Analysing Vote Choice Data

Final 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),
         sex1 = factor(sex,
```

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```
                    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))
```

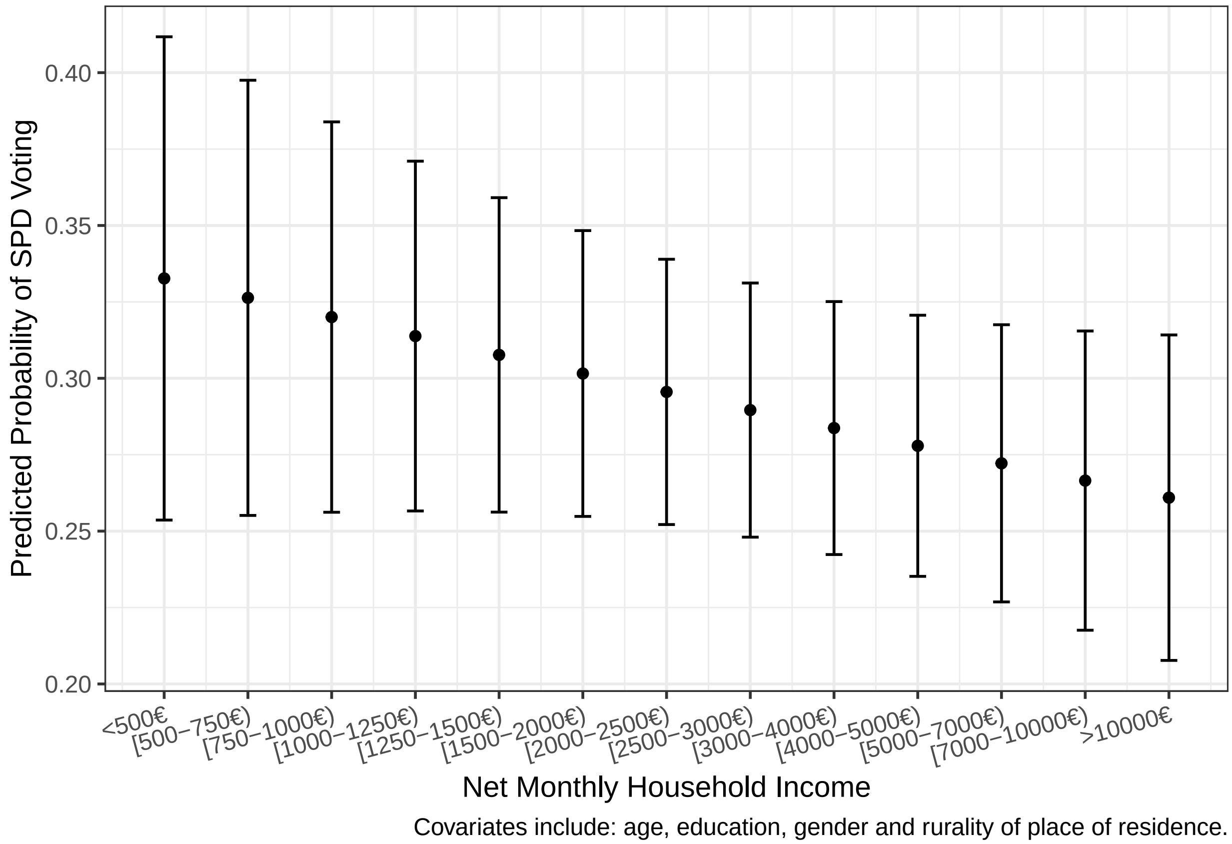
Some tentative analysis

SPD

Socio-Demographic Correlates

Relationship between household income and SPD voting

```
spd_income <- glm(spd_21 ~ household_income + age + abitur_factor + sex1 + urban_rural_factor + ostwest_
                  family = binomial(link = "logit"),
                  data = gles_mod)
# plot
cplot(spd_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€)",
                                "[5000-7000€)", "[7000-10000€)",
                                ">10000€")) +
  labs(y = "Predicted Probability of SPD Voting",
       caption = "Covariates include: age, education, gender and rurality of place of residence.") +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```

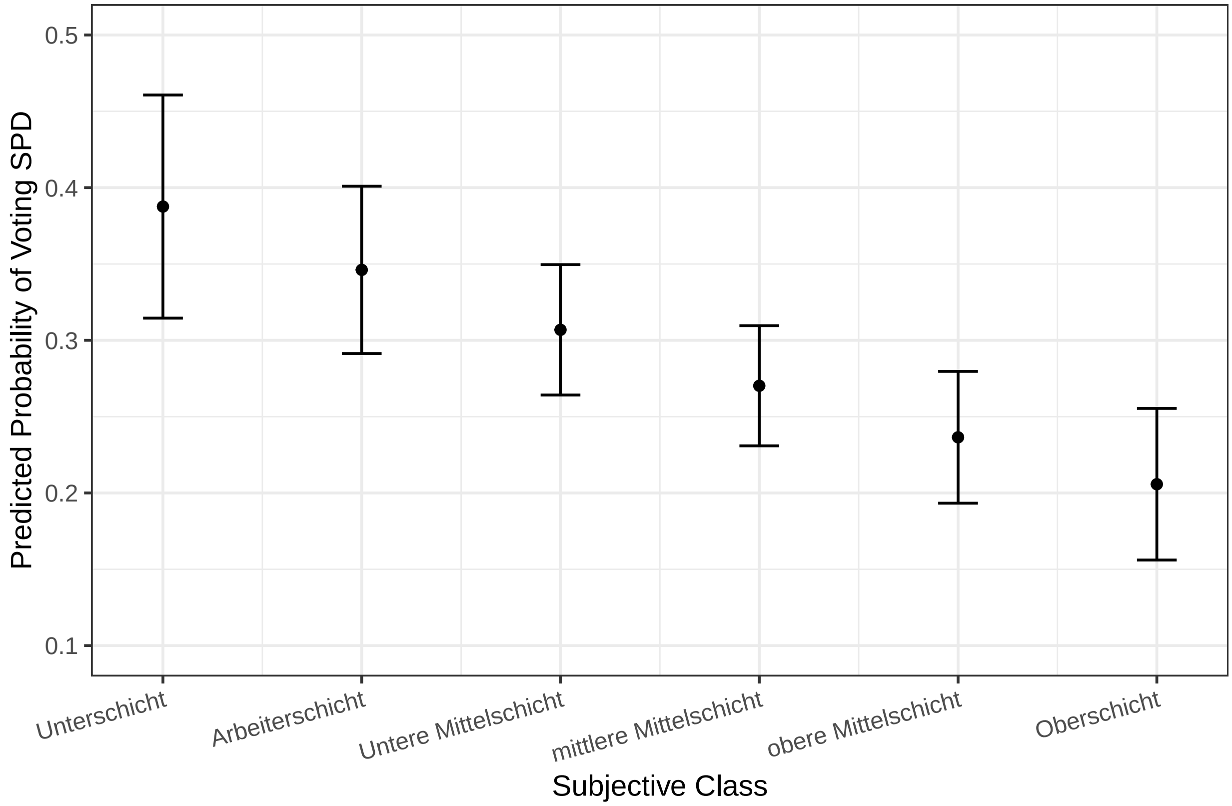


There is no robust relationship between net monthly household income and voting for the SPD.

Relationship between subjective class and SPD voting

```
spd_sclass <- glm(spd_21 ~ subjective_class + age + abitur_factor + sex1 + urban_rural_factor + ostwest_
                  family = binomial(link = "logit"),
                  data = gles_mod)
# plot
cplot(spd_sclass, 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", "Oberschicht")) +
  labs(y = "Predicted Probability of Voting SPD",
       caption = "Covariates include: age, education, gender and rurality of place of residence.") +
  ylim(c(0.1, 0.5)) +
```

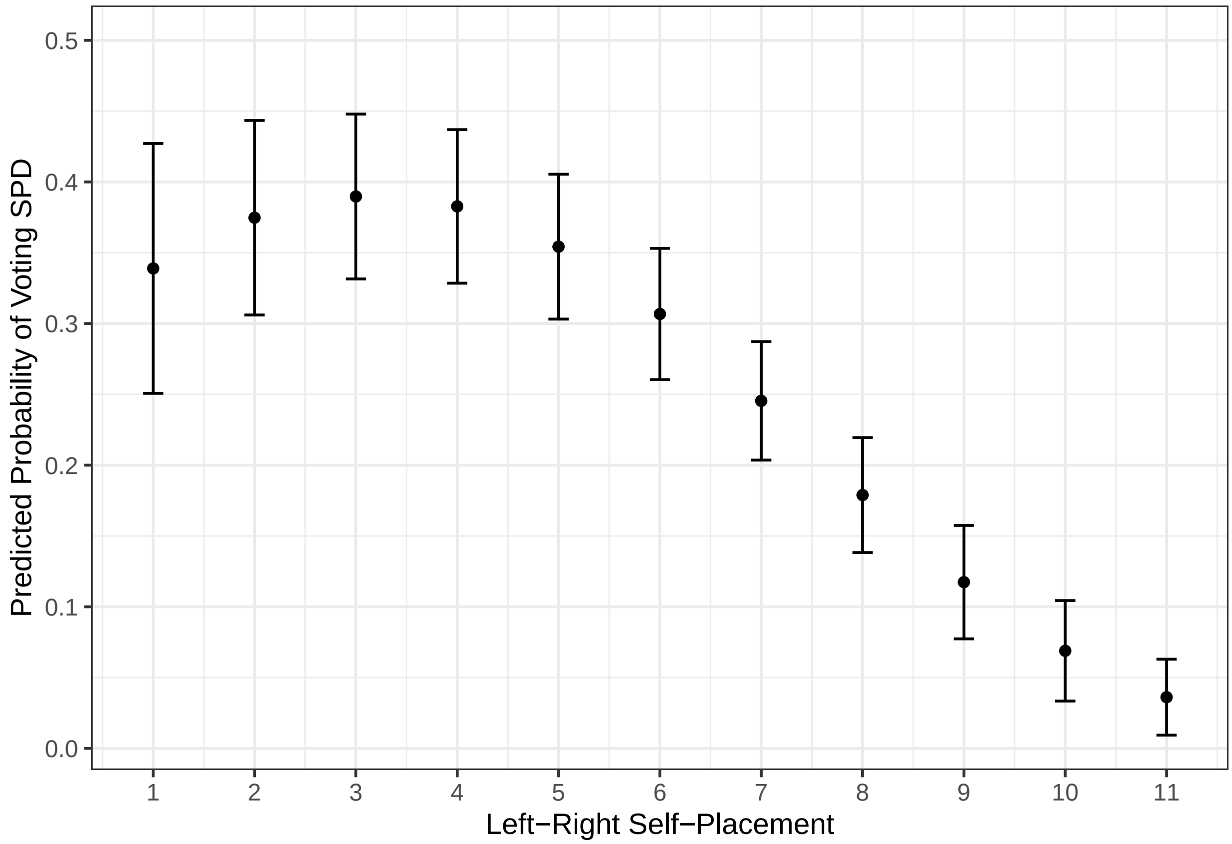
```
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



Covariates include: age, education, gender and rurality of place of residence.

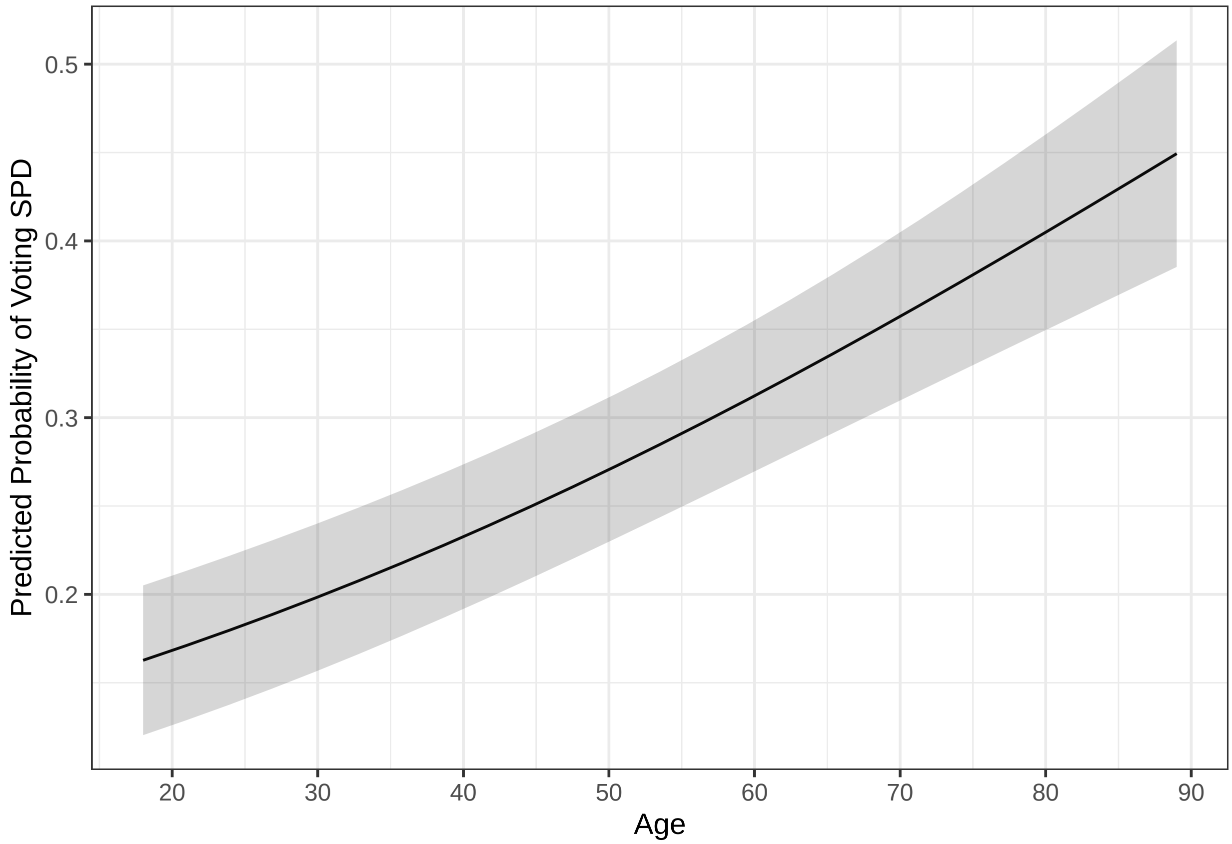
What is the relationship between left-right self-placement and SPD voting?

```
spd_left_right_self <- glm(spd_21 ~ left_right_self + I(left_right_self^2) + household_income + age + al
                           family = binomial(link = "logit"),
                           data = gles_mod)
# plot
cplot(spd_left_right_self, 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 = 0.5) +
  labs(y = "Predicted Probability of Voting SPD") +
  theme_bw()
```



