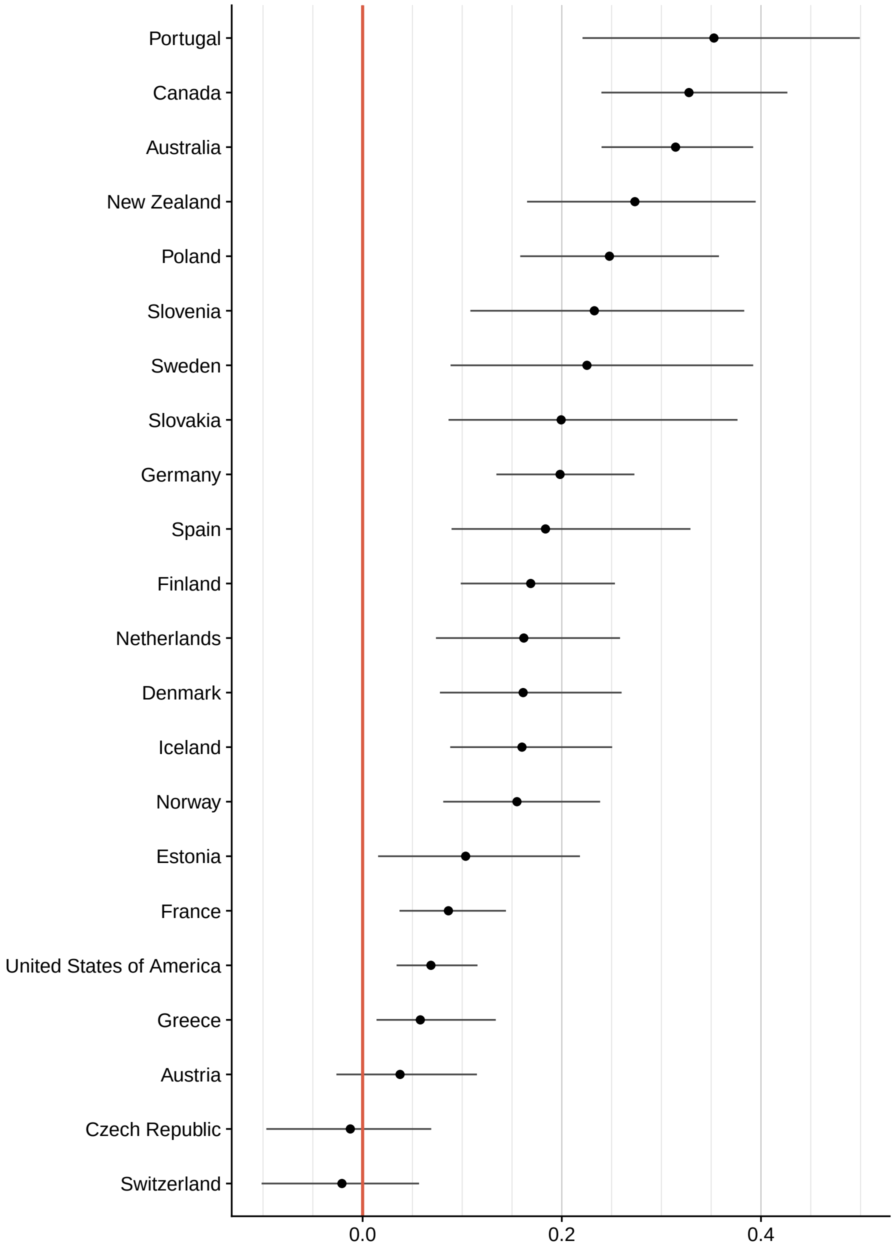
5.5 Parties reacting to voters or voters reaction to parties?



Note: Dots show the parties' issue attention on the problem they are perceived most competent. The orange line separates cases, where parties increases attention on this issue (above) from cases, where the party decreases attention on the issue (below). The average change is 0.43 percentage points (with a 1.17 standard error).

Figure 5.6: Issue emphasis change

5.6 Government Performance: First Differences



Note: First differences associated with changing evaluation of government performance from 'very bad' to 'very good'. Orange line indicates no change in predicted probability.

Figure 5.7: FDs: party competence and performance

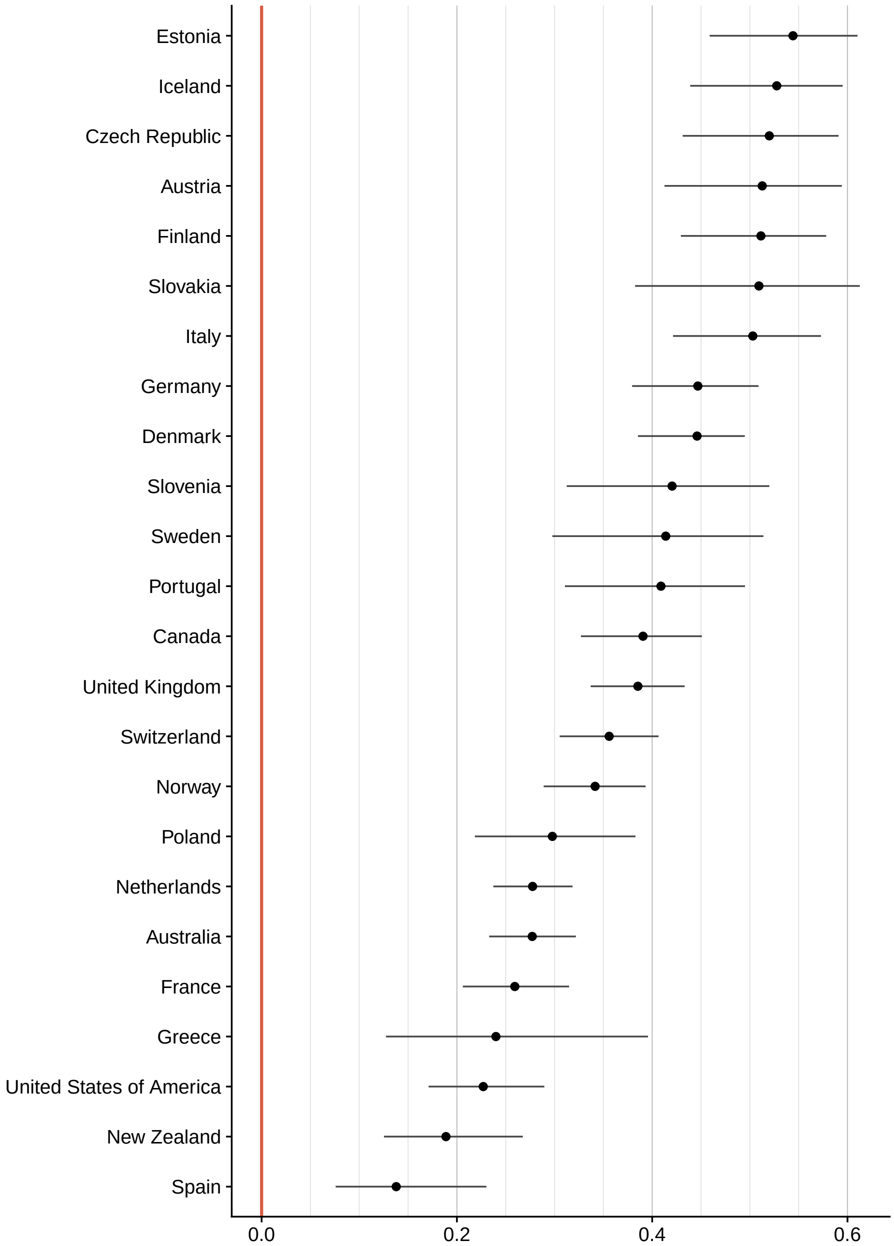
5.7 Controlling for Incumbency Status

Table 5.5: Sources of competence: controlling for incumbency status

Country	Emph., γ_1	Perf., γ_2	PI, γ_3	Dist., γ_4	Gov., γ_5	Cont.
Australia	0.06	0.65	1.58	-0.20	-1.63	✓
	[0.05, 0.07]	[0.52, 0.80]	[1.42, 1.74]	[-0.25, -0.14]	[-2.54, -0.68]	✓
Austria	0.19	0.11	2.87	-0.17	4.56	✓
	[0.14, 0.25]	[-0.08, 0.30]	[2.57, 3.19]	[-0.26, -0.07]	[-6.09, 10.57]	✓
Canada	0.05	0.80	2.37	-0.11	-0.38	✓
	[0.03, 0.06]	[0.64, 0.96]	[2.18, 2.57]	[-0.17, -0.05]	[-1.14, 0.50]	✓
Switzerland	0.10	-0.04	2.37	-0.39	0.16	✓
	[0.09, 0.11]	[-0.23, 0.13]	[2.16, 2.58]	[-0.44, -0.35]	[-1.04, 1.34]	✓
Czech Republic	0.09	-0.02	2.72	-0.36	2.92	✓
	[0.02, 0.16]	[-0.23, 0.19]	[2.45, 3.01]	[-0.,44 -0.28]	[0.67, 4.94]	✓
Australia	0.05	0.57	2.75	-0.38	0.41	✓
	[0.03, 0.07]	[0.42, 0.72]	[2.54, 2.97]	[-0.,45 -0.30]	[-1.50, 1.70]	✓
Denmark	0.02	0.35	2.14	-0.22	-1.36	✓
	[0.01, 0.03]	[0.18, 0.53]	[1.97, 2.31]	[-0.,28 -0.17]	[-2.32, -0.50]	✓
Spain	-0.17	0.88	2.39	-0.47	-1.79	✓
	[-0.32, -0.02]	[0.59, 1.19]	[1.86, 3.00]	[-0.64, -0.31]	[-5.12, 0.89]	✓
Estonia	-0.03	0.25	2.70	-0.14	0.79	✓
	[-0.09, 0.02]	[0.03, 0.46]	[2.39, 3.04]	[-0.23, -0.05]	[-0.84, 2.64]	✓
Finland	0.00	0.40	2.78	-0.26	-1.12	✓
	[0.00, 0.01]	[0.25, 0.56]	[2.57, 3.00]	[-0.33, -0.18]	[-3.15, -0.01]	✓
France	0.12	0.25	1.84	-0.35	5.81	✓
	[0.09, 0.16]	[0.11, 0.38]	[1.65, 2.04]	[-0.41, -0.28]	[-6.98, 16.5]	✓
Greece	-0.04	0.44	3.51	-0.33	-3.24	✓
	[-0.12, 0.03]	[0.15, 0.77]	[2.77, 4,43]	[-0.56, -0.11]	[-6.39, -0.42]	✓
Iceland	0.02	0.42	2.75	-0.23	2.79	✓
	[0.01, 0.04]	[0.26, 0.59]	[2.50, 3,00]	[-0.31, -0.14]	[0.76, 4.16]	✓
Netherlands	0.08	0.32	1.47	-0.22	-2.57	✓
	[0.06, 0.10]	[0.15, 0.51]	[1.32, 1.62]	[-0.26, -0.18]	[-3.51, -1.37]	✓
Norway	0.08	0.32	1.73	-0.36	0.79	✓
	[0.07, 0.09]	[0.17, 0,49]	[1.54, 1.92]	[-0.41, -0.31]	[-0.40, 1.81]	✓
New Zealand	0.02	0.88	1.93	-0.18	-2.02	✓
	[0.00, 0.04]	[0.59, 1.22]	[1.53, 2.38]	[-0.35, 0.00]	[-4.15, -0.56]	✓
Poland	0.03	0.72	2.70	-0.08	-2.11	✓
	[0.00, 0.06]	[0.53, 0.93]	[2.41, 3.00]	[-0.18, 0.01]	[-4.13, 0.99]	✓
Portugal	0.00	0.79	2.28	-0.17	0.17	✓
	[-0.03, 0.04]	[0.57, 1.01]	[1.97, 2.60]	[-0.26, -0.09]	[-1.35, 2.11]	✓
Slovakia	-0.02	0.69	3.13	-0.18	-4.40	✓
	[-0.05, 0.02]	[0.39, 1.02]	[2.84, 3.43]	[-0.30, -0.05]	[-6.93, -0.60]	✓
Slovenia	0.04	0.47	2.22	-0.26	-0.42	✓
	[0.01, 0.08]	[0.24, 0.73]	[1.77, 2.69]	[-0.38, -0.15]	[-1.91, 0.84]	✓
Sweden	0.04	0.54	2.83	-0.21	2.99	✓
	[0.01, 0.08]	[0.23, 0.89]	[2.52, 3.17]	[-0.30, -0.12]	[-1.59, 5.73]	✓
United States	0.02	0.27	1.97	-0.19	-1.98	✓
	[-0.02, 0.06]	[0.14, 0.40]	[1.75, 2.21]	[-0.26, -0.13]	[-3.53, -0.41]	✓

