# Supplementary Material for "Vigilantism and Institutions: Understanding Attitudes toward Lynching in Brazil"

## Contents

# A Introduction

This appendix contains the R code required to replicate the results we present in "*Vigilantism and Institutions: Understanding Attitudes towards Lynching in Brazil*". This file also includes the descriptive statistics of our sample, the average marginal component effects (AMCEs) for our conjoint experiment, and additional subgroup analyses for all three experiments.

The code below loads the required datasets and the R packages we use in our statistical analyses. It also translates the names of the factor variables from Portuguese into English.

```r
# Install and load required packages
packages <- c("bartCause", "cjoint", "cregg", "estimatr", "kableExtra",
              "janitor", "quanteda", "quanteda.textmodels", "quanteda.textplots",
              "quanteda.textstats", "seededlda", "stargazer", "tidyverse")
installed_packages <- packages %in% rownames(installed.packages())
if (any(installed_packages == FALSE)) {
  install.packages(packages[!installed_packages])
}
invisible(lapply(packages, library, character.only = TRUE))

# Load the dataset, remove unused rows and columns,
# and convert variable names to snake case
df <- read_csv("../data/data.csv") %>%
  clean_names() %>%
  mutate(response_id             = as.character(response_id),
         consent                 = as.factor(q1),
         progress                = as.numeric(progress),
         finished                = as.factor(finished),
         age                     = as.numeric(q2),
         gender                  = as.factor(q3),
         race                    = as.factor(q4),
         education               = as.factor(q5),
         region                  = as.factor(q6),
         household_income        = as.factor(q7),
         ideology                = as.factor(q8),
         death_penalty           = as.factor(q9),
         previous_victim         = as.character(q10),
         previous_victim_text    = as.character(q10_text),
```

```
       views_police           = as.factor(q11),
       views_justice          = as.factor(q12),
       exp01_control          = as.numeric(q18),
       exp01_police           = as.numeric(q19),
       exp01_slow_justice     = as.numeric(q20),
       exp01_small_punishment = as.numeric(q21),
       exp03_control          = as.numeric(q22),
       exp03_constitution     = as.numeric(q23),
       exp03_rights           = as.numeric(q24),
       exp03_vendetta         = as.numeric(q25)) %>%
  slice(-1L) %>%
  select(-c(q1:q12, q18:q25)) %>%
  relocate(response_id, consent, progress, finished,
         location_latitude, location_longitude) %>%
  mutate(across(where(is.character), tolower)) %>%
  mutate(across(where(is.factor), tolower))

# Translate factor values from Portuguese to English
df <- df %>%
  mutate(consent = recode(consent,
                        concordo      = "Agree",
                        `não concordo` = "Disagree"),
       gender = recode(gender,
                      "feminino"             = "Female",
                      "masculino"            = "Male",
                      "outro"                = "Other",
                      "prefiro não responder" = "Rather Not Say"),
       race = recode(race,
                    "amarela"              = "Asian",
                    "branca"               = "White",
                    "indígena"             = "Indigenous",
                    "outra"                = "Other",
                    "parda"                = "Mixed Race",
                    "prefiro não responder" = "Rather Not Say",
                    "preta"                = "Black"),
       race = fct_relevel(race, "Other", "Rather Not Say", after = Inf),
       education = recode(education,
```

```
                    "da 1ª à 4ª série do ensino fundamental (antigo primário)" = "Primary School",
                    "da 5ª à 8ª série do ensino fundamental (antigo ginásio)"  = "Secondary School",
                    "ensino médio (antigo 2º grau)"                            = "High School",
                    "ensino superior"                                          = "College",
                    "mestrado ou doutorado"                                    = "Graduate School",
                    "não sei"                                                  = "Don't Know"),
education = fct_relevel(education, "Primary School", "Secondary School", "High School",
                        "College", "Graduate School", "Don't Know"),
region = recode(region,
                "centro-oeste" = "Center-West",
                "nordeste"     = "Northeast",
                "norte"        = "North",
                "sudeste"      = "Southeast",
                "sul"          = "South"),
household_income = recode(household_income,
                          "acima de r$ 20.000"       = "Above R$20,000",
                          "até r$ 1.000"             = "Up to R$1,000",
                          "de r$ 1.001 a r$ 2.000"   = "From R$1,001 to R$2,000",
                          "de r$ 10.000 a r$ 20.000" = "From R$10,001 to R$20,000",
                          "de r$ 2.001 a r$ 3.000"   = "From R$2,001 to R$3,000",
                          "de r$ 3.001 a r$ 5.000"   = "From R$3,001 to R$5,000",
                          "de r$ 5.001 a r$ 10.000"  = "From R$5,001 to R$10,000"),
household_income = fct_relevel(household_income, "Up to R$1,000",
                               "From R$1,001 to R$2,000", "From R$2,001 to R$3,000",
                               "From R$3,001 to R$5,000", "From R$5,001 to R$10,000",
                               "From R$10,001 to R$20,000", "Above R$20,000"),
ideology = recode(ideology,
                  "centro"                = "Center",
                  "centro-direita"        = "Center-Right",
                  "centro-esquerda"       = "Center-Left",
                  "direita"               = "Right",
                  "esquerda"              = "Left",
                  "não sei"               = "Don't Know",
                  "prefiro não responder" = "Rather Not Say"),
ideology = fct_relevel(ideology, "Left", "Center-Left", "Center",
                       "Center-Right", "Right", "Don't Know",
                       "Rather Not Say"),
```

```
        death_penalty = recode(death_penalty,
                               "não"                     = "No",
                               "não sei"                 = "Don't Know",
                               "prefiro não responder" = "Rather Not Say",
                               "sim"                     = "Yes"),
        death_penalty = fct_relevel(death_penalty, "Don't Know",
                                    "Rather Not Say", after = Inf),
        views_police = recode(views_police,
                              "boa"                     = "Good",
                              "muito boa"               = "Very Good",
                              "muito ruim"              = "Very Bad",
                              "não sei"                 = "Don't Know",
                              "prefiro não responder" = "Rather Not Say",
                              "regular"                 = "Regular",
                              "ruim"                    = "Bad"),
        views_police = fct_relevel(views_police, "Very Good", "Good", "Regular",
                                   "Bad", "Very Bad", "Don't Know", "Rather Not Say"),
        views_justice = recode(views_justice,
                               "boa"                     = "Good",
                               "muito boa"               = "Very Good",
                               "muito ruim"              = "Very Bad",
                               "não sei"                 = "Don't Know",
                               "prefiro não responder" = "Rather Not Say",
                               "regular"                 = "Regular",
                               "ruim"                    = "Bad"),
        views_justice = fct_relevel(views_justice, "Very Good", "Good", "Regular",
                                   "Bad", "Very Bad", "Don't Know", "Rather Not Say"),
        previous_victim_dummy = recode(previous_victim,
                                       "nenhum" = "No",
                                       .missing = NA_character_,
                                       .default = "Yes")) %>%
  relocate(response_id:previous_victim, previous_victim_dummy,
           previous_victim_text:f_5_2_8)

# Check for duplicated values
count(get_dupes(df))
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1     0
```

# B Descriptive Statistics

We ran our survey experiments from October 30 to December 14, 2020 via Qualtrics. Our sample includes 2406 Brazilians older than 18 years of age from the five regions of the country (Center-West, North, Northeast, South, and Southeast). We used quotas for gender and region to ensure that our sample was similar to the Brazilian population in those characteristics. We also collected information about whether the subjects had been victimized in the previous 12 months, as well as their opinion of the Brazilian judicial system and the police forces. They follow in the graphs and tables below.

## B.1 Informed Consent

About 98% of the interviewees agreed to participate in the survey experiment. We excluded the remaining 2% from our analyses.

```
df %>%
  group_by(consent) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 2)) %>%
  rename(Consent = consent) %>%
  kbl(., booktabs = TRUE, caption = "Informed Consent") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 1: Informed Consent

| **Consent** | **N** | **Frequency** |
|---|---|---|
| Agree | 2406 | 0.98 |
| Disagree | 54 | 0.02 |

```
# Remove subjects who did not agree with consent form
df1 <- df %>% filter(consent == "Agree")
```

## B.2 Gender

The gender distribution of our sample is described below. It closely matches the official data from the Brazilian Census Bureau, which states that women are 51.8% of the population and men comprise 48.2%.

```
df1 %>%
  group_by(gender) %>%
  filter(!is.na(gender)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  rename(Gender = gender) %>%
  kbl(., booktabs = TRUE, caption = "Gender") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 2: Gender

| **Gender** | **N** | **Frequency** |
|---|---|---|
| Female | 1215 | 0.510 |
| Male | 1156 | 0.485 |
| Other | 3 | 0.001 |
| Rather Not Say | 9 | 0.004 |

## B.3 Age

The age distribution of our sample is shown below. The median age of the survey respondents is 41 years old, which indicates that our sample is older than the Brazilian population (median age = 33.4 years old) (?).

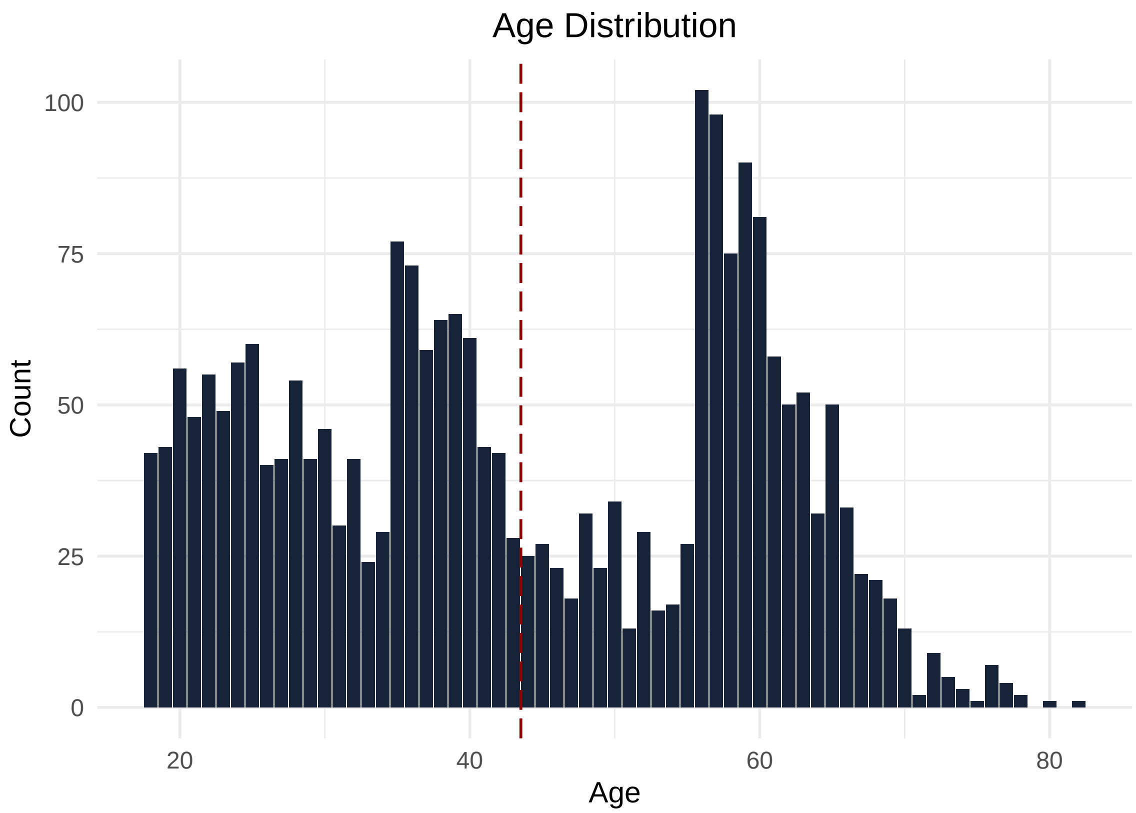
```
tibble(` `    = "Age",
       Median = round(median(df1$age, na.rm = TRUE), 2),
       Mean   = round(mean(df1$age, na.rm = TRUE), 2),
       SD     = round(sd(df1$age, na.rm = TRUE), 2),
       Min    = min(df1$age, na.rm = TRUE),
       Max    = max(df1$age, na.rm = TRUE),
       `NA`   = sum(is.na(df1$age))) %>%
kbl(., booktabs = TRUE, caption = "Age") %>%
```

```
row_spec(0, bold = TRUE) %>%
kable_styling(latex_options = "hold_position")
```

Table 3: Age

| | Median | Mean | SD | Min | Max | NA |
|---|---|---|---|---|---|---|
| Age | 41 | 43.52 | 15.55 | 18 | 82 | 24 |

```
ggplot(subset(df1, !is.na(age)), aes(age)) +
  geom_bar(fill = "#152238") +
  labs(title = "Age Distribution", x = "Age", y = "Count") +
  geom_vline(aes(xintercept = mean(age, na.rm = TRUE)),
             color = "darkred", linetype = 5, size = 0.5) +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5))
```




## B.4 Race

The next demographic variable we show here is race. According to the Brazilian Census Bureau, 42.7% of the Brazilian population identify as White, 46.8% as Mixed Race, 9.4% as Blacks, and 1,1% as Asians or Indigenous. As we see below, our sample includes more Whites and fewer individuals who identify as Mixed Race. The number of Blacks roughly coincide with the population statistics.

```r
df1 %>%
  rename(Race = race) %>%
  mutate(Race = fct_relevel(Race, "White", "Other", "Rather Not Say", after = Inf)) %>%
  group_by(Race) %>%
  filter(!is.na(Race)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Race") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 4: Race

| **Race** | **N** | **Frequency** |
|---|---|---|
| Asian | 60 | 0.025 |
| Black | 231 | 0.097 |
| Indigenous | 8 | 0.003 |
| Mixed Race | 652 | 0.274 |
| White | 1407 | 0.590 |
| Other | 8 | 0.003 |
| Rather Not Say | 17 | 0.007 |

## B.5 Education

As expected, our sample is also more educated than the Brazilian population. About 51.2% of the respondents have a college degree, and 35.5% have graduate school education.

```r
df1 %>%
  rename(Education = education) %>%
  mutate(Education = fct_relevel(Education, "Primary School", "Secondary School",
                                "High School", "College", "Graduate School")) %>%
  group_by(Education) %>%
  filter(!is.na(Education)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Education") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 5: Education

| Education | N | Frequency |
|---|---|---|
| Primary School | 21 | 0.009 |
| Secondary School | 74 | 0.031 |
| High School | 846 | 0.355 |
| College | 1219 | 0.512 |
| Graduate School | 209 | 0.088 |
| Don't Know | 14 | 0.006 |

## B.6 Household Income

In terms of household income, 26.5% of the respondents earn from R$5,0001 to R$10,000 per month (US$915 to US$1830 as of January 2021), which comprise the largest group in our sample. However, the sample also contains 13% of participants whose household income ranges between R$1,001 and R$2,000 (US$ 184 to US$368) and 6.2% with household incomes up to R$1,000, which is roughly equivalent to Brazil's monthly minimum wage. In this respect, we have reached participants from all social classes.

```
df1 %>%
  rename(`Household Income` = household_income) %>%
  mutate(`Household Income` = fct_relevel(`Household Income`, "Up to R$1,000",
                                          "From R$1,001 to R$2,000", "From R$2,001 to R$3,000",
                                          "From R$3,001 to R$5,000", "From R$5,001 to R$10,000",
                                          "From R$10,001 to R$20,000", "Above R$20,000")) %>%
  group_by(`Household Income`) %>%
  filter(!is.na(`Household Income`)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Household Income") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

## B.7 Political Ideology

We have also collected information regarding the subjects' political ideology. Most respondents identify themselves as right-wingers (22.6%), followed by left-wingers (17.8%), and centrists (14.2%).

Table 6: Household Income

| **Household Income** | **N** | **Frequency** |
|---|---|---|
| Up to R$1,000 | 148 | 0.062 |
| From R$1,001 to R$2,000 | 309 | 0.130 |
| From R$2,001 to R$3,000 | 376 | 0.159 |
| From R$3,001 to R$5,000 | 539 | 0.227 |
| From R$5,001 to R$10,000 | 628 | 0.265 |
| From R$10,001 to R$20,000 | 267 | 0.113 |
| Above R$20,000 | 103 | 0.043 |

Subjects who do not know their ideology or prefer not to tell their political beliefs are also large in number (13.4% and 13.9%, respectively).

```
df1 %>%
  rename(Ideology = ideology) %>%
  mutate(Ideology = fct_relevel(Ideology, "Left", "Center-Left", "Center",
                                "Center-Right", "Right")) %>%
  group_by(Ideology) %>%
  filter(!is.na(Ideology)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Political Ideology") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 7: Political Ideology

| **Ideology** | **N** | **Frequency** |
|---|---|---|
| Left | 423 | 0.178 |
| Center-Left | 217 | 0.092 |
| Center | 337 | 0.142 |
| Center-Right | 209 | 0.088 |
| Right | 536 | 0.226 |
| Don’t Know | 318 | 0.134 |
| Rather Not Say | 330 | 0.139 |

## B.8 Support for Death Penalty

Below you may find how many respondents support the death penalty.

```
df1 %>%
  rename(`Support for Death Penalty` = death_penalty) %>%
  mutate(`Support for Death Penalty` = fct_relevel(`Support for Death Penalty`, "Yes", "No")) %>%
  group_by(`Support for Death Penalty`) %>%
  filter(!is.na(`Support for Death Penalty`)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Support for Death Penalty") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 8: Support for Death Penalty

| **Support for Death Penalty** | **N** | **Frequency** |
|---|---|---|
| Yes | 971 | 0.410 |
| No | 1100 | 0.464 |
| Don't Know | 167 | 0.070 |
| Rather Not Say | 132 | 0.056 |

## B.9 Previous Victimization

We asked subjects whether they had been victimized in the previous 12 months, as crime victims may be more likely to support lynchings. The responses follow below.