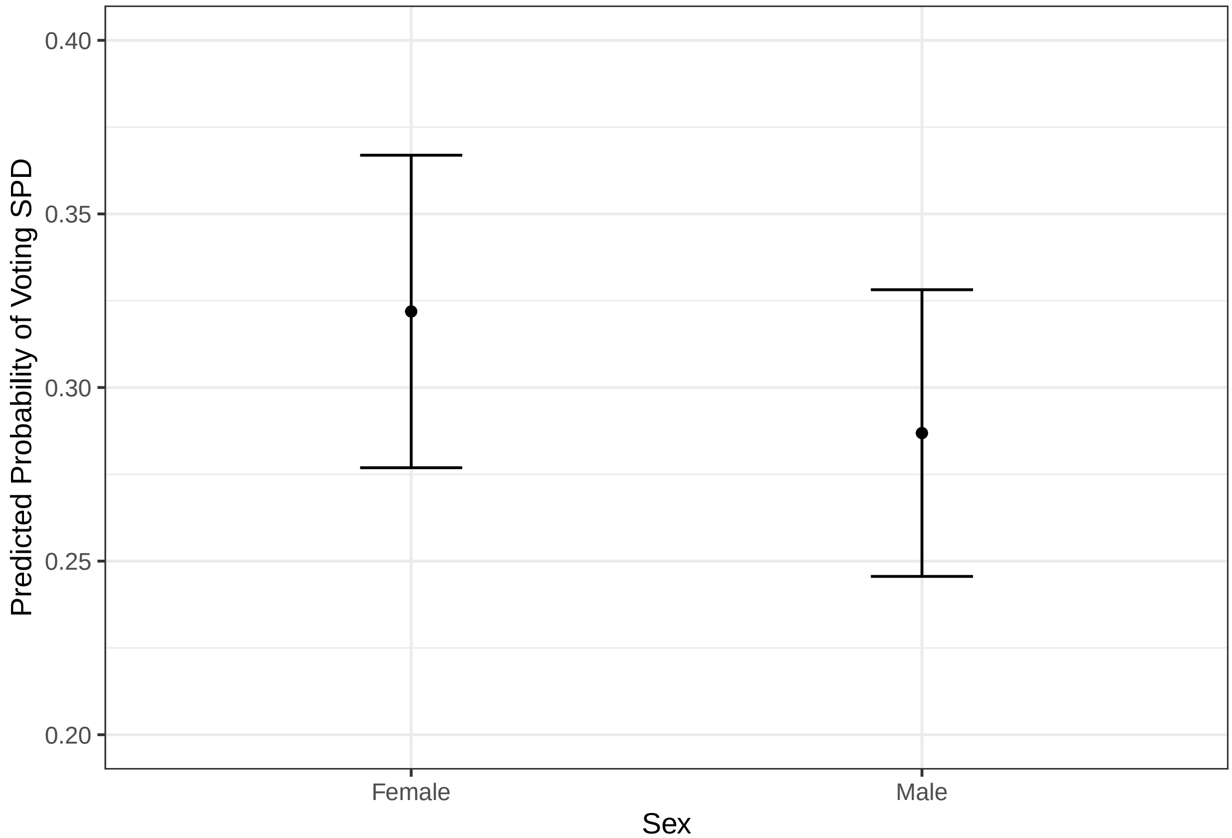
Relationship between age and SPD voting

```
spd_age <- glm(spd_21 ~ household_income + age + abitur_factor + sex1 + urban_rural_factor + ostwest_fac
               family = binomial(link = "logit"),
               data = gles_mod)
# plot
cplot(spd_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 SPD") +
  theme_bw()
```



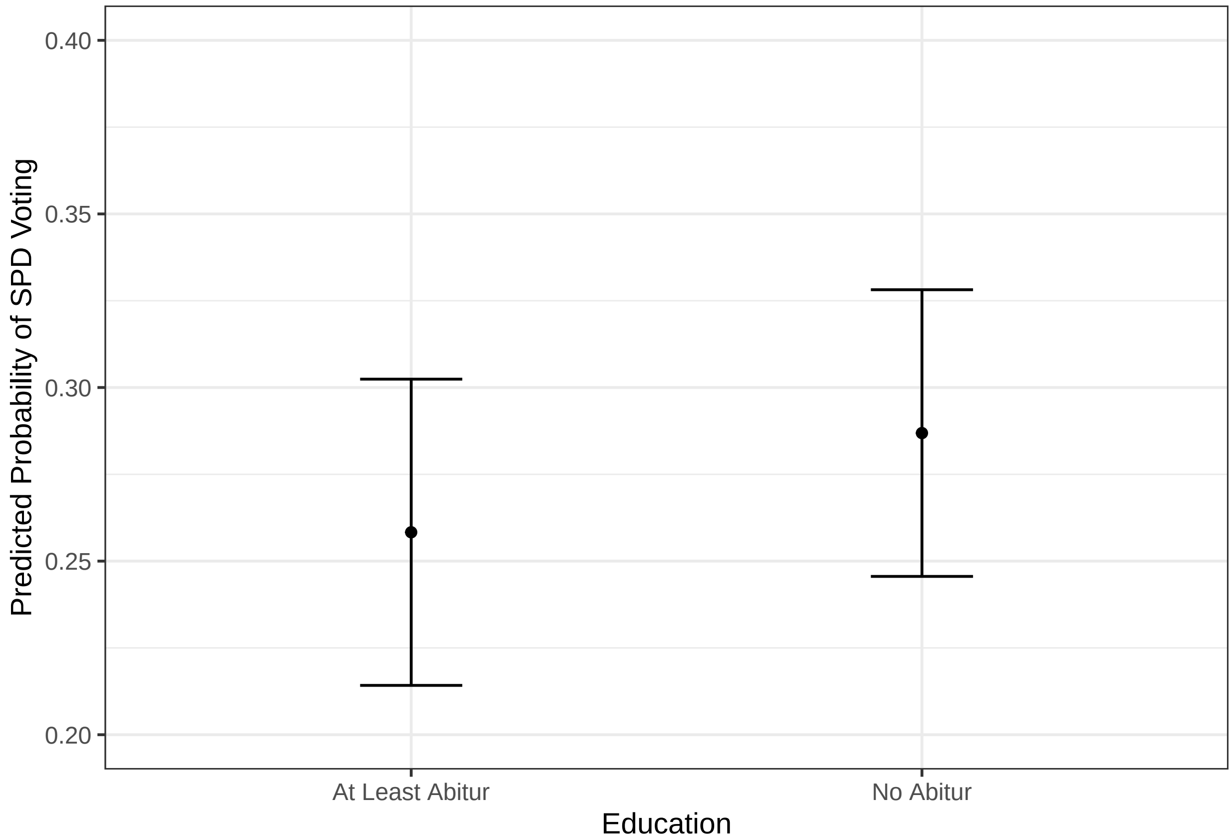
Relationship between sex and SPD voting

```
cplot(spd_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) +
  ylim(c(0.2, 0.4)) +
  scale_x_discrete("Sex", labels = c("Female", "Male")) +
  labs(y = "Predicted Probability of Voting SPD") +
  theme_bw()
```

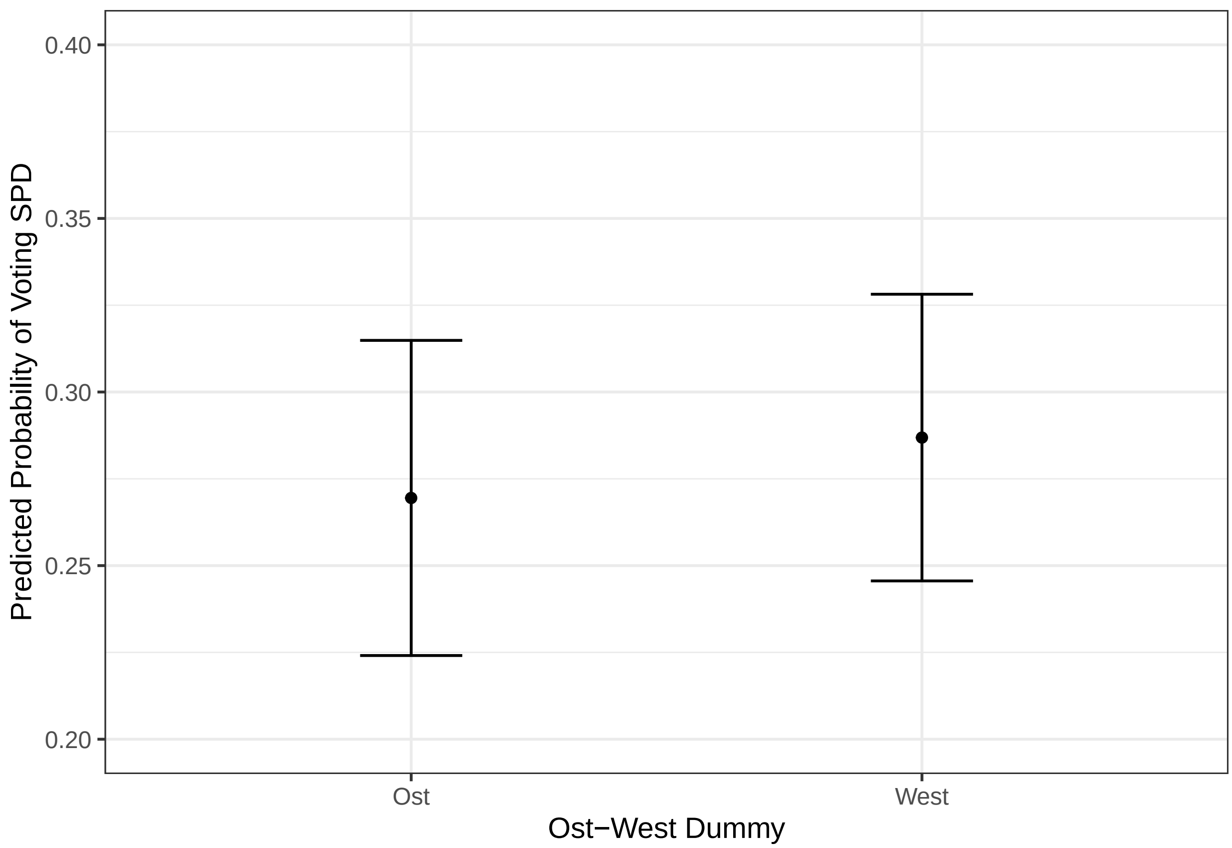


Relationship between education and SPD

```
cplot(spd_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")) +
  ylim(c(0.2, 0.4)) +
  labs(y = "Predicted Probability of SPD Voting") +
  theme_bw()
```

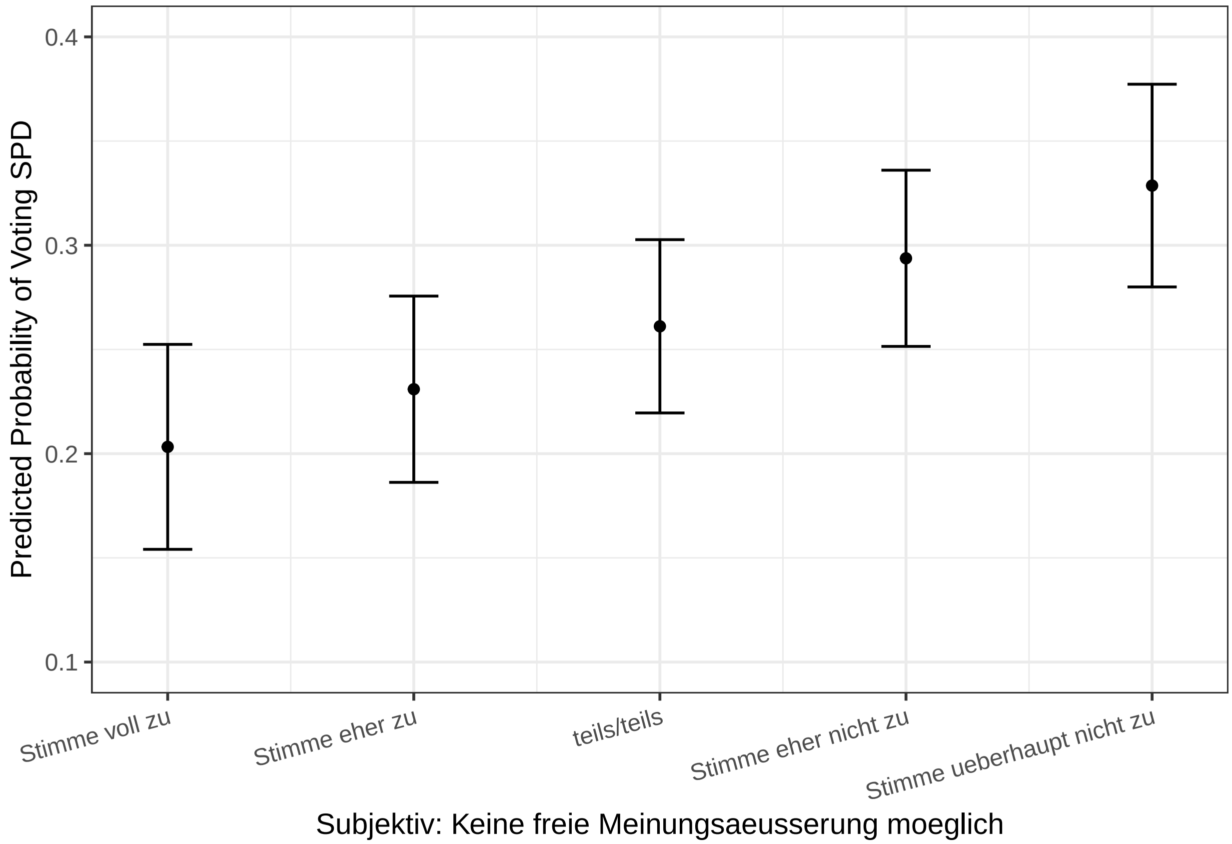



```
cplot(spd_income, x = "ostwest_factor", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Ost-West Dummy", labels = c("Ost", "West")) +
  ylim(c(0.2, 0.4)) +
  labs(y = "Predicted Probability of Voting SPD") +
  theme_bw()
```