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 it. after 50,000 it. burn-in. Emph. = party issue emphasis, Perf. = government performance , PI = party identification, Dist. = voter-party distance, Cont. = control variables.

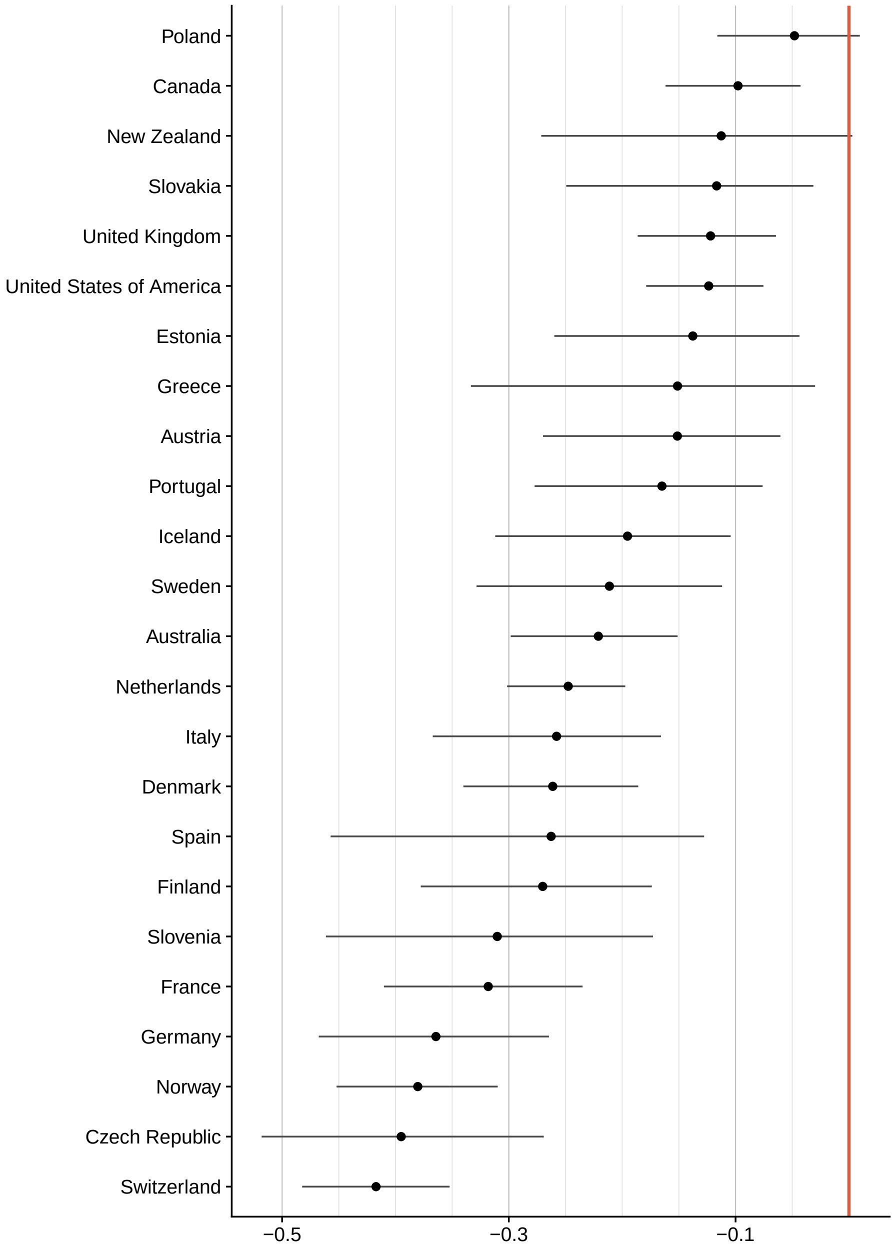
5.8 Partisanship: First Differences



Note: First differences associated with changing party identification from ‘no’ to ‘yes’. Orange line indicates no change in predicted probability.

Figure 5.8: FDs: party competence and partisanship

5.9 Voter-Party Distance: First Differences



Note: First differences associated with changing voter-party distance from 0 to 7. Orange line indicates no change in predicted probability.

Figure 5.9: FDs: party competence and voter-party distance

6 Appendix: Issue Ownership Voting

6.1 JAGS Code Baseline Models

This code is for a country with five parties (e.g. Austria, Canada, or Iceland). The second line of code loops over observations `(i in 1:NOBS)`, the third line of code loops over choice alternatives `(j in 1:5)`. `beta[j,2]` to `beta[j,12]` introduce sex, age, education, political sophistication and `i`'s MIP. These covariates all vary across individuals but are constant over choice alternatives. `gamma*comp[i,j]` introduces a party's issue handling competence (varying over `i` and `j`) and picks up the `gamma` parameter. `p[i,j]` is the probability of voting for each party `j` and follows Equation ??. The priors are set in the lines following `#priors`.

```
model{
     for(i in 1:NOBS){
          for(j in 1:5){
               mu[i,j] <- beta[j,1]
                         + beta[j,2]*sex[i]
                         + beta[j,3]*age[i]
                         + beta[j,4]*educ[i]
                         + beta[j,5]*know[i]
                         + beta[j,6]*mip1[i]
                         + beta[j,7]*mip2[i]
                         + beta[j,8]*mip3[i]
                         + beta[j,9]*mip5[i]
                         + beta[j,10]*mip6[i]
                         + beta[j,11]*mip7[i]
                         + beta[j,12]*mip8[i]
                         + gamma*comp[i,j]
               emu[i,j] <- exp(mu[i,j])
               p[i,j] <- emu[i,j]/sum(emu[i,1:5])
          }
          y[i] ~ dcat(p[i,1:5])
     }

     # priors
     for(k in 1:12){
          beta[1,k] <- 0
     }
     for(j in 2:5){
          beta[j,1:12] ~ dmnorm(b0,B0)
```

```
    }
    gamma ~ dnorm(0,.01)
}
```

6.2 JAGS Code Full Models

This code is for a country with five parties (e.g. Austria, Canada, or Iceland). In addition to the control variables in the intermediate model (Appendix 6.1), the full model introduces, the voter-party distance, partisanship, party issue attention, and party performance. These covariates vary across individuals `i` and parties `j`.

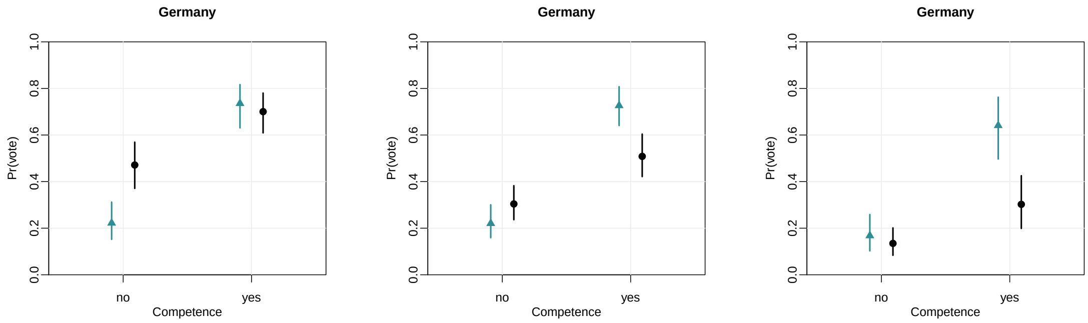
```
model{
     for(i in 1:NOBS){
          for(j in 1:5){
               mu[i,j] <- beta[j,1]
                        + beta[j,2]*sex[i]
                        + beta[j,3]*age[i]
                        + beta[j,4]*educ[i]
                        + beta[j,5]*know[i]
                        + beta[j,6]*mip1[i]
                        + beta[j,7]*mip2[i]
                        + beta[j,8]*mip3[i]
                        + beta[j,9]*mip5[i]
                        + beta[j,10]*mip6[i]
                        + beta[j,11]*mip7[i]
                        + beta[j,12]*mip8[i]
                        + gamma[1]*dist[i,j]
                        + gamma[2]*pi[i,j]
                        + gamma[3]*comp[i,j]
                        + gamma[4]*att[i,j]
                        + gamma[5]*perf[i,j]
               emu[i,j] <- exp(mu[i,j])
               p[i,j] <- emu[i,j]/sum(emu[i,1:5])
          }
          y[i] ~ dcat(p[i,1:5])
     }

     # priors
     for(k in 1:12){
          beta[1,k] <- 0
     }
     for(j in 2:5){
          beta[j,1:12] ~ dmnorm(b0,B0)
     }
     for(h in 1:5){
          gamma[h] ~ dnorm(0,.01)
     }
```

```
}
```

6.3 Probabilities for the Smallest & the Largest Party

Figure 6.1 shows the predicted probabilities to vote for the observed party (left panel), the largest party (middle panel) and the smallest party (right panel) in Germany.[9] In all predictions, the input variables take their observed values.