```
df1 %>%
  rename(Victimization = previous_victim_dummy) %>%
  mutate(Victimization = fct_relevel(Victimization, "Yes", "No")) %>%
  group_by(Victimization) %>%
  filter(!is.na(Victimization)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Previous Victimization (12 Months)") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 9: Previous Victimization (12 Months)

| **Victimization** | **N** | **Frequency** |
|---|---|---|
| Yes | 934 | 0.401 |
| No | 1397 | 0.599 |

## B.10 Opinion on the Police

Here we show the results for our question on how respondents see the police forces.

```
df1 %>%
  rename(`Opinion on the Police` = views_police) %>%
  mutate(`Opinion on the Police` = fct_relevel(`Opinion on the Police`, "Very Good", "Good",
                                               "Regular", "Bad", "Very Bad")) %>%
  group_by(`Opinion on the Police`) %>%
  filter(!is.na(`Opinion on the Police`)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Opinion on the Police") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 10: Opinion on the Police

| **Opinion on the Police** | **N** | **Frequency** |
|---|---|---|
| Very Good | 132 | 0.056 |
| Good | 472 | 0.200 |
| Regular | 914 | 0.387 |
| Bad | 468 | 0.198 |
| Very Bad | 335 | 0.142 |
| Don't Know | 25 | 0.011 |
| Rather Not Say | 15 | 0.006 |

## B.11 Opinion on the Judicial System

Lastly, we asked how respondents evaluate their local judiciary. As in the previous question, subjects could choose among five options, as well as affirm that they do not have an opinion or decline to answer the question.

```
df1 %>%
  rename(`Opinion on the Justice System` = views_justice) %>%
  mutate(`Opinion on the Justice System` = fct_relevel(`Opinion on the Justice System`, "Very Good",
                                                      "Good", "Regular", "Bad", "Very Bad")) %>%
  group_by(`Opinion on the Justice System`) %>%
  filter(!is.na(`Opinion on the Justice System`)) %>%
  summarise(N = n()) %>%
  mutate(Frequency = round(N / sum(N), 3)) %>%
  kbl(., booktabs = TRUE,  linesep = "", caption = "Opinion on the Justice System") %>%
  row_spec(0, bold = TRUE) %>%
  kable_styling(latex_options = "hold_position")
```

Table 11: Opinion on the Justice System

| **Opinion on the Justice System** | **N** | **Frequency** |
|---|---|---|
| Very Good | 45 | 0.019 |
| Good | 323 | 0.137 |
| Regular | 812 | 0.344 |
| Bad | 605 | 0.256 |
| Very Bad | 508 | 0.215 |
| Don't Know | 48 | 0.020 |
| Rather Not Say | 20 | 0.008 |

# C Experiment 01

## C.1 Description

In our first experiment, we present five pairs of criminal profiles to respondents. Each profile consists of eight attributes: 1) gender of the crime perpetrator; 2) age of the crime perpetrator; 3) race of the crime perpetrator; 4) residency of crime perpetrator; 5) offense; 6) gender of the victim of the motivating crime; 7) age of the victim of the motivating crime; 8) lynching perpetrators. The attributes and levels are displayed in table 12 below.

Table 12: **Attributes and Levels**

| Attribute | Levels |
|---|---|
| Gender of crime perpetrator | Male; female |
| Age of crime perpetrator | Teenager; adult; elderly |
| Race of crime perpetrator | Black; White; Native Brazilian; Asian |
| Residency of crime perpetrator | Resident in the community; outsider |
| Offense | Picks the pocket; steals the car; molests; rapes; murders |
| Gender of crime victim | Male; female |
| Age of crime victim | Child; teenager; adult; elderly |
| Lynching perpetrators | Bystanders; neighbours; family of the victim; gangs; police |

We added three restrictions to the conjoint design to avoid implausible scenarios. First, female rapists were excluded from the model, but we did include female molesters in the conjoint experiment. Second, when the offense was car theft, the victim could not be a child. Lastly, teenagers could not be victims of car theft either. All other combinations were allowed. We randomized the attributes using a `.php` script, which is available at https://github.com/danilofreire/lynching-experiment-brazil/blob/master/conjoint/portuguese/lynching-conjoint-pt.php.

Respondents indicated which profile they preferred for extrajudicial punishment. Prior to the experiments, they had read the following prompt:

- Lynchings are often used as social punishment in Brazil. Lynchings are cases in which three or more people physically attack or execute a suspected criminal in public. We are interested in knowing more about how Brazilians see these episodes. In the next five questions, please read the description of two possible lynching victims in Brazil and indicate in which case you believe the punishment is more justified. Even if you are not entirely sure, please select one of the cases.[1]

## C.2 Marginal Means Estimator

We estimate the conjoint experiment with the `cregg` package (Leeper 2018) for the `R` statistical language (R Core Team 2018). We follow **?** and report marginal means as our main estimates.

[1]Original text in Portuguese: Linchamentos são às vezes usados como punição social no Brasil. Linchamentos são casos nos quais três ou mais pessoas agridem fisicamente ou executam em público um suspeito de um crime. Estamos interessados em saber mais sobre como os brasileiros vêem estes episódios. Nas próximas cinco questões, por favor, leia a descrição de duas possíveis vítimas de linchamento no Brasil e indique em quais delas você acredita que a punição é mais justificada. Mesmo que você não tenha certeza, por favor, escolha um dos casos.

Marginal means are easy to interpret and they are not sensitive to choice of the reference category in subgroup analyses. The $H_0$ in all models is that the coefficient is equal to 0.5, that is, that respondents are indifferent to that attribute level. Standard errors are clustered by respondent. The code follows below.

```
conjoint_data <- read.qualtrics("../data/data-conjoint.csv",
                                responses = c("Q13", "Q14", "Q15",
                                              "Q16", "Q17"),
                                covariates = c("ResponseId",
                                               "Q1", "Q2", "Q3", "Q4",
                                               "Q5", "Q6", "Q7",
                                               "Q8", "Q9", "Q10",
                                               "Q11", "Q12"),
                                new.format = FALSE, respondentID = NULL)
```

```
## [1] "Old qualtrics format detected."
```

```
conjoint_data <- conjoint_data %>%
  rename(response_id                     = ResponseId,
         Age                             = Q2,
         Gender                          = Q3,
         Race                            = Q4,
         Education                       = Q5,
         Region                          = Q6,
         "Household Income"              = Q7,
         Ideology                        = Q8,
         "Support death penalty"         = Q9,
         "Previous Victimization"        = Q10,
         "Offense"                       = Crime,
         "Opinion on Policing"           = Q11,
         "Opinion on Judiciary"          = Q12,
         "Gender of crime victim"        = "Gênero.da.vítima",
         "Gender of crime perpetrator"   = "Gênero.do(a).criminoso(a)",
         "Age of crime victim"           = "Idade.da.vítima",
         "Age of crime perpetrator"      = "Idade.do(a).criminoso(a)",
         "Lynching perpetrators"         = "Linchadores",
         "Race of crime perpetrator"     = "Raça.do(a).criminoso(a)",
         "Residency of crime perpetrator" = "Residência.do.criminoso") %>%
```

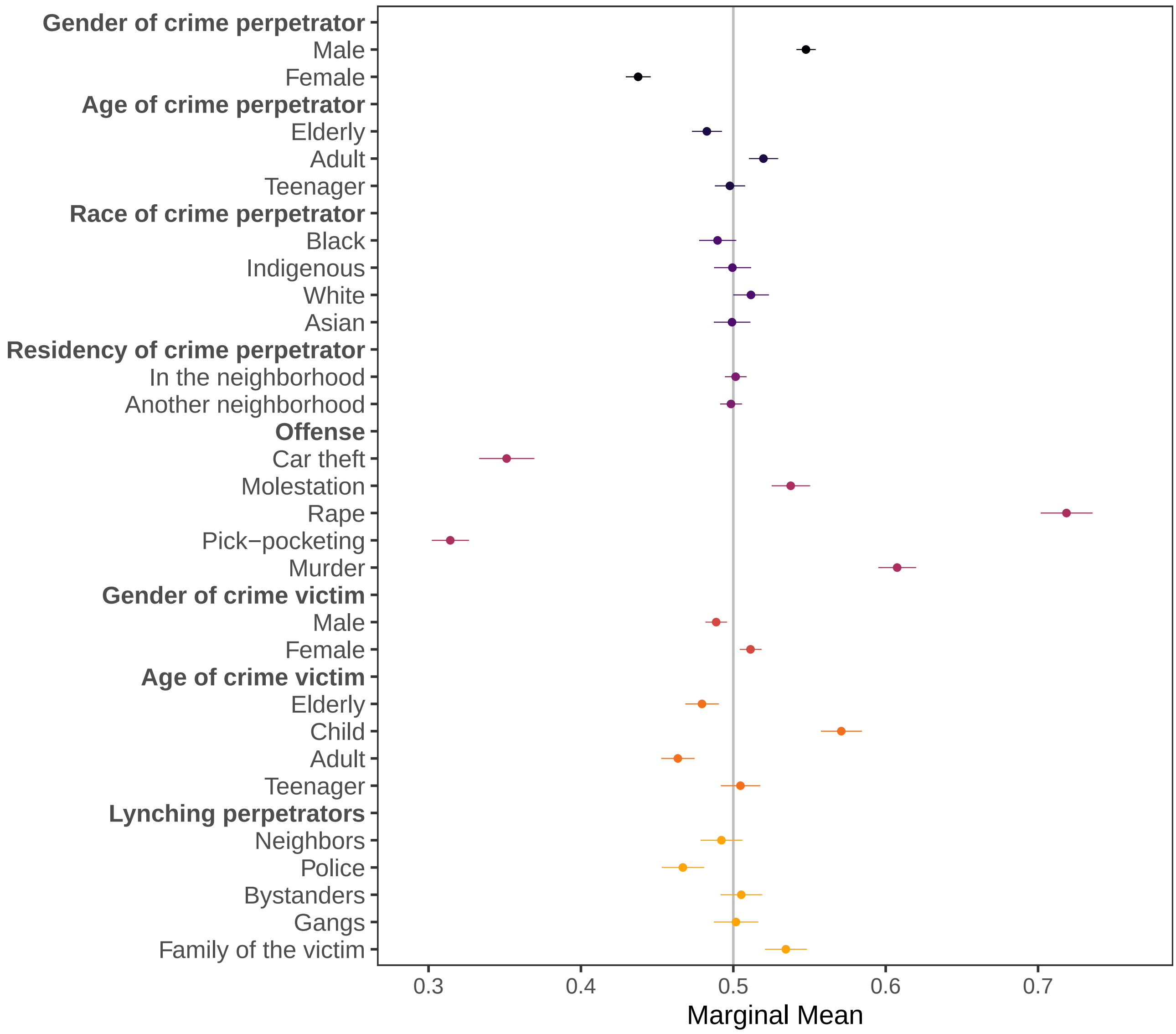
```
mutate(`Gender of crime perpetrator` = fct_recode(`Gender of crime perpetrator`,
                                                  "Male"   = "Masculino",
                                                  "Female" = "Feminino"),
       `Age of crime perpetrator` = fct_recode(`Age of crime perpetrator`,
                                               "Teenager" = "Adolescente",
                                               "Adult"    = "Adulto(a)",
                                               "Elderly"  = "Idoso(a)"),
       `Race of crime perpetrator` = fct_recode(`Race of crime perpetrator`,
                                                "Asian"      = "Asiático(a)",
                                                "White"      = "Branco(a)",
                                                "Indigenous" = "Indígena",
                                                "Black"      = "Negro(a)"),
       `Residency of crime perpetrator` = fct_recode(`Residency of crime perpetrator`,
                                                     "Another neighborhood" = "Mora em outro bairro",
                                                     "In the neighborhood"  = "Mora na vizinhança"),
       `Offense` = fct_recode(`Offense`,
                              "Murder"        = "Assassinou",
                              "Pick-pocketing" = "Bateu a carteira",
                              "Rape"          = "Estuprou",
                              "Molestation"   = "Molestou",
                              "Car theft"     = "Roubou o carro"),
       `Gender of crime victim` = fct_recode(`Gender of crime victim`,
                                             " Male"   = "Masculino",
                                             " Female" = "Feminino"),
       `Age of crime victim` = fct_recode(`Age of crime victim`,
                                          " Teenager" = "Adolescente",
                                          " Child"    = "Criança",
                                          " Adult"    = "Adulto(a)",
                                          " Elderly"  = "Idoso(a)"),
       `Lynching perpetrators` = fct_recode(`Lynching perpetrators`,
                                            "Family of the victim" = "Família da vítima",
                                            "Gangs"                = "Gangues",
                                            "Bystanders"           = "Pedestres",
                                            "Police"               = "Polícia",
                                            "Neighbors"            = "Vizinhos")) %>%
select(-c(16, 18, 20, 22, 24, 26, 28, 30)) %>%
mutate(response_id = tolower(response_id))
```

```r
# Model
fm <- selected ~ `Gender of crime perpetrator` +
  `Age of crime perpetrator` + `Race of crime perpetrator` +
  `Residency of crime perpetrator` + `Offense` +
  `Gender of crime victim` + `Age of crime victim` +
  `Lynching perpetrators`

mms <- mm(conjoint_data, fm, id = ~response_id, h0 = 0.5)

# Plot
faces <- c(rep("plain", 5), "bold",
           rep("plain", 4), "bold",
           rep("plain", 2), "bold",
           rep("plain", 5), "bold",
           rep("plain", 2), "bold",
           rep("plain", 4), "bold",
           rep("plain", 3), "bold",
           rep("plain", 2), "bold")

plot(mms, vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "none", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
# Table

table_mm <- function(mms, capt) {

dfr <- data.frame(feature = mms[, c(4)],

                  round(mms[, c(5, 6, 8, 9, 10)], digits = 3))

names(dfr) <- c("Feature", "Estimate", "Std. Error",

                "P-Value", "Lower", "Upper")

return(kbl(dfr, "latex", caption = capt, linesep = "",

           booktabs = TRUE) %>%

kable_styling(font_size = 12, full_width = TRUE,

              latex_options = "hold_position") %>%

pack_rows("Gender of crime perpetrator", 1, 2) %>%

pack_rows("Age of crime perpetrator", 3, 5) %>%

pack_rows("Race of crime perpetrator", 6, 9) %>%

pack_rows("Residency of crime perpetrator", 10, 11) %>%

pack_rows("Offense", 12, 16) %>%
```

```
pack_rows("Gender of crime victim", 17, 18) %>%
pack_rows("Age of crime victim", 19, 22) %>%
pack_rows("Lynching perpetrators", 23, 27) %>%
column_spec(1, width = "6cm"))
}