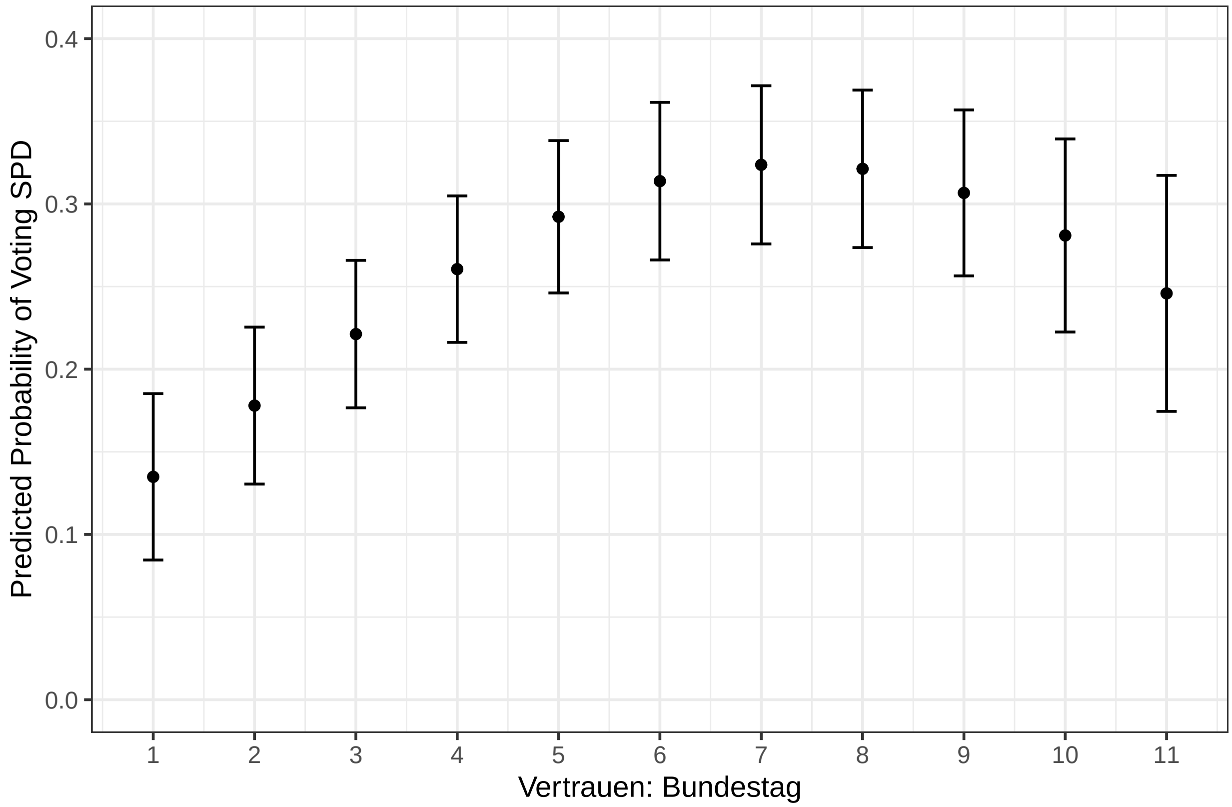


Attiudinal Correlates

```
# none of the other abgehaengt variables is significant
spd_cancel_culture <- glm(spd_21 ~ cancel_culture_subjektiv + household_income + age + abitur_factor + s
# plot
cplot(spd_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 SPD") +
  ylim(c(0.1, 0.4)) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```

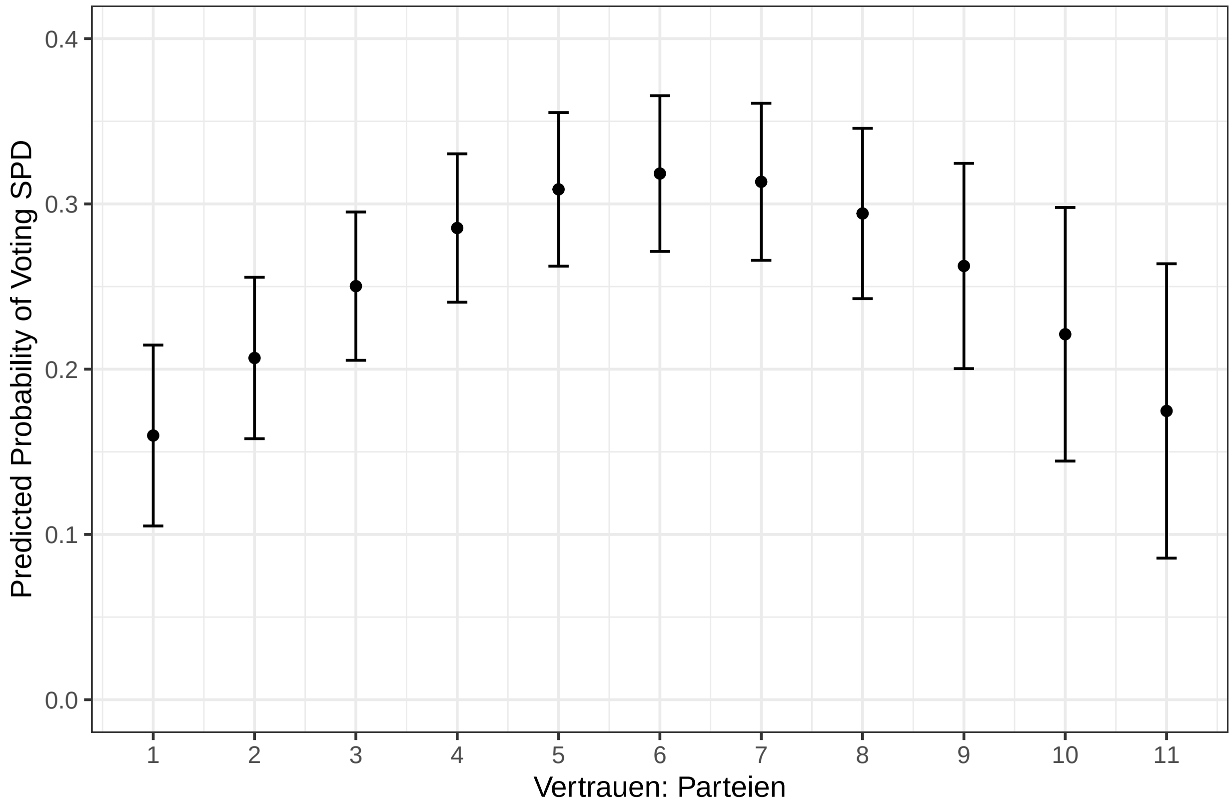



```r
# general trust is not significant
# trust in parliament is significant
spd_trust_parliament <- glm(spd_21 ~ trust_in_parliament + I(trust_in_parliament^2) + household_income +
# plot
cplot(spd_trust_parliament, x = "trust_in_parliament",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  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 SPD",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.4)) +
  theme_bw()
```

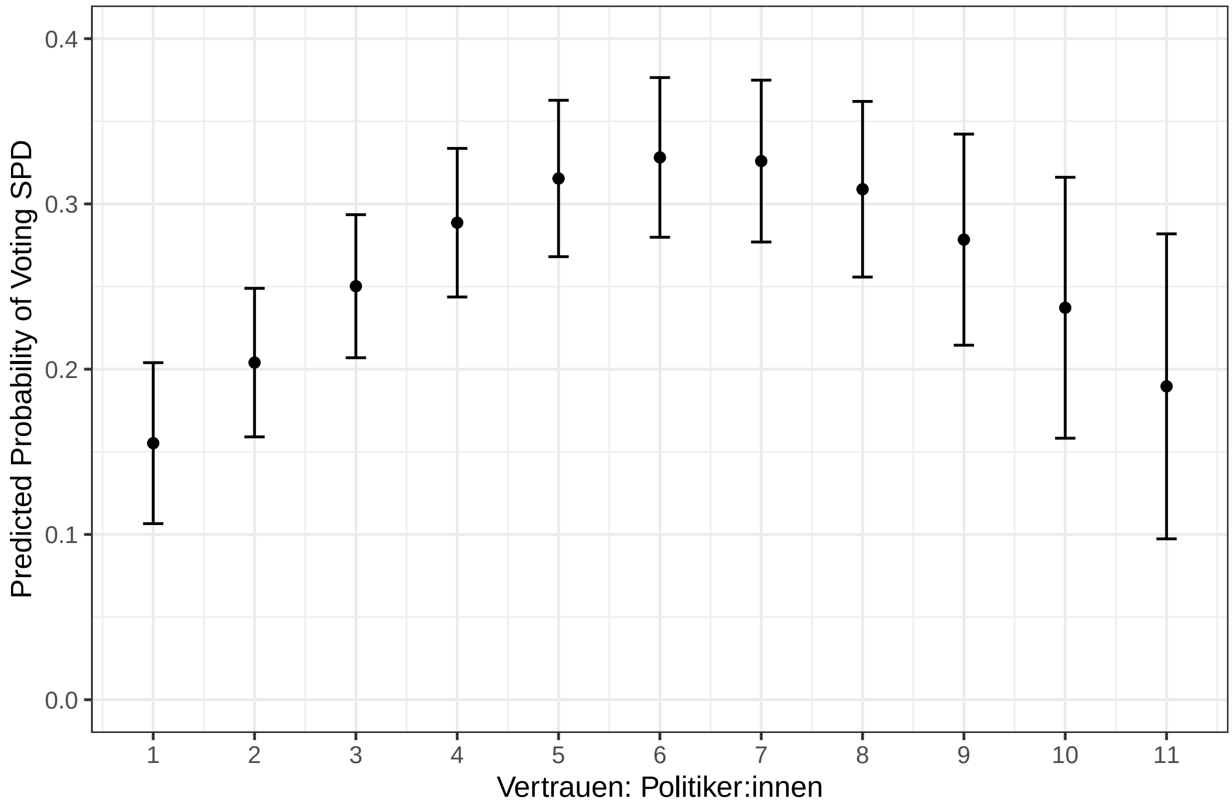


'1' indicates 'no trust', while 11 indicates 'full trust'.

```
# trust in parties
spd_trust_parties <- glm(spd_21 ~ trust_in_parties + I(trust_in_parties^2) + household_income + age + al
# plot
cplot(spd_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 SPD",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.4)) +
  theme_bw()
```

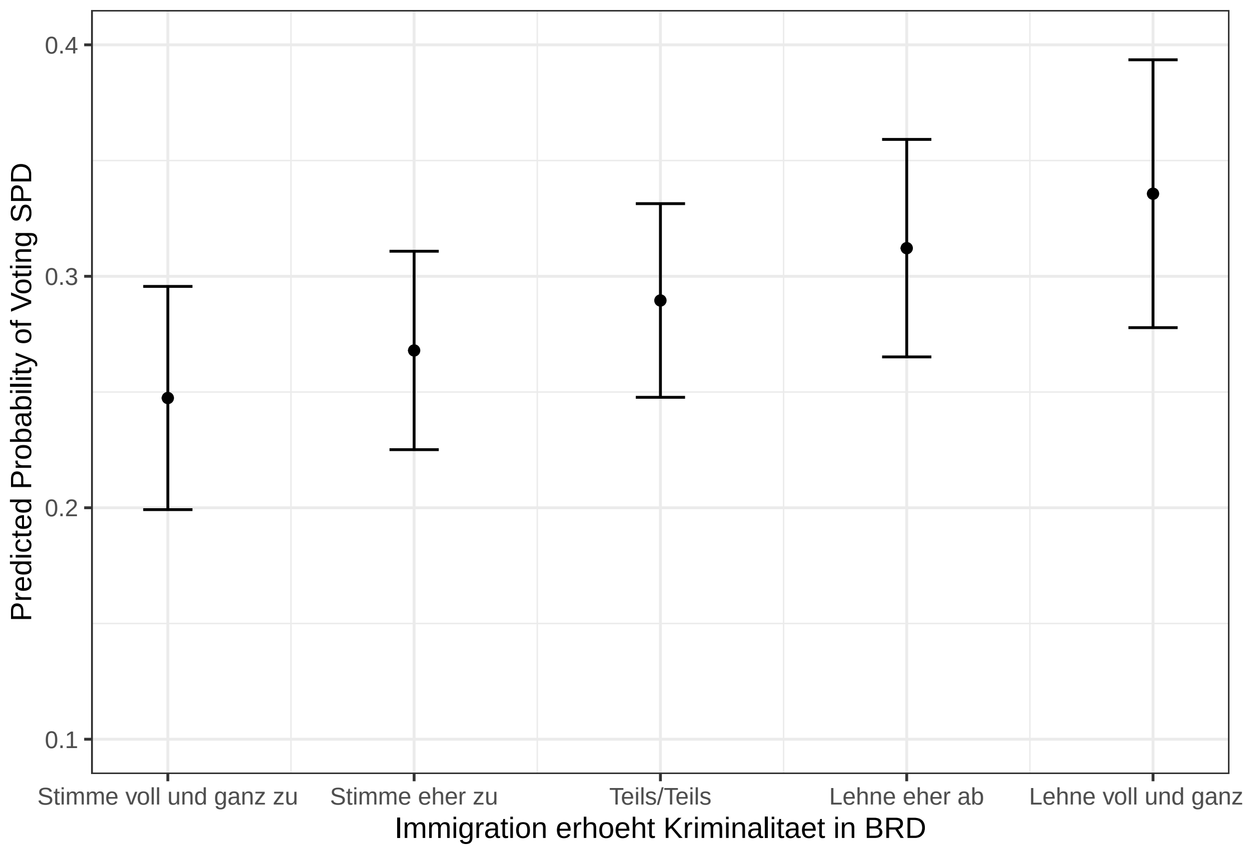



```
# trust in politicians
spd_trust_politicians <- glm(spd_21 ~ trust_in_politicians + I(trust_in_politicians^2) + household_incom
# plot
cplot(spd_trust_politicians, x = "trust_in_politicians",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = 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 SPD",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.4)) +
  theme_bw()
```



'1' indicates 'no trust', while 11 indicates 'full trust'.