Note: Effects estimated for the observed party choice. Left panel = predictions for the observed outcome, middle panel = predictions for the largest party (CDU/CSU), right panel = predictions for the smallest party (Die Linke). Whiskers indicate 95% HPD. Triangle marker = baseline model, round marker = full model.

Figure 6.1: Predicted party support and competence: smallest and largest party

In the study, I report results for the observed party. That is, I estimate the probability of voter i to vote for the party she actually supported in the election. This guarantees that all predictions are based on a highly likely scenario where only one variable (competence) is manipulated. This also means that in the 'party not competent' scenario the probability to support a party increases sharply once I introduce partisanship and voter-party distance to the model (see the difference between the triangle and the round marker in the not-competent condition). The reason for this is, that the voter is often close to the party and maybe even a partisan of the party she supported and that this information is included in the predicted probability.

In the other two panels, I estimate the probability to vote for one specific party given the voters observed profiles. Often, this means estimating the probability to support the CDU/CSU, even when the voter is actually a partisan of a different party. As a consequence, the difference between the intermediate model and the full model (controlling for alternative explanations of the vote) vanishes in the 'party not competent' scenario. Similarly, in the 'party competent' scenario, the overall probability to support either the largest or the smallest party is smaller than in the observed-outcome panel. This is again linked to the fact that the probabilities are often estimated for voters who do not feel close to the CDU/CSU (middle panel) or Die Linke (right panel).

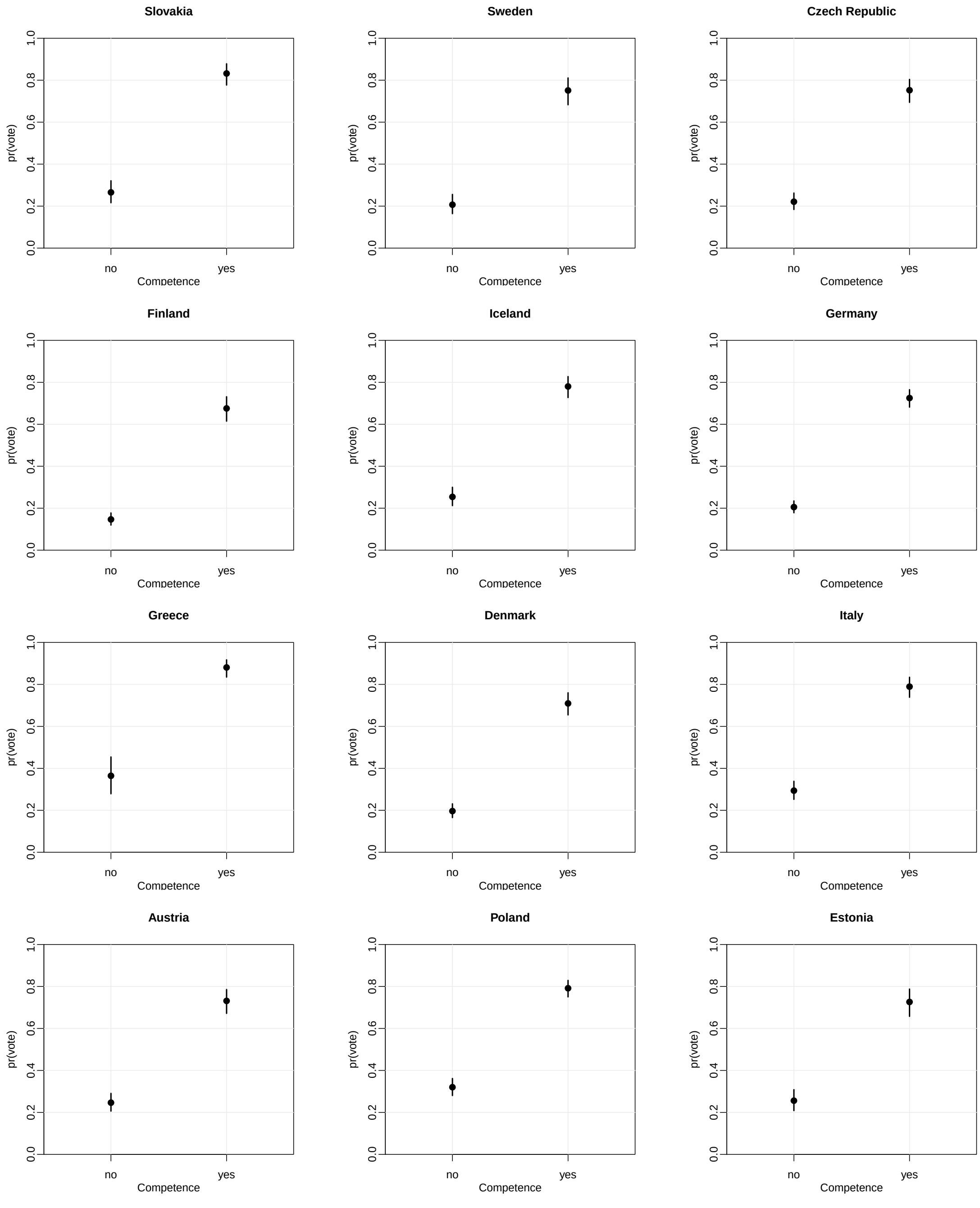
In most countries, the difference in predicted probabilities associated with changing the competence from 'not competent' to 'competent' are lowest if I predict the vote choice for the smallest party. In the full model the average FD is 0.12 when I predict the probability to support the smallest party. This value is 0.16 for the largest-party and the observed-party approaches. However, while the magnitude of the FD change slightly depending on the prediction technique, the credibility of the effects remain the same in cases. This is true for all results presented in this study.

6.4 Issue Ownership Voting Model: No Controls

Table 6.1: Issue ownership voting: no controls

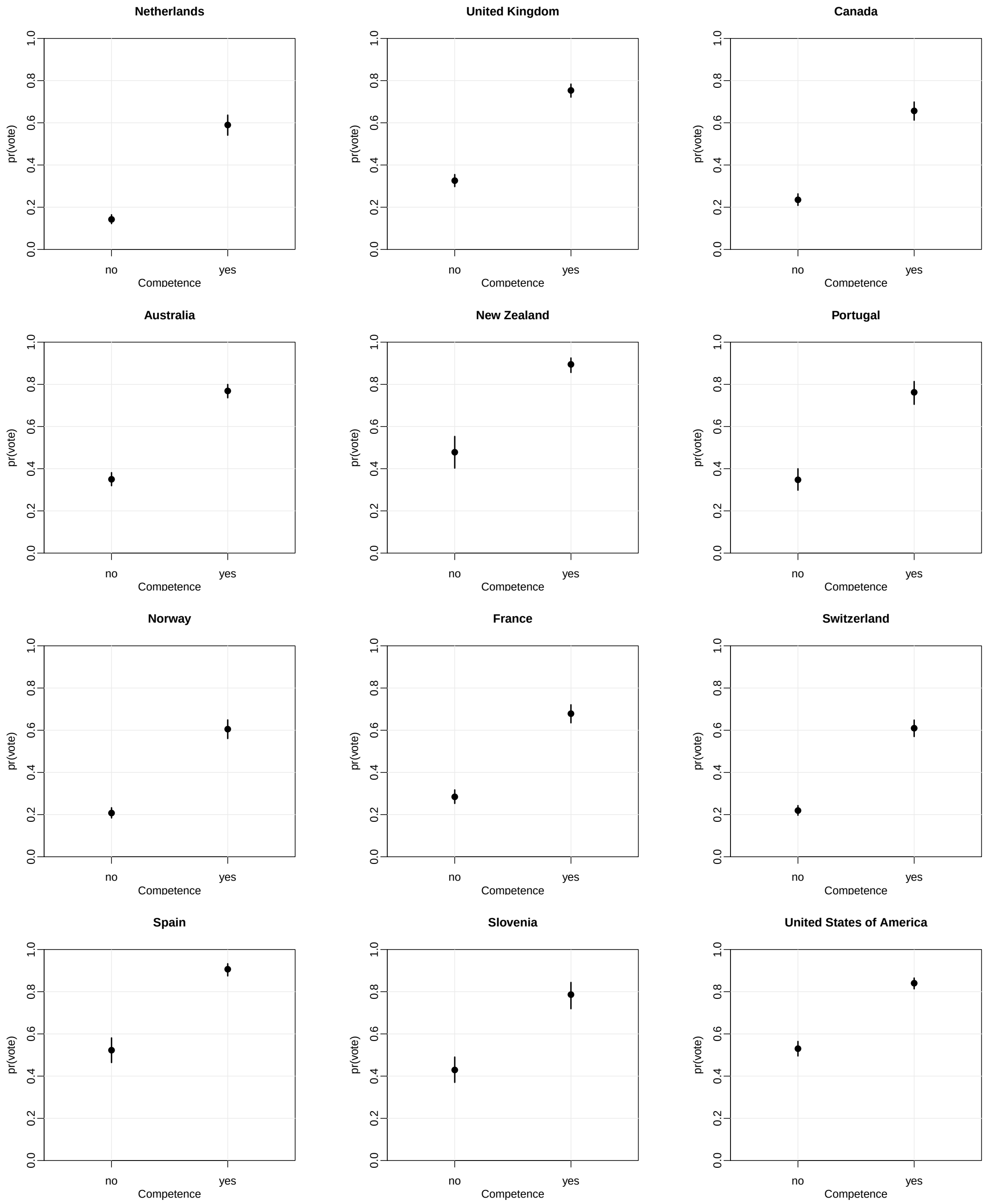
Country	Competence, γ	γ HPD	Controls
Australia	1.94	[1.81, 2.07]	✗
Austria	2.20	[2.02, 2.39]	✗
Canada	1.87	[1.74, 2.00]	✗
Czech Republic	2.46	[2.28, 2.65]	✗
Denmark	2.40	[2.25, 2.55]	✗
Estonia	2.11	[1.89, 2.34]	✗
Finland	2.55	[2.39, 2.71]	✗
France	1.73	[1.573 1.88]	✗
Germany	2.33	[2.19, 2.47]	✗
Greece	2.77	[2.36, 3.23]	✗
Iceland	2.35	[2.17, 2.54]	✗
Italy	2.30	[2.11, 2.51]	✗
Netherlands	2.17	[2.05, 2.30]	✗
New Zealand	2.27	[1.95, 2.62]	✗
Norway	1.91	[1.79, 2.03]	✗
Poland	2.17	[1.99, 2.34]	✗
Portugal	2.01	[1.79, 2.23]	✗
Slovakia	2.83	[2.61, 3.06]	✗
Slovenia	1.87	[1.51, 2.15]	✗
Spain	2.27	[2.02, 2.54]	✗
Sweden	2.59	[2.37, 2.83]	✗
Switzerland	1.75	[1.65, 1.86]	✗
United Kingdom	1.85	[1.72, 1.98]	✗
United States	1.57	[1.43, 1.72]	✗

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 iterations after 50,000 iterations burn-in.