table_mm(mms, capt = "Marginal Means -- Full Model")
```

Table 13: Marginal Means – Full Model

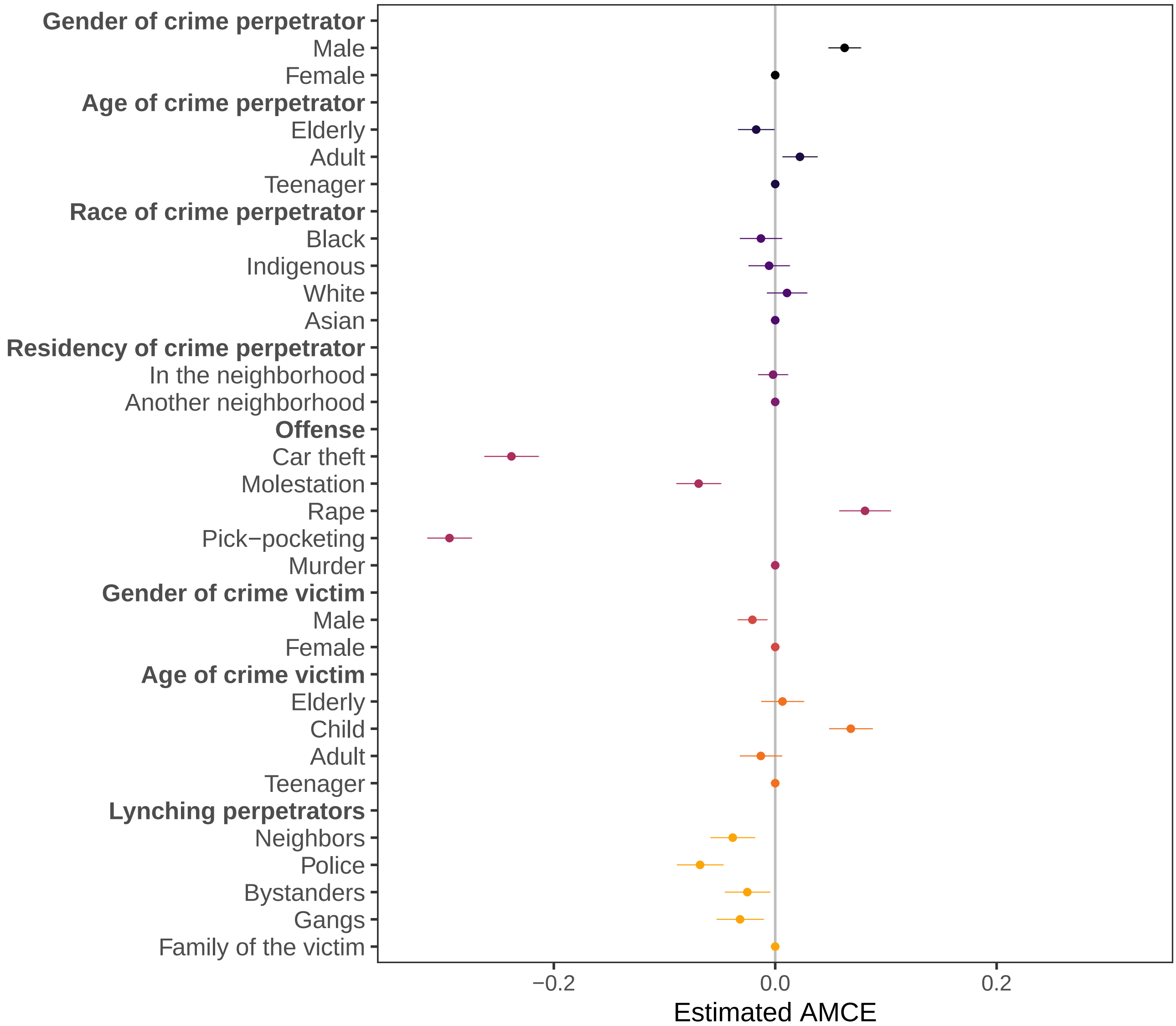
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.438 | 0.004 | 0.000 | 0.429 | 0.446 |
| Male | 0.548 | 0.003 | 0.000 | 0.541 | 0.554 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.498 | 0.005 | 0.650 | 0.488 | 0.508 |
| Adult | 0.520 | 0.005 | 0.000 | 0.510 | 0.529 |
| Elderly | 0.483 | 0.005 | 0.000 | 0.473 | 0.492 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.499 | 0.006 | 0.887 | 0.487 | 0.511 |
| White | 0.512 | 0.006 | 0.050 | 0.500 | 0.523 |
| Indigenous | 0.499 | 0.006 | 0.924 | 0.487 | 0.511 |
| Black | 0.490 | 0.006 | 0.092 | 0.478 | 0.502 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.004 | 0.668 | 0.491 | 0.506 |
| In the neighborhood | 0.502 | 0.004 | 0.668 | 0.495 | 0.509 |
| **Offense** | | | | | |
| Murder | 0.608 | 0.006 | 0.000 | 0.595 | 0.620 |
| Pick-pocketing | 0.314 | 0.006 | 0.000 | 0.302 | 0.326 |
| Rape | 0.719 | 0.009 | 0.000 | 0.702 | 0.735 |
| Molestation | 0.538 | 0.006 | 0.000 | 0.525 | 0.550 |
| Car theft | 0.351 | 0.009 | 0.000 | 0.333 | 0.369 |
| **Gender of crime victim** | | | | | |
| Female | 0.511 | 0.004 | 0.002 | 0.504 | 0.518 |
| Male | 0.489 | 0.004 | 0.002 | 0.482 | 0.496 |
| **Age of crime victim** | | | | | |
| Teenager | 0.505 | 0.007 | 0.474 | 0.492 | 0.517 |
| Adult | 0.464 | 0.006 | 0.000 | 0.453 | 0.474 |
| Child | 0.571 | 0.007 | 0.000 | 0.558 | 0.584 |
| Elderly | 0.479 | 0.006 | 0.000 | 0.469 | 0.490 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.534 | 0.007 | 0.000 | 0.521 | 0.548 |
| Gangs | 0.502 | 0.007 | 0.815 | 0.487 | 0.516 |
| Bystanders | 0.505 | 0.007 | 0.450 | 0.492 | 0.519 |
| Police | 0.467 | 0.007 | 0.000 | 0.453 | 0.481 |
| Neighbors | 0.492 | 0.007 | 0.262 | 0.479 | 0.506 |

## C.3 Average Marginal Component Effect (AMCE) Estimator

We also estimate AMCE coefficients for our conjoint experiment. This method selects one reference category for each attribute and looks at changes from the baseline level. The reference categories are marked as zero in our models.

```
amces <- cj(conjoint_data, fm, id = ~response_id)
```

```
plot(amces, vline = 0.0, header_fmt = "%s") +
  theme(legend.position = "none",
        axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
table_mm(amces, capt = "Average Marginal Component Effects -- Full Model")
```

Table 14: Average Marginal Component Effects – Full Model

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.000 | NA | NA | NA | NA |
| Male | 0.063 | 0.007 | 0.000 | 0.048 | 0.077 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.000 | NA | NA | NA | NA |
| Adult | 0.022 | 0.008 | 0.005 | 0.007 | 0.038 |
| Elderly | -0.017 | 0.008 | 0.038 | -0.033 | -0.001 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.000 | NA | NA | NA | NA |
| White | 0.011 | 0.009 | 0.248 | -0.007 | 0.029 |
| Indigenous | -0.006 | 0.009 | 0.557 | -0.024 | 0.013 |
| Black | -0.013 | 0.010 | 0.181 | -0.032 | 0.006 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.000 | NA | NA | NA | NA |
| In the neighborhood | -0.002 | 0.007 | 0.776 | -0.015 | 0.011 |
| **Offense** | | | | | |
| Murder | 0.000 | NA | NA | NA | NA |
| Pick-pocketing | -0.294 | 0.010 | 0.000 | -0.314 | -0.274 |
| Rape | 0.081 | 0.012 | 0.000 | 0.058 | 0.104 |
| Molestation | -0.069 | 0.010 | 0.000 | -0.089 | -0.049 |
| Car theft | -0.238 | 0.012 | 0.000 | -0.263 | -0.214 |
| **Gender of crime victim** | | | | | |
| Female | 0.000 | NA | NA | NA | NA |
| Male | -0.021 | 0.007 | 0.002 | -0.034 | -0.007 |
| **Age of crime victim** | | | | | |
| Teenager | 0.000 | NA | NA | NA | NA |
| Adult | -0.013 | 0.010 | 0.179 | -0.032 | 0.006 |
| Child | 0.068 | 0.010 | 0.000 | 0.049 | 0.088 |
| Elderly | 0.007 | 0.010 | 0.504 | -0.013 | 0.026 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.000 | NA | NA | NA | NA |
| Gangs | -0.032 | 0.011 | 0.003 | -0.053 | -0.011 |
| Bystanders | -0.025 | 0.010 | 0.015 | -0.046 | -0.005 |
| Police | -0.068 | 0.011 | 0.000 | -0.089 | -0.047 |
| Neighbors | -0.038 | 0.010 | 0.000 | -0.058 | -0.018 |

## C.4 Subgroup Analyses

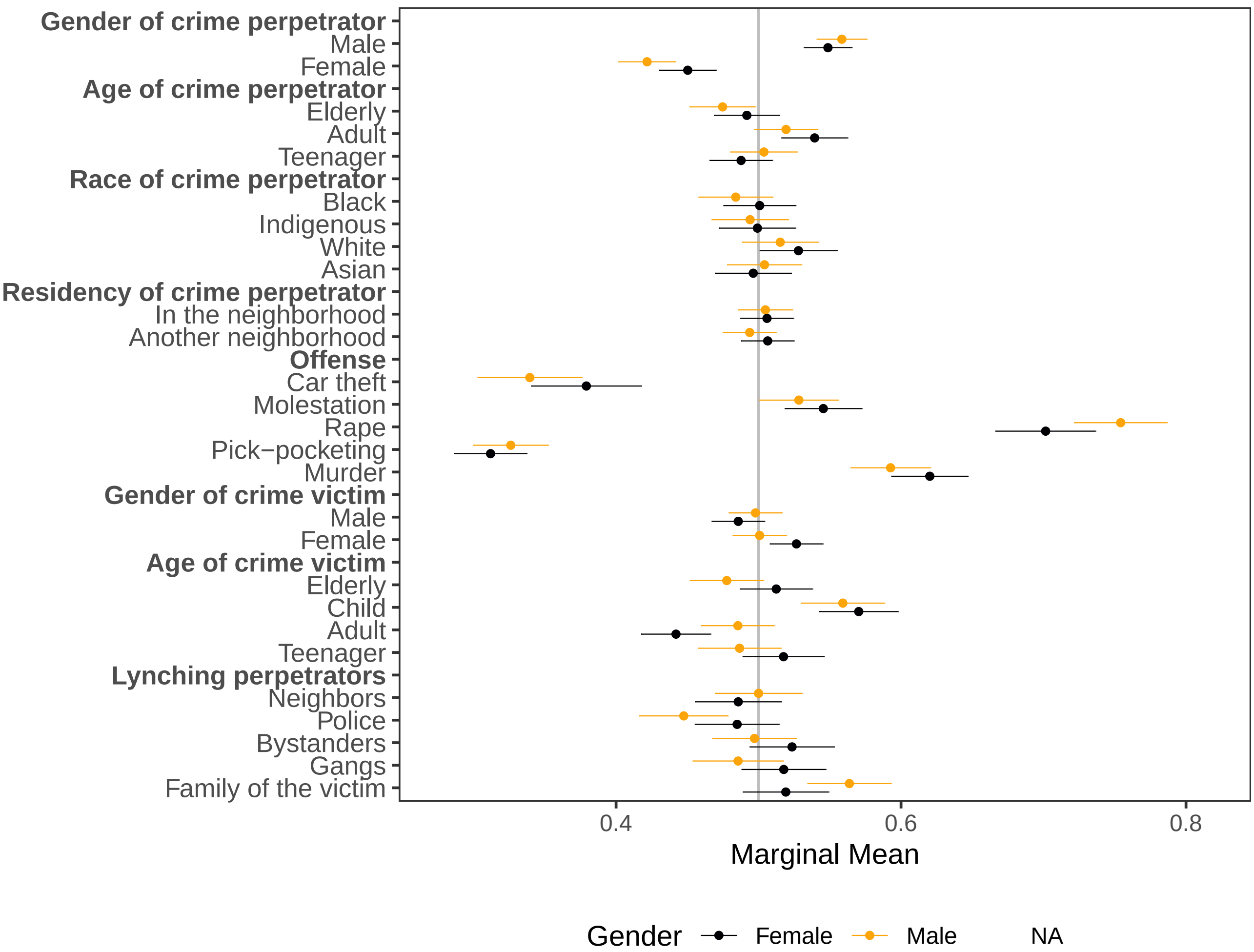
In this subsection, we test whether our results vary according to individual characteristics, such as gender, age, race, income, support for death penalty, and the respondents' opinions on the judicial system and the police forces. All models report marginal means. As we shall see, the results are very robust across all model specifications.

### C.4.1 Gender

Results do not seem to vary according to the gender of the respondent. We focus here on the differences between males and females and exclude the 11 observations in which respondents preferred not to say their gender or marked "other" in our questionnaire. Across all conjoint experiment attributes, we see an overlap between the 95% confidence intervals for males and females.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(gender) %>%
  filter(gender == c("Male", "Female"))
cjdt$Gender <- factor(cjdt$gender)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Gender)

# Plot
plot(mm_by, group = "Gender", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```r
# Tables

table_mm_by <- function(mm_by, capt) {

dfr <- data.frame(feature = mm_by[, c(5)],

                  round(mm_by[, c(6, 7, 9, 10, 11)], digits = 3))

names(dfr) <- c("Feature", "Estimate", "Std. Error",

                "P-Value", "Lower", "Upper")

return(kbl(dfr, "latex", caption = capt, linesep = "",

           booktabs = TRUE) %>%

kable_styling(font_size = 12, full_width = TRUE,

              latex_options = "hold_position") %>%

pack_rows("Gender of crime perpetrator", 1, 2) %>%

pack_rows("Age of crime perpetrator", 3, 5) %>%

pack_rows("Race of crime perpetrator", 6, 9) %>%

pack_rows("Residency of crime perpetrator", 10, 11) %>%

pack_rows("Offense", 12, 16) %>%

pack_rows("Gender of crime victim", 17, 18) %>%

pack_rows("Age of crime victim", 19, 22) %>%

pack_rows("Lynching perpetrators", 23, 27) %>%
```

```
column_spec(1, width = "6cm"))
}
```

```
mm_females <- mm_by %>% filter(BY == "Female")
table_mm_by(mm_females, capt = "Marginal Means -- Females")
```

Table 15: Marginal Means – Females

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.450 | 0.010 | 0.000 | 0.430 | 0.470 |
| Male | 0.549 | 0.009 | 0.000 | 0.532 | 0.566 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.488 | 0.011 | 0.278 | 0.466 | 0.510 |
| Adult | 0.539 | 0.012 | 0.001 | 0.516 | 0.563 |
| Elderly | 0.492 | 0.012 | 0.485 | 0.469 | 0.515 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.496 | 0.014 | 0.784 | 0.469 | 0.523 |
| White | 0.528 | 0.014 | 0.044 | 0.501 | 0.555 |
| Indigenous | 0.499 | 0.014 | 0.954 | 0.472 | 0.526 |
| Black | 0.501 | 0.013 | 0.951 | 0.475 | 0.526 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.506 | 0.009 | 0.499 | 0.488 | 0.525 |
| In the neighborhood | 0.506 | 0.010 | 0.535 | 0.487 | 0.525 |
| **Offense** | | | | | |
| Murder | 0.620 | 0.014 | 0.000 | 0.593 | 0.647 |
| Pick-pocketing | 0.312 | 0.013 | 0.000 | 0.286 | 0.338 |
| Rape | 0.701 | 0.018 | 0.000 | 0.666 | 0.737 |
| Molestation | 0.545 | 0.014 | 0.001 | 0.518 | 0.573 |
| Car theft | 0.379 | 0.020 | 0.000 | 0.340 | 0.418 |
| **Gender of crime victim** | | | | | |
| Female | 0.527 | 0.010 | 0.005 | 0.508 | 0.545 |
| Male | 0.486 | 0.010 | 0.133 | 0.467 | 0.504 |
| **Age of crime victim** | | | | | |
| Teenager | 0.518 | 0.015 | 0.232 | 0.489 | 0.546 |
| Adult | 0.442 | 0.012 | 0.000 | 0.418 | 0.466 |
| Child | 0.570 | 0.014 | 0.000 | 0.542 | 0.598 |
| Elderly | 0.512 | 0.013 | 0.341 | 0.487 | 0.538 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.519 | 0.015 | 0.215 | 0.489 | 0.549 |
| Gangs | 0.518 | 0.015 | 0.242 | 0.488 | 0.547 |
| Bystanders | 0.523 | 0.015 | 0.121 | 0.494 | 0.553 |
| Police | 0.485 | 0.015 | 0.322 | 0.455 | 0.515 |
| Neighbors | 0.486 | 0.016 | 0.358 | 0.455 | 0.516 |

```
mm_males <- mm_by %>% filter(BY == "Male")
table_mm_by(mm_males, capt = "Marginal Means -- Males")
```