```
# immigrants bring crime is significant
spd_immig_crime <- glm(spd_21 ~ out_group_immig_crime + household_income + age + abitur_factor + sex1 +
# plot
cplot(spd_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 SPD") +
  ylim(c(0.1, 0.4)) +
  theme_bw()
```




```
# immigrants pose cultural threat is not significant at 5% level
# immigrants are good for economics is not significant at 5% level
# majority will is paramount is not significant
# outgroups should assimilate not significant
```

Gruene

Spatial distance

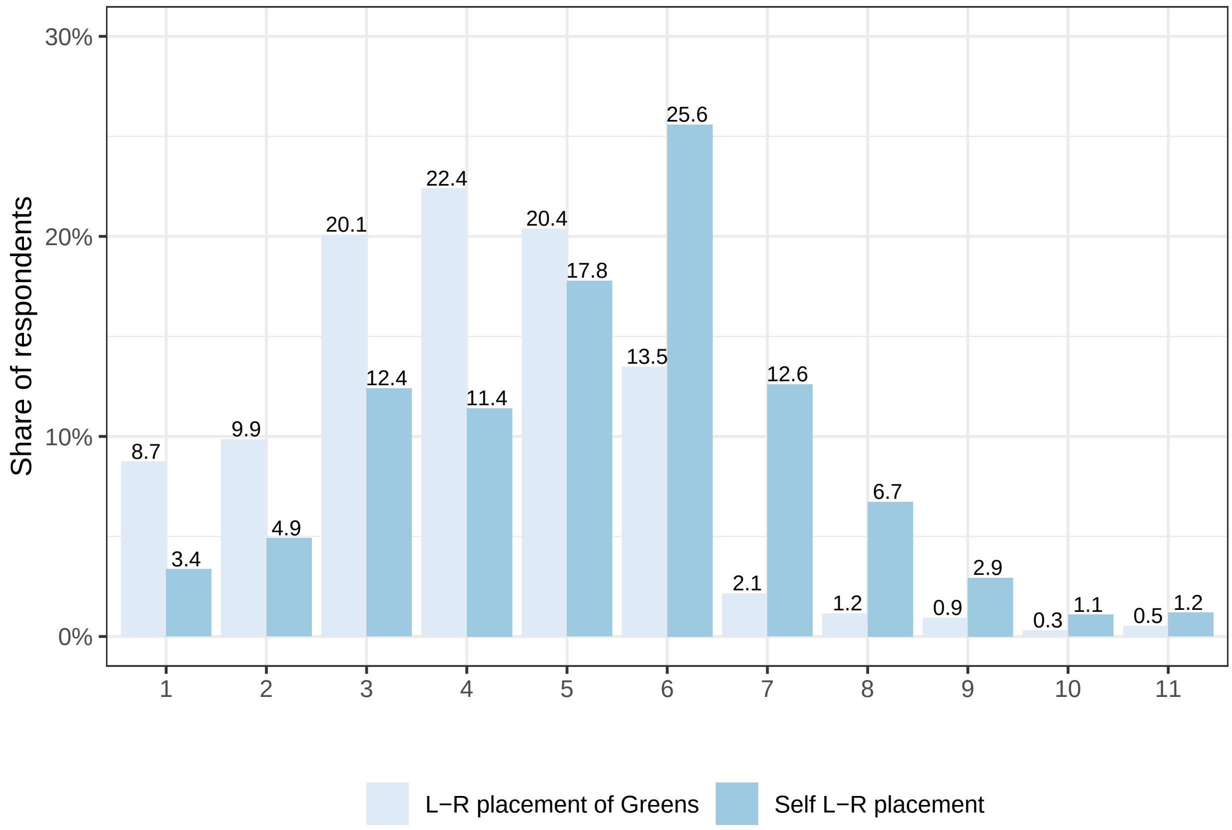
```
gruene_space <- glm(gruene_21 ~ distance_green + household_income + age + abitur_factor + sex1 + urban_r


summary(gruene_space)
```

```
##
## Call:
## glm(formula = gruene_21 ~ distance_green + household_income +
##     age + abitur_factor + sex1 + urban_rural_factor + ostwest_factor,
##     family = binomial(link = "logit"), data = gles_mod)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

```
## -1.5342  -0.7083  -0.3949  -0.0132   4.0312
##
## Coefficients:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)             0.163515   0.333388   0.490   0.6238
## distance_green         -0.218754   0.021620 -10.118  < 2e-16 ***
## household_income        0.045328   0.026401   1.717   0.0860 .
## age                    -0.021889   0.003562  -6.145 7.98e-10 ***
## abitur_factorno_abitur -0.750826   0.123852  -6.062 1.34e-09 ***
## sex1female              0.296052   0.115518   2.563   0.0104 *
## urban_rural_factor2    -0.195854   0.182306  -1.074   0.2827
## urban_rural_factor3    -0.326921   0.151903  -2.152   0.0314 *
## urban_rural_factor4    -0.395278   0.162413  -2.434   0.0149 *
## urban_rural_factor5     0.158309   0.576306   0.275   0.7835
## ostwest_factorwest      0.596282   0.138086   4.318 1.57e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2334.8  on 2243  degrees of freedom
## Residual deviance: 1848.4  on 2233  degrees of freedom
##   (1180 observations deleted due to missingness)
## AIC: 1870.4
##
## Number of Fisher Scoring iterations: 7
```

```r
# placement of greens
gles_mod %>%
  select(left_right_green_factor, left_right_self_factor) %>%
  filter(!is.na(left_right_green_factor) & !is.na(left_right_self_factor)) %>%
  pivot_longer(cols = everything(), names_to = "type", values_to = "value") %>%
  count(type, value) %>%
  group_by(type) %>%
  mutate(share = 100*(n/sum(n))) %>%
  ggplot(aes(x = value, y = share, fill = type)) +
  geom_col(position = "dodge") +
  geom_text(aes(label = round(share, 1)), vjust = -0.2, size = 2.7,
            position = position_dodge(width = 0.8)) +
  scale_y_continuous("Share of respondents", labels = scales::label_percent(scale = 1)) +
  scale_fill_brewer("",
                    labels = c("left_right_green_factor" = "L-R placement of Greens",
                               "left_right_self_factor" = "Self L-R placement")) +
  expand_limits(y = 30) +
```

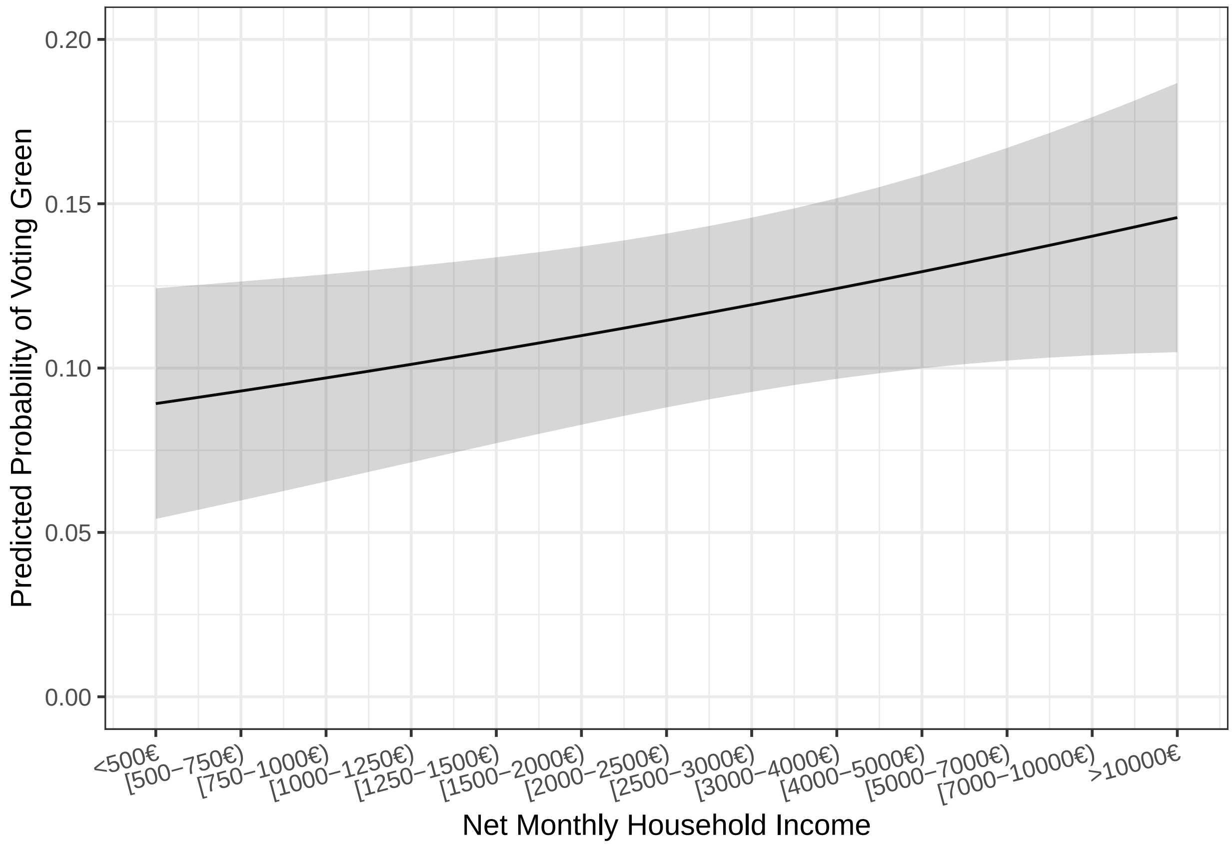
```
  labs(x = "") +
  theme_bw() +
  theme(legend.position = "bottom")
```