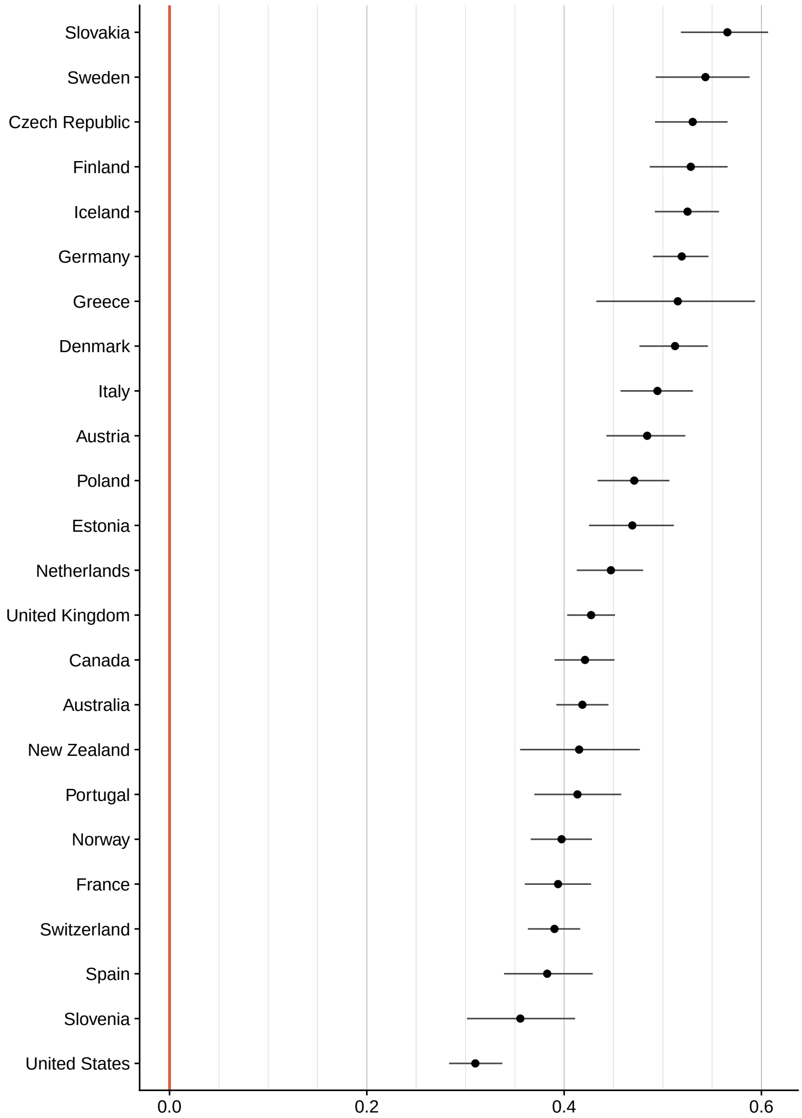
Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs.

Figure 6.2: [1/2] Predicted vote choice and party competence (no control variables)



Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs.

Figure 6.2: [2/2] Predicted vote choice and party competence (no control variables)



Note: First differences associated with changing party competence from 'not competent' to 'competent'. Whiskers indicate 95% CI.

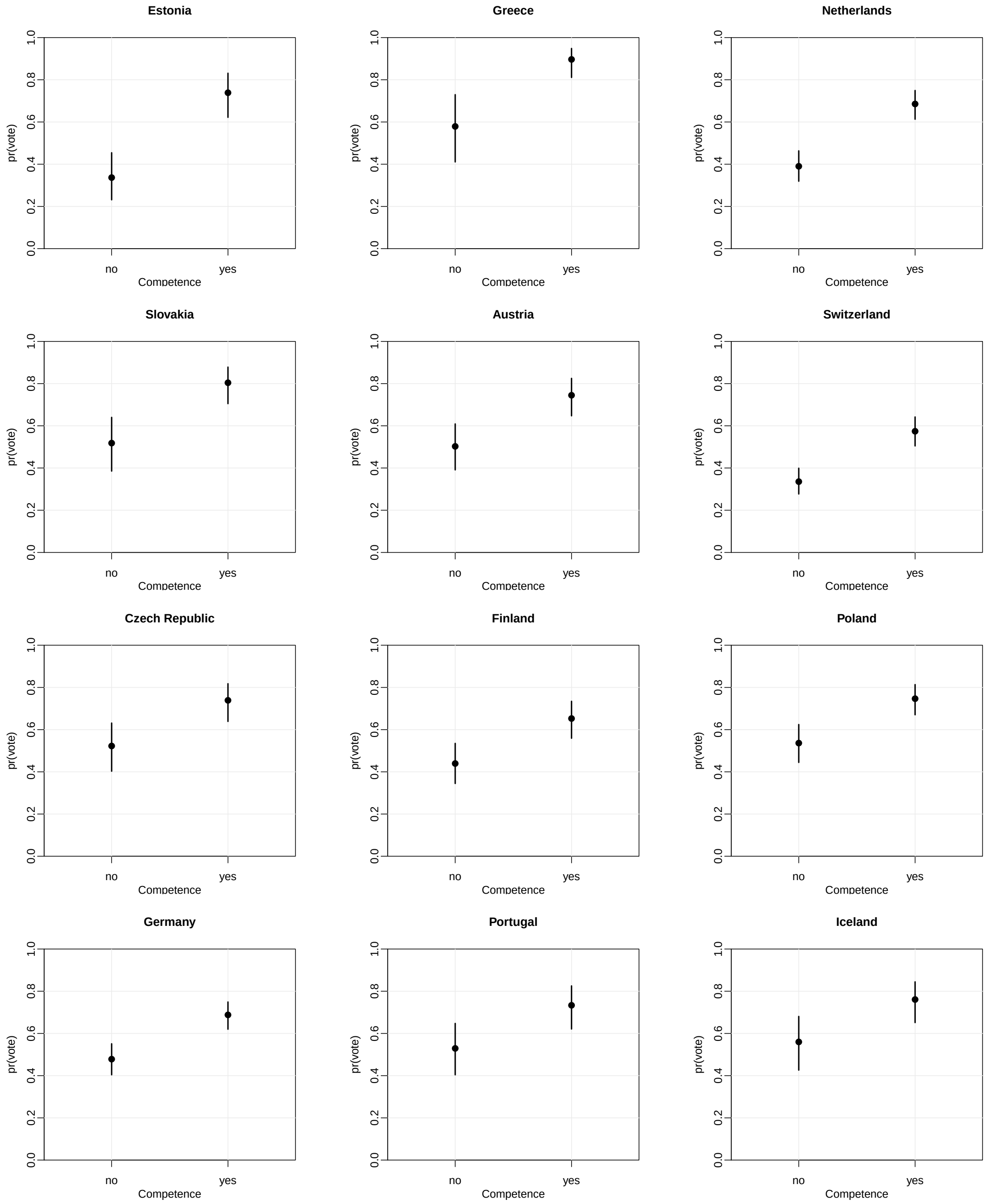
Figure 6.3: FDs: party support and competence (no control variables)

6.5 Issue Ownership Voting Model: Alternative Controls

Table 6.2: Issue ownership voting: full models (alternative control variables)