Table 16: Marginal Means – Males

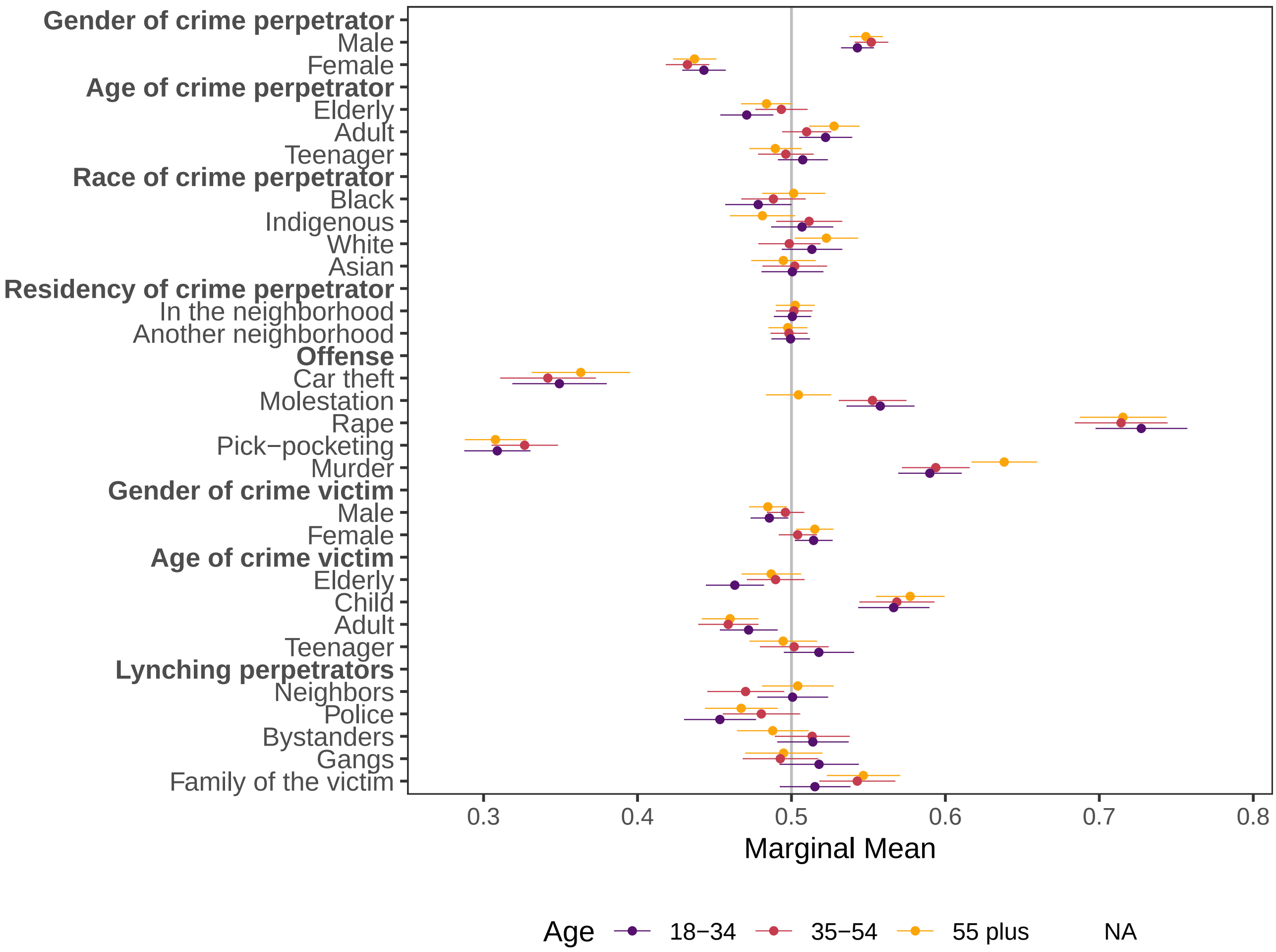
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.422 | 0.010 | 0.000 | 0.402 | 0.442 |
| Male | 0.558 | 0.009 | 0.000 | 0.541 | 0.576 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.504 | 0.012 | 0.754 | 0.480 | 0.527 |
| Adult | 0.519 | 0.011 | 0.091 | 0.497 | 0.542 |
| Elderly | 0.475 | 0.012 | 0.033 | 0.452 | 0.498 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.504 | 0.013 | 0.757 | 0.478 | 0.530 |
| White | 0.515 | 0.014 | 0.263 | 0.489 | 0.542 |
| Indigenous | 0.494 | 0.014 | 0.666 | 0.467 | 0.521 |
| Black | 0.484 | 0.013 | 0.229 | 0.458 | 0.510 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.494 | 0.010 | 0.519 | 0.475 | 0.513 |
| In the neighborhood | 0.505 | 0.010 | 0.625 | 0.486 | 0.524 |
| **Offense** | | | | | |
| Murder | 0.593 | 0.014 | 0.000 | 0.565 | 0.621 |
| Pick-pocketing | 0.326 | 0.013 | 0.000 | 0.300 | 0.353 |
| Rape | 0.754 | 0.017 | 0.000 | 0.721 | 0.787 |
| Molestation | 0.528 | 0.014 | 0.048 | 0.500 | 0.556 |
| Car theft | 0.339 | 0.019 | 0.000 | 0.303 | 0.376 |
| **Gender of crime victim** | | | | | |
| Female | 0.501 | 0.010 | 0.937 | 0.482 | 0.520 |
| Male | 0.498 | 0.010 | 0.823 | 0.479 | 0.517 |
| **Age of crime victim** | | | | | |
| Teenager | 0.487 | 0.015 | 0.373 | 0.457 | 0.516 |
| Adult | 0.485 | 0.013 | 0.269 | 0.460 | 0.511 |
| Child | 0.559 | 0.015 | 0.000 | 0.530 | 0.589 |
| Elderly | 0.478 | 0.013 | 0.092 | 0.452 | 0.504 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.564 | 0.015 | 0.000 | 0.534 | 0.593 |
| Gangs | 0.486 | 0.016 | 0.376 | 0.454 | 0.517 |
| Bystanders | 0.497 | 0.015 | 0.851 | 0.468 | 0.527 |
| Police | 0.447 | 0.016 | 0.001 | 0.416 | 0.479 |
| Neighbors | 0.500 | 0.016 | 1.000 | 0.469 | 0.531 |

### C.4.2 Age

As our age variable is continuous, we divide the data into three age brackets: 18-34 years old, 35-54 years old, and 55+ years old. The results show that seniors (55+) are more likely to select profiles that include murder as an offense, and less inclined to choose cases involving molestation. The remaining attributes show little variation.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(age) %>%
  mutate(age2 = case_when(age >= 18 & age <= 34 ~ "18-34", age >= 35 & age <= 54 ~ "35-54",
                          age >= 55 ~ "55 plus", TRUE ~ as.character(age)))
cjdt$Age <- factor(cjdt$age2)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Age)

# Plot
plot(mm_by, group = "Age", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8, begin = 0.25)
```



```r
# Tables
mm_young <- mm_by %>% filter(BY == "18-34")
table_mm_by(mm_young, capt = "Marginal Means -- 18-34 Years Old")
```

Table 17: Marginal Means – 18-34 Years Old

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.443 | 0.007 | 0.000 | 0.429 | 0.457 |
| Male | 0.543 | 0.005 | 0.000 | 0.532 | 0.553 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.507 | 0.008 | 0.370 | 0.491 | 0.523 |
| Adult | 0.522 | 0.009 | 0.011 | 0.505 | 0.539 |
| Elderly | 0.471 | 0.009 | 0.001 | 0.454 | 0.488 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.501 | 0.010 | 0.955 | 0.481 | 0.521 |
| White | 0.513 | 0.010 | 0.182 | 0.494 | 0.533 |
| Indigenous | 0.507 | 0.010 | 0.501 | 0.487 | 0.527 |
| Black | 0.478 | 0.011 | 0.047 | 0.457 | 0.500 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.499 | 0.006 | 0.926 | 0.487 | 0.512 |
| In the neighborhood | 0.501 | 0.006 | 0.926 | 0.489 | 0.513 |
| **Offense** | | | | | |
| Murder | 0.590 | 0.010 | 0.000 | 0.569 | 0.610 |
| Pick-pocketing | 0.309 | 0.011 | 0.000 | 0.288 | 0.330 |
| Rape | 0.727 | 0.015 | 0.000 | 0.698 | 0.757 |
| Molestation | 0.558 | 0.011 | 0.000 | 0.536 | 0.580 |
| Car theft | 0.349 | 0.016 | 0.000 | 0.319 | 0.380 |
| **Gender of crime victim** | | | | | |
| Female | 0.514 | 0.006 | 0.020 | 0.502 | 0.526 |
| Male | 0.486 | 0.006 | 0.020 | 0.474 | 0.498 |
| **Age of crime victim** | | | | | |
| Teenager | 0.518 | 0.012 | 0.124 | 0.495 | 0.540 |
| Adult | 0.472 | 0.009 | 0.003 | 0.454 | 0.491 |
| Child | 0.566 | 0.012 | 0.000 | 0.543 | 0.589 |
| Elderly | 0.463 | 0.010 | 0.000 | 0.444 | 0.482 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.515 | 0.012 | 0.191 | 0.492 | 0.538 |
| Gangs | 0.518 | 0.013 | 0.170 | 0.492 | 0.544 |
| Bystanders | 0.514 | 0.012 | 0.237 | 0.491 | 0.537 |
| Police | 0.454 | 0.012 | 0.000 | 0.430 | 0.477 |
| Neighbors | 0.501 | 0.012 | 0.950 | 0.478 | 0.524 |

```r
mm_adult <- mm_by %>% filter(BY == "35-54")
table_mm_by(mm_adult, capt = "Marginal Means -- 35-54 Years Old")
```

Table 18: Marginal Means – 35-54 Years Old

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.432 | 0.007 | 0.000 | 0.418 | 0.446 |
| Male | 0.552 | 0.006 | 0.000 | 0.541 | 0.563 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.496 | 0.009 | 0.685 | 0.478 | 0.514 |
| Adult | 0.510 | 0.008 | 0.221 | 0.494 | 0.526 |
| Elderly | 0.493 | 0.009 | 0.445 | 0.477 | 0.510 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.502 | 0.011 | 0.845 | 0.481 | 0.523 |
| White | 0.499 | 0.010 | 0.888 | 0.479 | 0.519 |
| Indigenous | 0.511 | 0.011 | 0.292 | 0.490 | 0.533 |
| Black | 0.488 | 0.011 | 0.268 | 0.467 | 0.509 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.006 | 0.788 | 0.486 | 0.510 |
| In the neighborhood | 0.502 | 0.006 | 0.788 | 0.490 | 0.513 |
| **Offense** | | | | | |
| Murder | 0.594 | 0.011 | 0.000 | 0.572 | 0.616 |
| Pick-pocketing | 0.327 | 0.011 | 0.000 | 0.305 | 0.348 |
| Rape | 0.714 | 0.015 | 0.000 | 0.684 | 0.744 |
| Molestation | 0.553 | 0.011 | 0.000 | 0.531 | 0.574 |
| Car theft | 0.342 | 0.016 | 0.000 | 0.311 | 0.373 |
| **Gender of crime victim** | | | | | |
| Female | 0.504 | 0.006 | 0.520 | 0.492 | 0.516 |
| Male | 0.496 | 0.006 | 0.520 | 0.484 | 0.508 |
| **Age of crime victim** | | | | | |
| Teenager | 0.502 | 0.011 | 0.877 | 0.480 | 0.524 |
| Adult | 0.459 | 0.010 | 0.000 | 0.440 | 0.478 |
| Child | 0.568 | 0.012 | 0.000 | 0.544 | 0.593 |
| Elderly | 0.490 | 0.009 | 0.277 | 0.471 | 0.508 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.543 | 0.013 | 0.001 | 0.518 | 0.567 |
| Gangs | 0.493 | 0.012 | 0.560 | 0.468 | 0.517 |
| Bystanders | 0.513 | 0.012 | 0.277 | 0.489 | 0.538 |
| Police | 0.480 | 0.013 | 0.125 | 0.455 | 0.505 |
| Neighbors | 0.470 | 0.013 | 0.019 | 0.445 | 0.495 |

```
mm_senior <- mm_by %>% filter(BY == "55 plus")

table_mm_by(mm_senior, capt = "Marginal Means -- 55+ Years Old")
```

Table 19: Marginal Means – 55+ Years Old

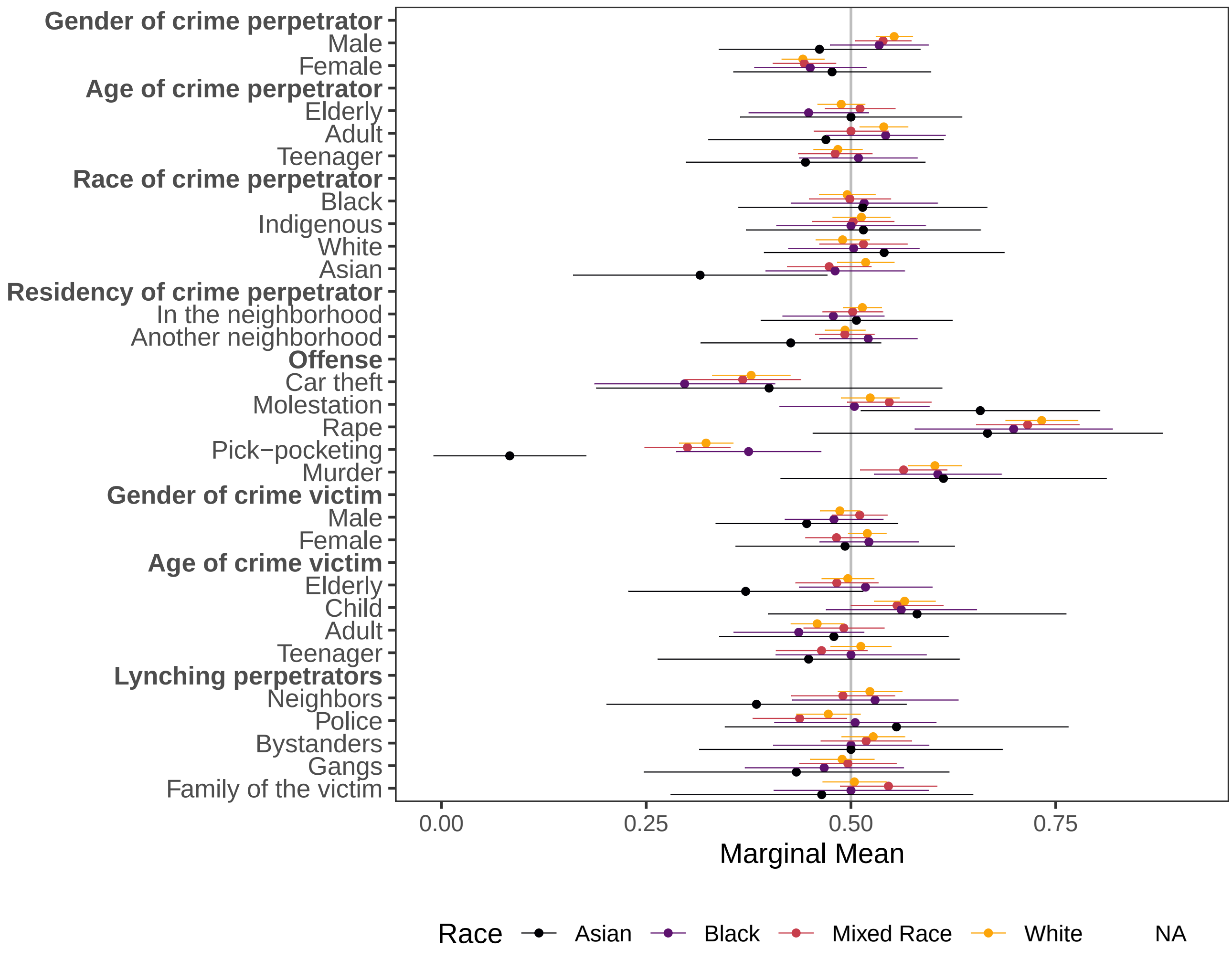
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.437 | 0.007 | 0.000 | 0.423 | 0.451 |
| Male | 0.548 | 0.005 | 0.000 | 0.538 | 0.559 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.489 | 0.009 | 0.221 | 0.473 | 0.506 |
| Adult | 0.528 | 0.008 | 0.001 | 0.511 | 0.544 |
| Elderly | 0.484 | 0.008 | 0.052 | 0.467 | 0.500 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.495 | 0.011 | 0.618 | 0.474 | 0.515 |
| White | 0.523 | 0.010 | 0.030 | 0.502 | 0.543 |
| Indigenous | 0.481 | 0.011 | 0.079 | 0.460 | 0.502 |
| Black | 0.501 | 0.010 | 0.892 | 0.481 | 0.522 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.006 | 0.707 | 0.485 | 0.510 |
| In the neighborhood | 0.502 | 0.006 | 0.707 | 0.490 | 0.515 |
| **Offense** | | | | | |
| Murder | 0.638 | 0.011 | 0.000 | 0.617 | 0.659 |
| Pick-pocketing | 0.308 | 0.010 | 0.000 | 0.288 | 0.328 |
| Rape | 0.715 | 0.014 | 0.000 | 0.687 | 0.743 |
| Molestation | 0.505 | 0.011 | 0.673 | 0.484 | 0.526 |
| Car theft | 0.363 | 0.016 | 0.000 | 0.331 | 0.395 |
| **Gender of crime victim** | | | | | |
| Female | 0.515 | 0.006 | 0.013 | 0.503 | 0.527 |
| Male | 0.485 | 0.006 | 0.013 | 0.473 | 0.497 |
| **Age of crime victim** | | | | | |
| Teenager | 0.495 | 0.011 | 0.627 | 0.473 | 0.516 |
| Adult | 0.460 | 0.009 | 0.000 | 0.442 | 0.478 |
| Child | 0.577 | 0.011 | 0.000 | 0.555 | 0.599 |
| Elderly | 0.487 | 0.010 | 0.177 | 0.468 | 0.506 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.547 | 0.012 | 0.000 | 0.523 | 0.570 |
| Gangs | 0.495 | 0.013 | 0.690 | 0.470 | 0.520 |
| Bystanders | 0.488 | 0.012 | 0.303 | 0.465 | 0.511 |
| Police | 0.467 | 0.012 | 0.006 | 0.444 | 0.491 |
| Neighbors | 0.504 | 0.012 | 0.728 | 0.481 | 0.527 |

### C.4.3 Race

Below are our results when we disaggregate the data by race. We find that they are almost identical is all dimensions except for offense. Asian respondents are much less likely to select profiles that contain pickpocketing as a crime.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(race) %>%
  filter(race == c("Asian", "Black", "Mixed Race", "White"))
cjdt$Race <- factor(cjdt$race)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Race)


# Plot
plot(mm_by, group = "Race", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
# Tables
```

```r
mm_asian <- mm_by %>% filter(BY == "Asian")

table_mm_by(mm_asian, capt = "Marginal Means -- Asian")
```