Socio-demographic Correlates

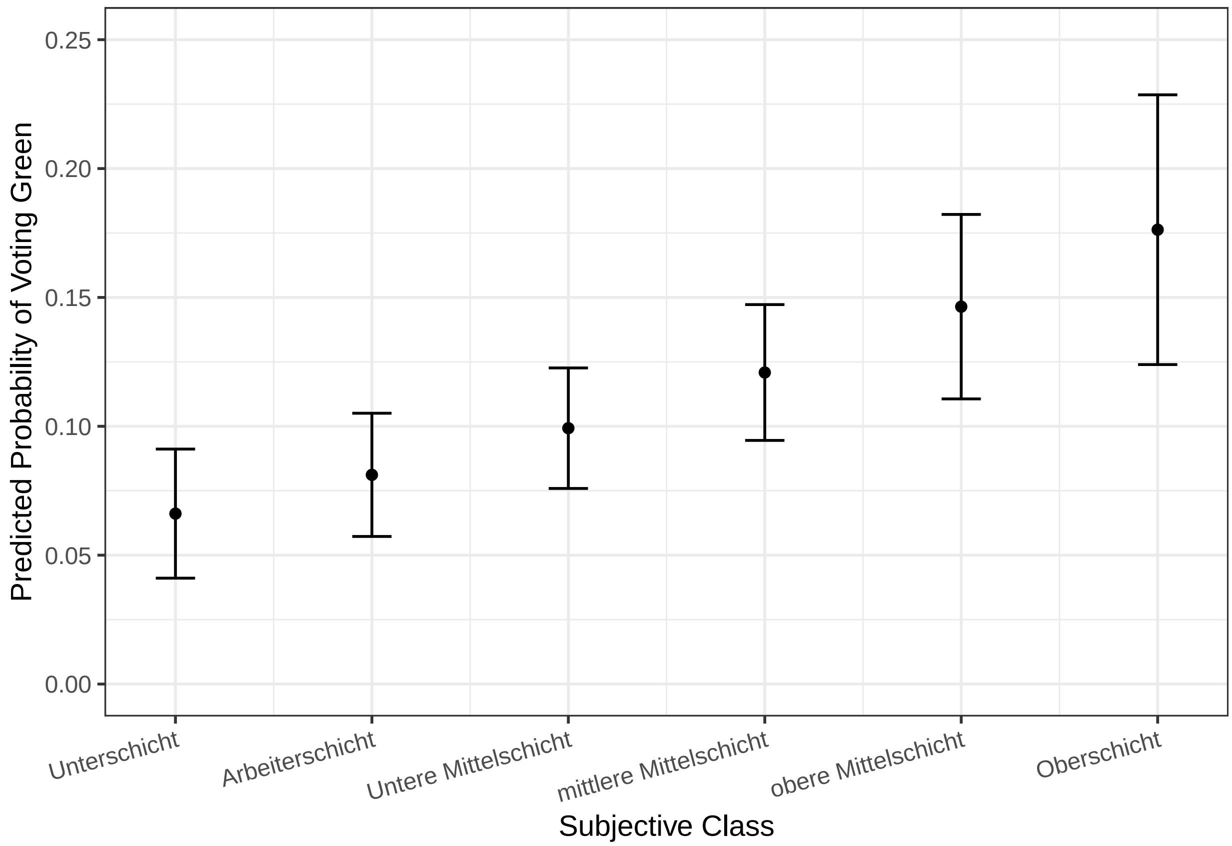
```
gruene_income <- glm(gruene_21 ~ household_income + age + abitur_factor + sex1 + urban_rural_factor + o
# plot
cplot(gruene_income, x = "household_income", draw = F) %>%
  as_tibble() %>%
   ggplot(aes(x = xvals)) +
   geom_line(aes(y = yvals)) +
   geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.2) +
   scale_x_continuous("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€)",
                                 "[5000-7000€)", "[7000-10000€)",
```

```
                                 ">10000€")) +
  labs(y = "Predicted Probability of Voting Green") +
  ylim(c(0, 0.2)) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```

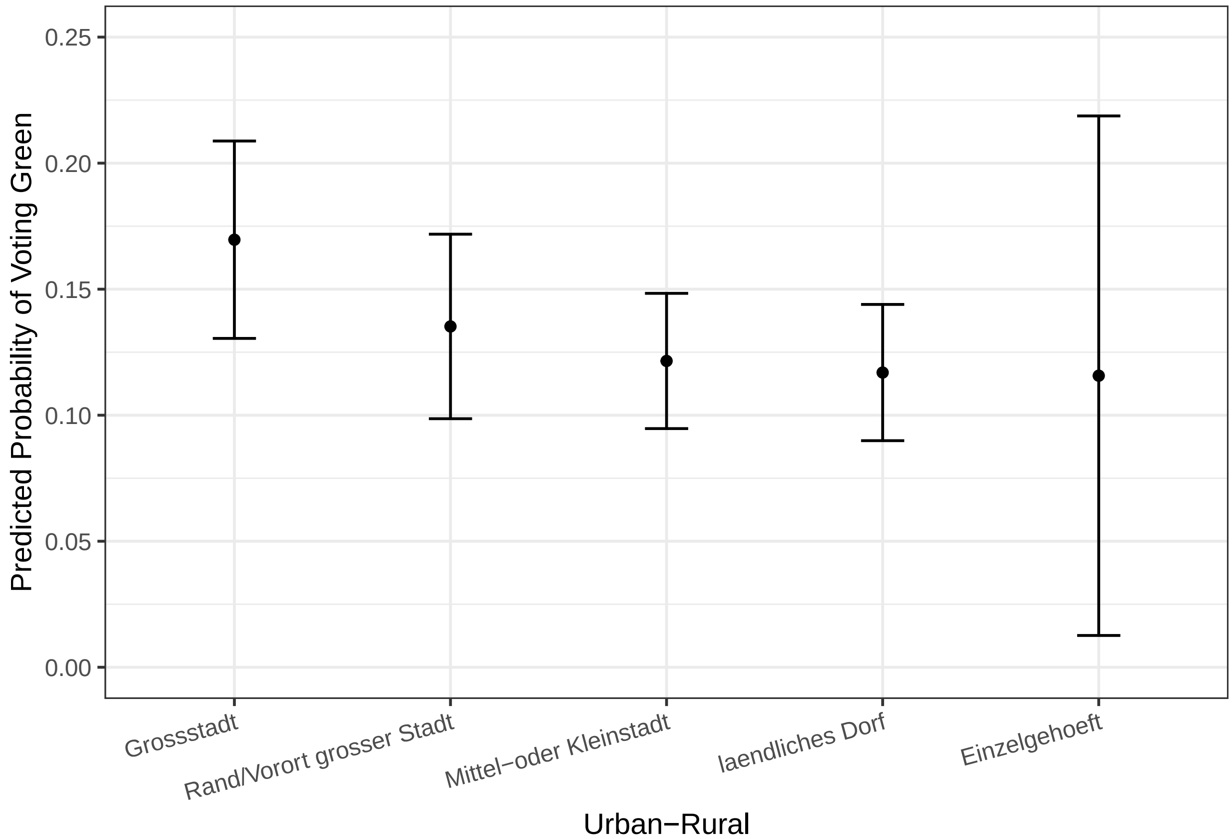



```
gruene_sclass <- glm(gruene_21 ~ subjective_class + age + abitur_factor + sex1 + urban_rural_factor + os
# plot
cplot(gruene_sclass, x = "subjective_class",
      xvals = seq(1, 6, 1),
      draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = 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 Green") +
  ylim(c(0, 0.25)) +
```

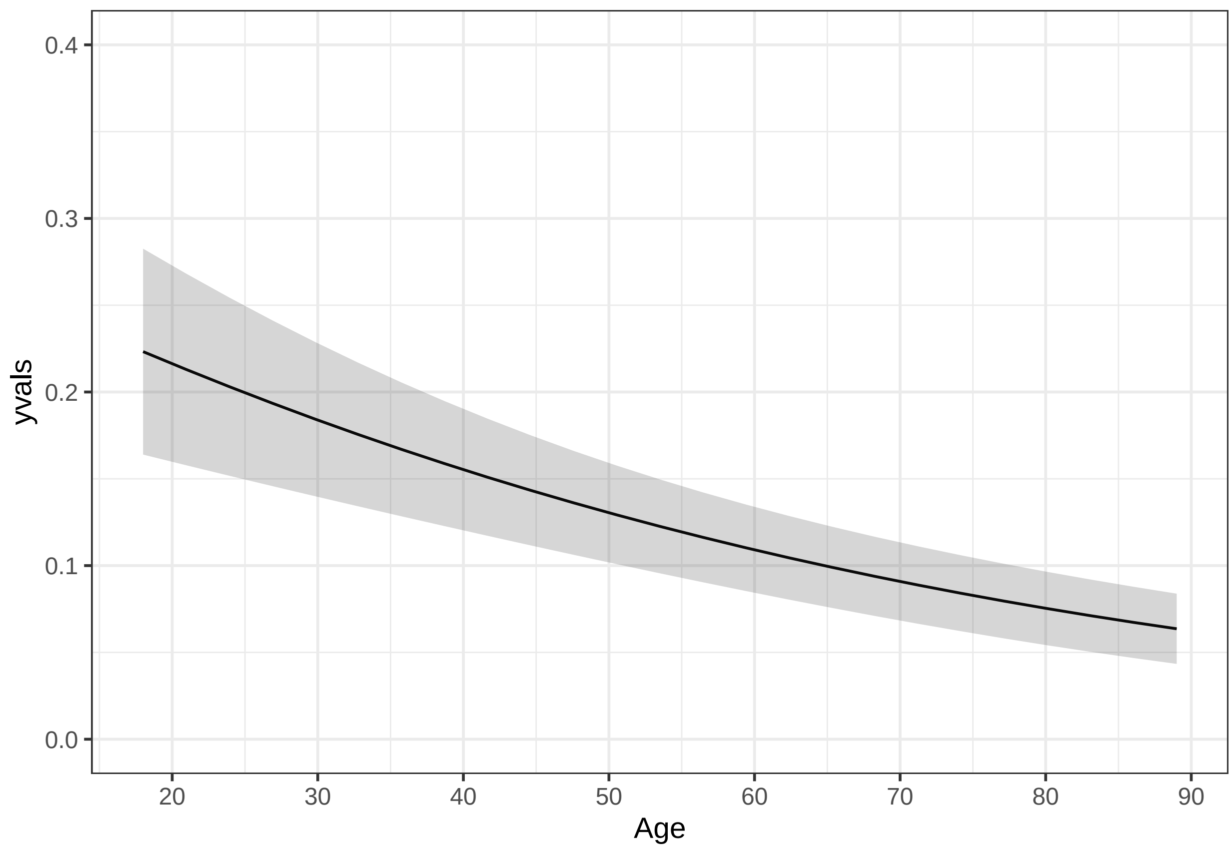
```
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



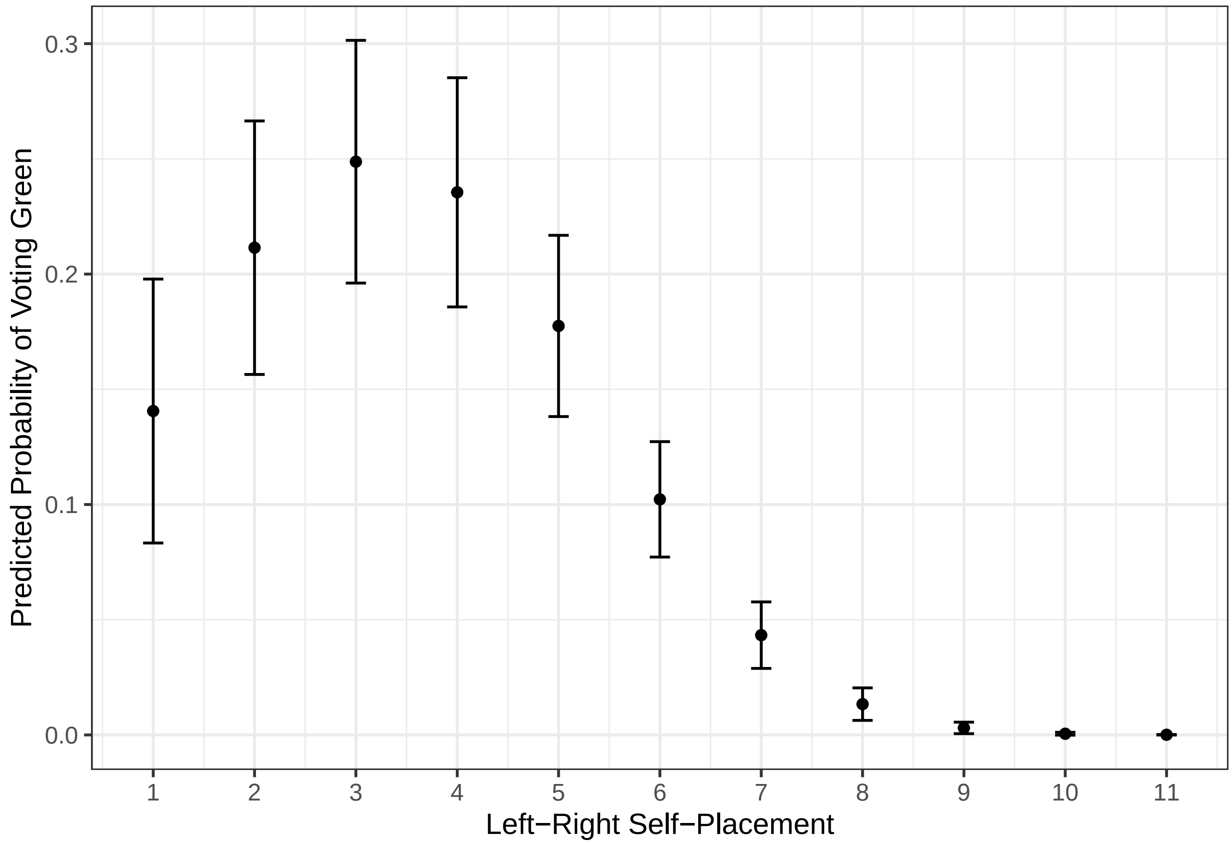

```
cplot(gruene_income, x = "urban_rural_factor", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Urban-Rural",
                   labels = c("Grossstadt", "Rand/Vorort grosser Stadt",
                              "Mittel-oder Kleinstadt", "laendliches Dorf",
                              "Einzelgehoeft")) +
 labs(y = "Predicted Probability of Voting Green") +
 ylim(c(0, 0.25)) +
 theme_bw() +
 theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



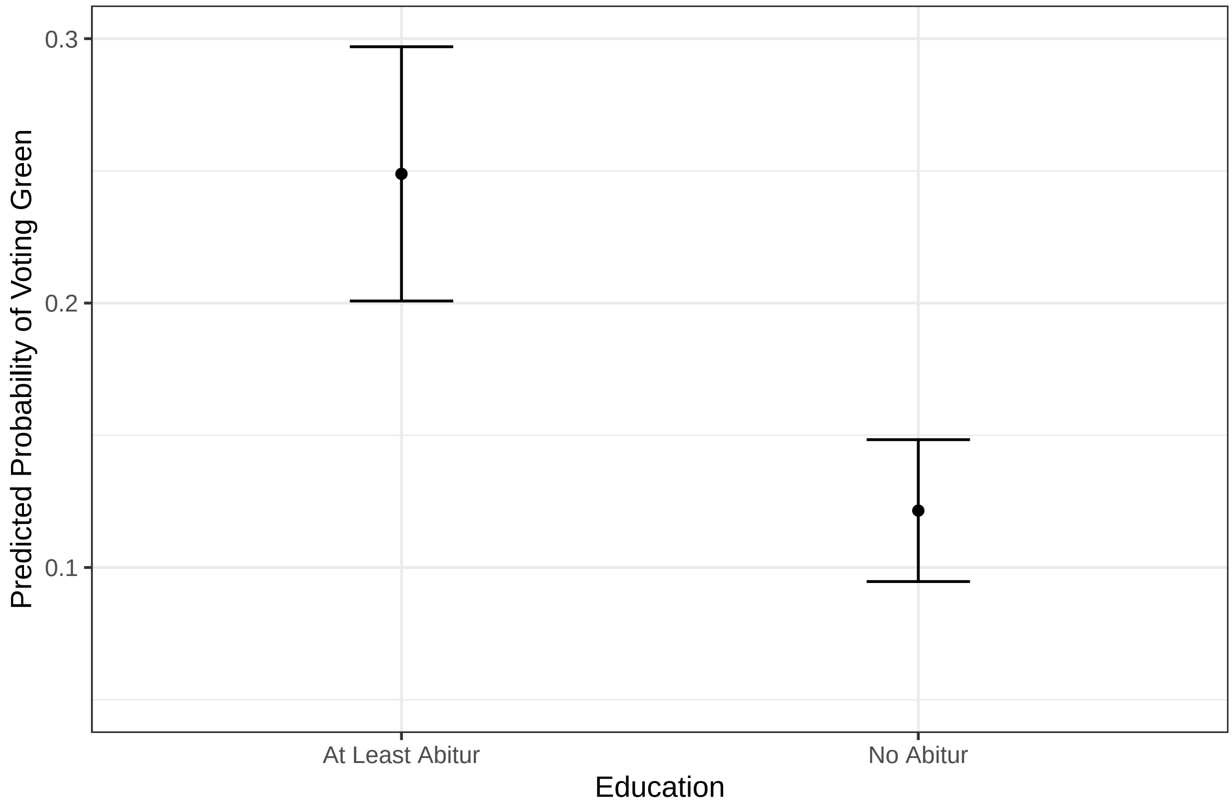

