Did political trust moderate the relationship between economic insecurity and AfD voting in the 2021 extit{Bundestagswahl}?

Final AVCD assignment

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Preliminaries

```
# load relevant packages
library(tidyverse)
library(haven)
library(modelsummary)
library(survey)
library(here)
library(ggeffects)
library(margins)

# import data
gles <- read_dta(paste0(here(), "/Data/german_longitudinal_election_study_cross_section_post_election202
gles1 <- read_dta(paste0(here(), "/Data/gles_panel_wave20.dta"))
```

Next, we will create some new variables:

```
gles_mod <- gles %>%
  select(1:100, grep("d38|d4|q18|d63|d18|q63|d17|d8|d7|wum6|q13|q14|q15|q16|q18|q23|q24|q25|q26||q27q35
  mutate(btw17_zweitstimme = ifelse(q34ba < 0, NA, q34ba),
         btw21_zweitstimme = ifelse(q114ba < 0, NA, q114ba),
         btw21_turnout = ifelse(q111 < 0 | q111 == 8, NA, q111),
         btw21_turnout1 = ifelse(btw21_turnout == 1, 1, 0),
         year_born = ifelse(grepl("-99|frueher", d2a), NA, d2a),
         ostwest2_dummy = ifelse(ostwest2 < 0, NA, ostwest2),
         ostwest_factor = factor(ostwest2_dummy,
                                 levels = c(0, 1),
                                 labels = c("ost", "west")),
         sex = ifelse(d1 < 0, NA, d1),
```

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```
        sex1 = factor(sex,
                      levels = c(1, 2),
                      labels = c("male", "female")),
        year_born1 = as.numeric(as.character(year_born)),
        age = 2021 - as.numeric(as.character(year_born)),
        spd_21 = ifelse(btw21_zweitstimme == 4, 1, 0),
        union_21 = ifelse(btw21_zweitstimme == 1, 1, 0),
        gruene_21 = ifelse(btw21_zweitstimme == 6, 1, 0),
        fdp_21 = ifelse(btw21_zweitstimme == 5, 1, 0),
        afd_21 = ifelse(btw21_zweitstimme == 322, 1, 0),
        linke_21 = ifelse(btw21_zweitstimme == 7, 1, 0),
        spd_to_switch = ifelse(btw21_zweitstimme == 4 & btw17_zweitstimme != 4, 1, 0),
        afd_away_switch = ifelse(btw17_zweitstimme == 322 & btw21_zweitstimme != 322, 1, 0),
        constituency_centric_rep = ifelse(q63a < 0, NA, q63a),
        party_centric_rep = ifelse(q63c < 0, NA, q63c),
        household_income = ifelse(d63 < 0, NA, d63),
        household_income_factor = as.factor(household_income),
        bachelor_dummy = ifelse(d8j1 < 0, NA, d8j1),
        school = ifelse(d7 < 0, NA, d7),
        abitur = ifelse(d7 == 5, 1, 0),
        abitur_factor = ifelse(abitur == 1, "abitur", "no_abitur"),
        urban_rural = ifelse(wum6 < 0, NA, wum6),
        urban_rural_factor = as.factor(urban_rural),
        subjective_class = ifelse(d38 < 0, NA, d38),
        left_right_self = ifelse(q37 < 0, NA, q37),
        left_right_self_factor = as.factor(left_right_self),
        left_right_cdu = ifelse(q35b < 0, NA, q35b),
        left_right_cdu_factor = as.factor(left_right_cdu),
        distance_cdu = (left_right_cdu-left_right_self)^2,
        left_right_csu = ifelse(q35c < 0, NA, q35c),
        left_right_csu_factor = as.factor(left_right_csu),
        distance_csu = (left_right_csu-left_right_self)^2,
        left_right_spd = ifelse(q35d < 0, NA, q35d),
        left_right_spd_factor = as.factor(left_right_spd),
        distance_spd = (left_right_spd-left_right_self)^2,
        left_right_afd = ifelse(q35h < 0, NA, q35h),
        left_right_afd_factor = as.factor(left_right_afd),
        distance_afd = (left_right_afd-left_right_self)^2,
        left_right_fdp = ifelse(q35e < 0, NA, q35e),
        left_right_fdp_factor = as.factor(left_right_fdp),
        distance_fdp = (left_right_fdp-left_right_self)^2,
        left_right_green = ifelse(q35f < 0, NA, q35f),
        left_right_green_factor = as.factor(left_right_green),
```

```
        distance_green = (left_right_green-left_right_self)^2,
        left_right_linke = ifelse(q35g < 0, NA, q35g),
        left_right_linke_factor = as.factor(left_right_linke),
        distance_linke = (left_right_linke-left_right_self)^2,
        scholz_love = ifelse(q18b < 0, NA, q18b),
        scholz_love_factor = as.factor(scholz_love),
        finzanz_abgehangt_subjektiv = ifelse(q46a < 0, NA, q46a),
        finzanz_abgehangt_subjektiv_factor = as.factor(finzanz_abgehangt_subjektiv),
        arbeit_abgehant_subjektiv = ifelse(q46b < 0, NA, q46b),
        arbeit_abgehant_subjektiv_factor = as.factor(arbeit_abgehant_subjektiv),
        cancel_culture_subjektiv = ifelse(q46d < 0, NA, q46d),
        cancel_culture_subjektiv_factor = as.factor(cancel_culture_subjektiv),
        infrastruktur_subjektiv = ifelse(q46c < 0, NA, q46c),
        infrastruktur_subjektiv_factor = as.factor(infrastruktur_subjektiv),
        unemployed_last10_yrs = ifelse(d17a < 0, NA, d17a),
        unemployed_last10yrs_months = ifelse(d17b < 0, NA, d17b),
        unemployed_last10yrs_weeks = ifelse(d17c < 0, NA, d17c),
        unemployed_dummy = ifelse(unemployed_last10_yrs != 0, 1, 0),
        unemployed_dummy_factor = as.factor(unemployed_dummy),
        trust_in_politicians = ifelse(q79d < 0, NA, q79d),
        trust_in_politicians_factor = as.factor(trust_in_politicians),
        trust_in_parliament = ifelse(q79b < 0, NA, q79b),
        trust_in_parliament_factor = as.factor(trust_in_parliament),
        trust_in_parties = ifelse(q79c < 0, NA, q79c),
        trust_in_parties_factor = as.factor(trust_in_parties),
        trust_in_public_broadcast = ifelse(q79i < 0, NA, q79i),
        trust_in_public_broadcast_factor = as.factor(trust_in_public_broadcast),
        trust_general = ifelse(q78 < 0, NA, q78),
        trust_general_factor = as.factor(trust_general),
        out_group_minorities_assim = ifelse(q125a < 0, NA, q125a),
        out_group_minorities_assim_factor = as.factor(out_group_minorities_assim),
        out_group_majority_will = ifelse(q125b < 0, NA, q125b),
        out_group_majority_will_factor = as.factor(out_group_majority_will),
        out_group_immig_econ_good = ifelse(q125c < 0, NA, q125c),
        out_group_immig_econ_good_factor = as.factor(out_group_immig_econ_good),
        out_group_immig_culture_threat = ifelse(q125d < 0, NA, q125d),
        out_group_immig_culture_threat_factor = as.factor(out_group_immig_culture_threat),
        out_group_immig_crime = ifelse(q125e < 0, NA, q125e),
        out_group_immig_crime_factor = as.factor(out_group_immig_crime),
        scale_pol_lasceht = ifelse(q18a < 0, NA, q18a),
        scale_pol_scholz = ifelse(q18b < 0, NA, q18b),
        scale_pol_baerbock = ifelse(q18c < 0, NA, q18c),
        econ_current_eval_general = ifelse(q23 < 0, NA, q23),
```