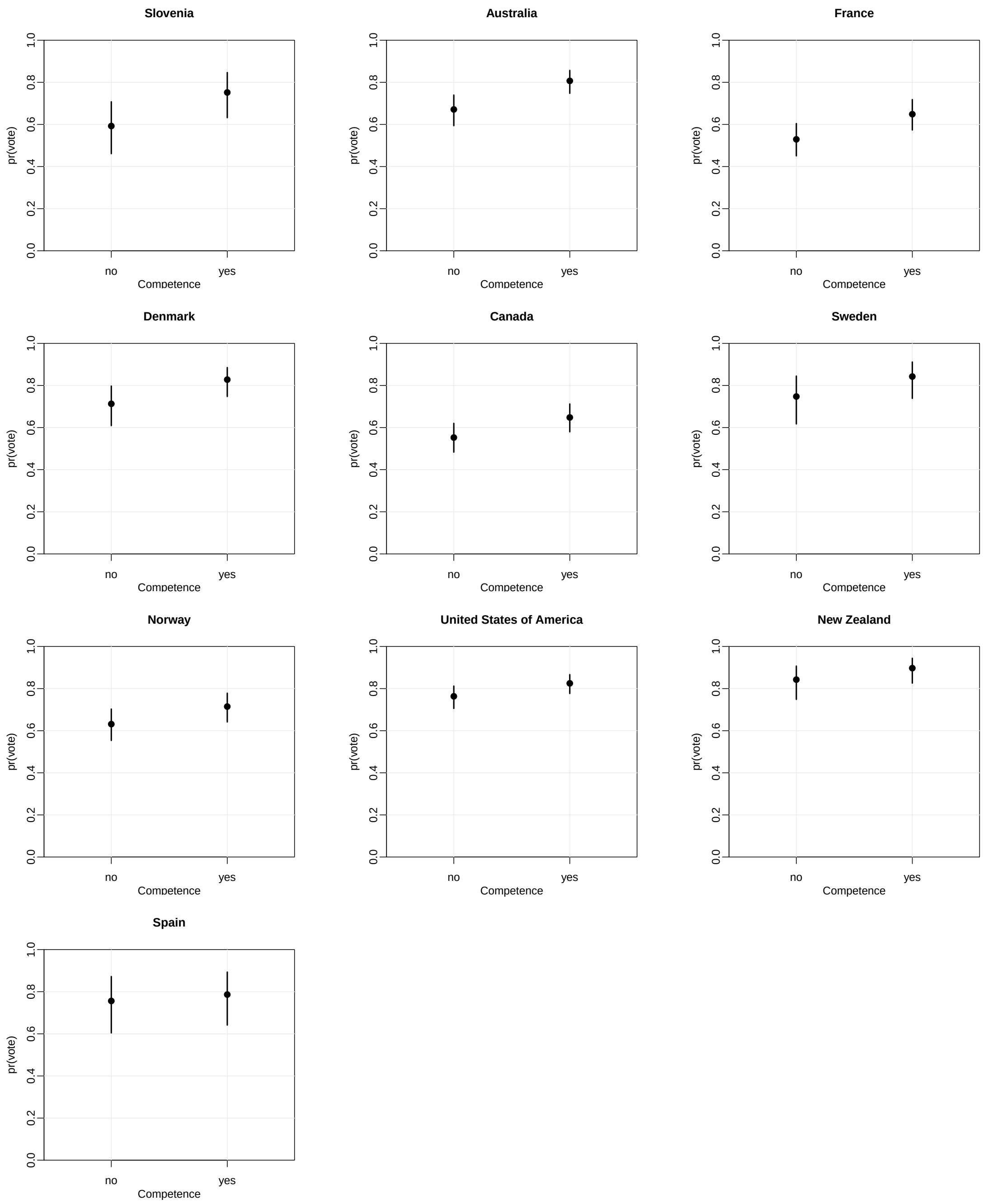
Country	Comp., γ_1	Emph., γ_2	Perf., γ_3	Like, γ_4	V. dist., γ_5	Cont.
Australia	1.03	0.00	0.10	0.50	-0.16	✓
	[0.85, 1.21]	[-0.02, 0.01]	[-0.058, 0.26]	[0.44, 0.56]	[-0.22, -0.09]	
Austria	1.47	-0.01	0.11	0.26	-0.23	✓
	[1.24, 1.70]	[-0.07, 0.04]	[-0.06, 0.28]	[0.22, 0.32]	[-0.30, -0.16]	
Canada	0.58	-0.01	-0.21	0.57	-0.05	✓
	[0.41, 0.76]	[-0.03, 0.01]	[-0.33, -0.09]	[0.51, 0.62]	[-0.11, 0.01]	
Czech Republic	1.26	-0.07	0.09	0.37	-0.11	✓
	[1.02, 1.50]	[-0.14, 0.00]	[-0.16, 0.33]	[0.31, 0.44]	[-0.19, -0.03]	
Denmark	0.99	0.02	-0.10	1.21	-0.27	✓
	[0.77, 1.21]	[0.00, 0.04]	[-0.30, 0.11]	[1.08, 1.36]	[-0.39, -0.17]	
Estonia	0.64	0.22	0.26	0.18	-0.19	✓
	[0.25, 1.05]	[-0.03, 0.38]	[0.03, 0.51]	[0.08, 0.28]	[-0.30, -0.08]	
Finlad	1.16	0.00	0.07	0.55	-0.15	✓
	[0.97, 1.35]	[-0.01, 0.00]	[-0.07, 0.22]	[0.48, 0.61]	[-0.22, -0.08]	
France	0.69	0.03	0.05	0.30	-0.15	✓
	[0.50, 0.88]	[0.00, 0.07]	[-0.08, 0.17]	[0.25, 0.36]	[-0.21, -0.10]	
Germany	1.12	-0.01	-0.03	0.45	-0.11	✓
	[0.94, 1.29]	[-0.03, 0.01]	[-0.15, 0.09]	[0.39, 0.51]	[-0.17, -0.04]	
Greece	2.20	0.01	0.11	0.22	-0.25	✓
	[1.76, 2.68]	[-0.03, 0.05]	[-0.14, 0.35]	[0.11, 0.33]	[-0.37, -0.14]	
Iceland	1.19	0.002	-0.02	0.44	-0.19	✓
	[0.95, 1.44]	[-0.02, 0.02]	[-0.16, 0.14]	[0.35, 0.52]	[-0.28, -0.10]	
Netherlands	1.62	-0.02	0.21	0.64	-0.34	✓
	[1.47, 1.77]	[-0.05, 0.00]	[0.01, 0.42]	[0.58, 0.70]	[-0.39, -0.29]	
New Zealand	0.74	0.03	0.14	0.45	-0.10	✓
	[0.30, 1.18]	[0.00, 0.06]	[-0.16, 0.45]	[0.33, 0.59]	[-0.23, 0.03]	
Norway	0.58	-0.02	-0.02	1.04	-0.12	✓
	[0.41, 0.75]	[-0.04, 0.00]	[-0.26, 0.23]	[0.96, 1.12]	[-0.19, -0.04]	
Poland	1.20	0.01	0.08	0.22	-0.15	✓
	[0.98 , 1.42]	[-0.01, 0.03]	[-0.08, 0.24]	[0.17, 0.27]	[-0.21, -0.10]	
Portugal	1.20	-0.01	0.16	0.22	-0.01	✓
	[0.91, 1.51]	[-0.05, 0.03]	[-0.02, 0.33]	[0.16, 0.28]	[-0.08, 0.06]	
Slovakia	1.80	0.01	-0.08	0.33	-0.02	✓
	[1.50, 2.11]	[-0.02, 0.04]	[-0.34, 0.20]	[0.24, 0.42]	[-0.11, 0.07]	
Slovenia	0.99	-0.15	0.32	0.20	-0.13	✓
	[0.64, 1.36]	[-0.26, -0.06]	[0.04, 0.63]	[0.11, 0.29]	[-0.23, -0.03]	
Spain	0.64	0.22	0.26	0.18	-0.19	✓
	[0.25, 1.05]	[-0.03, 0.38]	[0.03, 0.51]	[0.08, 0.28]	[-0.30, -0.08]	
Sweden	0.95	-0.03	0.06	1.40	-0.14	✓
	[0.61, 1.30]	[-0.08, 0.02]	[-0.34, 0.47]	[1.20, 1.61]	[-0.30, 0.01]	
Switzerland	1.14	0.00	0.00	0.18	-0.11	✓
	[1.01, 1.27]	[-0.01, 0.01]	[-0.19, 0.18]	[0.16, 0.21]	[-0.15, -0.08]	
United States	0.53	0.00	0.06	0.24	-0.16	✓
	[0.32, 0.74]	[-0.04, 0.04]	[-0.04, 0.17]	[0.19, 0.29]	[-0.21, -0.10]	

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 it. after 50,000 it. burn-in. Comp. = competence, emph. = party issue emphasis, perf. = government performance, dist. = voter-party distance (voter evaluation of party position), Like = dislike/like of party, cont. = control variables.



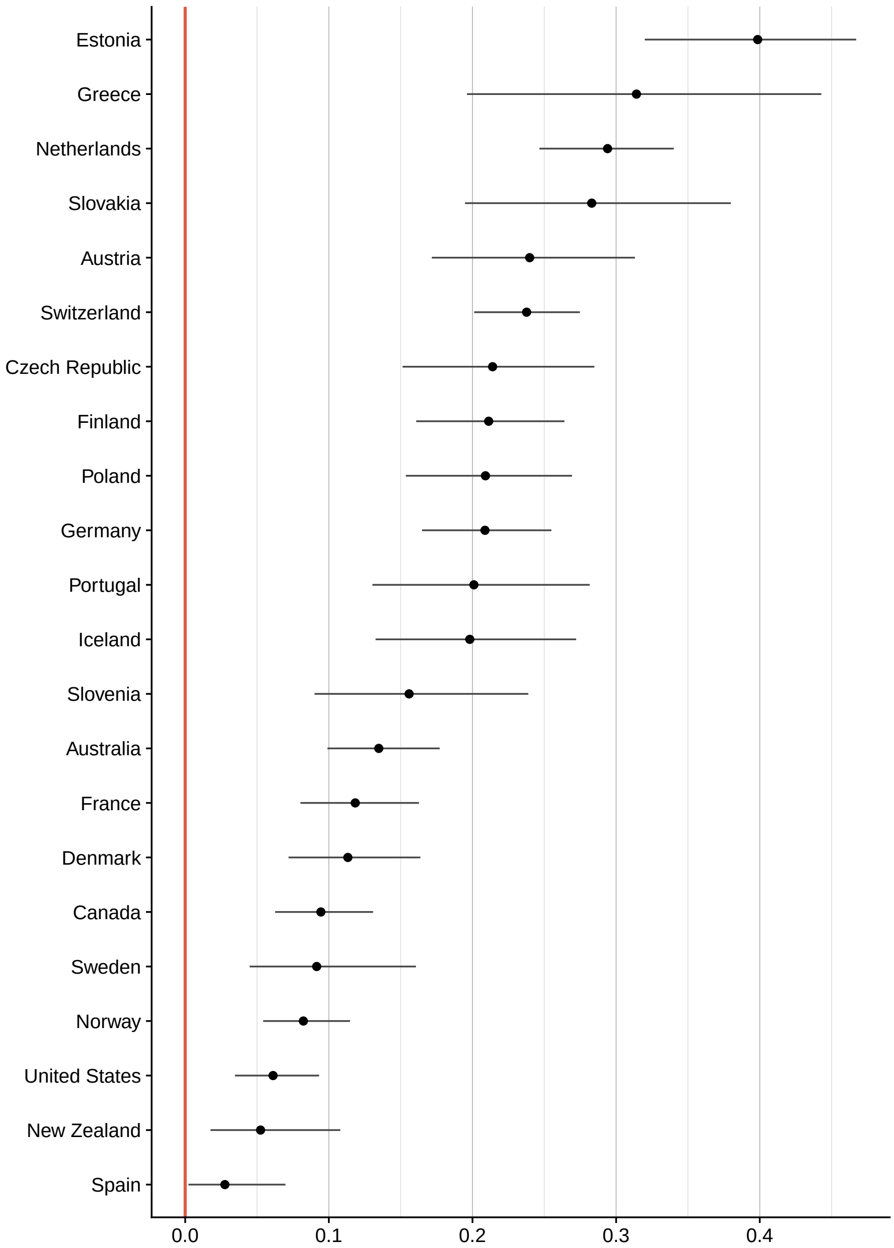
Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs. Triangle markers = baseline models, round markers = full models.

Figure 6.4: [1/2] Predicted vote choice and party competence (alternative control variables)



Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs. Triangle markers = baseline models, round markers = full models.

Figure 6.4: [2/2] Predicted vote choice and party competence (alternative control variables)



Note: FDs associated with changing party competence from 'not competent' to 'competent'. Whiskers = 95% HPD.