```r
# plot
cplot(gruene_income,
      x = "age", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_line(aes(y = yvals)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.2) +
  scale_x_continuous("Age", breaks = seq(20, 90, 10)) +
  ylim(c(0, 0.4)) +
  theme_bw()
```




```
gruene_left_right_self <- glm(gruene_21 ~ left_right_self + I(left_right_self^2) + age + abitur_factor +
# plot
cplot(gruene_left_right_self, 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)) +
  labs(y = "Predicted Probability of Voting Green") +
  theme_bw()
```

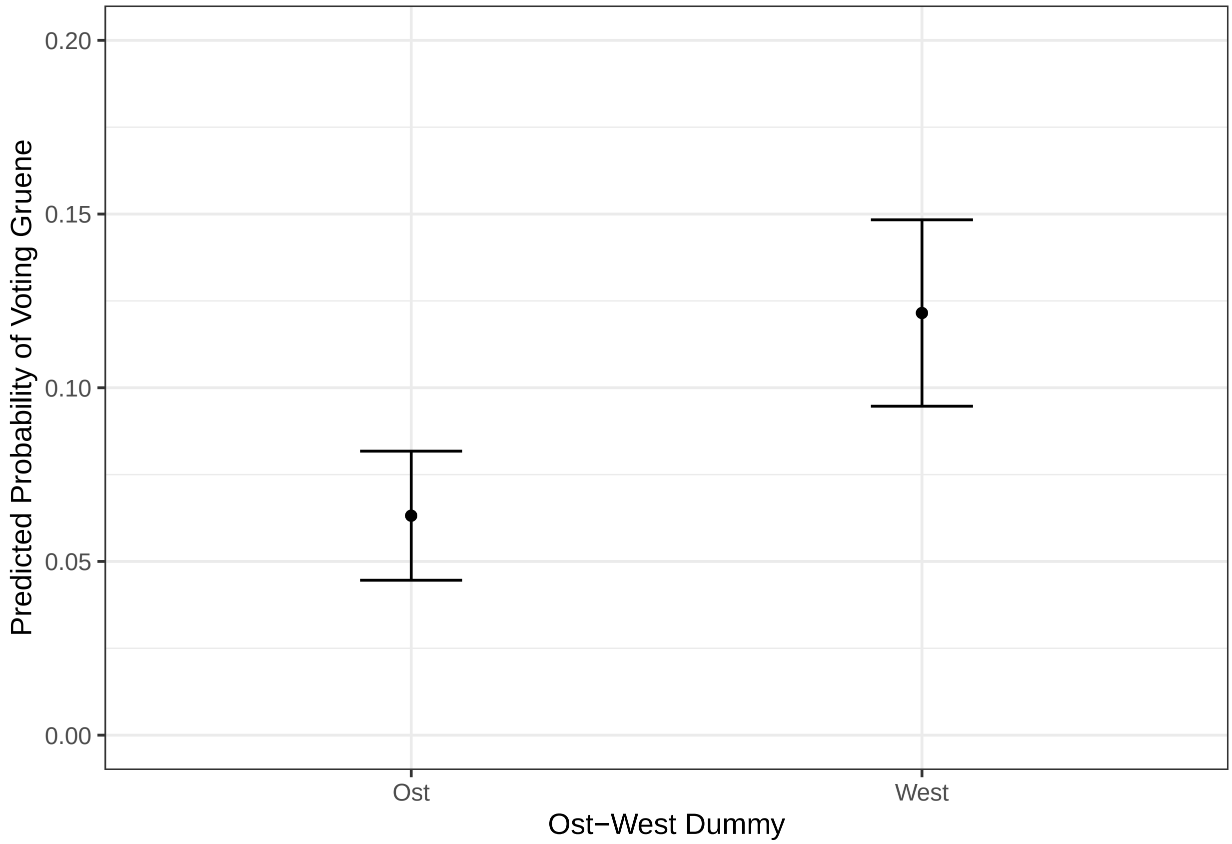



```
cplot(gruene_income, x = "abitur_factor", draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_discrete("Education", labels = c("At Least Abitur",
                                           "No Abitur")) +
  labs(y = "Predicted Probability of Voting Green",
       caption = "Covariates include: age, household income, sex, rurality of place of residence and an
  ylim(c(0.05, 0.3)) +
  theme_bw()
```



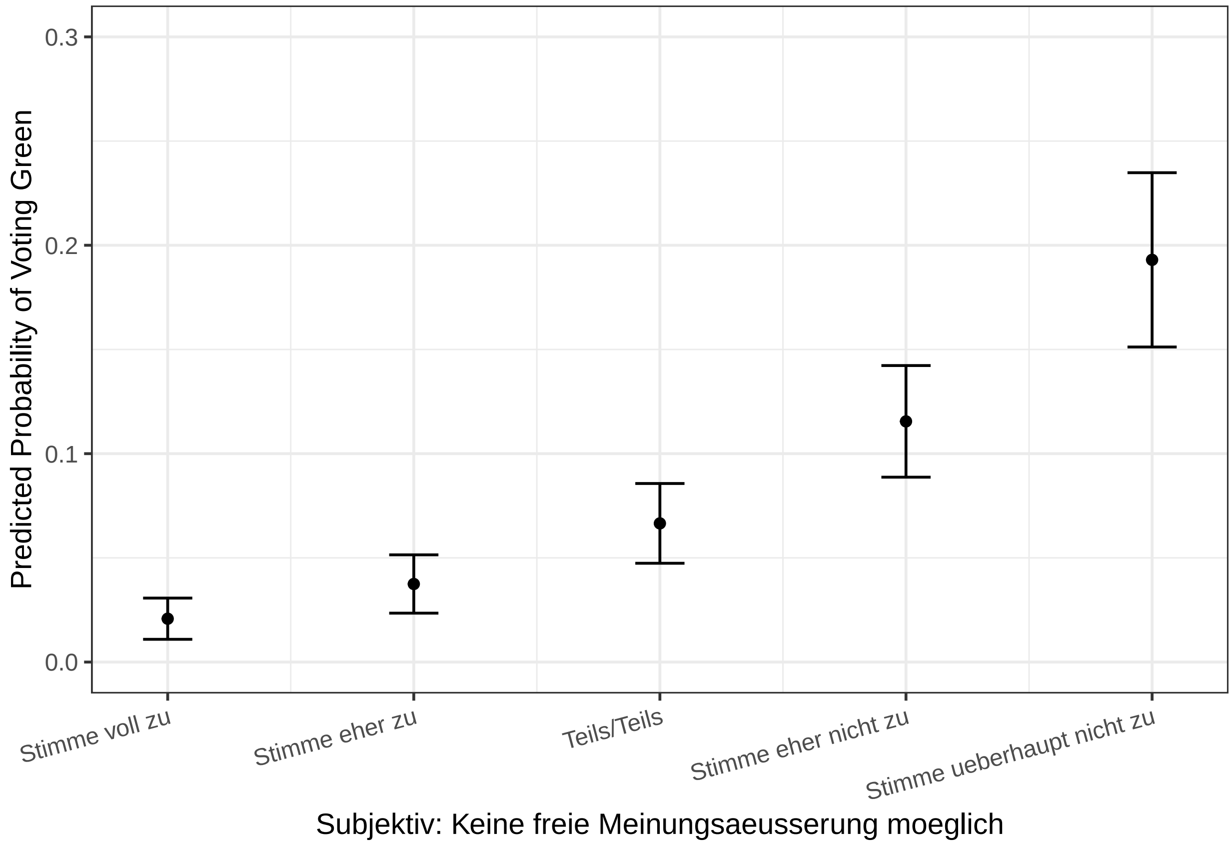
Covariates include: age, household income, sex, rurality of place of residence and an east−west dummy.

```
cplot(gruene_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, 0.2)) +
  labs(y = "Predicted Probability of Voting Gruene") +
  theme_bw()
```

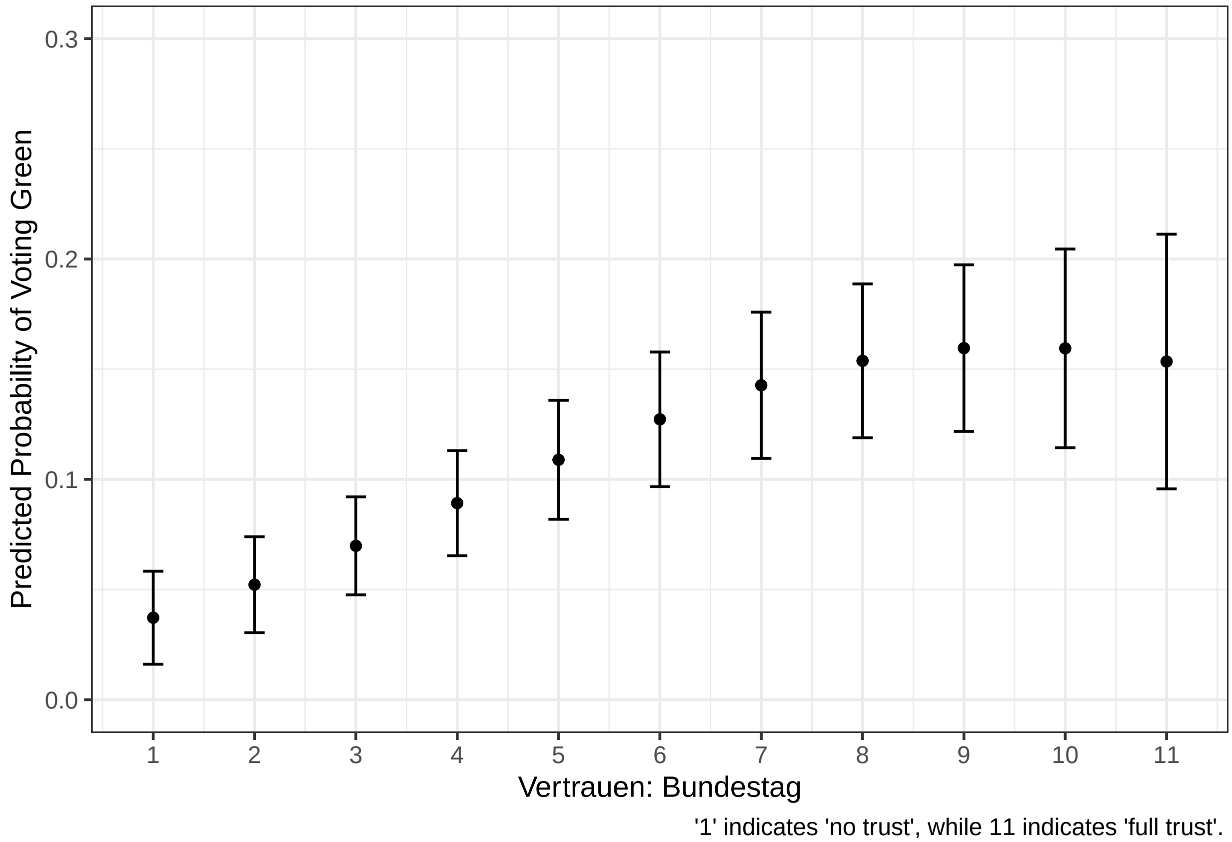


Attiudinal Correlates

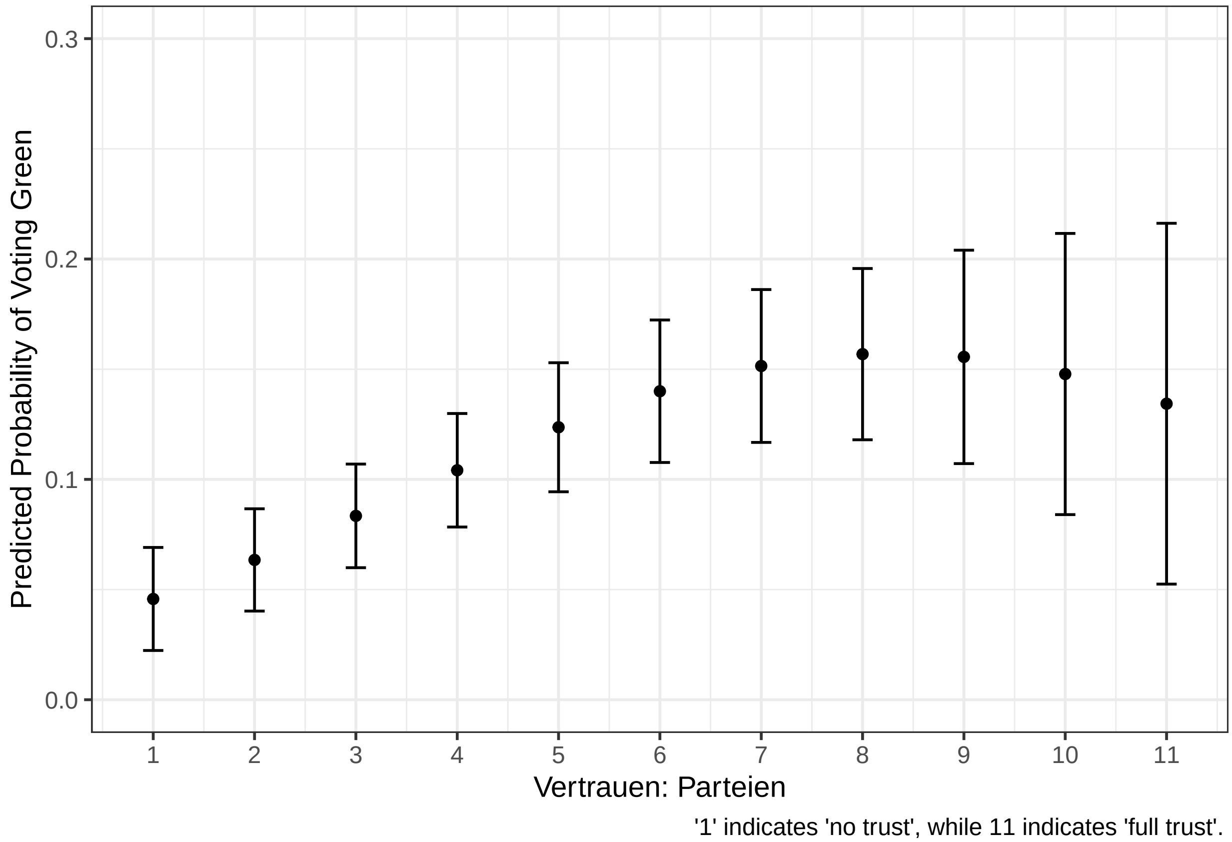
```
gruene_cancel <- glm(gruene_21 ~ cancel_culture_subjektiv + household_income + age + abitur_factor + se
# plot
cplot(gruene_cancel, x = "cancel_culture_subjektiv",
      xvals = seq(1, 5, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = 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 Green") +
  ylim(c(0, 0.3)) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1))
```



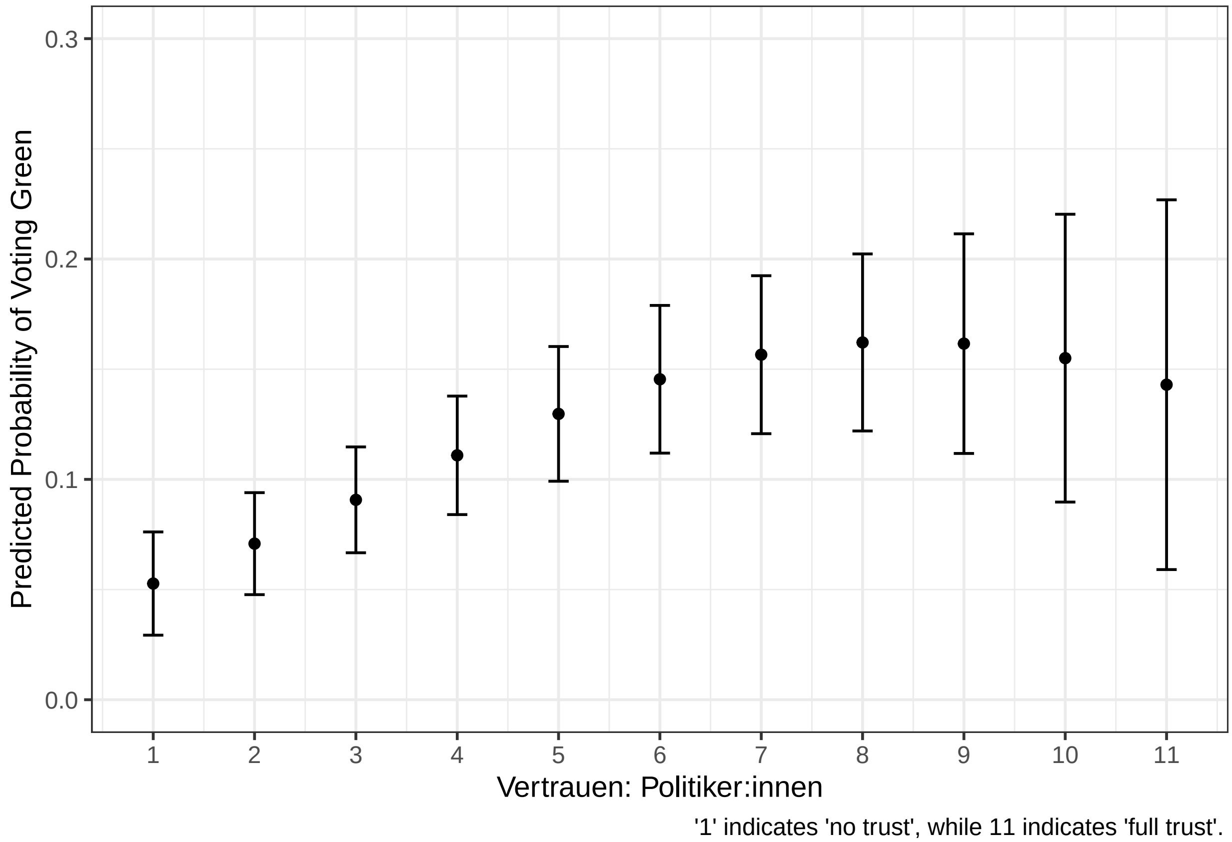