```
      econ_current_eval_general_factor = as.factor(econ_current_eval_general),
      econ_current_personal = ifelse(q13 < 0, NA, q13),
      econ_current_personal_factor = factor(econ_current_personal),
      econ_personal_gov_resp = ifelse(q15 < 0, NA, q15),
      gender_too_far = ifelse(q27g < 0, NA, q27g),
      gender_too_far_factor = factor(gender_too_far),
      job_loss_year_next2yrs = ifelse(d18 < 0, NA, d18),
      job_loss_year_next2yrs_factor = factor(job_loss_year_next2yrs),
      length_unemp_last10yrs_yrs = ifelse(d17a < 0, NA, d17a),
      length_unemp_last10yrs_mon = ifelse(d17b < 0, NA, d17b),
      unemp_at_least_one_year = ifelse(length_unemp_last10yrs_yrs >= 1, 1, 0),
      unemp_at_least_one_year_factor = factor(unemp_at_least_one_year),
      profession_loss_next2yrs = ifelse(d19 < 0, NA, d19),
      profession_loss_next2yrs_factor = factor(profession_loss_next2yrs),
      profession_current = ifelse(d11 < 0, NA, d11),
      type_of_emp_contract = ifelse(d13 < 0, NA, d13),
      difference_whos_gov = ifelse(q117 < 0, NA, q117),
      difference_whos_gov_factor = factor(difference_whos_gov),
      difference_who_votes = ifelse(q118 < 0, NA, q118),
      difference_who_votes_factor = factor(difference_who_votes))
```

Introduction

- State research questions.
- Structure of essay.

Motivation

- case selection
  - country
  - election
- motivating correlation

Theory

- Ivanov
- Eichengreen + Tabellini + Dustmann
- Sonin + Eichengreen + Schäfer/Zürn + Katz/Mair (cartelisation of party system)
- Write out hypotheses.
- gap:

- no systematic testing of Eichengreen's theory or model
    - mainly historical analytical narratives

- while it is beyond the scope of my essay to provide such a systematic test, I will here take a first step.

- Why this election?

    - uncertain time in general
    - end of Merkel era
    - distributional consequences of pandemic?

Data and variables

- GLES Nachwahlbefragung

Data source and operationalisation

- dependent variable -> binary, Why?
    - Eichengreen focuses mainly on radical right, as Sonin notes
    - hence focus justified
- proxy for economic insecurity -> justification

Descriptives

- Do I need this?

- How do I operationalise economic insecurity?

    - unemployed (actual experience) (`unemp_at_least_one_year`)
    - fear of job loss (`job_loss_year_next2yrs`)
    - fear of losing profession or having to change profession (`profession_loss_next2yrs`)
    - subjective evaluation of current economic situation

- How do I operationalise trust?

    - trust in politicians
    - trust in parties
    - trust in parliament

- How do I operationalise lack of representation?

    - no difference who one is voting for
    - no difference who governs

Methodology and Results

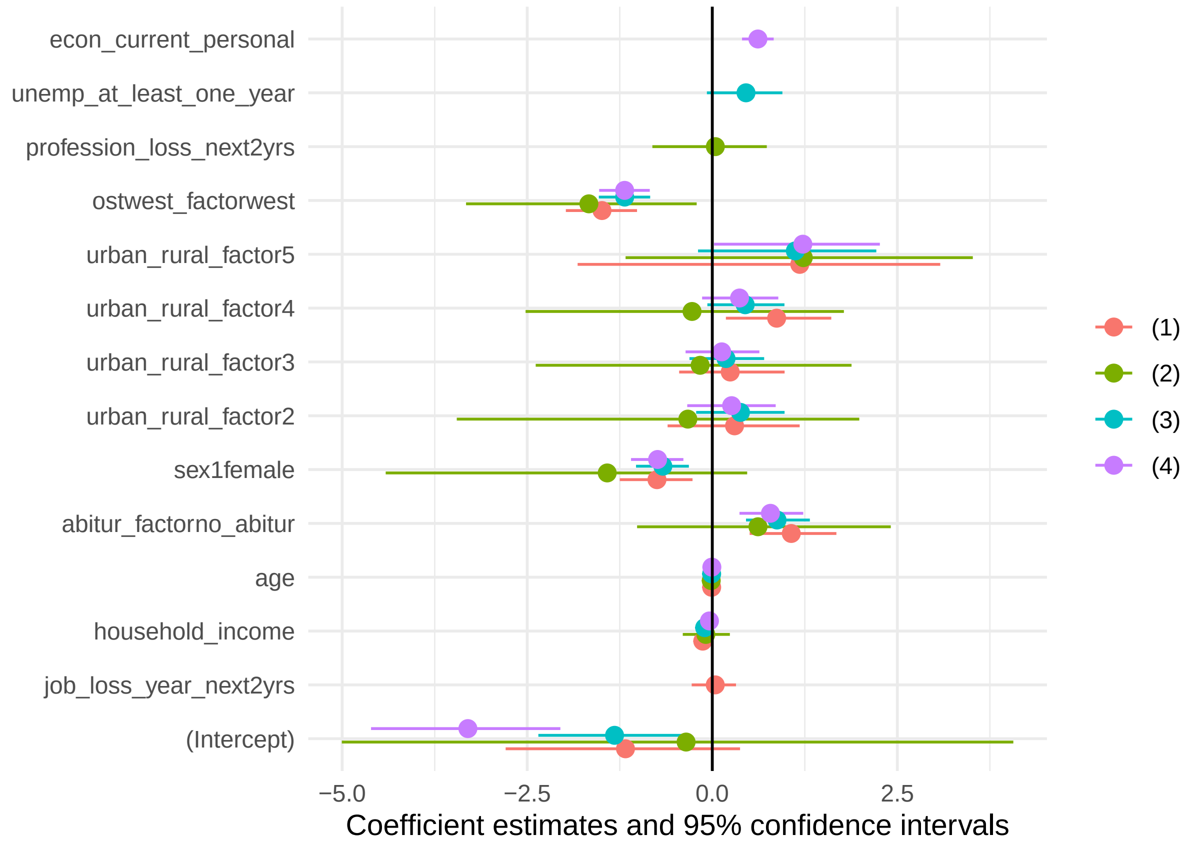
- Justify model specification.

- DAG would be cool, but probably not possible.

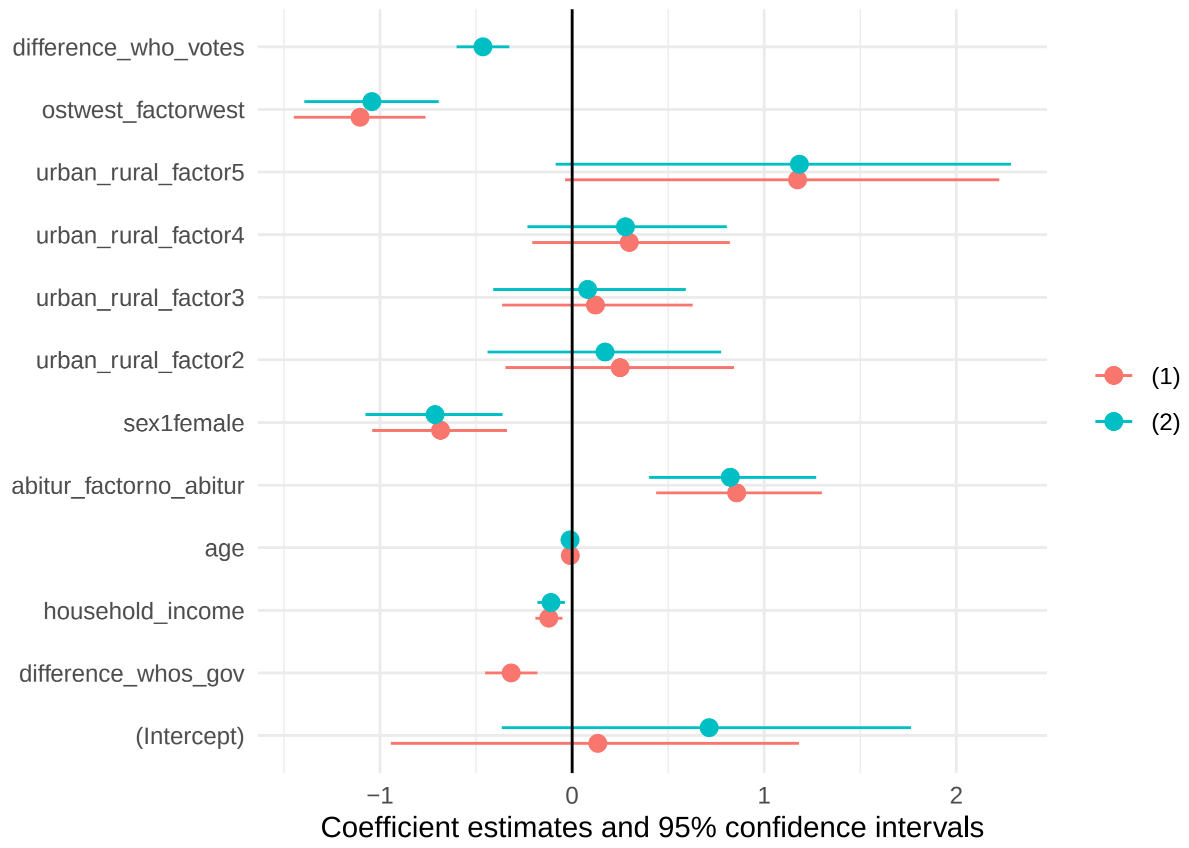
- Presentation of results + interpretation.

- Caveats.
    - not causal, correlational analysis

```
# simple models
## job loss fear
afd_job_loss_fear <- glm(afd_21 ~ job_loss_year_next2yrs + household_income + age + abitur_factor + sex1
                         data = gles_mod)
## loss of profession
afd_prof_loss_fear <- glm(afd_21 ~ profession_loss_next2yrs + household_income + age + abitur_factor + s
                          data = gles_mod)
## unemployment experience
afd_unemp_exp <- glm(afd_21 ~ unemp_at_least_one_year + household_income + age + abitur_factor + sex1 +
                     data = gles_mod)
## econ current general situation
afd_econ_current <- glm(afd_21 ~ econ_current_personal + household_income + age + abitur_factor + sex1 +
                        data = gles_mod)

# modelplot
modelplot(list(afd_job_loss_fear, afd_prof_loss_fear,
               afd_unemp_exp, afd_econ_current)) +
  geom_vline(xintercept = 0)
```

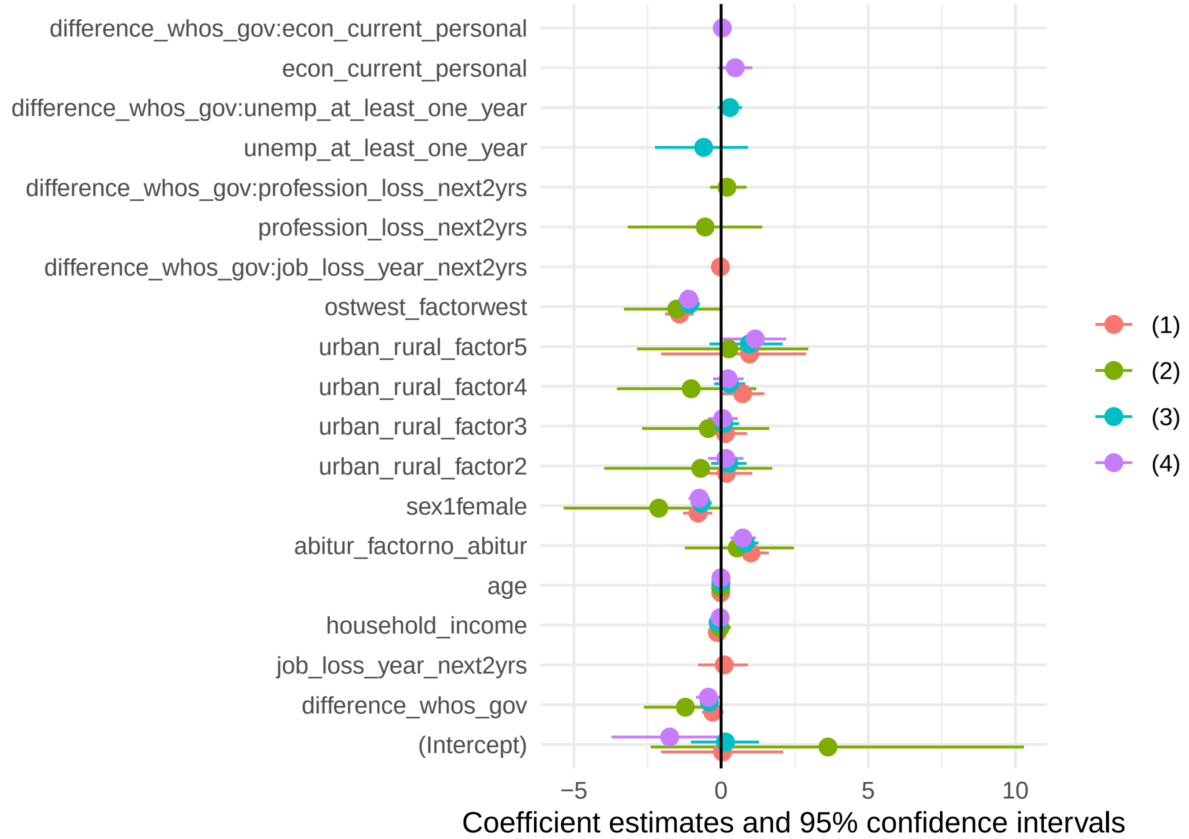


```r
# simple models
## difference gov
afd_diff_gov <- glm(afd_21 ~ difference_whos_gov + household_income + age + abitur_factor + sex1 + urban
                          data = gles_mod)
## difference voting
afd_prof_loss_fear <- glm(afd_21 ~ difference_who_votes + household_income + age + abitur_factor + sex1
                          data = gles_mod)
# modelplot
modelplot(list(afd_diff_gov, afd_prof_loss_fear)) +
  geom_vline(xintercept = 0)
```




```r
# interaction models
## difference gov
### job loss fear
afd_diff_gov_int1 <- glm(afd_21 ~ difference_whos_gov*job_loss_year_next2yrs + household_income + age +
                          data = gles_mod)
### profession loss fear
afd_diff_gov_int2 <- glm(afd_21 ~ difference_whos_gov*profession_loss_next2yrs + household_income + age
                          data = gles_mod)
### unemployment experience
afd_diff_gov_int3 <- glm(afd_21 ~ difference_whos_gov*unemp_at_least_one_year + household_income + age +
```

```r
                          data = gles_mod)
### personal current situation
afd_diff_gov_int4 <- glm(afd_21 ~ difference_whos_gov*econ_current_personal + household_income + age + a
                          data = gles_mod)
# modelplot
modelplot(list(afd_diff_gov_int1, afd_diff_gov_int2,
               afd_diff_gov_int3, afd_diff_gov_int4)) +
  geom_vline(xintercept = 0)
```




```r
# models
## trust in parliament
afd_job_loss_fear_int1 <- glm(afd_21 ~ job_loss_year_next2yrs*trust_in_parliament + household_income + a
                              family = binomial(link = "logit"),
                              data = gles_mod)
## trust in parties
afd_job_loss_fear_int2 <- glm(afd_21 ~ job_loss_year_next2yrs*trust_in_parties + household_income + age
                              family = binomial(link = "logit"),
                              data = gles_mod)
## trust in politicians
afd_job_loss_fear_int3 <- glm(afd_21 ~ job_loss_year_next2yrs*trust_in_politicians + household_income +
                              family = binomial(link = "logit"),
```

```r
                                data = gles_mod)
# regression table
modelsummary(list(afd_job_loss_fear_int1, afd_job_loss_fear_int2, afd_job_loss_fear_int3),
             estimate = "{estimate}{stars}")
```

```r
# models
## trust in parliament
afd_prof_loss_fear_int1 <- glm(afd_21 ~ profession_loss_next2yrs*trust_in_parliament + household_income
                                family = binomial(link = "logit"),
                                data = gles_mod)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
## trust in parties
afd_prof_loss_fear_int2 <- glm(afd_21 ~ profession_loss_next2yrs*trust_in_parties + household_income + a
                                family = binomial(link = "logit"),
                                data = gles_mod)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
## trust in politicians
afd_prof_loss_fear_int3 <- glm(afd_21 ~ profession_loss_next2yrs*trust_in_politicians + household_income
                                family = binomial(link = "logit"),
                                data = gles_mod)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
# regression table
modelsummary(list(afd_prof_loss_fear_int1, afd_prof_loss_fear_int2, afd_prof_loss_fear_int3),
             estimate = "{estimate}{stars}")
```