Table 20: Marginal Means – Asian

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.477 | 0.061 | 0.707 | 0.356 | 0.597 |
| Male | 0.462 | 0.063 | 0.540 | 0.338 | 0.585 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.444 | 0.075 | 0.456 | 0.298 | 0.591 |
| Adult | 0.469 | 0.073 | 0.676 | 0.326 | 0.613 |
| Elderly | 0.500 | 0.069 | 1.000 | 0.365 | 0.635 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.316 | 0.079 | 0.020 | 0.161 | 0.471 |
| White | 0.541 | 0.075 | 0.588 | 0.394 | 0.687 |
| Indigenous | 0.515 | 0.073 | 0.836 | 0.372 | 0.658 |
| Black | 0.514 | 0.077 | 0.854 | 0.363 | 0.666 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.426 | 0.056 | 0.190 | 0.316 | 0.536 |
| In the neighborhood | 0.507 | 0.060 | 0.911 | 0.390 | 0.624 |
| **Offense** | | | | | |
| Murder | 0.613 | 0.101 | 0.266 | 0.414 | 0.812 |
| Pick-pocketing | 0.083 | 0.047 | 0.000 | -0.010 | 0.176 |
| Rape | 0.667 | 0.109 | 0.126 | 0.453 | 0.880 |
| Molestation | 0.658 | 0.074 | 0.034 | 0.512 | 0.804 |
| Car theft | 0.400 | 0.108 | 0.353 | 0.189 | 0.611 |
| **Gender of crime victim** | | | | | |
| Female | 0.493 | 0.068 | 0.915 | 0.359 | 0.626 |
| Male | 0.446 | 0.057 | 0.341 | 0.335 | 0.557 |
| **Age of crime victim** | | | | | |
| Teenager | 0.448 | 0.094 | 0.582 | 0.264 | 0.633 |
| Adult | 0.479 | 0.071 | 0.771 | 0.339 | 0.619 |
| Child | 0.581 | 0.093 | 0.385 | 0.399 | 0.763 |
| Elderly | 0.371 | 0.073 | 0.079 | 0.228 | 0.515 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.464 | 0.094 | 0.704 | 0.280 | 0.649 |
| Gangs | 0.433 | 0.095 | 0.483 | 0.247 | 0.620 |
| Bystanders | 0.500 | 0.095 | 1.000 | 0.315 | 0.685 |
| Police | 0.556 | 0.107 | 0.603 | 0.346 | 0.765 |
| Neighbors | 0.385 | 0.093 | 0.217 | 0.202 | 0.568 |

```r
mm_black <- mm_by %>% filter(BY == "Black")

table_mm_by(mm_black, capt = "Marginal Means -- Black")
```

```r
mm_mixed <- mm_by %>% filter(BY == "Mixed Race")

table_mm_by(mm_mixed, capt = "Marginal Means -- Mixed Race")
```

Table 21: Marginal Means – Black

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.450 | 0.035 | 0.153 | 0.382 | 0.519 |
| Male | 0.534 | 0.031 | 0.261 | 0.474 | 0.595 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.509 | 0.037 | 0.805 | 0.437 | 0.581 |
| Adult | 0.542 | 0.037 | 0.255 | 0.469 | 0.615 |
| Elderly | 0.448 | 0.037 | 0.166 | 0.375 | 0.521 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.481 | 0.043 | 0.654 | 0.396 | 0.565 |
| White | 0.503 | 0.041 | 0.935 | 0.423 | 0.583 |
| Indigenous | 0.500 | 0.046 | 1.000 | 0.409 | 0.591 |
| Black | 0.516 | 0.046 | 0.724 | 0.426 | 0.606 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.521 | 0.030 | 0.489 | 0.461 | 0.581 |
| In the neighborhood | 0.478 | 0.032 | 0.496 | 0.416 | 0.540 |
| **Offense** | | | | | |
| Murder | 0.606 | 0.040 | 0.008 | 0.528 | 0.684 |
| Pick-pocketing | 0.375 | 0.045 | 0.006 | 0.287 | 0.463 |
| Rape | 0.699 | 0.062 | 0.001 | 0.578 | 0.819 |
| Molestation | 0.504 | 0.047 | 0.928 | 0.413 | 0.596 |
| Car theft | 0.297 | 0.056 | 0.000 | 0.187 | 0.407 |
| **Gender of crime victim** | | | | | |
| Female | 0.522 | 0.031 | 0.476 | 0.462 | 0.582 |
| Male | 0.479 | 0.031 | 0.498 | 0.419 | 0.539 |
| **Age of crime victim** | | | | | |
| Teenager | 0.500 | 0.047 | 1.000 | 0.408 | 0.592 |
| Adult | 0.436 | 0.041 | 0.116 | 0.357 | 0.516 |
| Child | 0.561 | 0.047 | 0.190 | 0.469 | 0.653 |
| Elderly | 0.518 | 0.041 | 0.669 | 0.436 | 0.599 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.500 | 0.048 | 1.000 | 0.406 | 0.594 |
| Gangs | 0.467 | 0.049 | 0.508 | 0.370 | 0.564 |
| Bystanders | 0.500 | 0.049 | 1.000 | 0.405 | 0.595 |
| Police | 0.505 | 0.050 | 0.919 | 0.406 | 0.604 |
| Neighbors | 0.529 | 0.052 | 0.570 | 0.428 | 0.631 |

```
mm_white <- mm_by %>% filter(BY == "White")

table_mm_by(mm_white, capt = "Marginal Means -- White")
```

Table 22: Marginal Means – Mixed Race

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.443 | 0.020 | 0.004 | 0.404 | 0.481 |
| Male | 0.539 | 0.018 | 0.025 | 0.505 | 0.574 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.481 | 0.023 | 0.402 | 0.436 | 0.526 |
| Adult | 0.500 | 0.023 | 1.000 | 0.454 | 0.546 |
| Elderly | 0.511 | 0.022 | 0.613 | 0.468 | 0.554 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.473 | 0.026 | 0.310 | 0.422 | 0.525 |
| White | 0.515 | 0.027 | 0.578 | 0.462 | 0.569 |
| Indigenous | 0.503 | 0.025 | 0.916 | 0.453 | 0.553 |
| Black | 0.499 | 0.025 | 0.956 | 0.449 | 0.548 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.492 | 0.019 | 0.685 | 0.456 | 0.529 |
| In the neighborhood | 0.502 | 0.019 | 0.913 | 0.465 | 0.539 |
| **Offense** | | | | | |
| Murder | 0.564 | 0.027 | 0.018 | 0.511 | 0.617 |
| Pick-pocketing | 0.300 | 0.027 | 0.000 | 0.248 | 0.353 |
| Rape | 0.716 | 0.032 | 0.000 | 0.653 | 0.779 |
| Molestation | 0.547 | 0.026 | 0.075 | 0.495 | 0.598 |
| Car theft | 0.368 | 0.036 | 0.000 | 0.297 | 0.439 |
| **Gender of crime victim** | | | | | |
| Female | 0.482 | 0.019 | 0.361 | 0.444 | 0.520 |
| Male | 0.511 | 0.017 | 0.536 | 0.477 | 0.545 |
| **Age of crime victim** | | | | | |
| Teenager | 0.464 | 0.028 | 0.206 | 0.408 | 0.520 |
| Adult | 0.491 | 0.025 | 0.729 | 0.442 | 0.541 |
| Child | 0.556 | 0.029 | 0.051 | 0.500 | 0.613 |
| Elderly | 0.483 | 0.026 | 0.501 | 0.432 | 0.533 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.546 | 0.030 | 0.130 | 0.487 | 0.605 |
| Gangs | 0.496 | 0.030 | 0.900 | 0.437 | 0.555 |
| Bystanders | 0.519 | 0.028 | 0.513 | 0.463 | 0.574 |
| Police | 0.437 | 0.029 | 0.032 | 0.380 | 0.495 |
| Neighbors | 0.490 | 0.032 | 0.762 | 0.427 | 0.554 |

Table 23: Marginal Means – White

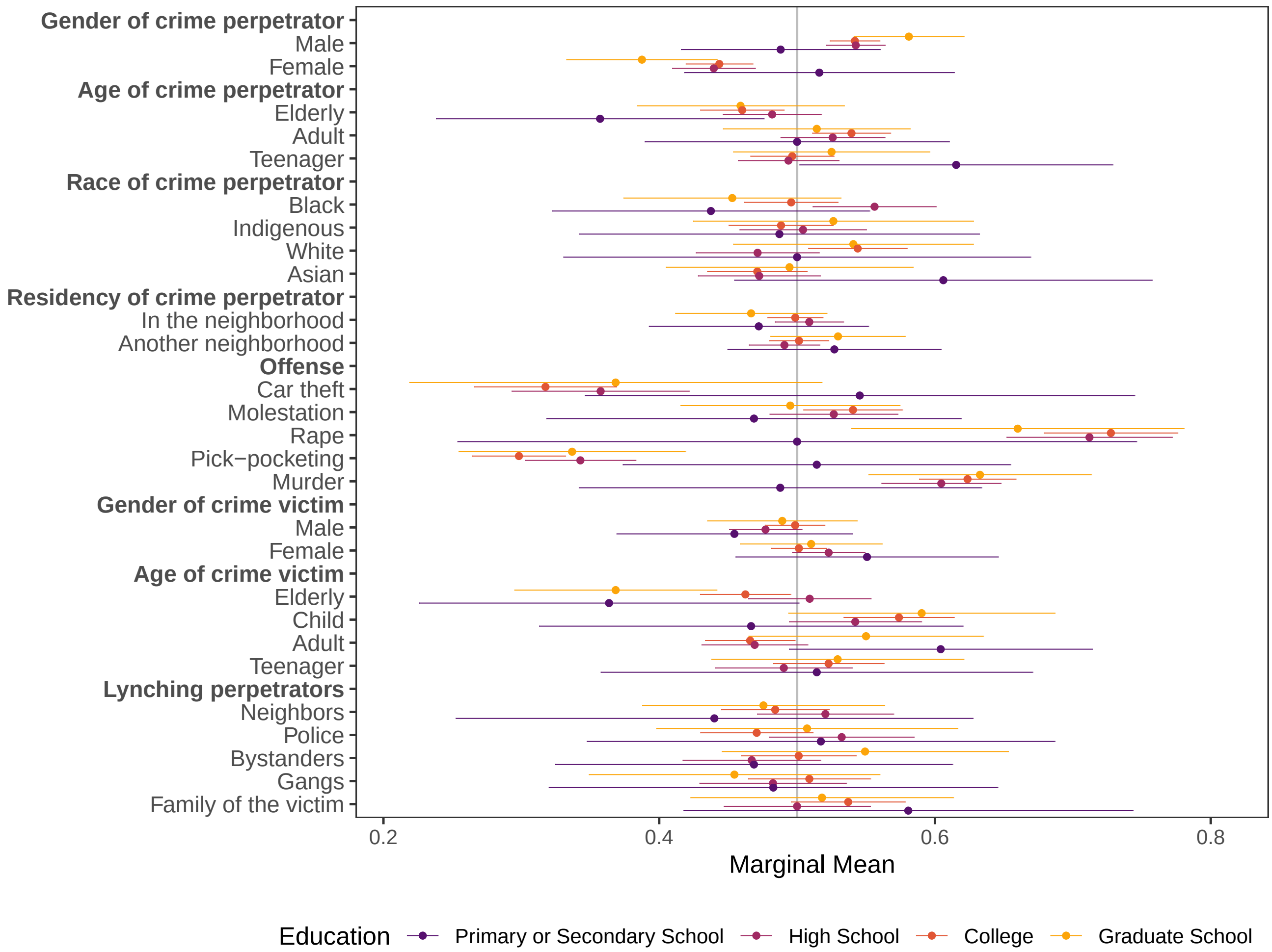
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.441 | 0.013 | 0.000 | 0.415 | 0.467 |
| Male | 0.553 | 0.011 | 0.000 | 0.530 | 0.575 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.484 | 0.015 | 0.292 | 0.454 | 0.514 |
| Adult | 0.540 | 0.015 | 0.008 | 0.511 | 0.569 |
| Elderly | 0.488 | 0.015 | 0.419 | 0.459 | 0.517 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.518 | 0.018 | 0.312 | 0.483 | 0.553 |
| White | 0.490 | 0.017 | 0.541 | 0.457 | 0.523 |
| Indigenous | 0.513 | 0.018 | 0.479 | 0.478 | 0.548 |
| Black | 0.495 | 0.018 | 0.793 | 0.461 | 0.530 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.493 | 0.013 | 0.561 | 0.468 | 0.517 |
| In the neighborhood | 0.514 | 0.012 | 0.242 | 0.491 | 0.537 |
| **Offense** | | | | | |
| Murder | 0.602 | 0.017 | 0.000 | 0.570 | 0.635 |
| Pick-pocketing | 0.323 | 0.017 | 0.000 | 0.290 | 0.356 |
| Rape | 0.733 | 0.023 | 0.000 | 0.689 | 0.777 |
| Molestation | 0.523 | 0.018 | 0.197 | 0.488 | 0.559 |
| Car theft | 0.378 | 0.024 | 0.000 | 0.330 | 0.426 |
| **Gender of crime victim** | | | | | |
| Female | 0.520 | 0.012 | 0.097 | 0.496 | 0.544 |
| Male | 0.486 | 0.012 | 0.274 | 0.462 | 0.511 |
| **Age of crime victim** | | | | | |
| Teenager | 0.512 | 0.019 | 0.525 | 0.475 | 0.549 |
| Adult | 0.459 | 0.016 | 0.012 | 0.426 | 0.491 |
| Child | 0.565 | 0.019 | 0.001 | 0.528 | 0.603 |
| Elderly | 0.496 | 0.016 | 0.812 | 0.464 | 0.528 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.504 | 0.020 | 0.833 | 0.465 | 0.543 |
| Gangs | 0.489 | 0.020 | 0.589 | 0.450 | 0.528 |
| Bystanders | 0.527 | 0.020 | 0.168 | 0.489 | 0.566 |
| Police | 0.472 | 0.020 | 0.166 | 0.433 | 0.512 |
| Neighbors | 0.523 | 0.020 | 0.248 | 0.484 | 0.562 |

### C.4.4 Education

Next, we divide our data according to respondents' level of education. As the number of interviewees with primary or secondary education is low, we merge them into a single category, while the other levels (high school, college, and graduate school) remain the same as in our questionnaire.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(education) %>%
  filter(education == c("College", "Graduate School",
                        "Primary School", "Secondary School",
                        "High School")) %>%
  mutate(education2 = case_when(education == "Primary School" ~ "Primary or Secondary School",
                                education == "Secondary School" ~ "Primary or Secondary School",
                                TRUE ~ as.character(education)),
         education2 = fct_relevel(education2, "Primary or Secondary School",
                                  "High School", "College", "Graduate School"))
cjdt$Education <- factor(cjdt$education2)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Education)

# Plot
plot(mm_by, group = "Education", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8, begin = 0.25)
```




```r
# Tables

mm_pri_sec <- mm_by %>% filter(BY == "Primary or Secondary School")

table_mm_by(mm_pri_sec, capt = "Marginal Means -- Primary or Secondary School Degree")


mm_high <- mm_by %>% filter(BY == "High School")

table_mm_by(mm_high, capt = "Marginal Means -- High School Degree")


mm_college <- mm_by %>% filter(BY == "College")

table_mm_by(mm_college, capt = "Marginal Means -- College Degree")


mm_grad <- mm_by %>% filter(BY == "Graduate School")