```
gruene_trust_parliament <- glm(gruene_21 ~ trust_in_parliament + I(trust_in_parliament^2) + household_i
# plot
cplot(gruene_trust_parliament, x = "trust_in_parliament",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Vertrauen: Bundestag",
                     breaks = seq(1, 11, 1)) +
  labs(y = "Predicted Probability of Voting Green",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.3)) +
  theme_bw()
```



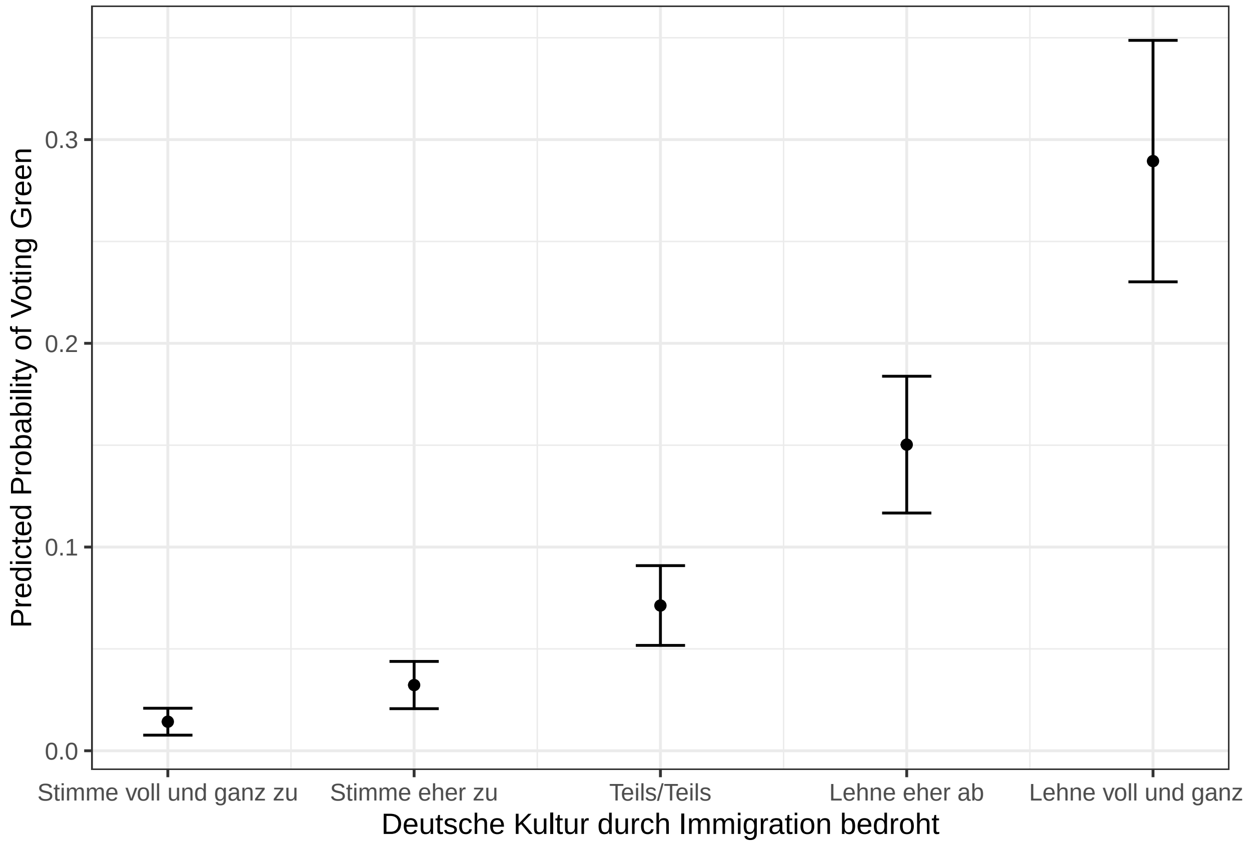

```
gruene_trust_parties <- glm(gruene_21 ~ trust_in_parties + I(trust_in_parties^2) + household_income + ag
# plot
cplot(gruene_trust_parties, x = "trust_in_parties",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Vertrauen: Parteien",
                     breaks = seq(1, 11, 1)) +
  labs(y = "Predicted Probability of Voting Green",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.3)) +
  theme_bw()
```



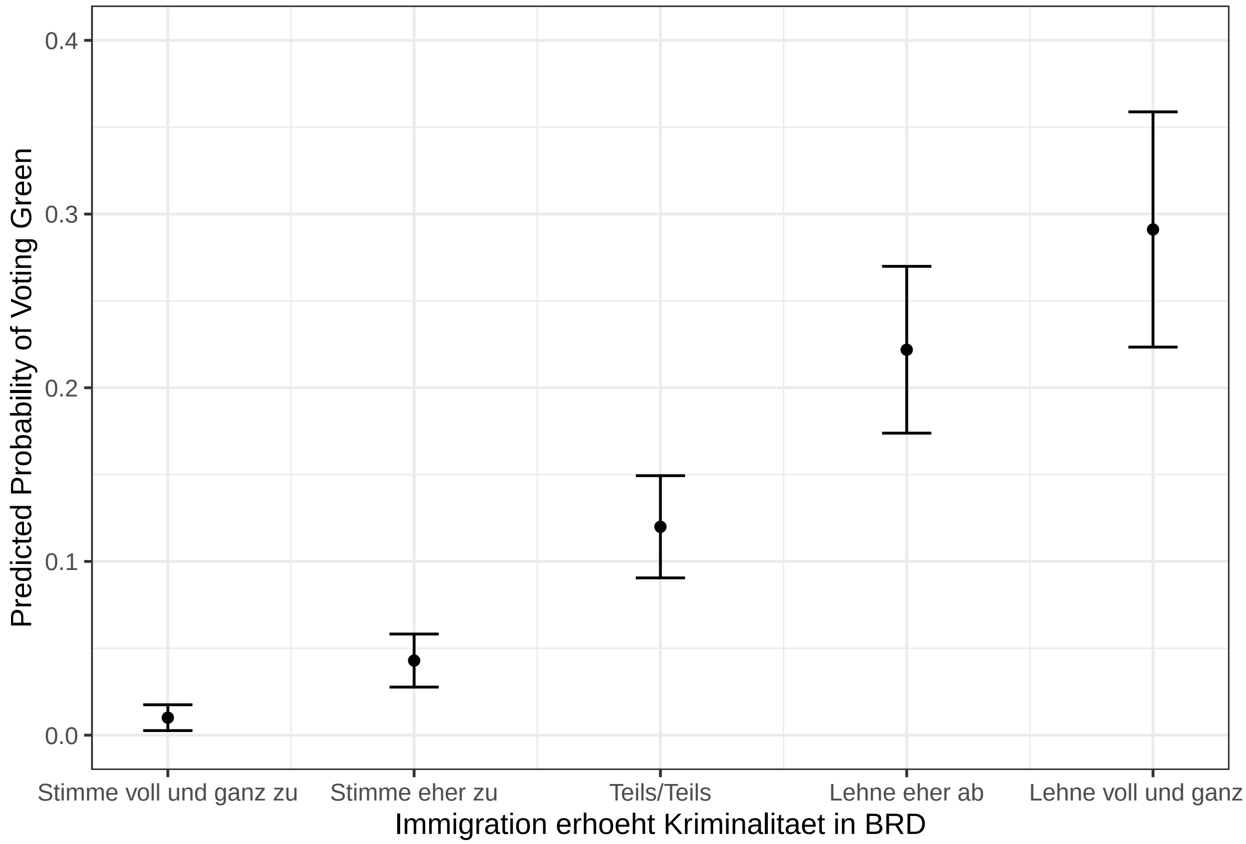

```
gruene_trust_politicians <- glm(gruene_21 ~ trust_in_politicians + I(trust_in_politicians^2) + househol
# plot
cplot(gruene_trust_politicians, x = "trust_in_politicians",
      xvals = seq(1, 11, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.2) +
  scale_x_continuous("Vertrauen: Politiker:innen",
                     breaks = seq(1, 11, 1)) +
  labs(y = "Predicted Probability of Voting Green",
       caption = "'1' indicates 'no trust', while 11 indicates 'full trust'.") +
  ylim(c(0, 0.3)) +
  theme_bw()
```



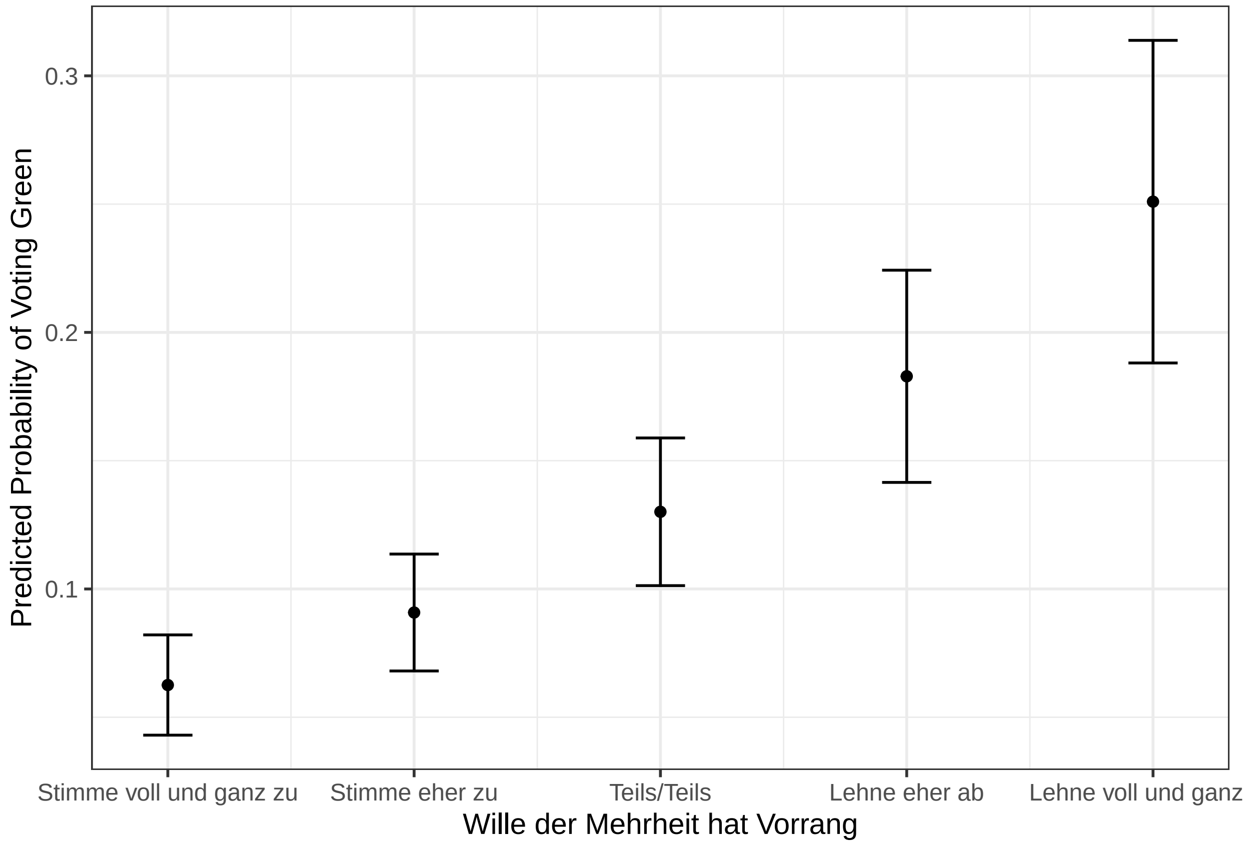