```r
# models
## trust in parliament
afd_unemp_exp_int1 <- glm(afd_21 ~ unemp_at_least_one_year*trust_in_parliament + household_income + age
                                family = binomial(link = "logit"),
                                data = gles_mod)
## trust in parties
afd_unemp_exp_int2 <- glm(afd_21 ~ unemp_at_least_one_year*trust_in_parties + household_income + age + a
                                family = binomial(link = "logit"),
                                data = gles_mod)
## trust in politicians
afd_unemp_exp_int3 <- glm(afd_21 ~ unemp_at_least_one_year*trust_in_politicians + household_income + age
                                family = binomial(link = "logit"),
                                data = gles_mod)
# regression table
modelsummary(list(afd_unemp_exp_int1, afd_unemp_exp_int2, afd_unemp_exp_int3),
             estimate = "{estimate}{stars}")
```

	(1)	(2)	(3)
(Intercept)	0.376	0.765	0.153
	(0.989)	(0.984)	(0.960)
job_loss_year_next2yrs	0.506	0.240	0.333
	(0.343)	(0.349)	(0.337)
trust_in_parliament	−0.160		
	(0.169)		
household_income	−0.080	−0.110+	−0.112+
	(0.067)	(0.065)	(0.064)
age	−0.004	−0.006	−0.001
	(0.011)	(0.011)	(0.011)
abitur_factorno_abitur	0.959**	1.057***	1.071***
	(0.319)	(0.311)	(0.312)
sex1female	−0.909***	−0.937***	−0.854**
	(0.272)	(0.272)	(0.266)
urban_rural_factor2	−0.008	0.045	0.129
	(0.485)	(0.479)	(0.477)
urban_rural_factor3	−0.225	0.076	0.067
	(0.390)	(0.378)	(0.378)
urban_rural_factor4	0.584	0.646+	0.659+
	(0.381)	(0.373)	(0.374)
urban_rural_factor5	1.496	−13.252	1.370
	(1.147)	(751.057)	(1.160)
ostwest_factorwest	−1.332***	−1.308***	−1.464***
	(0.264)	(0.258)	(0.256)
job_loss_year_next2yrs × trust_in_parliament	−0.280+		
	(0.148)		
trust_in_parties		−0.404**	
		(0.155)	
job_loss_year_next2yrs × trust_in_parties		−0.119	
		(0.114)	
trust_in_politicians			−0.320*
			(0.152)
job_loss_year_next2yrs × trust_in_politicians			−0.148
			(0.116)
Num.Obs.	1247	1242	1244
AIC	467.0	480.6	491.9
BIC	533.7	547.2	558.6
Log.Lik.	−220.509	−227.283	−232.956
RMSE	0.22	0.22	0.23

	(1)	(2)	(3)
(Intercept)	−49.880	−1.123	−7.002
	(5687.044)	(3.719)	(974.853)
profession_loss_next2yrs	44.364	2.110	7.241
	(5687.037)	(1.659)	(974.848)
trust_in_parliament	20.849		
	(2843.518)		
household_income	0.768	0.136	0.173
	(0.493)	(0.227)	(0.233)
age	−0.039	−0.046	−0.033
	(0.057)	(0.049)	(0.048)
abitur_factorno_abitur	1.344	1.013	0.889
	(1.143)	(1.048)	(1.026)
sex1female	−21.845	−17.891	−20.004
	(13548.639)	(1978.524)	(5283.111)
urban_rural_factor2	0.044	−0.357	−0.457
	(1.593)	(1.446)	(1.506)
urban_rural_factor3	1.567	0.563	0.796
	(1.450)	(1.181)	(1.214)
urban_rural_factor4	−0.530	−1.627	−1.656
	(1.530)	(1.512)	(1.530)
urban_rural_factor5	3.433	2.063	1.934
	(2.259)	(1.528)	(1.656)
ostwest_factorwest	−1.564	−1.439	−1.267
	(1.074)	(0.929)	(0.949)
profession_loss_next2yrs × trust_in_parliament	−21.450		
	(2843.518)		
trust_in_parties		0.371	
		(0.763)	
profession_loss_next2yrs × trust_in_parties		−0.825	
		(0.673)	
trust_in_politicians			5.726
			(974.847)
profession_loss_next2yrs × trust_in_politicians			−6.253
			(974.847)
Num.Obs.	155	156	155
AIC	58.5	66.2	63.1
BIC	98.0	105.9	102.7
Log.Lik.	−16.227	−20.123	−18.554
RMSE	0.18	0.18	0.18

	(1)	(2)	(3)
(Intercept)	0.428	0.906	0.434
	(0.618)	(0.606)	(0.599)
unemp_at_least_one_year	1.066+	0.360	0.537
	(0.600)	(0.621)	(0.579)
trust_in_parliament	−0.493***		
	(0.045)		
household_income	−0.049	−0.082+	−0.074+
	(0.044)	(0.042)	(0.043)
age	0.003	−0.004	0.000
	(0.006)	(0.006)	(0.006)
abitur_factorno_abitur	0.670**	0.802***	0.779***
	(0.234)	(0.231)	(0.231)
sex1female	−0.822***	−0.825***	−0.763***
	(0.202)	(0.199)	(0.197)
urban_rural_factor2	0.098	0.105	0.130
	(0.331)	(0.325)	(0.325)
urban_rural_factor3	−0.046	0.039	0.015
	(0.278)	(0.272)	(0.272)
urban_rural_factor4	0.287	0.270	0.268
	(0.285)	(0.279)	(0.279)
urban_rural_factor5	1.241+	0.685	1.226+
	(0.691)	(0.709)	(0.661)
ostwest_factorwest	−1.075***	−1.073***	−1.148***
	(0.193)	(0.190)	(0.189)
unemp_at_least_one_year × trust_in_parliament	−0.211		
	(0.153)		
trust_in_parties		−0.577***	
		(0.059)	
unemp_at_least_one_year × trust_in_parties		0.000	
		(0.163)	
trust_in_politicians			−0.539***
			(0.056)
unemp_at_least_one_year × trust_in_politicians			−0.076
			(0.165)
Num.Obs.	2272	2263	2266
AIC	840.2	870.5	875.9
BIC	914.7	944.9	950.3
Log.Lik.	−407.109	−422.250	−424.940
RMSE	0.22	0.23	0.23

```r
# models
## trust in parliament
afd_econ_current_int1 <- glm(afd_21 ~ econ_current_personal*trust_in_parliament + household_income + ag
                             family = binomial(link = "logit"),
                             data = gles_mod)
## trust in parties
afd_econ_current_int2 <- glm(afd_21 ~ econ_current_personal*trust_in_parties + household_income + age +
                             family = binomial(link = "logit"),
                             data = gles_mod)
## trust in politicians
afd_econ_current_int3 <- glm(afd_21 ~ econ_current_personal*trust_in_politicians + household_income + ag
                             family = binomial(link = "logit"),
                             data = gles_mod)
# regression table
modelsummary(list(afd_econ_current_int1, afd_econ_current_int2, afd_econ_current_int3),
             estimate = "{estimate}{stars}")
```

Conclusion

References

Appendix

Analysis - AfD

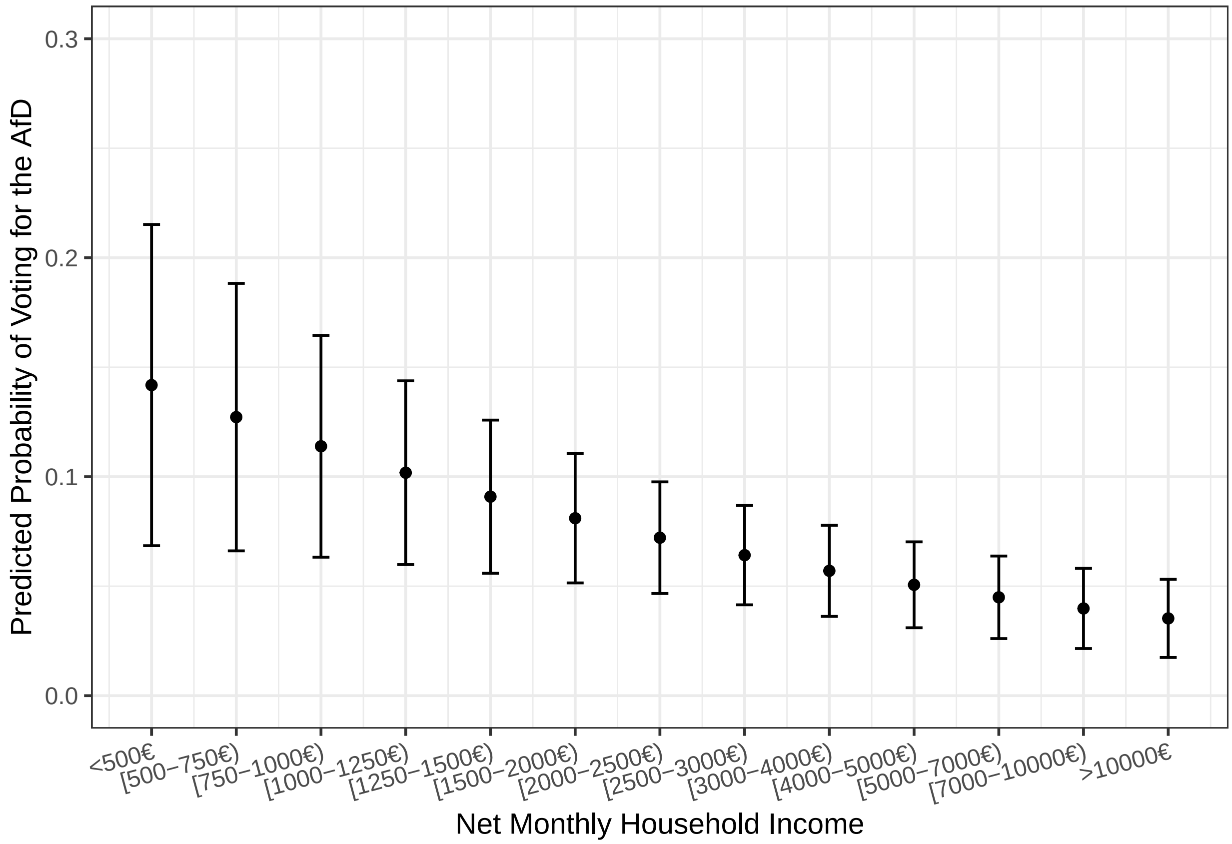
Socio-demographic Correlates

Relationship between household income and AfD voting