table_mm_by(mm_grad, capt = "Marginal Means -- Graduate School Degree")
```

Table 24: Marginal Means – Primary or Secondary School Degree

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.516 | 0.050 | 0.747 | 0.418 | 0.614 |
| Male | 0.488 | 0.037 | 0.747 | 0.416 | 0.560 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.615 | 0.058 | 0.047 | 0.502 | 0.729 |
| Adult | 0.500 | 0.056 | 1.000 | 0.390 | 0.610 |
| Elderly | 0.357 | 0.061 | 0.019 | 0.238 | 0.476 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.606 | 0.077 | 0.170 | 0.454 | 0.758 |
| White | 0.500 | 0.086 | 1.000 | 0.331 | 0.669 |
| Indigenous | 0.487 | 0.074 | 0.862 | 0.342 | 0.632 |
| Black | 0.437 | 0.059 | 0.288 | 0.322 | 0.553 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.527 | 0.040 | 0.494 | 0.450 | 0.605 |
| In the neighborhood | 0.472 | 0.041 | 0.494 | 0.393 | 0.552 |
| **Offense** | | | | | |
| Murder | 0.488 | 0.075 | 0.870 | 0.342 | 0.634 |
| Pick-pocketing | 0.514 | 0.072 | 0.842 | 0.374 | 0.655 |
| Rape | 0.500 | 0.126 | 1.000 | 0.254 | 0.746 |
| Molestation | 0.469 | 0.077 | 0.684 | 0.318 | 0.619 |
| Car theft | 0.545 | 0.102 | 0.655 | 0.346 | 0.745 |
| **Gender of crime victim** | | | | | |
| Female | 0.551 | 0.049 | 0.297 | 0.455 | 0.646 |
| Male | 0.455 | 0.044 | 0.297 | 0.369 | 0.540 |
| **Age of crime victim** | | | | | |
| Teenager | 0.514 | 0.080 | 0.858 | 0.358 | 0.671 |
| Adult | 0.604 | 0.056 | 0.063 | 0.494 | 0.714 |
| Child | 0.467 | 0.078 | 0.671 | 0.313 | 0.620 |
| Elderly | 0.364 | 0.070 | 0.052 | 0.226 | 0.501 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.581 | 0.083 | 0.332 | 0.418 | 0.744 |
| Gangs | 0.483 | 0.083 | 0.836 | 0.320 | 0.646 |
| Bystanders | 0.469 | 0.074 | 0.671 | 0.325 | 0.613 |
| Police | 0.517 | 0.087 | 0.842 | 0.347 | 0.687 |
| Neighbors | 0.440 | 0.096 | 0.531 | 0.252 | 0.628 |

Table 25: Marginal Means – High School Degree

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.440 | 0.015 | 0.000 | 0.409 | 0.470 |
| Male | 0.543 | 0.011 | 0.000 | 0.521 | 0.564 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.494 | 0.019 | 0.738 | 0.457 | 0.530 |
| Adult | 0.526 | 0.019 | 0.181 | 0.488 | 0.564 |
| Elderly | 0.482 | 0.018 | 0.322 | 0.446 | 0.518 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.473 | 0.023 | 0.225 | 0.428 | 0.517 |
| White | 0.471 | 0.023 | 0.210 | 0.427 | 0.516 |
| Indigenous | 0.504 | 0.023 | 0.854 | 0.458 | 0.550 |
| Black | 0.556 | 0.023 | 0.014 | 0.511 | 0.601 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.491 | 0.013 | 0.484 | 0.465 | 0.517 |
| In the neighborhood | 0.509 | 0.013 | 0.484 | 0.484 | 0.534 |
| **Offense** | | | | | |
| Murder | 0.605 | 0.022 | 0.000 | 0.561 | 0.648 |
| Pick-pocketing | 0.343 | 0.021 | 0.000 | 0.303 | 0.383 |
| Rape | 0.712 | 0.031 | 0.000 | 0.652 | 0.772 |
| Molestation | 0.527 | 0.024 | 0.262 | 0.480 | 0.573 |
| Car theft | 0.358 | 0.033 | 0.000 | 0.293 | 0.422 |
| **Gender of crime victim** | | | | | |
| Female | 0.523 | 0.013 | 0.090 | 0.496 | 0.549 |
| Male | 0.477 | 0.013 | 0.090 | 0.451 | 0.504 |
| **Age of crime victim** | | | | | |
| Teenager | 0.490 | 0.025 | 0.704 | 0.441 | 0.540 |
| Adult | 0.469 | 0.020 | 0.118 | 0.431 | 0.508 |
| Child | 0.542 | 0.025 | 0.086 | 0.494 | 0.590 |
| Elderly | 0.509 | 0.023 | 0.688 | 0.465 | 0.554 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.500 | 0.027 | 1.000 | 0.447 | 0.553 |
| Gangs | 0.483 | 0.027 | 0.520 | 0.429 | 0.536 |
| Bystanders | 0.467 | 0.026 | 0.198 | 0.417 | 0.517 |
| Police | 0.532 | 0.027 | 0.228 | 0.480 | 0.585 |
| Neighbors | 0.521 | 0.025 | 0.416 | 0.471 | 0.570 |

Table 26: Marginal Means – College Degree

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.444 | 0.012 | 0.000 | 0.419 | 0.468 |
| Male | 0.542 | 0.009 | 0.000 | 0.524 | 0.560 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.496 | 0.015 | 0.819 | 0.466 | 0.527 |
| Adult | 0.539 | 0.014 | 0.006 | 0.511 | 0.568 |
| Elderly | 0.460 | 0.016 | 0.010 | 0.430 | 0.491 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.471 | 0.019 | 0.119 | 0.435 | 0.507 |
| White | 0.544 | 0.018 | 0.016 | 0.508 | 0.580 |
| Indigenous | 0.488 | 0.019 | 0.549 | 0.450 | 0.526 |
| Black | 0.496 | 0.017 | 0.805 | 0.462 | 0.530 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.501 | 0.011 | 0.897 | 0.480 | 0.523 |
| In the neighborhood | 0.499 | 0.010 | 0.897 | 0.479 | 0.519 |
| **Offense** | | | | | |
| Murder | 0.624 | 0.018 | 0.000 | 0.588 | 0.659 |
| Pick-pocketing | 0.298 | 0.017 | 0.000 | 0.264 | 0.332 |
| Rape | 0.728 | 0.025 | 0.000 | 0.679 | 0.776 |
| Molestation | 0.541 | 0.018 | 0.027 | 0.505 | 0.576 |
| Car theft | 0.318 | 0.026 | 0.000 | 0.266 | 0.369 |
| **Gender of crime victim** | | | | | |
| Female | 0.501 | 0.010 | 0.897 | 0.481 | 0.521 |
| Male | 0.499 | 0.011 | 0.897 | 0.477 | 0.520 |
| **Age of crime victim** | | | | | |
| Teenager | 0.523 | 0.021 | 0.265 | 0.483 | 0.563 |
| Adult | 0.466 | 0.017 | 0.041 | 0.433 | 0.499 |
| Child | 0.574 | 0.020 | 0.000 | 0.534 | 0.614 |
| Elderly | 0.463 | 0.017 | 0.026 | 0.430 | 0.495 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.537 | 0.021 | 0.080 | 0.496 | 0.579 |
| Gangs | 0.509 | 0.023 | 0.694 | 0.464 | 0.553 |
| Bystanders | 0.501 | 0.021 | 0.957 | 0.459 | 0.543 |
| Police | 0.471 | 0.021 | 0.160 | 0.430 | 0.512 |
| Neighbors | 0.484 | 0.020 | 0.427 | 0.445 | 0.523 |

Table 27: Marginal Means – Graduate School Degree

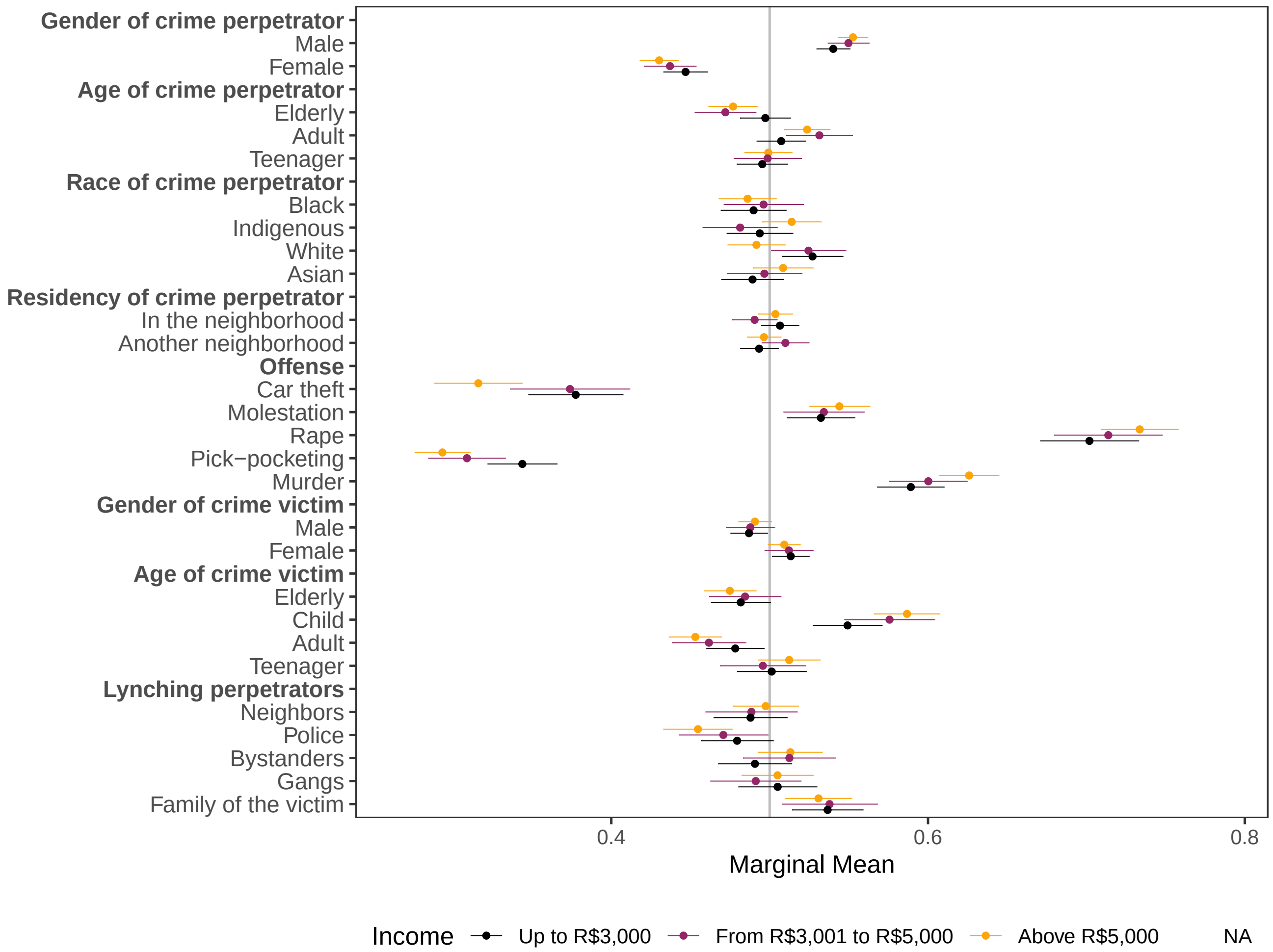
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.387 | 0.028 | 0.000 | 0.333 | 0.442 |
| Male | 0.581 | 0.020 | 0.000 | 0.541 | 0.621 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.525 | 0.036 | 0.492 | 0.454 | 0.596 |
| Adult | 0.514 | 0.035 | 0.681 | 0.446 | 0.582 |
| Elderly | 0.459 | 0.038 | 0.286 | 0.384 | 0.534 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.495 | 0.046 | 0.904 | 0.405 | 0.584 |
| White | 0.541 | 0.044 | 0.358 | 0.454 | 0.628 |
| Indigenous | 0.526 | 0.052 | 0.612 | 0.425 | 0.628 |
| Black | 0.453 | 0.040 | 0.243 | 0.374 | 0.532 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.530 | 0.025 | 0.235 | 0.481 | 0.579 |
| In the neighborhood | 0.467 | 0.028 | 0.235 | 0.412 | 0.522 |
| **Offense** | | | | | |
| Murder | 0.633 | 0.041 | 0.001 | 0.552 | 0.714 |
| Pick-pocketing | 0.337 | 0.042 | 0.000 | 0.254 | 0.419 |
| Rape | 0.660 | 0.062 | 0.009 | 0.539 | 0.781 |
| Molestation | 0.495 | 0.041 | 0.903 | 0.415 | 0.575 |
| Car theft | 0.368 | 0.076 | 0.085 | 0.219 | 0.518 |
| **Gender of crime victim** | | | | | |
| Female | 0.510 | 0.026 | 0.698 | 0.459 | 0.562 |
| Male | 0.489 | 0.028 | 0.698 | 0.435 | 0.544 |
| **Age of crime victim** | | | | | |
| Teenager | 0.529 | 0.047 | 0.529 | 0.438 | 0.621 |
| Adult | 0.550 | 0.043 | 0.250 | 0.465 | 0.635 |
| Child | 0.590 | 0.049 | 0.067 | 0.494 | 0.687 |
| Elderly | 0.368 | 0.037 | 0.000 | 0.295 | 0.442 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.518 | 0.049 | 0.710 | 0.423 | 0.613 |
| Gangs | 0.455 | 0.054 | 0.399 | 0.349 | 0.560 |
| Bystanders | 0.549 | 0.053 | 0.353 | 0.445 | 0.653 |
| Police | 0.507 | 0.056 | 0.897 | 0.398 | 0.617 |
| Neighbors | 0.476 | 0.045 | 0.587 | 0.388 | 0.564 |

### C.4.5 Household Income

We also disaggregate the results by monthly household income. As some categories have few respondents, we group them into three categories: (i) up to R$3,000 (US$550); (ii) from R$3,001 to R$5,000 (US$550-915); and (iii) above R$5,000 (US$915+). The levels roughly represent low, middle, and high-income households. We find no considerable differences among them.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(household_income) %>%
  mutate(household_income2 = case_when(household_income == "Up to R$1,000" ~ "Up to R$3,000",
                                       household_income == "From R$1,001 to R$2,000" ~ "Up to R$3,000",
                                       household_income == "From R$2,001 to R$3,000" ~ "Up to R$3,000",
                                       household_income == "From R$3,001 to R$5,000" ~ "From R$3,001 to R$5,000",
                                       household_income == "From R$5,001 to R$10,000" ~ "Above R$5,000",
                                       household_income == "From R$10,001 to R$20,000" ~ "Above R$5,000",
                                       household_income == "Above R$20,000" ~ "Above R$5,000",
                                       TRUE ~ NA_character_),
         household_income2 = fct_relevel(household_income2, "Up to R$3,000", "From R$3,001 to R$5,000",
                                         "Above R$5,000"))
cjdt$Income <- factor(cjdt$household_income2)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Income)

# Plot
plot(mm_by, group = "Income", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
# Tables

mm_3k <- mm_by %>% filter(BY == "Up to R$3,000")

table_mm_by(mm_3k, capt = "Marginal Means -- Up to 3,000 BRL")


mm_5k <- mm_by %>% filter(BY == "From R$3,001 to R$5,000")

table_mm_by(mm_5k, capt = "Marginal Means -- From 3,001 to 5,000 BRL")


mm_abv5k <- mm_by %>% filter(BY == "Above R$5,000")

table_mm_by(mm_abv5k, capt = "Marginal Means -- Above 5,000 BRL")
```

Table 28: Marginal Means – Up to 3,000 BRL

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.447 | 0.007 | 0.000 | 0.433 | 0.461 |
| Male | 0.540 | 0.005 | 0.000 | 0.530 | 0.551 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.495 | 0.008 | 0.567 | 0.479 | 0.511 |
| Adult | 0.507 | 0.008 | 0.356 | 0.492 | 0.523 |
| Elderly | 0.497 | 0.008 | 0.738 | 0.481 | 0.513 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.489 | 0.010 | 0.282 | 0.469 | 0.509 |
| White | 0.527 | 0.010 | 0.006 | 0.508 | 0.546 |
| Indigenous | 0.494 | 0.011 | 0.558 | 0.473 | 0.515 |
| Black | 0.490 | 0.011 | 0.337 | 0.469 | 0.511 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.493 | 0.006 | 0.281 | 0.481 | 0.505 |
| In the neighborhood | 0.507 | 0.006 | 0.282 | 0.495 | 0.518 |
| **Offense** | | | | | |
| Murder | 0.589 | 0.011 | 0.000 | 0.568 | 0.610 |
| Pick-pocketing | 0.344 | 0.011 | 0.000 | 0.322 | 0.366 |
| Rape | 0.702 | 0.016 | 0.000 | 0.671 | 0.733 |
| Molestation | 0.532 | 0.011 | 0.003 | 0.511 | 0.554 |
| Car theft | 0.378 | 0.015 | 0.000 | 0.348 | 0.407 |
| **Gender of crime victim** | | | | | |
| Female | 0.513 | 0.006 | 0.028 | 0.501 | 0.525 |
| Male | 0.487 | 0.006 | 0.029 | 0.475 | 0.499 |
| **Age of crime victim** | | | | | |
| Teenager | 0.501 | 0.011 | 0.907 | 0.479 | 0.523 |
| Adult | 0.478 | 0.009 | 0.019 | 0.460 | 0.496 |
| Child | 0.549 | 0.011 | 0.000 | 0.527 | 0.571 |
| Elderly | 0.482 | 0.010 | 0.057 | 0.463 | 0.501 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.537 | 0.011 | 0.001 | 0.514 | 0.559 |
| Gangs | 0.505 | 0.013 | 0.689 | 0.480 | 0.530 |
| Bystanders | 0.491 | 0.012 | 0.432 | 0.468 | 0.514 |
| Police | 0.479 | 0.012 | 0.078 | 0.457 | 0.502 |
| Neighbors | 0.488 | 0.012 | 0.309 | 0.465 | 0.511 |

Table 29: Marginal Means – From 3,001 to 5,000 BRL

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.437 | 0.008 | 0.000 | 0.421 | 0.454 |
| Male | 0.550 | 0.007 | 0.000 | 0.537 | 0.563 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.499 | 0.011 | 0.907 | 0.477 | 0.520 |
| Adult | 0.531 | 0.011 | 0.003 | 0.511 | 0.552 |
| Elderly | 0.472 | 0.010 | 0.004 | 0.453 | 0.491 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.497 | 0.012 | 0.783 | 0.473 | 0.520 |
| White | 0.525 | 0.012 | 0.041 | 0.501 | 0.548 |
| Indigenous | 0.481 | 0.012 | 0.123 | 0.458 | 0.505 |
| Black | 0.496 | 0.013 | 0.764 | 0.471 | 0.521 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.510 | 0.008 | 0.191 | 0.495 | 0.525 |
| In the neighborhood | 0.491 | 0.007 | 0.191 | 0.476 | 0.505 |
| **Offense** | | | | | |
| Murder | 0.600 | 0.013 | 0.000 | 0.575 | 0.625 |
| Pick-pocketing | 0.309 | 0.012 | 0.000 | 0.284 | 0.333 |
| Rape | 0.714 | 0.017 | 0.000 | 0.680 | 0.748 |
| Molestation | 0.534 | 0.013 | 0.008 | 0.509 | 0.560 |
| Car theft | 0.374 | 0.019 | 0.000 | 0.336 | 0.412 |
| **Gender of crime victim** | | | | | |
| Female | 0.512 | 0.008 | 0.121 | 0.497 | 0.528 |
| Male | 0.488 | 0.008 | 0.121 | 0.472 | 0.503 |
| **Age of crime victim** | | | | | |
| Teenager | 0.496 | 0.014 | 0.756 | 0.469 | 0.523 |
| Adult | 0.462 | 0.012 | 0.001 | 0.438 | 0.485 |
| Child | 0.576 | 0.015 | 0.000 | 0.547 | 0.604 |
| Elderly | 0.484 | 0.012 | 0.179 | 0.462 | 0.507 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.538 | 0.015 | 0.014 | 0.508 | 0.568 |
| Gangs | 0.491 | 0.015 | 0.547 | 0.463 | 0.520 |
| Bystanders | 0.512 | 0.015 | 0.404 | 0.483 | 0.542 |
| Police | 0.471 | 0.014 | 0.042 | 0.443 | 0.499 |
| Neighbors | 0.488 | 0.015 | 0.435 | 0.460 | 0.517 |