Figure 6.5: FDs: party support and competence (alternative control variables)

6.6 Full Multilevel Model

Table 6.3: Issue ownership voting: all countries

COUNTRY	COMP., γ_1	EMPH., γ_2	PERF., γ_3	PI, γ_4	DIST., γ_5	CONT.
All countries	1.25 [1.21, 1.30]	0.00 [-0.01, 0.01]	1.26 [0.09, 0.61]	2.05 [1.99, 2.10]	-0-21 [-0.22, -0.19]	✓

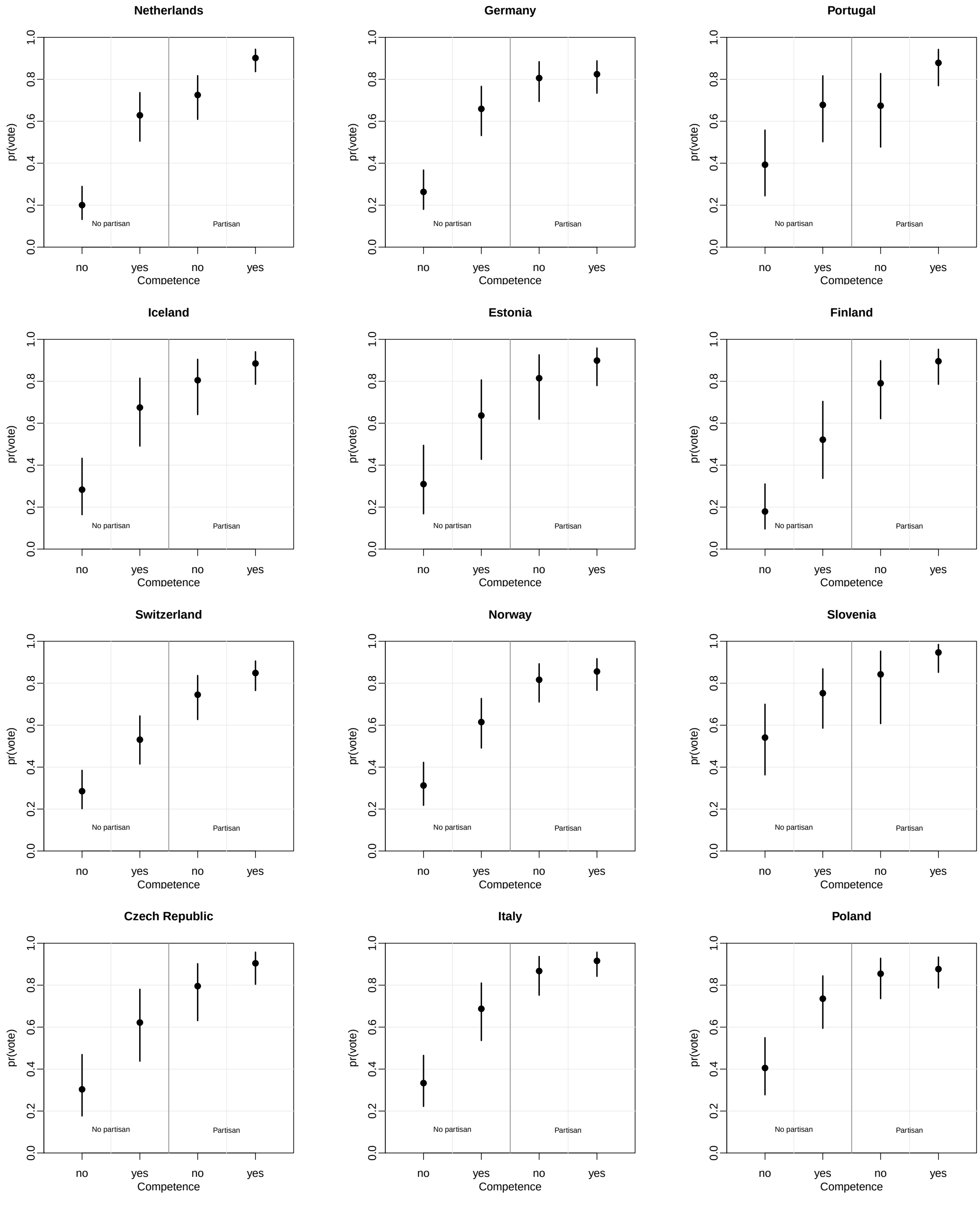
Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 it. after 50,000 it. burn-in. Comp. = competence, Emph. = party issue emphasis, Perf. = government performance, Dist. = voter-party distance, PI = party identification, Cont. = control variables.

6.7 Interaction Comp. Evaluation & Partisanship

Table 6.4: Issue ownership voting: full models, interaction with partisanship

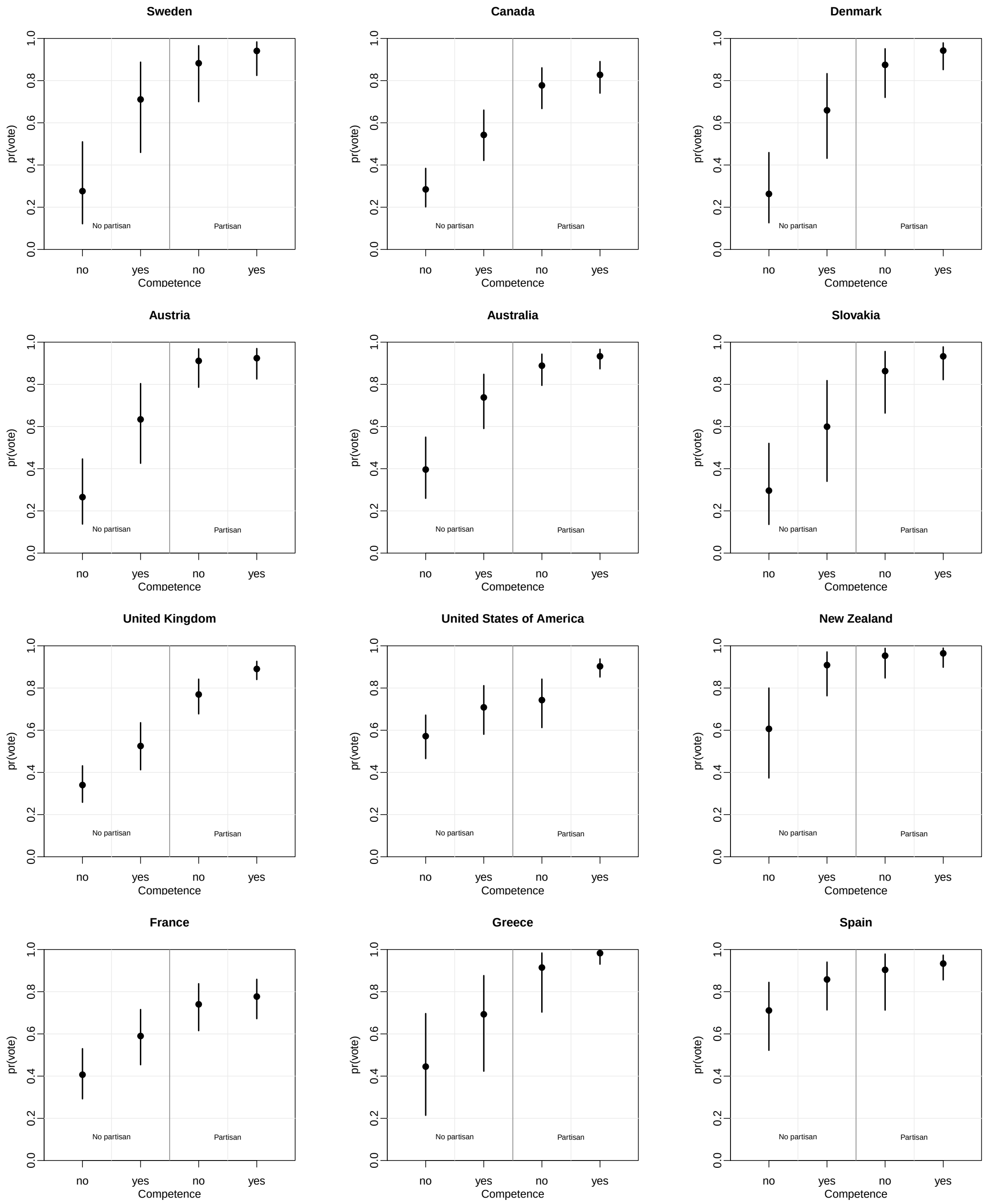
Country	Comp., γ_1	PI, γ_2	Comp_PI, γ_3	Cont.
Australia	2.73	1.60	-1.00	✓
	[2.38, 3.09]	[1.30 , 1.90]	[-1.62 , -0.39]	
Austria	3.69	1.73	-1.55	✓
	[3.09, 4.33]	[1.36, 2.11]	[-2.45, -0.69]	
Canada	2.40	1.22	-0.87	✓
	[2.10, 2.72]	[1.00, 1.44]	[-1.35, -0.40]	
Czech Republic	2.47	1.49	-0.50	✓
	[2.02, 2.93]	[1.18, 1.81]	[-1.21, 0.20]	
Denmark	3.41	1.95	-1.02	✓
	[3.00, 3.85]	[1.52, 2.40]	[1.86, -0.22]	
Estonia	2.62	1.58	-0.80	✓
	[1.97, 3.31]	[1.19, 1.96]	[-1.75, 0.15]	
Finlad	3.17	1.80	-0.92	✓
	[2.81, 3.54]	[1.48, 2.12]	[-1.55, -0.31]	
France	1.68	0.87	-0.63	✓
	[1.35, 2.03]	[0.56, 1.19]	[-1.22, -0.06]	
Germany	2.59	1.78	-1.65	✓
	[2.23, 2.95]	[1.54, 2.03]	[-2.19, -1.13]	
Greece	2.98	1.22	0.57	✓
	[1.88, 4.26]	[1.22, 2.02]	[-1.13, 2.18]	
Iceland	2.45	1.74	-1.10	✓
	[1.93, 2.98]	[1.36, 2.12]	[-1.91, -0,31]	
Italy	2.82	1.64	-1.11	✓
	[2.31, 3.38]	[1.30, 2.00]	[-1.92, -0.32]	
Netherlands	2.58	2.09	-0.76	✓
	[2.37, 2.80]	[1.91, 2.29]	[-1.19, -0.32]	
New Zealand	2.94	2.17	-1.86	✓
	[2-04, 3.94]	[1.45, 2.99]	[-3.45, -0.39]	
Norway	2.75	1.51	-1.18	✓
	[2.41, 3.10]	[1.32, 1.70]	[-169, -0.66]	
Poland	2.38	1.56	-1.35	✓
	[1.92, 2.87]	[1.22, 1.89]	[-2.07, -0.64]	
Portugal	1.37	1.39	0.07	✓
	[0.80, 1.94]	[1.00, 1.78]	[-0.80, 0.93]	
Slovakia	3.15	1.49	-0.62	✓
	[2.48, 3.85]	[0.87, 2.12]	[-1.80, 0.49]	
Slovenia	1.96	1.23	0.25	✓
	[0.67, 3.29]	[0.83, 1.63]	[-1.43, 2.01]	
Spain	1.55	1.05	-0.60	✓
	[0.27, 3.00]	[0.50, 1.65]	[-2.33, 0.96]	
Sweden	3.47	2.18	-1.35	✓
	[2.89, 4.12]	[1.64, 2.77]	[-2.43, -0.32]	
Switzerland	2.20	1.15	-0.45	✓
	[1.88, 2.52]	[0.98, 1.33]	[-0.89, -0.01]	
United Kingdom	1.93	0.79	0.12	✓
	[1-68, 2.19]	[0.53, 1.05]	[-0.34, 0.57]	
United States	0.81	0.63	0.59	✓
	[0.37, 1.27]	[0.24, 1.03]	[-0.23, 1.38]	

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 it. after 50,000 it. burn-in. Comp. = competence, PI = party identification, Cont. = control variables.



Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs.

Figure 6.6: [1/2] Predicted vote choice and party competence (int. partisanship)



Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs.

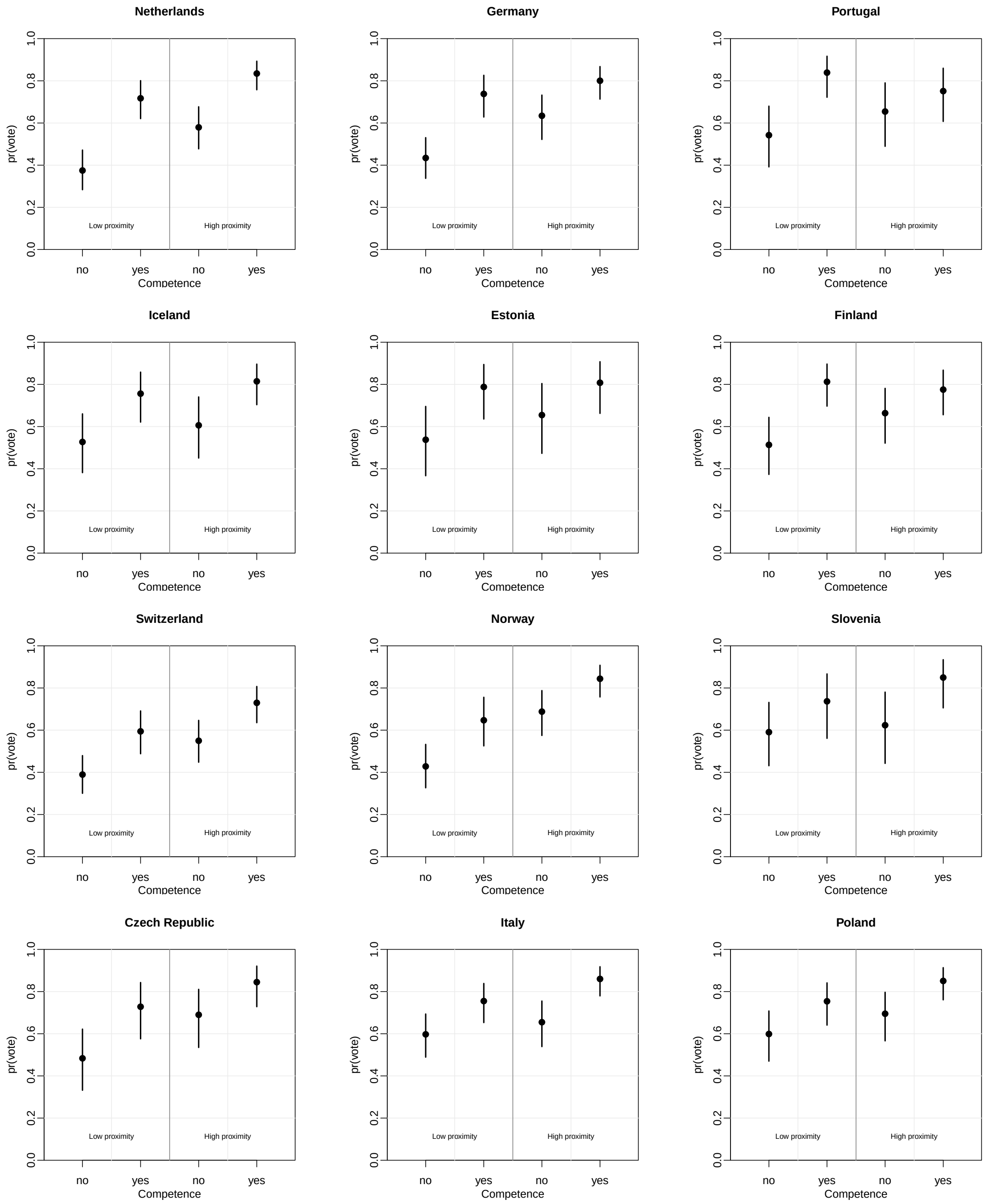
Figure 6.6: [2/2] Predicted vote choice and party competence (int. partisanship)

6.8 Interaction Comp. Evaluation & Proximity

Table 6.5: Issue ownership voting: full models, interaction with voter-party distance

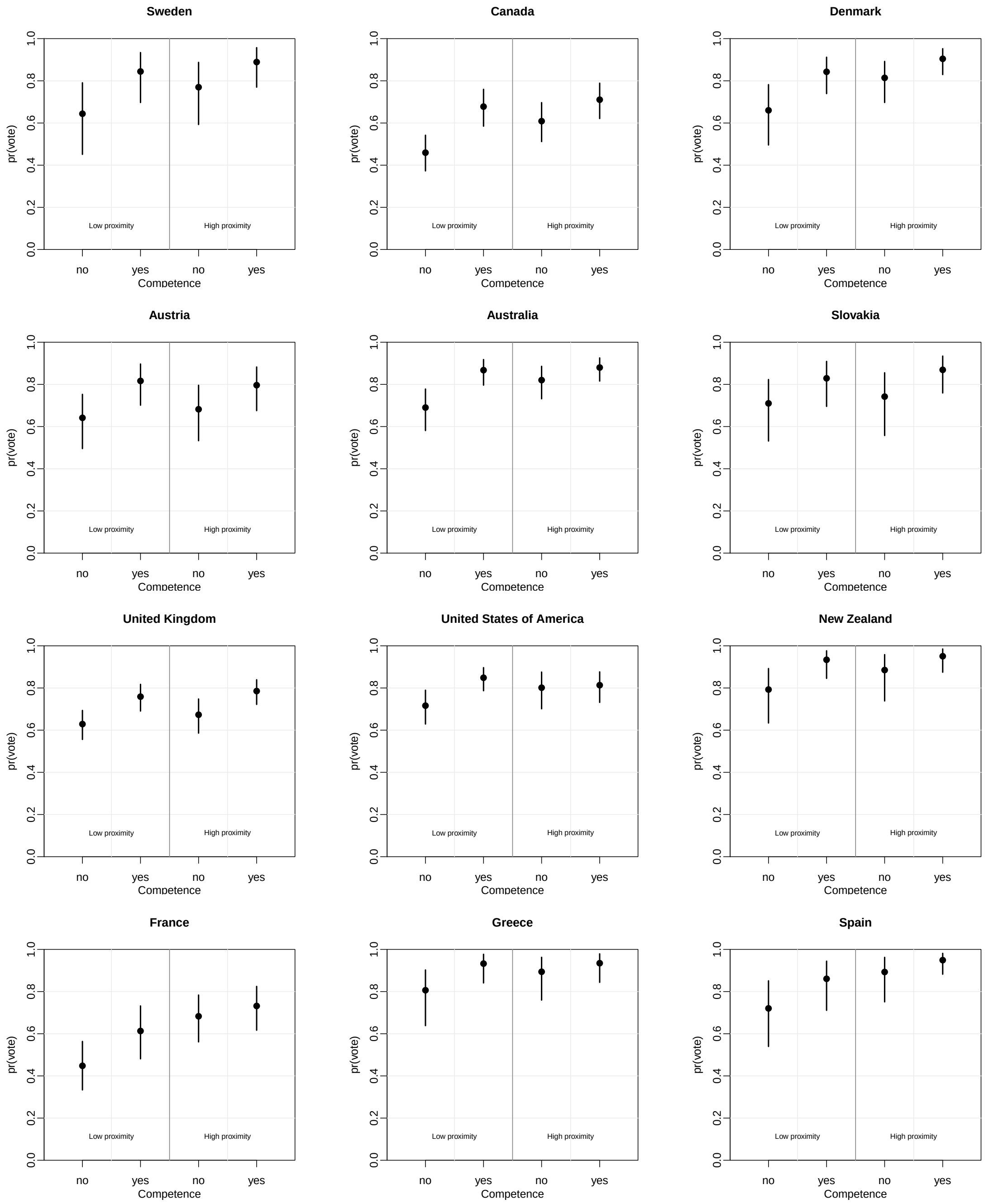
COUNTRY	COMP., γ_1	PI, γ_2	COMP__PI, γ_3	CONT.
Australia	-0.28	0.74	0.24	✓
	[-0.39, -0.18]	[0.34, 1.13]	[0.07, 0.41]	
Austria	-0.08	1.02	0.13	✓
	[-0.19, -0.04]	[0.49, 1.56]	[-0.07, 0.34]	
Canada	-0.21	0.63	0.16	✓
	[-0.28, -0.14]	[0.30, 0.96]	[0.03, 0.28]	
Czech Republic	-0.31	1.22	0.07	✓
	[-0.41, -0.21]	[0.80, 1.65]	[-0.12, 0.25]	
Denmark	-0.34	1.34	0.10	✓
	[-0.45, -0.24]	[0.93, 1.75]	[-0.07, 0.28]	
Estonia	-0.17	1.12	0.13	✓
	[-0.30, -0.05]	[0.59, 1.64]	[-0.07, 0.34]	
Finlad	-0.25	0.90	0.33	✓
	[-0.36, -0.14]	[0.49, 1.30]	[0.14, 0.53]	
France	-0.34	0.33	0.15	✓
	[-0.42, -0.26]	[-0.03, 0.68]	[0.00, 0.31]	
Germany	-0.26	1.06	0.15	✓
	[-0.34, -0.19]	[0.76, 1.36]	[0.00, 0.31]	
Greece	-0.29	0.81	0.27	✓
	[-0.54, -0.06]	[-0.17, 1.80]	[-0.04, 0.61]	
Iceland	-0.10	1.38	-0.01	✓
	[-0.21, 0.00]	[0.95, 1.82]	[-0.19, 0.17]	
Italy	-0.09	1.68	-0.15	✓
	[-0.18, 0.00]	[1.19, 2.18]	[-0.32, 0.02]	
Netherlands	-0.30	1.82	0.07	✓
	[-0.37, -0.25]	[1.55, 2.08]	[-0.03, 0.18]	
New Zealand	-0.24	1.22	0.14	✓
	[-0.49, 0.01]	[0.43, 2.03]	[-0.18, 0.48]	
Norway	-0.40	1.22	0.03	✓
	[-0.48, -0.32]	[0.91, 1.55]	[-0.12, 0.18]	
Poland	-0.14	1.25	-0.07	✓
	[-0.23, -0.06]	[0.85, 1.64]	[-0.21, 0.08]	
Portugal	-0.16	0.64	0.34	✓
	[-0.,28 -0.04]	[0.11, 1.18]	[0.15, 0.55]	
Slovakia	-0.07	1.43	-0.07	✓
	[-0.21, -0.08]	[0.79, 2.07]	[-0.32, 0.18]	
Slovenia	-0.05	1.64	-0.18	✓
	[-0.19, 0.09]	[0.96, 2.34]	[-0.45, 0.09]	
Spain	-0.35	0.91	0.03	✓
	[-0.56, -0.15]	[-0.07, 1.86]	[-0.30, 0.39]	
Sweden	-0.26	1.45	0.10	✓
	[-0.42, -0.11]	[0.08, 2.12]	[-0.18, 0.39]	
Switzerland	-0.22	1.02	0.02	✓
	[-0.,27 -0.16]	[0.78, 1.27]	[-0.08, 0.12]	
United Kingdom	-0.07	0.82	0.01	✓
	[-0.15, 0.01]	[0.52, 1.12]	[-0.11, 0.14]	
United States	-0.15	0.10	0.23	✓
	[-0.27, -0.03]	[-0.64, 0.81]	[0.03, 0.44]	