```r
afd_income <- glm(afd_21 ~ household_income + age + abitur_factor + sex1 + urban_rural_factor + ostwest_
cplot(afd_income, x = "household_income",
      xvals = seq(1, 13, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Net Monthly Household Income",
                     breaks = seq(1, 13, 1),
                     labels = c("<500€", "[500-750€)",
                                "[750-1000€)", "[1000-1250€)",
                                "[1250-1500€)", "[1500-2000€)",
                                "[2000-2500€)", "[2500-3000€)",
                                "[3000-4000€)", "[4000-5000€)",
```

	(1)	(2)	(3)
(Intercept)	−1.341	−1.939*	−2.230*
	(0.923)	(0.953)	(0.915)
econ_current_personal	0.611**	0.892***	0.844***
	(0.210)	(0.236)	(0.216)
trust_in_parliament	−0.242*		
	(0.120)		
household_income	−0.022	−0.025	−0.018
	(0.046)	(0.045)	(0.045)
age	0.003	−0.002	0.001
	(0.006)	(0.006)	(0.006)
abitur_factorno_abitur	0.691**	0.796***	0.812***
	(0.234)	(0.231)	(0.231)
sex1female	−0.883***	−0.940***	−0.891***
	(0.201)	(0.202)	(0.200)
urban_rural_factor2	0.059	0.092	0.107
	(0.328)	(0.326)	(0.324)
urban_rural_factor3	−0.006	0.080	0.032
	(0.276)	(0.273)	(0.272)
urban_rural_factor4	0.299	0.247	0.259
	(0.282)	(0.280)	(0.279)
urban_rural_factor5	1.500*	0.876	1.368*
	(0.627)	(0.649)	(0.618)
ostwest_factorwest	−1.090***	−1.130***	−1.187***
	(0.191)	(0.189)	(0.188)
econ_current_personal × trust_in_parliament	−0.103*		
	(0.047)		
trust_in_parties		−0.177	
		(0.156)	
econ_current_personal × trust_in_parties		−0.146*	
		(0.060)	
trust_in_politicians			−0.176
			(0.147)
econ_current_personal × trust_in_politicians			−0.140*
			(0.058)
Num.Obs.	2351	2341	2346
AIC	866.9	890.4	894.3
BIC	941.8	965.3	969.2
Log.Lik.	−420.467	−432.214	−434.139
F		16.825	16.786
RMSE	0.22	0.22	0.23

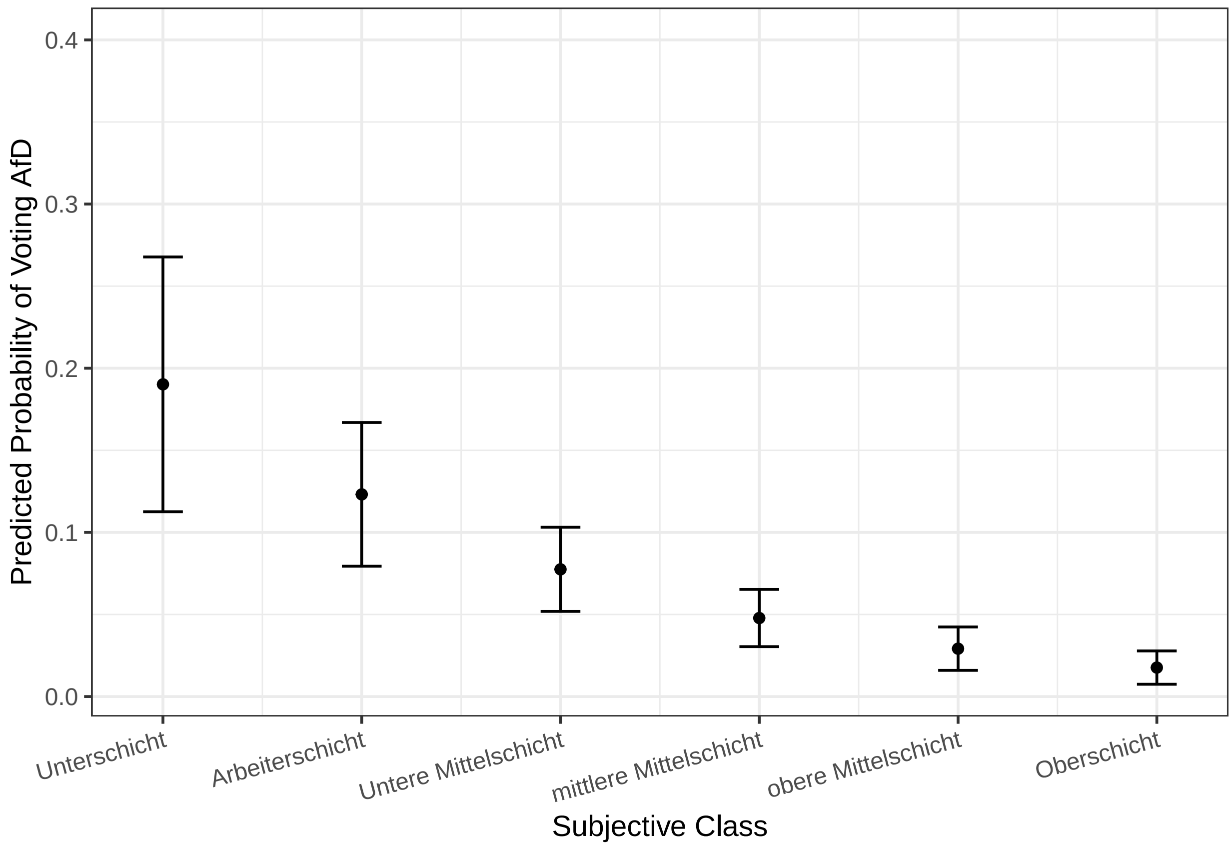
```
                                "[5000-7000€)", "[7000-10000€)",
                                ">10000€")) +
  labs(y = "Predicted Probability of Voting for the AfD") +
  ylim(c(0, 0.3)) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



Relationship between subjective class and AfD voting

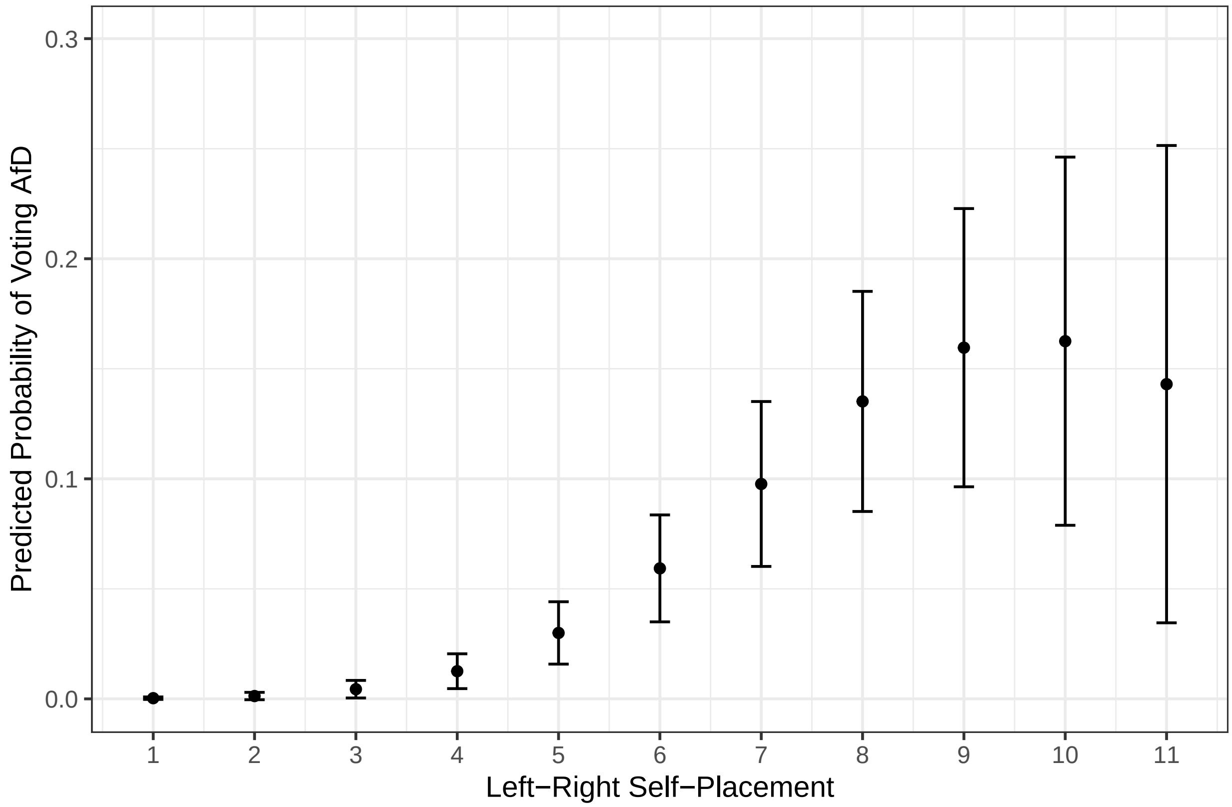
```
# model
afd_class <- glm(afd_21 ~ subjective_class + age + abitur_factor + sex1 + urban_rural_factor + ostwest_
# plot
cplot(afd_class, x = "subjective_class",
      xvals = seq(1, 6, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Subjective Class",
                     breaks = seq(1, 6, 1),
                     labels = c("Unterschicht", "Arbeiterschicht",
                                "Untere Mittelschicht", "mittlere Mittelschicht", "obere Mittelschicht"
```

```
  labs(y = "Predicted Probability of Voting AfD") +
  expand_limits(y = 0.4) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



What is the relationship between left-right self-placement and AfD voting?

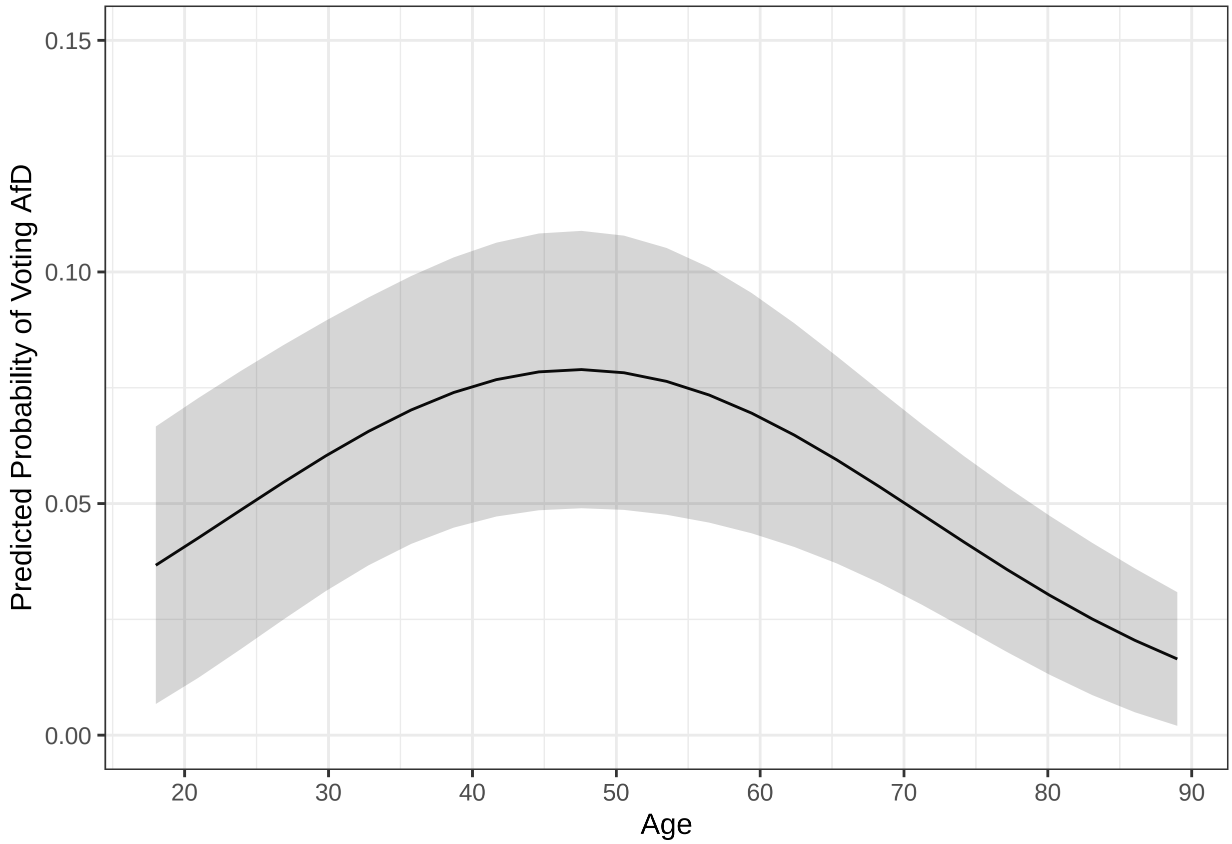
```
afd_left_right_placement <- glm(afd_21 ~ left_right_self + I(left_right_self^2) + household_income + age
# plot this model
cplot(afd_left_right_placement, x = "left_right_self",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Left-Right Self-Placement",
                     breaks = seq(1, 11, 1)) +
  expand_limits(y = 0.3) +
  labs(y = "Predicted Probability of Voting AfD",
       caption = "'1' indicates respondents who locate themselves on the left of the ideological spectru
  theme_bw()
```



ıdicates respondents who locate themselves on the left of the ideological spectrum, while '11' indicates the opposite.

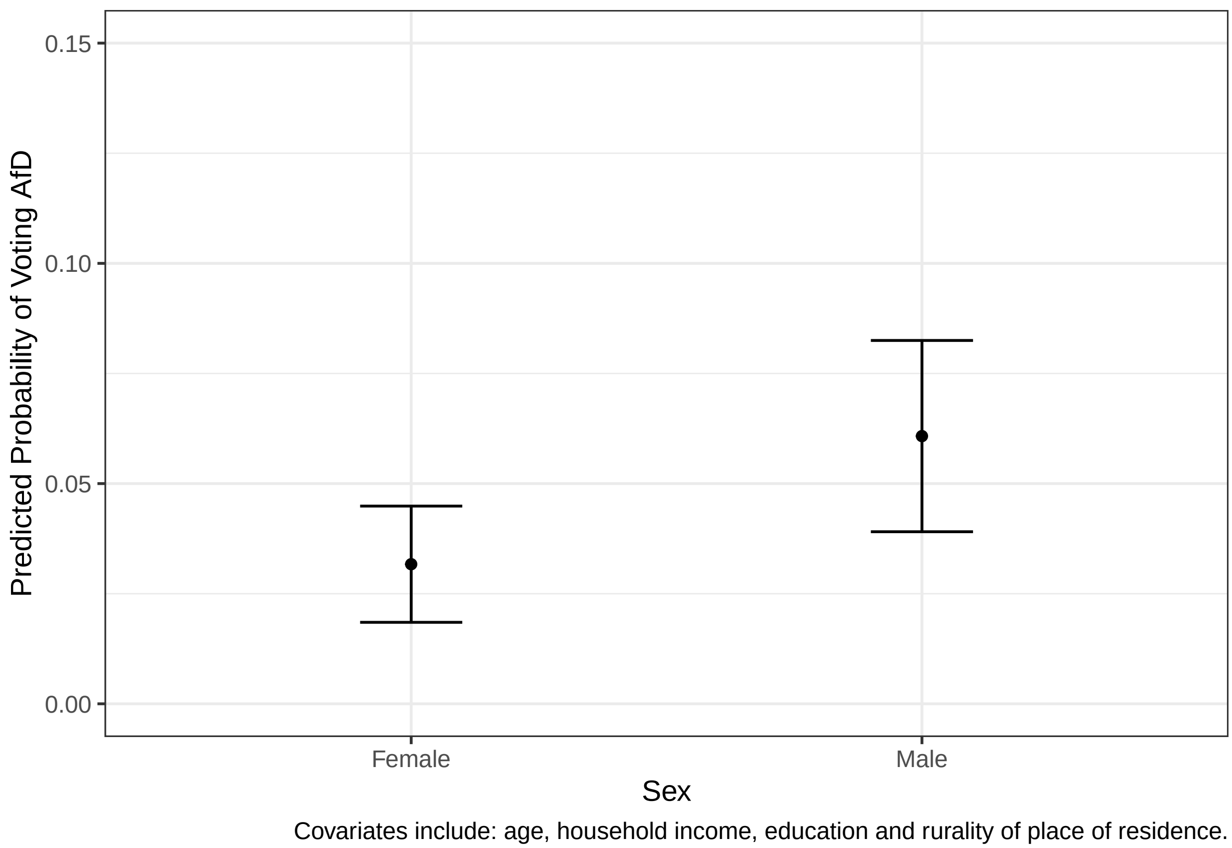
Relationship between age and AfD voting