Table 30: Marginal Means – Above 5,000 BRL

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.430 | 0.006 | 0.000 | 0.418 | 0.442 |
| Male | 0.553 | 0.005 | 0.000 | 0.543 | 0.562 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.499 | 0.008 | 0.912 | 0.484 | 0.514 |
| Adult | 0.524 | 0.007 | 0.001 | 0.509 | 0.538 |
| Elderly | 0.477 | 0.008 | 0.004 | 0.461 | 0.492 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.509 | 0.010 | 0.377 | 0.490 | 0.527 |
| White | 0.492 | 0.009 | 0.369 | 0.473 | 0.510 |
| Indigenous | 0.514 | 0.009 | 0.142 | 0.495 | 0.533 |
| Black | 0.486 | 0.009 | 0.134 | 0.468 | 0.504 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.496 | 0.005 | 0.512 | 0.486 | 0.507 |
| In the neighborhood | 0.504 | 0.006 | 0.512 | 0.493 | 0.514 |
| **Offense** | | | | | |
| Murder | 0.626 | 0.010 | 0.000 | 0.607 | 0.645 |
| Pick-pocketing | 0.293 | 0.009 | 0.000 | 0.276 | 0.311 |
| Rape | 0.734 | 0.013 | 0.000 | 0.709 | 0.758 |
| Molestation | 0.544 | 0.010 | 0.000 | 0.525 | 0.563 |
| Car theft | 0.316 | 0.014 | 0.000 | 0.288 | 0.344 |
| **Gender of crime victim** | | | | | |
| Female | 0.509 | 0.005 | 0.081 | 0.499 | 0.520 |
| Male | 0.491 | 0.005 | 0.081 | 0.480 | 0.501 |
| **Age of crime victim** | | | | | |
| Teenager | 0.512 | 0.010 | 0.213 | 0.493 | 0.532 |
| Adult | 0.453 | 0.008 | 0.000 | 0.437 | 0.470 |
| Child | 0.587 | 0.011 | 0.000 | 0.566 | 0.607 |
| Elderly | 0.475 | 0.008 | 0.003 | 0.458 | 0.491 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.531 | 0.011 | 0.004 | 0.510 | 0.552 |
| Gangs | 0.505 | 0.012 | 0.667 | 0.482 | 0.528 |
| Bystanders | 0.513 | 0.010 | 0.205 | 0.493 | 0.533 |
| Police | 0.455 | 0.011 | 0.000 | 0.433 | 0.477 |
| Neighbors | 0.498 | 0.011 | 0.813 | 0.477 | 0.518 |

### C.4.6 Political Ideology

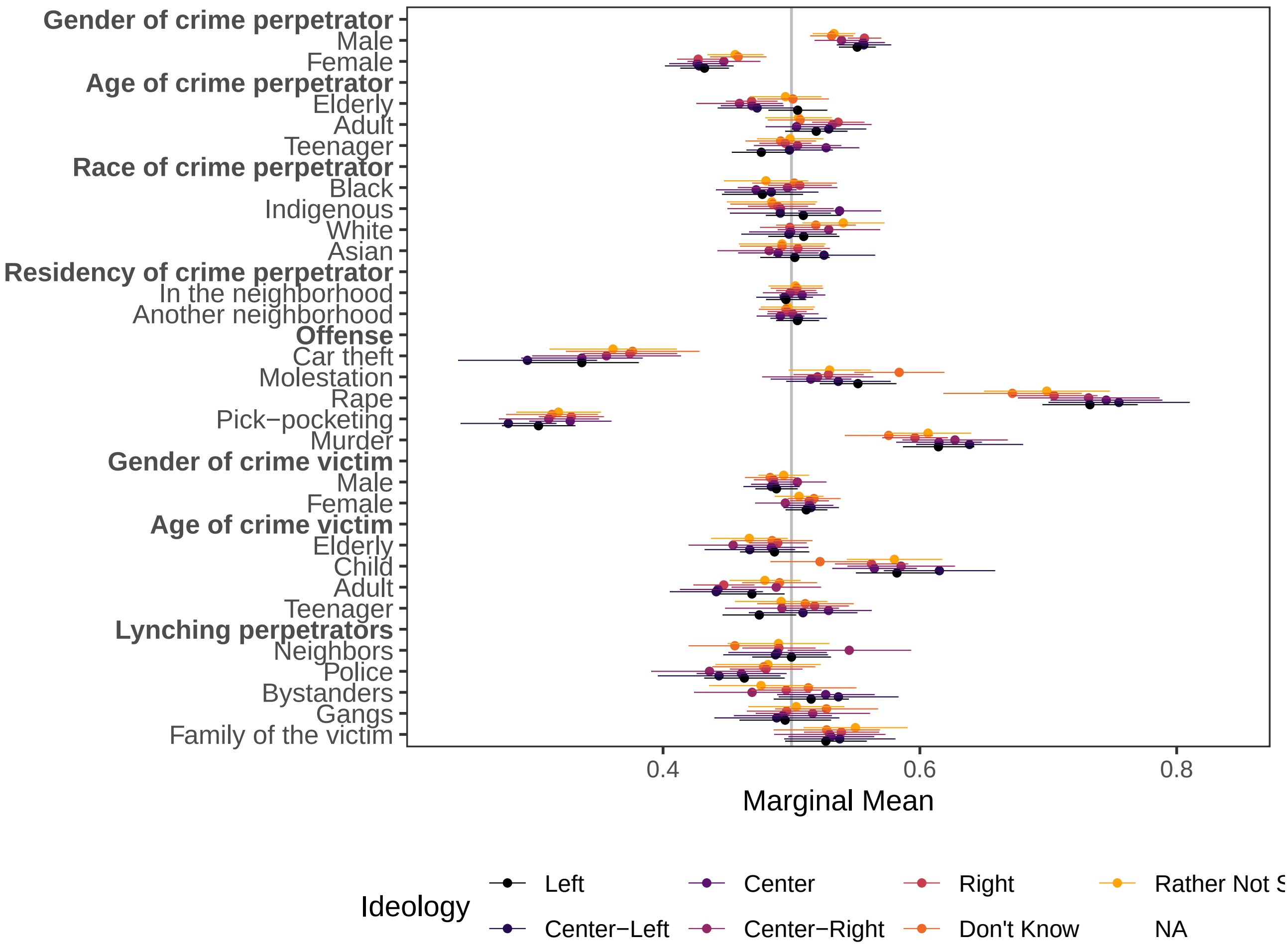
Here we disaggregate the results according to political ideology. We see that political views do not change the overall responses.

```r
# Model

cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(ideology)
cjdt$Ideology <- factor(cjdt$ideology)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by =
            ~Ideology)


# Plot

plot(mm_by, group = "Ideology", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```r
# Tables

mm_left <- mm_by %>% filter(BY == "Left")
table_mm_by(mm_left, capt = "Marginal Means -- Left")
```

Table 31: Marginal Means – Left

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.432 | 0.010 | 0.000 | 0.413 | 0.451 |
| Male | 0.551 | 0.007 | 0.000 | 0.537 | 0.565 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.477 | 0.012 | 0.045 | 0.454 | 0.500 |
| Adult | 0.519 | 0.012 | 0.116 | 0.495 | 0.543 |
| Elderly | 0.505 | 0.012 | 0.676 | 0.482 | 0.528 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.503 | 0.014 | 0.850 | 0.476 | 0.529 |
| White | 0.510 | 0.014 | 0.497 | 0.482 | 0.537 |
| Indigenous | 0.509 | 0.015 | 0.534 | 0.480 | 0.538 |
| Black | 0.477 | 0.016 | 0.156 | 0.446 | 0.509 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.505 | 0.008 | 0.582 | 0.488 | 0.521 |
| In the neighborhood | 0.496 | 0.008 | 0.582 | 0.480 | 0.511 |
| **Offense** | | | | | |
| Murder | 0.614 | 0.014 | 0.000 | 0.587 | 0.642 |
| Pick-pocketing | 0.303 | 0.014 | 0.000 | 0.275 | 0.331 |
| Rape | 0.732 | 0.019 | 0.000 | 0.695 | 0.769 |
| Molestation | 0.552 | 0.015 | 0.001 | 0.522 | 0.581 |
| Car theft | 0.337 | 0.023 | 0.000 | 0.293 | 0.381 |
| **Gender of crime victim** | | | | | |
| Female | 0.512 | 0.008 | 0.160 | 0.495 | 0.528 |
| Male | 0.488 | 0.008 | 0.159 | 0.472 | 0.505 |
| **Age of crime victim** | | | | | |
| Teenager | 0.475 | 0.015 | 0.085 | 0.446 | 0.503 |
| Adult | 0.469 | 0.013 | 0.016 | 0.444 | 0.494 |
| Child | 0.582 | 0.016 | 0.000 | 0.550 | 0.614 |
| Elderly | 0.487 | 0.014 | 0.333 | 0.460 | 0.514 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.527 | 0.016 | 0.097 | 0.495 | 0.558 |
| Gangs | 0.495 | 0.018 | 0.786 | 0.460 | 0.531 |
| Bystanders | 0.515 | 0.015 | 0.301 | 0.486 | 0.544 |
| Police | 0.463 | 0.016 | 0.021 | 0.432 | 0.494 |
| Neighbors | 0.500 | 0.016 | 1.000 | 0.470 | 0.530 |

```r
mm_center_left <- mm_by %>% filter(BY == "Center-Left")

table_mm_by(mm_center_left, capt = "Marginal Means -- Center-Left")
```

```r
mm_center <- mm_by %>% filter(BY == "Center")

table_mm_by(mm_center, capt = "Marginal Means -- Center")
```

```r
mm_center_right <- mm_by %>% filter(BY == "Center-Right")

table_mm_by(mm_center_right, capt = "Marginal Means -- Center-Right")
```

Table 32: Marginal Means – Center-Left

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.428 | 0.014 | 0.000 | 0.402 | 0.455 |
| Male | 0.556 | 0.011 | 0.000 | 0.535 | 0.577 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.498 | 0.017 | 0.928 | 0.465 | 0.532 |
| Adult | 0.529 | 0.015 | 0.049 | 0.500 | 0.558 |
| Elderly | 0.473 | 0.016 | 0.087 | 0.443 | 0.504 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.525 | 0.020 | 0.207 | 0.486 | 0.565 |
| White | 0.498 | 0.019 | 0.916 | 0.461 | 0.535 |
| Indigenous | 0.491 | 0.020 | 0.663 | 0.452 | 0.530 |
| Black | 0.484 | 0.019 | 0.398 | 0.448 | 0.521 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.505 | 0.011 | 0.623 | 0.484 | 0.527 |
| In the neighborhood | 0.495 | 0.011 | 0.623 | 0.473 | 0.516 |
| **Offense** | | | | | |
| Murder | 0.639 | 0.021 | 0.000 | 0.597 | 0.680 |
| Pick-pocketing | 0.280 | 0.019 | 0.000 | 0.242 | 0.317 |
| Rape | 0.755 | 0.028 | 0.000 | 0.700 | 0.810 |
| Molestation | 0.536 | 0.021 | 0.077 | 0.496 | 0.577 |
| Car theft | 0.294 | 0.028 | 0.000 | 0.240 | 0.348 |
| **Gender of crime victim** | | | | | |
| Female | 0.515 | 0.011 | 0.163 | 0.494 | 0.537 |
| Male | 0.484 | 0.011 | 0.159 | 0.463 | 0.506 |
| **Age of crime victim** | | | | | |
| Teenager | 0.509 | 0.021 | 0.677 | 0.467 | 0.551 |
| Adult | 0.441 | 0.018 | 0.001 | 0.405 | 0.477 |
| Child | 0.615 | 0.022 | 0.000 | 0.572 | 0.658 |
| Elderly | 0.468 | 0.018 | 0.069 | 0.432 | 0.503 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.538 | 0.022 | 0.088 | 0.494 | 0.581 |
| Gangs | 0.488 | 0.025 | 0.641 | 0.440 | 0.537 |
| Bystanders | 0.537 | 0.024 | 0.123 | 0.490 | 0.583 |
| Police | 0.444 | 0.024 | 0.020 | 0.396 | 0.491 |
| Neighbors | 0.488 | 0.021 | 0.548 | 0.447 | 0.528 |

```
mm_right <- mm_by %>% filter(BY == "Right")

table_mm_by(mm_right, capt = "Marginal Means -- Right")


mm_dont_know <- mm_by %>% filter(BY == "Don't Know")

table_mm_by(mm_dont_know, capt = "Marginal Means -- Don't Know")


mm_not_say <- mm_by %>% filter(BY == "Rather Not Say")

table_mm_by(mm_not_say, capt = "Marginal Means -- Rather Not Say")
```

Table 33: Marginal Means – Center

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.427 | 0.011 | 0.000 | 0.405 | 0.448 |
| Male | 0.556 | 0.009 | 0.000 | 0.539 | 0.573 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.527 | 0.013 | 0.038 | 0.501 | 0.553 |
| Adult | 0.504 | 0.012 | 0.748 | 0.480 | 0.528 |
| Elderly | 0.469 | 0.012 | 0.013 | 0.445 | 0.494 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.490 | 0.016 | 0.518 | 0.459 | 0.521 |
| White | 0.499 | 0.016 | 0.968 | 0.467 | 0.532 |
| Indigenous | 0.537 | 0.016 | 0.022 | 0.505 | 0.570 |
| Black | 0.472 | 0.016 | 0.085 | 0.441 | 0.504 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.491 | 0.009 | 0.356 | 0.473 | 0.510 |
| In the neighborhood | 0.508 | 0.009 | 0.358 | 0.491 | 0.526 |
| **Offense** | | | | | |
| Murder | 0.615 | 0.017 | 0.000 | 0.582 | 0.648 |
| Pick-pocketing | 0.328 | 0.016 | 0.000 | 0.296 | 0.360 |
| Rape | 0.745 | 0.022 | 0.000 | 0.702 | 0.789 |
| Molestation | 0.515 | 0.016 | 0.344 | 0.484 | 0.546 |
| Car theft | 0.337 | 0.024 | 0.000 | 0.290 | 0.384 |
| **Gender of crime victim** | | | | | |
| Female | 0.514 | 0.009 | 0.137 | 0.496 | 0.532 |
| Male | 0.486 | 0.009 | 0.137 | 0.469 | 0.504 |
| **Age of crime victim** | | | | | |
| Teenager | 0.529 | 0.017 | 0.089 | 0.496 | 0.562 |
| Adult | 0.443 | 0.015 | 0.000 | 0.413 | 0.472 |
| Child | 0.565 | 0.017 | 0.000 | 0.532 | 0.597 |
| Elderly | 0.484 | 0.015 | 0.283 | 0.456 | 0.513 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.531 | 0.017 | 0.068 | 0.498 | 0.564 |
| Gangs | 0.493 | 0.019 | 0.727 | 0.455 | 0.531 |
| Bystanders | 0.527 | 0.019 | 0.167 | 0.489 | 0.564 |
| Police | 0.461 | 0.018 | 0.028 | 0.426 | 0.496 |
| Neighbors | 0.489 | 0.019 | 0.574 | 0.451 | 0.527 |

Table 34: Marginal Means – Center-Right

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.447 | 0.014 | 0.000 | 0.419 | 0.476 |
| Male | 0.539 | 0.011 | 0.000 | 0.518 | 0.560 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.505 | 0.017 | 0.787 | 0.471 | 0.538 |
| Adult | 0.532 | 0.015 | 0.037 | 0.502 | 0.562 |
| Elderly | 0.460 | 0.017 | 0.018 | 0.426 | 0.493 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.483 | 0.021 | 0.397 | 0.442 | 0.523 |
| White | 0.529 | 0.020 | 0.152 | 0.489 | 0.569 |
| Indigenous | 0.491 | 0.021 | 0.682 | 0.450 | 0.533 |
| Black | 0.497 | 0.020 | 0.875 | 0.458 | 0.535 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.501 | 0.010 | 0.920 | 0.481 | 0.521 |
| In the neighborhood | 0.499 | 0.011 | 0.920 | 0.478 | 0.520 |
| **Offense** | | | | | |
| Murder | 0.627 | 0.021 | 0.000 | 0.586 | 0.668 |
| Pick-pocketing | 0.311 | 0.020 | 0.000 | 0.272 | 0.350 |
| Rape | 0.731 | 0.028 | 0.000 | 0.676 | 0.786 |
| Molestation | 0.520 | 0.022 | 0.355 | 0.477 | 0.563 |
| Car theft | 0.356 | 0.029 | 0.000 | 0.298 | 0.414 |
| **Gender of crime victim** | | | | | |
| Female | 0.495 | 0.012 | 0.689 | 0.472 | 0.519 |
| Male | 0.505 | 0.011 | 0.689 | 0.482 | 0.527 |
| **Age of crime victim** | | | | | |
| Teenager | 0.493 | 0.023 | 0.740 | 0.448 | 0.537 |
| Adult | 0.488 | 0.018 | 0.501 | 0.453 | 0.523 |
| Child | 0.585 | 0.021 | 0.000 | 0.544 | 0.627 |
| Elderly | 0.455 | 0.018 | 0.010 | 0.420 | 0.489 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.530 | 0.022 | 0.178 | 0.487 | 0.573 |
| Gangs | 0.517 | 0.023 | 0.465 | 0.472 | 0.561 |
| Bystanders | 0.469 | 0.023 | 0.183 | 0.424 | 0.514 |
| Police | 0.436 | 0.023 | 0.006 | 0.391 | 0.482 |
| Neighbors | 0.545 | 0.024 | 0.066 | 0.497 | 0.593 |