Note: Marginal posterior densities of γ. Numbers in brackets are 95% HPD. MCMC with 150,000 it. after 50,000 it. burn-in. Comp. = competence, Dist. = voter-party distance, Cont. = control variables.



Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs.

Figure 6.7: [1/2] Predicted vote choice and party competence (int. voter-party distance)



Note: Effects estimated for the observed outcome. Whiskers = 95% HPDs.

Figure 6.7: [2/2] Predicted vote choice and party competence (int. voter-party distance)

7 Appendix: Issue Ownership Voting across Contexts

7.1 JAGS Code

```
model{
     for(c in 1:NCTRY){
          for(i in 1:NOBS[,c]){
               for(j in 1:NPTRY[,c]){
                    mu[i,j,c] <-beta[j,1,c]
                              + beta[j,2,c]*sex[i,1,c]
                              + beta[j,3,c]*age[i,1,c]
                              + beta[j,4,c]*educ[i,1,c]
                              + beta[j,5,c]*know[i,1,c]
                              + beta[j,6,c]*mip1[i,1,c]
                              + beta[j,7,c]*mip2[i,1,c]
                              + beta[j,8,c]*mip3[i,1,c]
                              + beta[j,9,c]*mip5[i,1,c]
                              + beta[j,10,c]*mip6[i,1,c]
                              + beta[j,11,c]*mip7[i,1,c]
                              + beta[j,12,c]*mip8[i,1,c]
                              + gamma[1]*comp[i,j,c]
                              + gamma[2]*leri[i,j,c]
                              + gamma[3]*pi[i,j,c]
                              + gamma[4]*perf[i,j,c]
                              + gamma[5]*agg[i,j,c]
                    emu[i,j,c] <- exp(mu[i,j,c])
                    p[i,j,c] <- emu[i,j,c]/sum(emu[i,1:NPTRY[,c],c])
               }
          y[i,1,c] ~ dcat(p[i,1:NPTRY[,c],c])
          }
     }

     #priors
     for(c in 1:NCTRY){
          for(y in 1:12){
               for(z in (1+NPTRY[,c]):8){
                    beta[z,y,c] <- 0
               }
          }
          for(k in 1:12){
               beta[1,k,c] <- 0
          }
          for(j in 2:NPTRY[,c]){
               beta[j,1:4,c] ~ dmnorm(b0,B0)
          }
     }

      for(f in 1:5){
               gamma[f] ~ dnorm(0,.01)
```

```
        }
    }
```

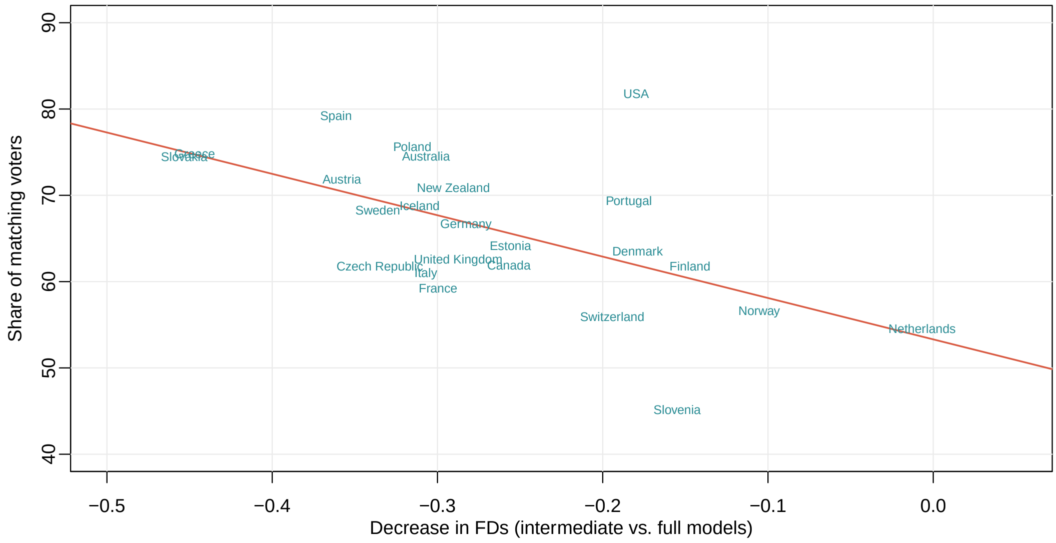
7.2 Descriptives: Matching Vote Choice

Table 7.1: Matching vote choice

COUNTRY	N	MATCHING VOTE
Australia	1,672	75%
Austria	686	72%
Canada	1,360	61%
Czech Republic	790	62%
Denmark	998	64%
Estonia	522	64%
Finland	956	62%
France	1,344	59%
Germany	1,404	67%
Greece	493	75%
Iceland	786	69%
Italy	822	61%
Netherlands	1,585	55%
New Zealand	707	71%
Norway	1,396	57%
Poland	1,091	76%
Portugal	592	69%
Slovakia	698	74%
Slovenia	454	45%
Spain	842	79%
Sweden	625	68%
Switzerland	1,833	56%
UK	1,975	62%
United States	1,618	82%
TOTAL	25,271	66%

Note: N = number of respondents.

7.3 Explaining the Share of Matching Vote Choice



Note: The values for 'decrease in FDs' are from the right panel of Figure **??**). Orange line = OLS regression line.

Figure 7.1: Change in FDs and matching vote choice

Notes

[1]Interested readers will find more on the topic in the many books on Bayesian statistical analysis (e.g. Gelman and Hill 2007; Gelman, Carlin, Stern, Dunson, Vehtari and Rubin 2013; Jackman 2009; Kruschke 2014)

[2]For the definition of the probability density function, see e.g. Jackman (2009: 499).

[3]In some cases, Bayes's theorem therefore is written as $p(\theta|\mathbf{y}) \propto \mathcal{L}(\theta|\mathbf{y})p(\theta)$ (e.g. Jackman 2000: 377).

[4]For a detailed assessment of the differences between frequentist and Bayesian inference, see Kruschke (2014: 297-331).

[5]The idea for the Monte Carlo principle goes back to what was arguably the most productive sick day in the history of statistics. When a convalescing Stanislaw Ulam tried to fight boredom with playing solitaire, he was wondering about the chances of the game to come out successful. After failing to solve the problem analytically, he came up with the idea to play the game many times (i.e. sampling from the posterior density) and calculate the ratio of wins to trials (see Eckhardt 1987; Metropolis 1987).

[6]The software and the user manuals are available on `http://mcmc-jags.sourceforge.net/`.

[7]The package is available on: `https://cran.r-project.org/web/packages/rjags/index.html`.

[8]The package is available on: `https://cran.r-project.org/web/packages/coda/index.html`.

[9]Note that while I only report findings for the case of Germany, the described pattern is the same in all 24 countries.

References

Eckhardt, Roger. 1987. "Stan Ulam, John von Neumann, and the Monte Carlo Method." *Los Alamos Science* 15:131–137.

Gelman, Andrew and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambride University Press.

Gelman, Andrew, John B. Carlin, Hal S. Stern, David B. Dunson, Aki Vehtari and Donald B. Rubin. 2013. *Bayesian Data Analysis*. Boca Raton: Chapman and Hall/CRC.

Jackman, Simon. 2000. "Estimation and Inference via Bayesian Simulation: An Introduction to Markov Chain Monte Carlo." *American Journal of Political Science* 44(2):375–404.

Jackman, Simon. 2009. *Bayesian Analysis for the Social Sciences*. New York: Wiley.

Krauth, Werner. 2006. *Statistical Mechanics. Algorithms and Computations*. Oxford: Oxford University Press.

Kruschke, John. 2014. *Doing Bayesian Data Analysis, Second Edition: A Tutorial with R, JAGS, and Stan*. London: Academic Press.

Metropolis, N. 1987. "The Begin of Monte Carlo Method." *Los Alamos Science* 15:125–130.

Plummer, Martyn. 2015. *JAGS Version 4.0.0 User Manual*.

Plummer, Martyn. 2016. *Package rjags.*

Plummer, Martyn, Nicky Best, Kate Cowles, Karen Vines, Deepayan Sarkar, Douglas Bates, Russell Almond and Arni Magnusson. 2016. *Package coda.*

Tanner, Martin A. 1996. *Tools for Statistical Inference. Methods for the Exploration of Posterior Distributions and Likelihood Functions.* 3 ed. New York: Springer.