```
afd_age <- glm(afd_21 ~ age + I(age^2) + household_income + abitur_factor + sex1 + urban_rural_factor +
# plot
cplot(afd_age, x = "age", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_line(aes(y = yvals)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.2) +
  scale_x_continuous("Age", breaks = seq(20, 90, 10)) +
  labs(y = "Predicted Probability of Voting AfD") +
  ylim(c(0, 0.15)) +
  theme_bw()
```



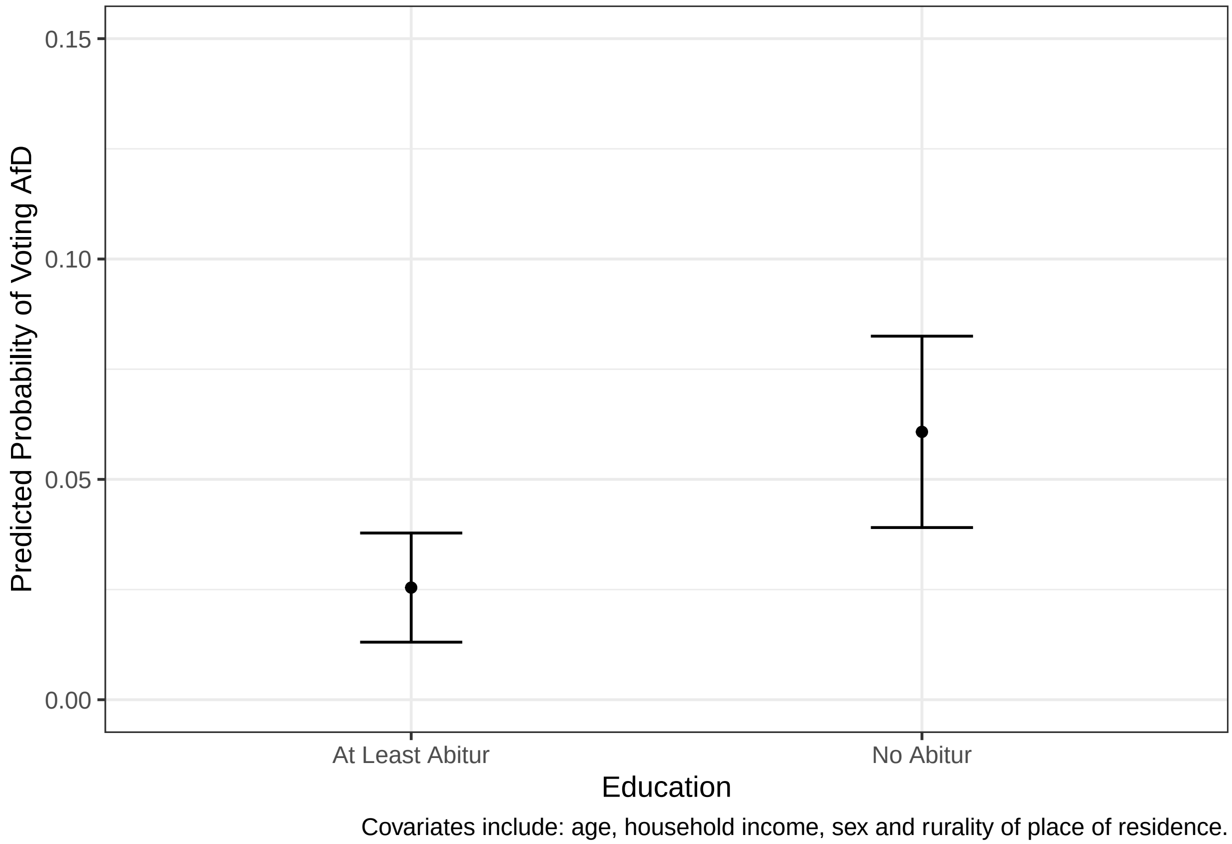
Relationship between sex and AfD

```
cplot(afd_income, x = "sex1", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Sex", labels = c("Female", "Male")) +
  ylim(c(0, 0.15)) +
  labs(y = "Predicted Probability of Voting AfD",
       caption = "Covariates include: age, household income, education and rurality of residen
  theme_bw()
```

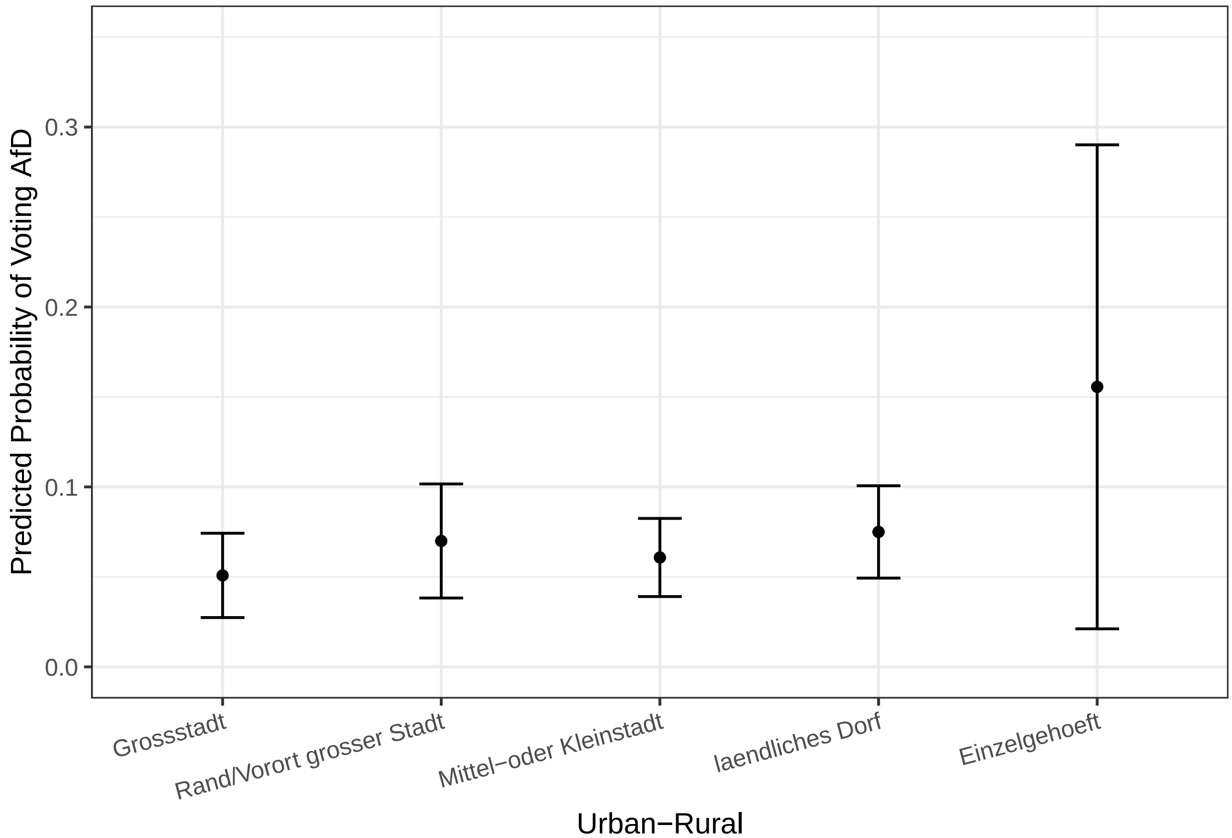


Relationship between education and AfD voting

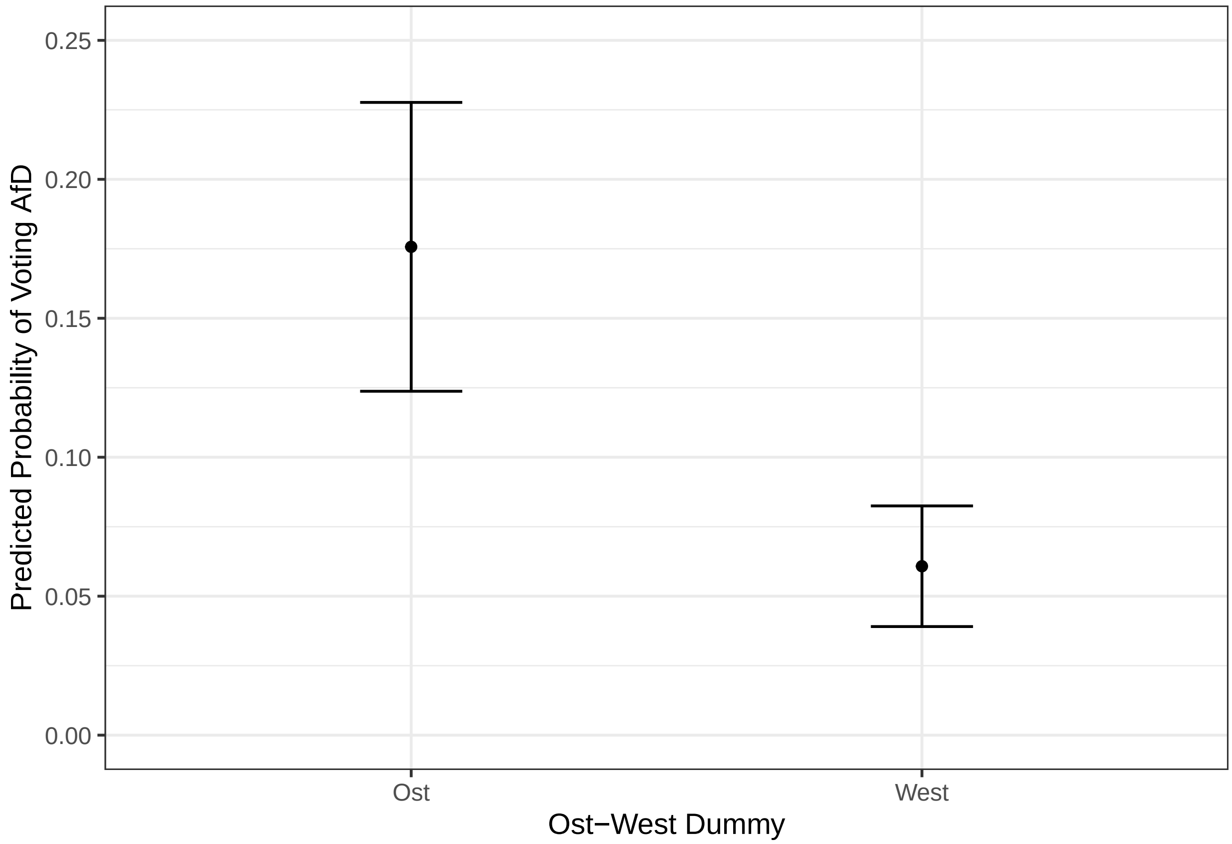
```
cplot(afd_income, x = "abitur_factor", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Education", labels = c("At Least Abitur",
                                           "No Abitur")) +
  labs(y = "Predicted Probability of Voting AfD",
       caption = "Covariates include: age, household income, sex and rurality of place of residence.") +
  ylim(c(0, 0.15)) +
  theme_bw()
```