```
gruene_immig_culture_threat <- glm(gruene_21 ~ out_group_immig_culture_threat + household_income + age +
# plot
cplot(gruene_immig_culture_threat, x = "out_group_immig_culture_threat",
      xvals = seq(1, 5, 1), draw = F) %>%
  as_tibble() %>%
  ggplot(aes(x = xvals)) +
  geom_point(aes(y = yvals)) +
  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 Green") +
  theme_bw()
```




```
gruene_immig_crime <- glm(gruene_21 ~ out_group_immig_crime + I(out_group_immig_crime^2) + household_inc
# plot
cplot(gruene_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 Green") +
  ylim(c(0, 0.4)) +
  theme_bw()
```




```r
gruene_majority <- glm(gruene_21 ~ out_group_majority_will + household_income + age + abitur_factor + se
# plot
cplot(gruene_majority, 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")) +
  labs(y = "Predicted Probability of Voting Green") +
  theme_bw()
```



Further analysis

Valence -> motivation: Baerbock's campaign

How can we measure valence vs spatial distance?

Who punished the Greens because of Baerbock? Who punished the CDU/CSU because of Laschet? (Lachet and so on) -> Those who are struggling / hard times.

-> egoistic vs sociotropic motivations/evaluations? -> egoistic evaluations matter more when one is ideologically closer to a candidate/party; spell this out -> sociotropic evaluations matter more when one thinks highly of a candidate

```
ego_socio_model1 <- glm(union_21 ~ econ_current_personal*econ_current_eval_general*scale_pol_lasceht,
                       family = binomial(link = "logit"),
                       data = gles_mod)
ego_socio_model2 <- glm(union_21 ~ econ_current_personal*econ_current_eval_general*scale_pol_lasceht + d
                       family = binomial(link = "logit"),
                       data = gles_mod)
ego_socio_model3 <- glm(union_21 ~ distance_cdu*econ_current_personal + econ_current_eval_general*scale_
                       family = binomial(link = "logit"),
                       data = gles_mod)
```

```
ego_socio_model4 <- glm(union_21 ~ distance_cdu*econ_current_personal + econ_current_eval_general*scale_
                        family = binomial(link = "logit"),
                        data = gles_mod)
ego_socio_model5 <- glm(union_21 ~ distance_cdu*econ_current_personal*scale_pol_lasceht + econ_current_e
                        family = binomial(link = "logit"),
                        data = gles_mod)
ego_socio_model6 <- glm(union_21 ~ distance_cdu + econ_current_eval_general*econ_current_personal*scale_
                        family = binomial(link = "logit"),
                        data = gles_mod)
# modelsummary
modelsummary(list(ego_socio_model1, ego_socio_model2, ego_socio_model3,
                  ego_socio_model4, ego_socio_model5),
             estimate = "{estimate}{stars}")
```

```
ego_socio_model11 <- glm(union_21 ~ distance_cdu*scale_pol_lasceht + sex + household_income + urban_rura
                        family = binomial(link = "logit"),
                        data = gles_mod)
ego_socio_model12 <- glm(spd_21 ~ distance_spd*scale_pol_scholz + sex + household_income + urban_rural +
                        family = binomial(link = "logit"),
                        data = gles_mod)
ego_socio_model13 <- glm(gruene_21 ~ distance_green*scale_pol_baerbock + sex + household_income + urban_
                        family = binomial(link = "logit"),
                        data = gles_mod)
ego_socio_model14 <- glm(afd_21 ~ distance_afd + sex + household_income + urban_rural + ostwest_factor +
                        family = binomial(link = "logit"),
                        data = gles_mod)
ego_socio_model15 <- glm(fdp_21 ~ econ_current_personal*econ_current_eval_general,
                        family = binomial(link = "logit"),
                        data = gles_mod)

# modelsummar<
modelsummary(list(ego_socio_model11, ego_socio_model12, ego_socio_model13, ego_socio_model14),
             estimate = "{estimate}{stars}",
             output = "kableExtra") %>%
  kableExtra::kable_styling(latex_options = "scale_down")
```

```
afd_gender1 <- glm(afd_21 ~ gender_too_far_factor + age + abitur_factor + sex1 + urban_rural_factor + os
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender2 <- glm(afd_21 ~ gender_too_far_factor*sex1 + age + abitur_factor +  urban_rural_factor + ost
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender3 <- glm(afd_21 ~ gender_too_far_factor*sex1 + age + abitur_factor +  urban_rural_factor + ost
                  family = binomial(link = "logit"),
```

	(1)	(2)	(3)	(4)
(Intercept)	−2.121*	−4.105**	−3.769***	−4.012***
	(1.067)	(1.396)	(0.697)	(0.713)
econ_current_personal	−0.110	0.097	−0.084	−0.088
	(0.457)	(0.582)	(0.106)	(0.106)
econ_current_eval_general	−0.304	0.166	−0.014	−0.027
	(0.406)	(0.495)	(0.177)	(0.179)
scale_pol_lasceht	0.363+	0.490*	0.410***	0.403***
	(0.189)	(0.228)	(0.081)	(0.082)
econ_current_personal × econ_current_eval_general	0.034	−0.055		
	(0.159)	(0.201)		
econ_current_personal × scale_pol_lasceht	0.013	−0.027		
	(0.082)	(0.100)		
econ_current_eval_general × scale_pol_lasceht	−0.004	−0.102	−0.054+	−0.050
	(0.074)	(0.089)	(0.032)	(0.032)
econ_current_personal × econ_current_eval_general × scale_pol_lasceht	−0.006	0.017		
	(0.029)	(0.036)		
distance_cdu		−0.138***	−0.213***	−0.210***
		(0.015)	(0.038)	(0.038)
household_income		0.062*	0.076*	0.072*
		(0.031)	(0.032)	(0.032)
age		0.022***	0.019***	0.019***
		(0.004)	(0.004)	(0.004)
abitur_factorno_abitur			0.386**	0.351*
			(0.139)	(0.141)
sex1female			−0.090	−0.077
			(0.123)	(0.124)
distance_cdu × econ_current_personal			0.035*	0.034*
			(0.014)	(0.014)
urban_rural_factor2				0.262
				(0.210)
urban_rural_factor3				0.313+
				(0.182)
urban_rural_factor4				0.331+
				(0.188)
urban_rural_factor5				0.634
				(0.484)
ostwest_factorwest				0.082
				(0.139)
distance_cdu × scale_pol_lasceht				
scale_pol_lasceht × econ_current_eval_general				
distance_cdu × econ_current_personal × scale_pol_lasceht				
Num.Obs.	2792	2225	2221	2211
AIC	2473.1	1732.5	1718.2	1715.3
BIC	2520.5	1795.3	1780.9	1806.6
Log.Lik.	−1228.528	−855.242	−848.079	−841.671
RMSE	0.37	0.35	0.35	0.35

	(1)	(2)	(3)	(4)
(Intercept)	−4.012***	−6.204***	−4.509***	1.651*
	(0.491)	(0.524)	(0.538)	(0.737)
distance_cdu	−0.138***			
	(0.030)			
scale_pol_lasceht	0.287***			
	(0.027)			
sex	−0.119	−0.126	0.215+	−0.269
	(0.121)	(0.113)	(0.128)	(0.229)
household_income	0.060*	−0.041	0.065*	−0.179***
	(0.028)	(0.025)	(0.028)	(0.045)
urban_rural	0.111*	0.015	−0.047	0.172+
	(0.055)	(0.049)	(0.056)	(0.100)
ostwest_factorwest	0.092	0.112	0.503**	−1.011***
	(0.137)	(0.124)	(0.153)	(0.216)
age	0.022***	0.009**	−0.030***	0.001
	(0.004)	(0.003)	(0.004)	(0.007)
distance_cdu × scale_pol_lasceht	0.000			
	(0.006)			
distance_spd		0.012		
		(0.031)		
scale_pol_scholz		0.678***		
		(0.043)		
distance_spd × scale_pol_scholz		−0.007*		
		(0.004)		
distance_green			−0.106	
			(0.074)	
scale_pol_baerbock			0.564***	
			(0.043)	
distance_green × scale_pol_baerbock			−0.005	
			(0.010)	
distance_afd				−0.183***
				(0.016)
Num.Obs.	2239	2233	2224	2225
AIC	1754.9	1974.2	1539.0	596.6
BIC	1806.3	2025.6	1590.4	636.5
Log.Lik.	−868.431	−978.124	−760.511	−291.289
RMSE	0.35	0.38	0.33	0.20

```
                  data = gles_mod)
afd_gender4 <- glm(afd_21 ~ gender_too_far_factor*sex1*unemployed_dummy + age + abitur_factor +  urban_r
                  family = binomial(link = "logit"),
                  data = gles_mod)
afd_gender5 <- glm(afd_21 ~ gender_too_far_factor*sex1*econ_current_personal + age + abitur_factor +  ur
                  family = binomial(link = "logit"),
                  data = gles_mod)

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

	(1)	(2)	(3)	(4)
(Intercept)	−0.510	−0.511	−0.584	−0.175
	(0.439)	(0.469)	(0.481)	(0.968)
gender_too_far_factor2	−0.997**	−0.929*	−0.968*	−1.446
	(0.343)	(0.410)	(0.411)	(1.135)
gender_too_far_factor3	−1.498***	−1.548***	−1.601***	−2.611*
	(0.318)	(0.377)	(0.378)	(1.071)
gender_too_far_factor4	−2.380***	−2.243***	−2.312***	−4.777***
	(0.329)	(0.390)	(0.392)	(1.163)
gender_too_far_factor5	−2.887***	−3.493***	−3.766***	−5.305**
	(0.372)	(0.565)	(0.608)	(1.668)
age	−0.004	−0.004	−0.003	−0.001
	(0.005)	(0.005)	(0.005)	(0.005)
abitur_factorno_abitur	0.922***	0.925***	0.889***	0.713**
	(0.213)	(0.213)	(0.217)	(0.218)
sex1female	−0.373*	−0.418	−0.507	−1.647
	(0.171)	(0.641)	(0.638)	(1.969)
urban_rural_factor2	0.243	0.258	0.303	0.261
	(0.294)	(0.295)	(0.301)	(0.302)
urban_rural_factor3	0.200	0.212	0.205	0.218
	(0.250)	(0.251)	(0.259)	(0.257)
urban_rural_factor4	0.420	0.433+	0.484+	0.404
	(0.257)	(0.257)	(0.264)	(0.263)
urban_rural_factor5	1.301*	1.366*	0.855	1.368*
	(0.552)	(0.558)	(0.652)	(0.565)
ostwest_factorwest	−1.311***	−1.319***	−1.255***	−1.305***
	(0.167)	(0.167)	(0.172)	(0.172)
gender_too_far_factor2 × sex1female		−0.179	−0.124	−2.211
		(0.757)	(0.760)	(2.441)
gender_too_far_factor3 × sex1female		0.161	0.239	−0.834
		(0.702)	(0.705)	(2.229)
gender_too_far_factor4 × sex1female		−0.373	−0.314	0.669
		(0.728)	(0.730)	(2.330)
gender_too_far_factor5 × sex1female		0.974	1.172	0.057
		(0.831)	(0.866)	(2.619)
unemployed_dummy_factor1			0.665**	
			(0.257)	
econ_current_personal				−0.148
				(0.361)
gender_too_far_factor2 × econ_current_personal				0.233
				(0.451)
gender_too_far_factor3 × econ_current_personal				0.454
				(0.422)
gender_too_far_factor4 × econ_current_personal				1.040*
				(0.446)
gender_too_far_factor5 × econ_current_personal				0.764
				(0.626)
sex1female × econ_current_personal				0.465
				(0.677)
gender_too_far_factor2 × sex1female × econ_current_personal				0.724
				(0.836)
gender_too_far_factor3 × sex1female × econ_current_personal				0.384
				(0.772)
gender_too_far_factor4 × sex1female × econ_current_personal				−0.458
				(0.797)
gender_too_far_factor5 × sex1female × econ_current_personal				0.176
				(0.896)
Num.Obs.	2703	2703	2581	2701
AIC	1145.5	1148.1	1081.3	1099.9
BIC	1222.3	1248.4	1186.7	1259.3
Log.Lik.	−559.768	−557.047	−522.647	−522.957
RMSE	0.24	0.24	0.23	0.23