```
cplot(afd_income, x = "urban_rural_factor", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Urban-Rural",
                   labels = c("Grossstadt", "Rand/Vorort grosser Stadt",
                              "Mittel-oder Kleinstadt", "laendliches Dorf",
                              "Einzelgehoeft")) +
 labs(y = "Predicted Probability of Voting AfD") +
 ylim(c(0, 0.35)) +
 theme_bw() +
 theme(axis.text.x = element_text(angle = 15, hjust = 1))
```

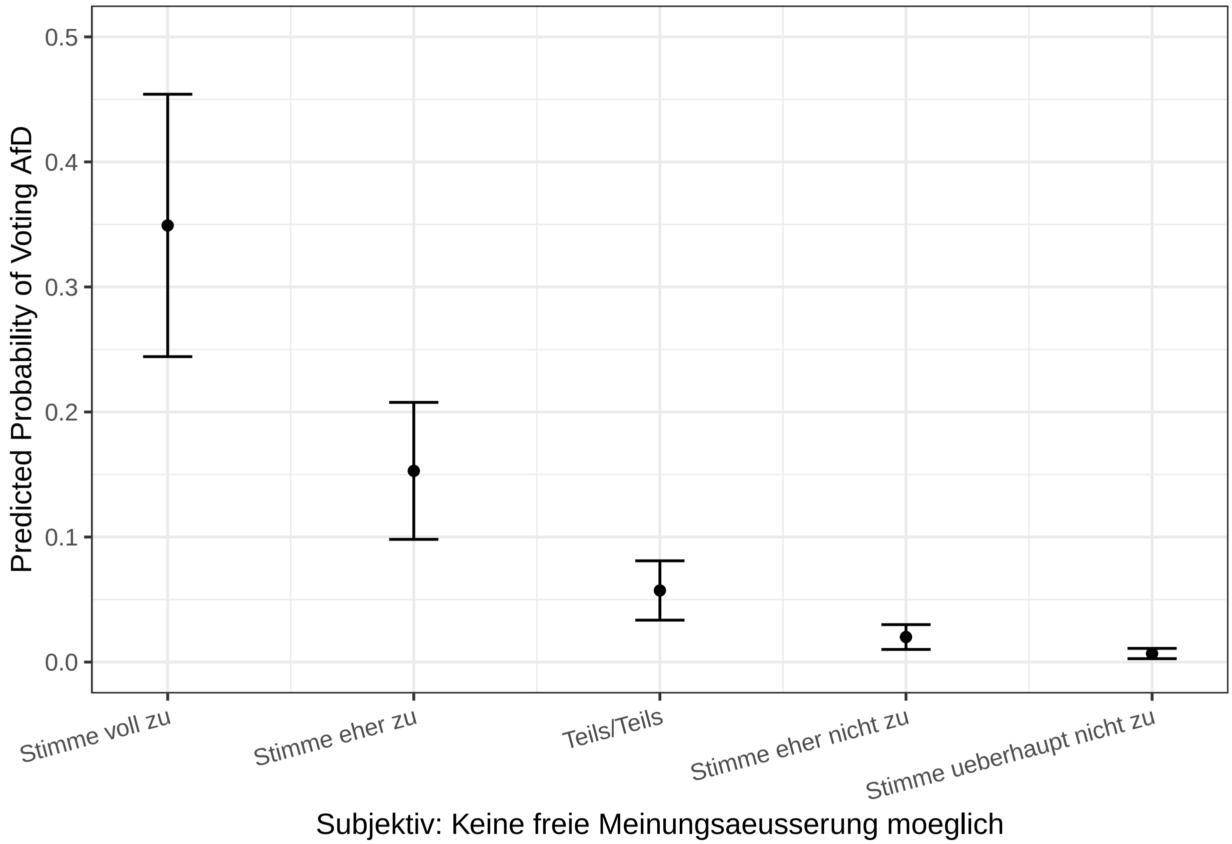



```
cplot(afd_income, x = "ostwest_factor", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Ost-West Dummy", labels = c("Ost", "West")) +
  ylim(c(0, 0.25)) +
  labs(y = "Predicted Probability of Voting AfD") +
  theme_bw()
```

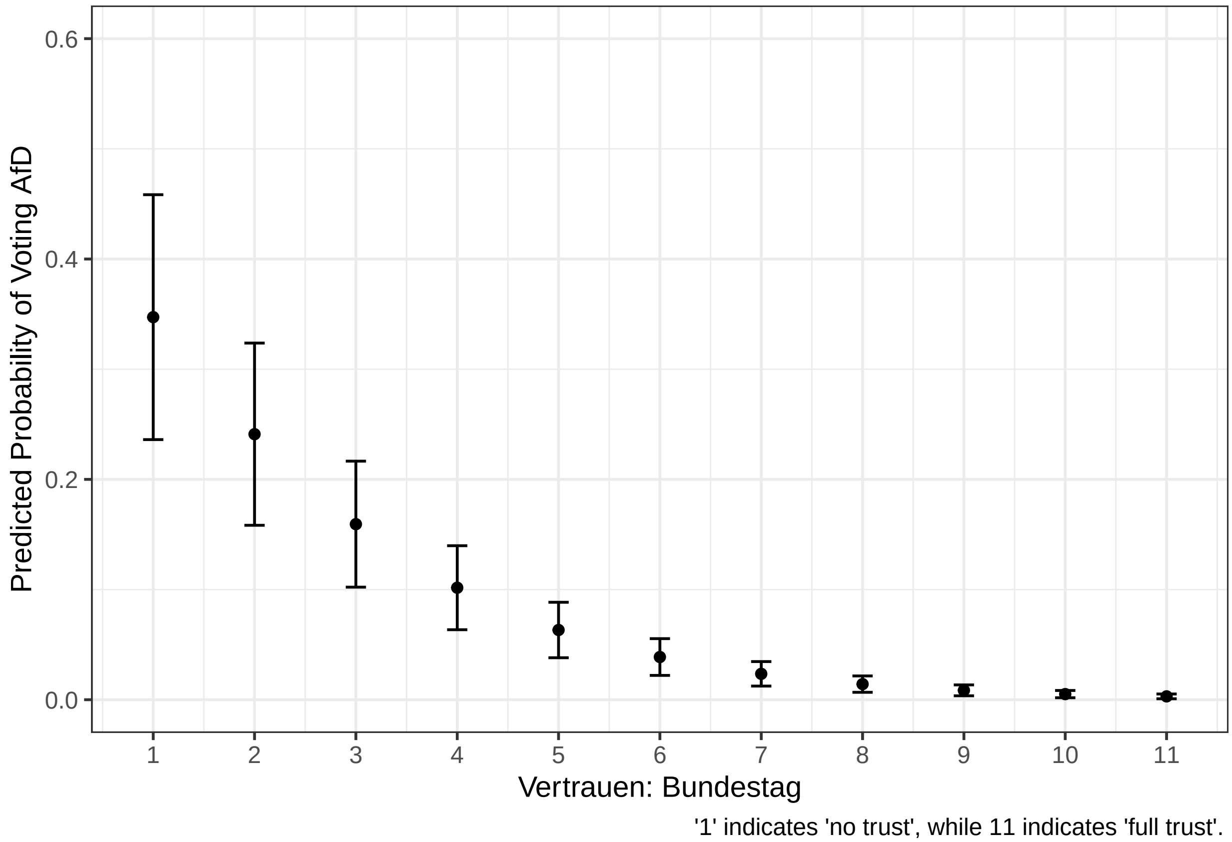


Attiudinal Correlates

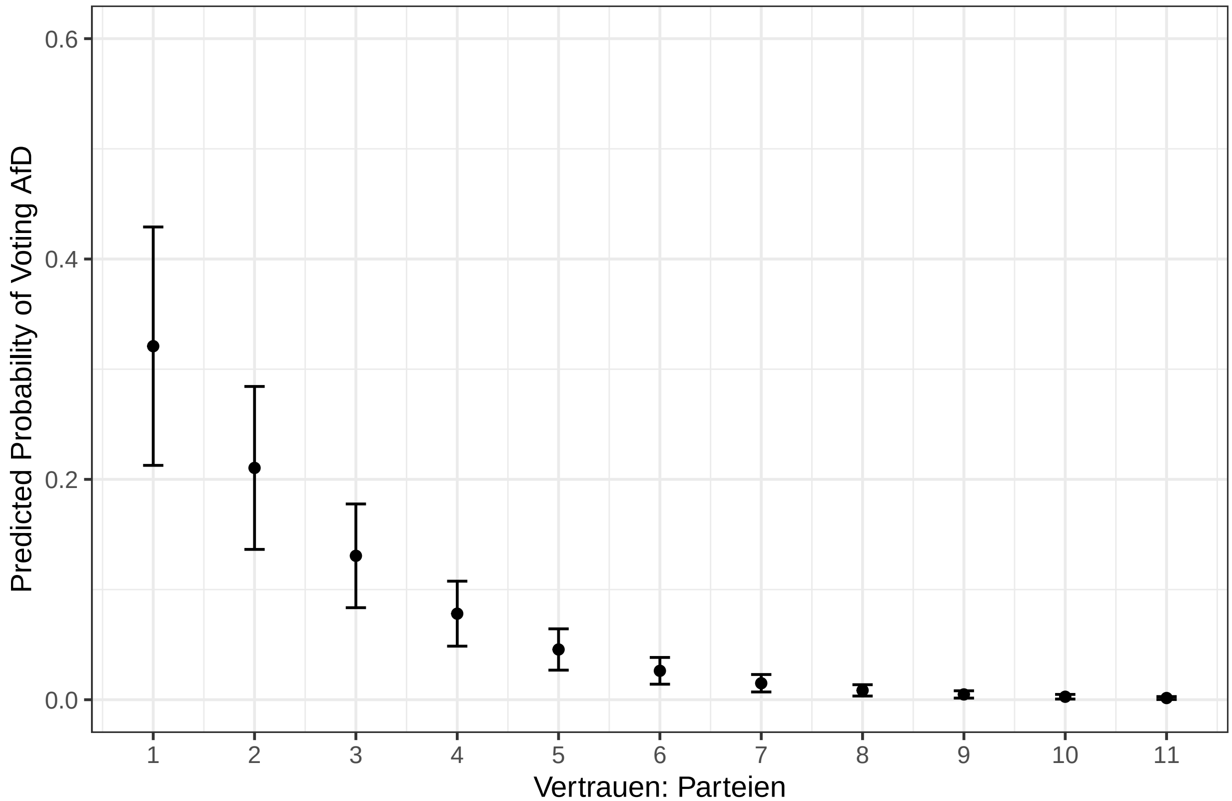
```
afd_cancel_culture <- glm(afd_21 ~ cancel_culture_subjektiv + household_income + age + abitur_factor + s
# plot
cplot(afd_cancel_culture, x = "cancel_culture_subjektiv",
      xvals = seq(1, 5, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Subjektiv: Keine freie Meinungsaeusserung moeglich",
                     breaks = seq(1, 5, 1),
                     labels = c("Stimme voll zu", "Stimme eher zu",
                                "Teils/Teils", "Stimme eher nicht zu",
                                "Stimme ueberhaupt nicht zu")) +
  labs(y = "Predicted Probability of Voting AfD") +
  ylim(c(0, 0.5)) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



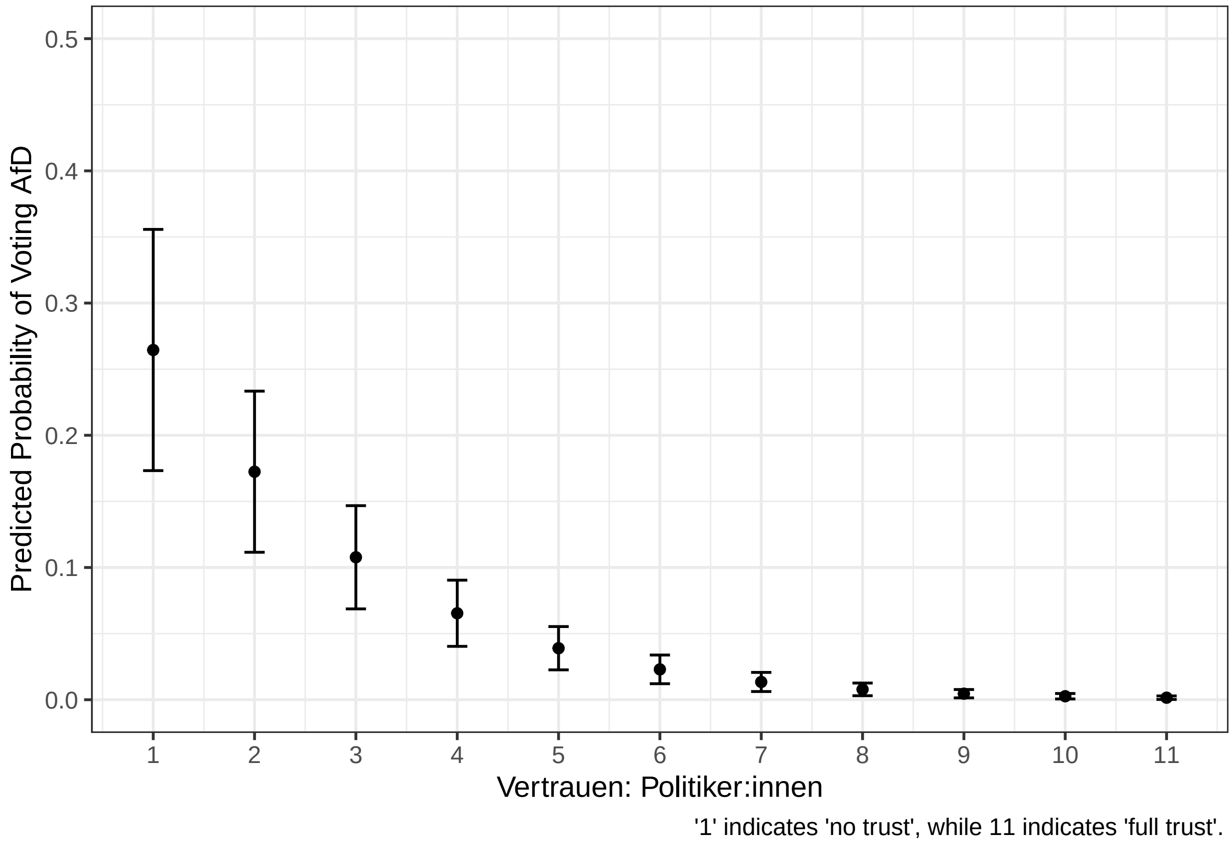

```
afd_trust_parliament <- glm(afd_21 ~ trust_in_parliament + household_income + age + abitur_factor + sex
# plot
cplot(afd_trust_parliament, x = "trust_in_parliament",
      xvals = seq(1, 11, 1), draw = F)  %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Vertrauen: Bundestag",
                     breaks = seq(1, 11, 1)) +
  labs(y = "Predicted Probability of Voting AfD",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.6)) +
  theme_bw()
```



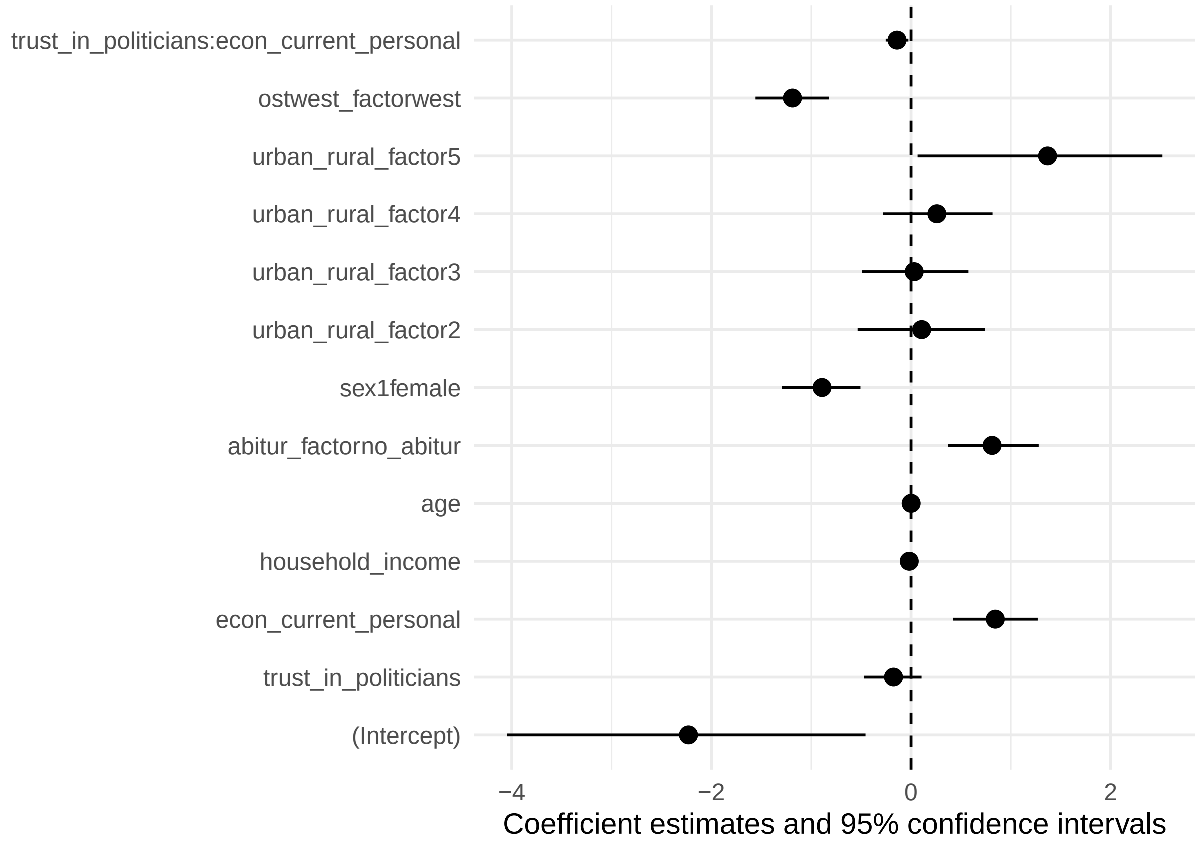

```
afd_trust_parties <- glm(afd_21 ~ trust_in_parties + household_income + age + abitur_factor + sex1 + url
# plot
cplot(afd_trust_parties, x = "trust_in_parties",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Vertrauen: Parteien",
                     breaks = seq(1, 11, 1)) +
  labs(y = "Predicted Probability of Voting AfD",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.6)) +
  theme_bw()
```



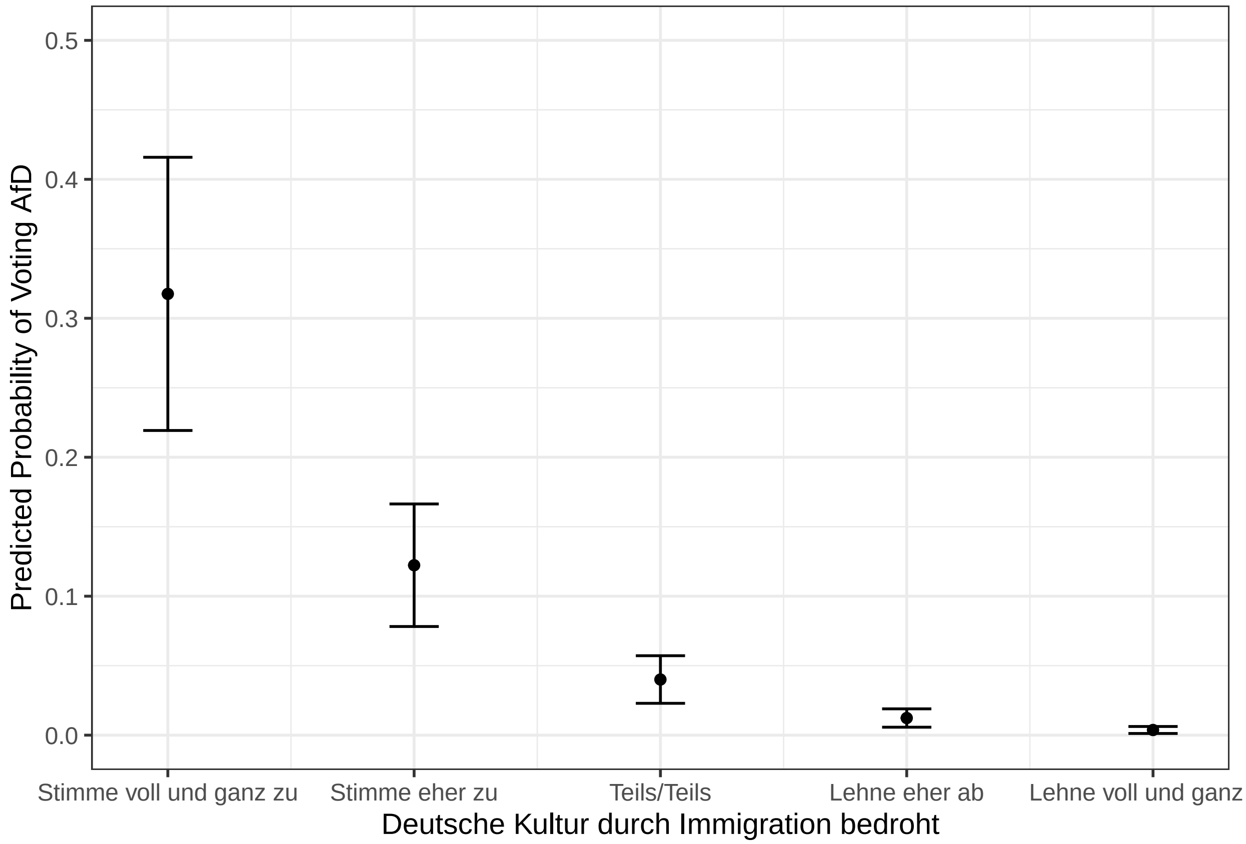

```
afd_trust_politicians <- glm(afd_21 ~ trust_in_politicians + household_income + age + abitur_factor + se
# plot
cplot(afd_trust_politicians, x = "trust_in_politicians",
      xvals = seq(1, 11, 1), draw = F)  %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Vertrauen: Politiker:innen",
                     breaks = seq(1, 11, 1)) +
  labs(y = "Predicted Probability of Voting AfD",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.5)) +
  theme_bw()
```



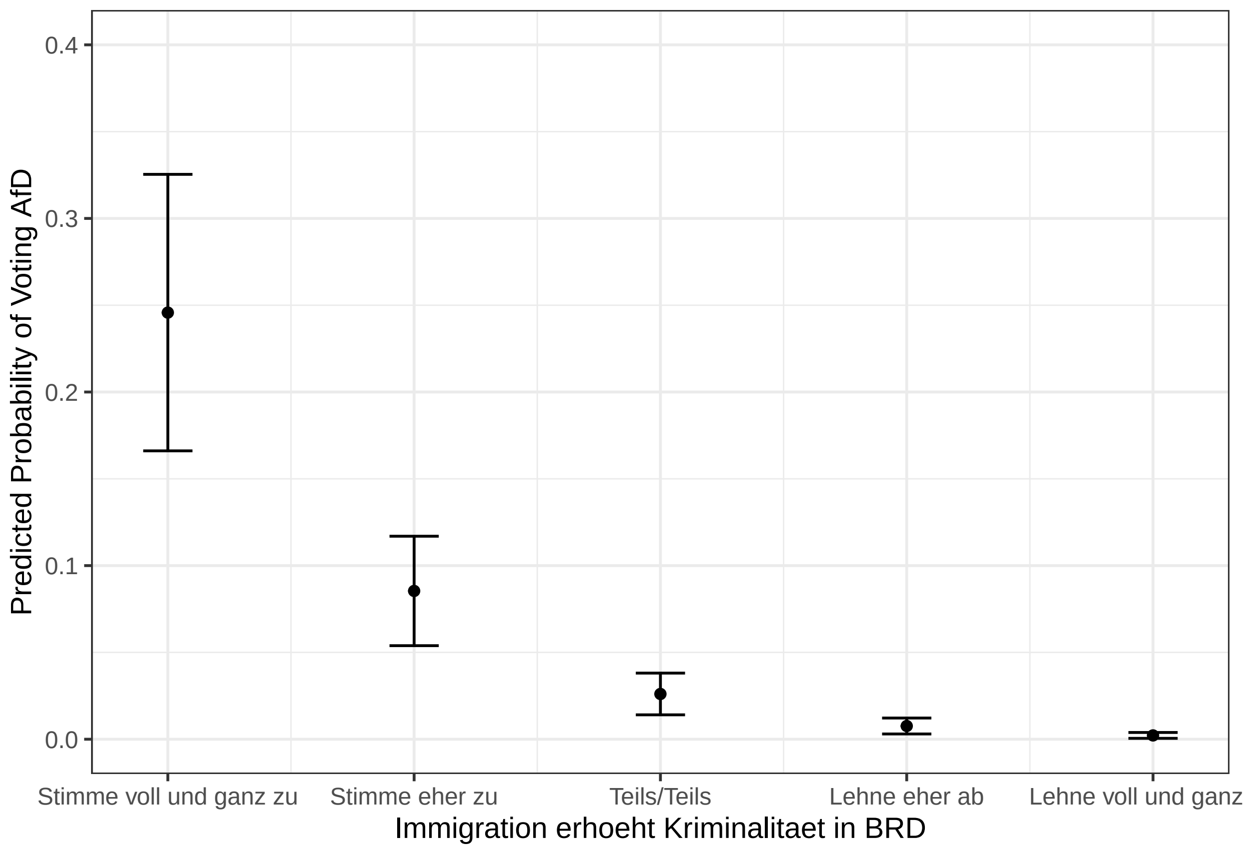

```
afd_trust_unemp_politicians <- glm(afd_21 ~ trust_in_politicians*econ_current_personal + household_incom

modelplot(afd_trust_unemp_politicians) +
  geom_vline(xintercept = 0, linetype = "dashed")
```



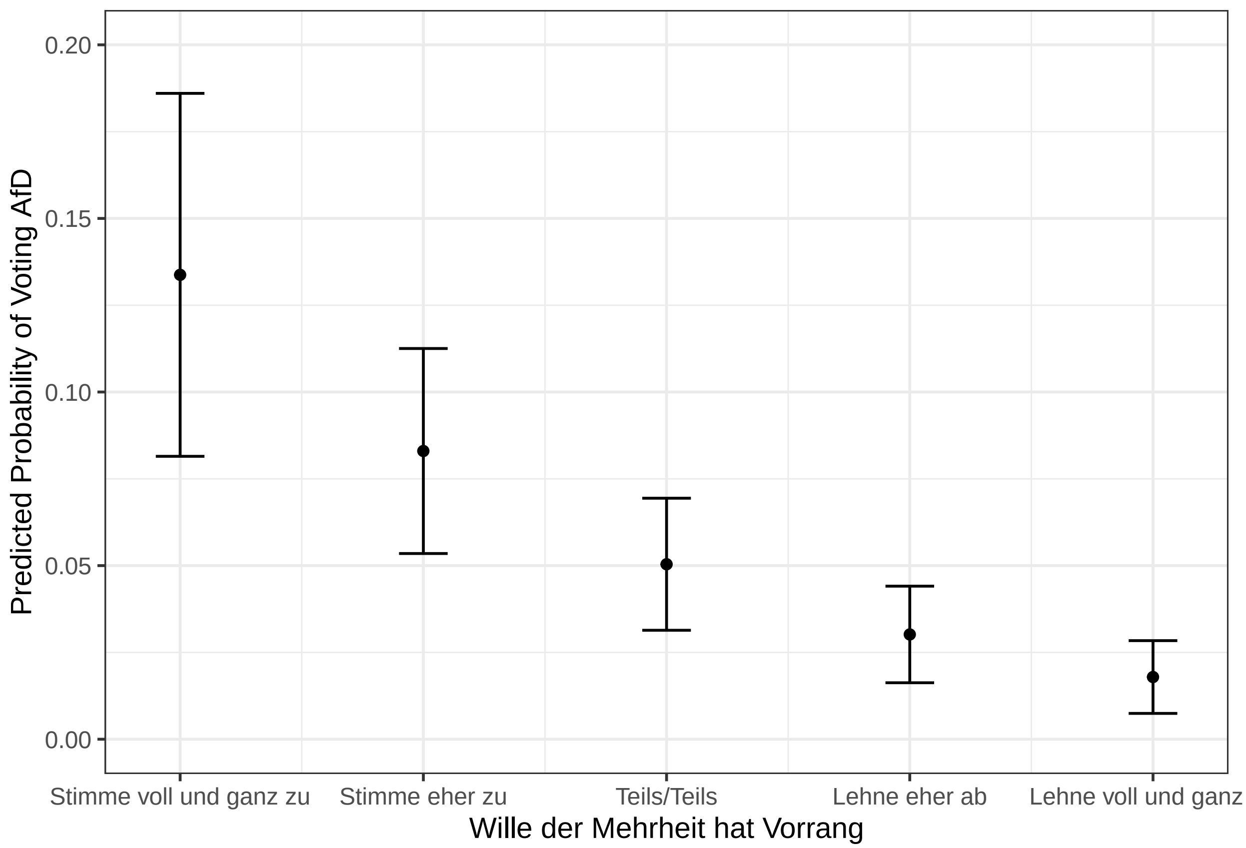

```
afd_immig_culture_threat <- glm(afd_21 ~ out_group_immig_culture_threat + household_income + age + abitu
# plot
cplot(afd_immig_culture_threat, x = "out_group_immig_culture_threat",
      xvals = seq(1, 5, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Deutsche Kultur durch Immigration bedroht",
                     breaks = seq(1, 5, 1),
                     labels = c("Stimme voll und ganz zu", "Stimme eher zu",
                                "Teils/Teils", "Lehne eher ab",
                                "Lehne voll und ganz ab")) +
  labs(y = "Predicted Probability of Voting AfD") +
  ylim(0, 0.5) +
  theme_bw()
```




```
afd_immig_crime <- glm(afd_21 ~ out_group_immig_crime + household_income + age + abitur_factor + sex1 +
# plot
cplot(afd_immig_crime, x = "out_group_immig_crime",
      xvals = seq(1, 5, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Immigration erhoeht Kriminalitaet in BRD",
                     breaks = seq(1, 5, 1),
                     labels = c("Stimme voll und ganz zu", "Stimme eher zu",
                                "Teils/Teils", "Lehne eher ab",
                                "Lehne voll und ganz ab")) +
  labs(y = "Predicted Probability of Voting AfD") +
  ylim(c(0, 0.4)) +
  theme_bw()
```




```
afd_majority_will <- glm(afd_21 ~ out_group_majority_will + household_income + age + abitur_factor + se
# plot
cplot(afd_majority_will, x = "out_group_majority_will",
      xvals = seq(1, 5, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Wille der Mehrheit hat Vorrang",
                     breaks = seq(1, 5, 1),
                     labels = c("Stimme voll und ganz zu", "Stimme eher zu",
                                "Teils/Teils", "Lehne eher ab",
                                "Lehne voll und ganz ab")) +
  ylim(c(0, 0.2)) +
  labs(y = "Predicted Probability of Voting AfD") +
  theme_bw()
```




```
afd_gender1 <- glm(afd_21 ~ gender_too_far + age + abitur_factor + sex1 + urban_rural_factor + ostwest_
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender2 <- glm(afd_21 ~ gender_too_far + unemployed_dummy + sex1 + age + abitur_factor +  urban_rura
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender3 <- glm(afd_21 ~ gender_too_far*econ_current_personal + abitur_factor + sex1 + age + abitur_
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender4 <- glm(afd_21 ~ gender_too_far*econ_personal_gov_resp + abitur_factor + sex1 + age + abitur
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender5 <- glm(afd_21 ~ gender_too_far*econ_current_eval_general + abitur_factor + age + abitur_fac
                  family = binomial(link = "logit"),
                  data = gles_mod)

# modelsummary
modelsummary(list(afd_gender1, afd_gender2, afd_gender3, afd_gender4, afd_gender5),
             estimate = "{estimate}{stars}",
             output = "kableExtra") %>%
  kableExtra::kable_styling(latex_options = "scale_down")
```

	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.052	0.017	0.570	0.532	−2.419*
	(0.418)	(0.435)	(0.798)	(0.675)	(1.083)
gender_too_far	−0.710***	−0.744***	−1.397***	−0.309+	−1.076***
	(0.075)	(0.077)	(0.226)	(0.168)	(0.307)
age	−0.004	−0.003	−0.001	−0.009+	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
abitur_factorno_abitur	0.911***	0.881***	0.693**	0.750***	0.675**
	(0.211)	(0.216)	(0.215)	(0.217)	(0.219)
sex1female	−0.379*	−0.412*	−0.485**	−0.372*	
	(0.170)	(0.177)	(0.174)	(0.173)	
urban_rural_factor2	0.252	0.297	0.247	0.191	0.313
	(0.294)	(0.300)	(0.299)	(0.299)	(0.306)
urban_rural_factor3	0.214	0.209	0.165	0.116	0.158
	(0.250)	(0.258)	(0.254)	(0.255)	(0.259)
urban_rural_factor4	0.427+	0.472+	0.418	0.295	0.379
	(0.256)	(0.264)	(0.260)	(0.261)	(0.265)
urban_rural_factor5	1.300*	0.827	1.235*	0.932	1.284*
	(0.550)	(0.645)	(0.551)	(0.601)	(0.602)
ostwest_factorwest	−1.309***	−1.250***	−1.266***	−1.207***	−1.248***
	(0.166)	(0.171)	(0.169)	(0.169)	(0.173)
unemployed_dummy		0.635*			
		(0.255)			
econ_current_personal			−0.145		
			(0.263)		
gender_too_far × econ_current_personal			0.255**		
			(0.078)		
econ_personal_gov_resp				0.027	
				(0.186)	
gender_too_far × econ_personal_gov_resp				−0.166**	
				(0.061)	
econ_current_eval_general					0.744*
					(0.320)
gender_too_far × econ_current_eval_general					0.129
					(0.095)
Num.Obs.	2703	2581	2701	2658	2669
AIC	1141.2	1074.4	1089.6	1082.2	1025.8
BIC	1200.2	1138.8	1160.4	1152.9	1090.6
Log.Lik.	−560.602	−526.215	−532.810	−529.122	−501.922
RMSE	0.24	0.23	0.23	0.23	0.23