Table 35: Marginal Means – Right

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.427 | 0.008 | 0.000 | 0.411 | 0.444 |
| Male | 0.557 | 0.007 | 0.000 | 0.544 | 0.570 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.495 | 0.010 | 0.635 | 0.475 | 0.515 |
| Adult | 0.536 | 0.010 | 0.000 | 0.516 | 0.557 |
| Elderly | 0.469 | 0.010 | 0.002 | 0.449 | 0.489 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.505 | 0.013 | 0.692 | 0.480 | 0.530 |
| White | 0.499 | 0.012 | 0.914 | 0.476 | 0.522 |
| Indigenous | 0.489 | 0.012 | 0.371 | 0.466 | 0.513 |
| Black | 0.506 | 0.013 | 0.607 | 0.482 | 0.531 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.497 | 0.008 | 0.648 | 0.482 | 0.512 |
| In the neighborhood | 0.504 | 0.008 | 0.648 | 0.488 | 0.519 |
| **Offense** | | | | | |
| Murder | 0.596 | 0.013 | 0.000 | 0.571 | 0.622 |
| Pick-pocketing | 0.329 | 0.013 | 0.000 | 0.303 | 0.354 |
| Rape | 0.705 | 0.017 | 0.000 | 0.671 | 0.738 |
| Molestation | 0.529 | 0.014 | 0.037 | 0.502 | 0.556 |
| Car theft | 0.374 | 0.019 | 0.000 | 0.338 | 0.411 |
| **Gender of crime victim** | | | | | |
| Female | 0.514 | 0.008 | 0.068 | 0.499 | 0.529 |
| Male | 0.486 | 0.008 | 0.069 | 0.471 | 0.501 |
| **Age of crime victim** | | | | | |
| Teenager | 0.518 | 0.014 | 0.182 | 0.492 | 0.544 |
| Adult | 0.447 | 0.012 | 0.000 | 0.424 | 0.471 |
| Child | 0.562 | 0.014 | 0.000 | 0.534 | 0.591 |
| Elderly | 0.489 | 0.011 | 0.349 | 0.467 | 0.512 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.539 | 0.015 | 0.009 | 0.510 | 0.568 |
| Gangs | 0.496 | 0.016 | 0.809 | 0.465 | 0.527 |
| Bystanders | 0.496 | 0.014 | 0.770 | 0.469 | 0.523 |
| Police | 0.480 | 0.014 | 0.167 | 0.452 | 0.508 |
| Neighbors | 0.490 | 0.014 | 0.498 | 0.462 | 0.519 |

Table 36: Marginal Means – Don't Know

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.458 | 0.011 | 0.000 | 0.437 | 0.480 |
| Male | 0.531 | 0.008 | 0.000 | 0.515 | 0.548 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.492 | 0.014 | 0.546 | 0.464 | 0.519 |
| Adult | 0.507 | 0.013 | 0.596 | 0.482 | 0.532 |
| Elderly | 0.501 | 0.014 | 0.935 | 0.473 | 0.529 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.493 | 0.017 | 0.656 | 0.460 | 0.525 |
| White | 0.519 | 0.016 | 0.228 | 0.488 | 0.550 |
| Indigenous | 0.485 | 0.017 | 0.382 | 0.452 | 0.518 |
| Black | 0.502 | 0.017 | 0.893 | 0.469 | 0.535 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.496 | 0.011 | 0.685 | 0.475 | 0.517 |
| In the neighborhood | 0.504 | 0.010 | 0.685 | 0.484 | 0.524 |
| **Offense** | | | | | |
| Murder | 0.576 | 0.017 | 0.000 | 0.542 | 0.610 |
| Pick-pocketing | 0.313 | 0.018 | 0.000 | 0.278 | 0.349 |
| Rape | 0.672 | 0.027 | 0.000 | 0.618 | 0.726 |
| Molestation | 0.584 | 0.018 | 0.000 | 0.549 | 0.619 |
| Car theft | 0.376 | 0.026 | 0.000 | 0.324 | 0.428 |
| **Gender of crime victim** | | | | | |
| Female | 0.518 | 0.010 | 0.094 | 0.497 | 0.538 |
| Male | 0.483 | 0.010 | 0.095 | 0.464 | 0.503 |
| **Age of crime victim** | | | | | |
| Teenager | 0.511 | 0.019 | 0.573 | 0.473 | 0.548 |
| Adult | 0.491 | 0.015 | 0.529 | 0.462 | 0.520 |
| Child | 0.522 | 0.020 | 0.259 | 0.484 | 0.561 |
| Elderly | 0.485 | 0.016 | 0.343 | 0.454 | 0.516 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.527 | 0.021 | 0.193 | 0.486 | 0.569 |
| Gangs | 0.527 | 0.020 | 0.181 | 0.487 | 0.567 |
| Bystanders | 0.513 | 0.019 | 0.488 | 0.476 | 0.550 |
| Police | 0.478 | 0.020 | 0.288 | 0.438 | 0.518 |
| Neighbors | 0.456 | 0.018 | 0.016 | 0.420 | 0.492 |

Table 37: Marginal Means – Rather Not Say

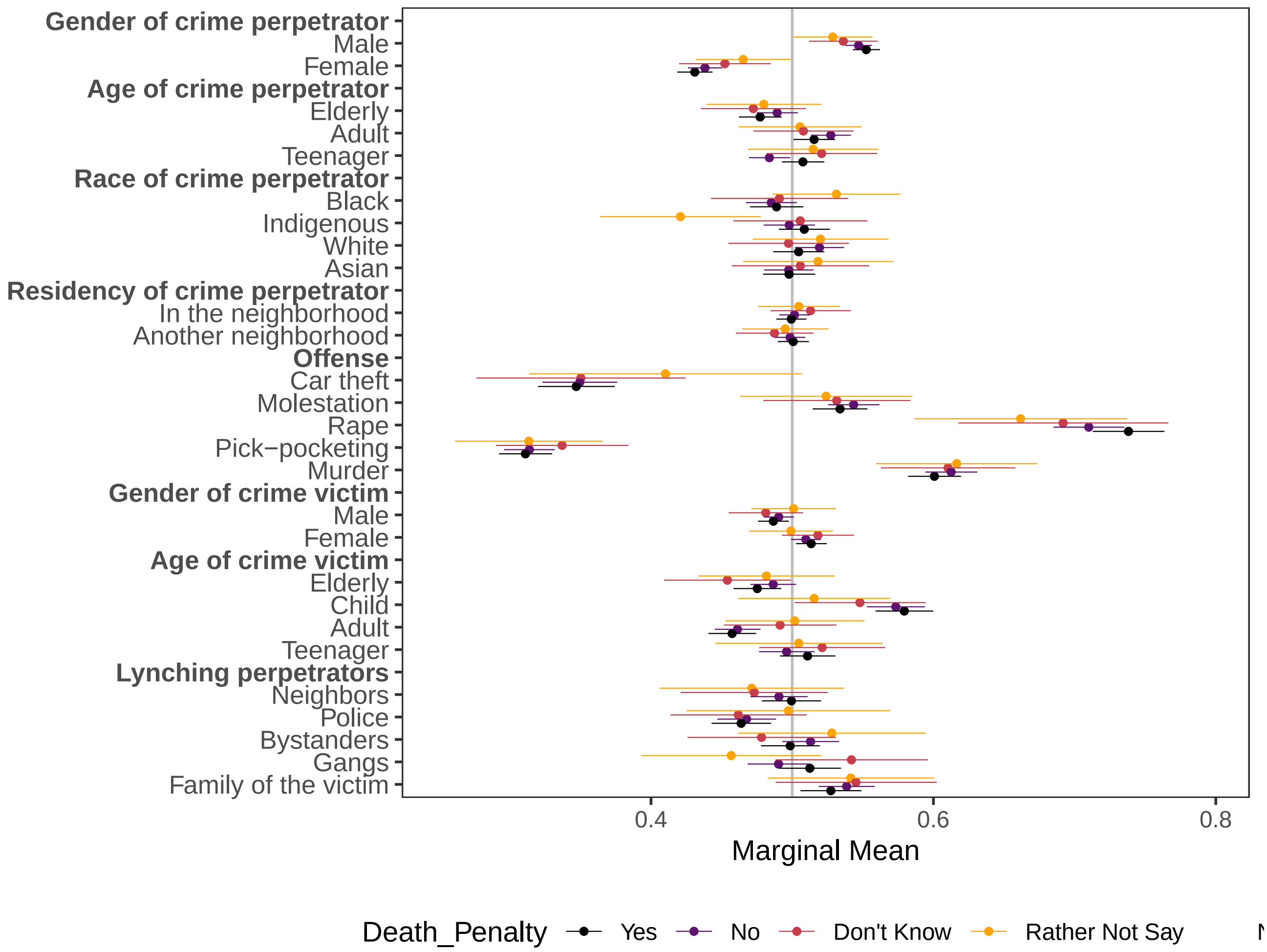
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.456 | 0.011 | 0.000 | 0.435 | 0.478 |
| Male | 0.533 | 0.008 | 0.000 | 0.517 | 0.549 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.499 | 0.013 | 0.933 | 0.473 | 0.525 |
| Adult | 0.505 | 0.013 | 0.678 | 0.480 | 0.531 |
| Elderly | 0.495 | 0.014 | 0.742 | 0.468 | 0.523 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.493 | 0.017 | 0.668 | 0.459 | 0.526 |
| White | 0.540 | 0.016 | 0.013 | 0.509 | 0.572 |
| Indigenous | 0.485 | 0.018 | 0.390 | 0.450 | 0.520 |
| Black | 0.480 | 0.017 | 0.233 | 0.447 | 0.513 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.497 | 0.011 | 0.779 | 0.476 | 0.518 |
| In the neighborhood | 0.503 | 0.011 | 0.779 | 0.482 | 0.524 |
| **Offense** | | | | | |
| Murder | 0.606 | 0.017 | 0.000 | 0.573 | 0.640 |
| Pick-pocketing | 0.319 | 0.017 | 0.000 | 0.286 | 0.351 |
| Rape | 0.699 | 0.025 | 0.000 | 0.650 | 0.748 |
| Molestation | 0.530 | 0.016 | 0.068 | 0.498 | 0.562 |
| Car theft | 0.361 | 0.025 | 0.000 | 0.312 | 0.410 |
| **Gender of crime victim** | | | | | |
| Female | 0.506 | 0.010 | 0.542 | 0.487 | 0.525 |
| Male | 0.494 | 0.010 | 0.542 | 0.474 | 0.513 |
| **Age of crime victim** | | | | | |
| Teenager | 0.492 | 0.018 | 0.660 | 0.456 | 0.528 |
| Adult | 0.479 | 0.014 | 0.139 | 0.452 | 0.507 |
| Child | 0.580 | 0.019 | 0.000 | 0.543 | 0.617 |
| Elderly | 0.467 | 0.015 | 0.030 | 0.437 | 0.497 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.550 | 0.021 | 0.015 | 0.510 | 0.590 |
| Gangs | 0.504 | 0.019 | 0.846 | 0.466 | 0.541 |
| Bystanders | 0.476 | 0.021 | 0.250 | 0.436 | 0.517 |
| Police | 0.482 | 0.021 | 0.379 | 0.441 | 0.522 |
| Neighbors | 0.490 | 0.020 | 0.615 | 0.450 | 0.529 |

### C.4.7 Support for Death Penalty

Here we assess whether subjects who support the death penalty have different preferences towards lynching victims. There are fewer respondents who answered “Don’t Know” or “Rather Not Say” to our question, so the confidence intervals from their estimates are larger than for the other two categories. The estimates largely overlap across the four groups, although those who answered “Rather Not Say” are less favorable to lynching Indigenous criminals.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(death_penalty) %>%
  mutate(death_penalty = fct_relevel(death_penalty, "Yes", "No",
                                     "Don't Know", "Rather Not Say"))
cjdt$Death_Penalty <- factor(cjdt$death_penalty)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Death_Penalty)

# Plot
plot(mm_by, group = "Death_Penalty", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
# Tables
mm_yes <- mm_by %>% filter(BY == "Yes")
table_mm_by(mm_yes, capt = "Marginal Means -- Support for Death Penalty: Yes")

mm_no <- mm_by %>% filter(BY == "No")
table_mm_by(mm_no, capt = "Marginal Means -- Support for Death Penalty: No")

mm_dk <- mm_by %>% filter(BY == "Don't Know")
table_mm_by(mm_dk, capt = "Marginal Means -- Support for Death Penalty: Do Not Know")

mm_rns <- mm_by %>% filter(BY == "Rather Not Say")
table_mm_by(mm_rns, capt = "Marginal Means -- Support for Death Penalty: Rather Not Say")
```

Table 38: Marginal Means – Support for Death Penalty: Yes

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.431 | 0.006 | 0.000 | 0.419 | 0.443 |
| Male | 0.552 | 0.005 | 0.000 | 0.543 | 0.562 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.508 | 0.008 | 0.317 | 0.493 | 0.522 |
| Adult | 0.516 | 0.007 | 0.036 | 0.501 | 0.530 |
| Elderly | 0.477 | 0.008 | 0.003 | 0.462 | 0.492 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.498 | 0.009 | 0.809 | 0.479 | 0.516 |
| White | 0.505 | 0.009 | 0.620 | 0.487 | 0.522 |
| Indigenous | 0.509 | 0.009 | 0.349 | 0.491 | 0.526 |
| Black | 0.489 | 0.009 | 0.242 | 0.470 | 0.507 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.501 | 0.006 | 0.900 | 0.490 | 0.512 |
| In the neighborhood | 0.499 | 0.005 | 0.900 | 0.489 | 0.510 |
| **Offense** | | | | | |
| Murder | 0.601 | 0.009 | 0.000 | 0.582 | 0.619 |
| Pick-pocketing | 0.311 | 0.009 | 0.000 | 0.292 | 0.330 |
| Rape | 0.738 | 0.013 | 0.000 | 0.713 | 0.763 |
| Molestation | 0.534 | 0.010 | 0.001 | 0.515 | 0.553 |
| Car theft | 0.347 | 0.014 | 0.000 | 0.320 | 0.374 |
| **Gender of crime victim** | | | | | |
| Female | 0.513 | 0.005 | 0.015 | 0.503 | 0.524 |
| Male | 0.487 | 0.005 | 0.015 | 0.476 | 0.497 |
| **Age of crime victim** | | | | | |
| Teenager | 0.511 | 0.010 | 0.273 | 0.491 | 0.530 |
| Adult | 0.457 | 0.009 | 0.000 | 0.441 | 0.474 |
| Child | 0.579 | 0.010 | 0.000 | 0.559 | 0.600 |
| Elderly | 0.475 | 0.009 | 0.004 | 0.459 | 0.492 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.527 | 0.011 | 0.012 | 0.506 | 0.549 |
| Gangs | 0.512 | 0.011 | 0.261 | 0.491 | 0.534 |
| Bystanders | 0.499 | 0.011 | 0.893 | 0.478 | 0.519 |
| Police | 0.464 | 0.011 | 0.001 | 0.443 | 0.485 |
| Neighbors | 0.499 | 0.011 | 0.957 | 0.479 | 0.520 |

Table 39: Marginal Means – Support for Death Penalty: No

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.438 | 0.006 | 0.000 | 0.426 | 0.450 |
| Male | 0.547 | 0.005 | 0.000 | 0.538 | 0.556 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.484 | 0.007 | 0.027 | 0.469 | 0.498 |
| Adult | 0.527 | 0.007 | 0.000 | 0.513 | 0.541 |
| Elderly | 0.489 | 0.007 | 0.146 | 0.475 | 0.504 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.498 | 0.009 | 0.780 | 0.480 | 0.515 |
| White | 0.519 | 0.009 | 0.028 | 0.502 | 0.536 |
| Indigenous | 0.498 | 0.009 | 0.816 | 0.480 | 0.516 |
| Black | 0.485 | 0.009 | 0.103 | 0.467 | 0.503 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.005 | 0.771 | 0.488 | 0.509 |
| In the neighborhood | 0.502 | 0.005 | 0.771 | 0.491 | 0.512 |
| **Offense** | | | | | |
| Murder | 0.613 | 0.009 | 0.000 | 0.594 | 0.631 |
| Pick-pocketing | 0.314 | 0.009 | 0.000 | 0.296 | 0.332 |
| Rape | 0.710 | 0.013 | 0.000 | 0.685 | 0.735 |
| Molestation | 0.543 | 0.009 | 0.000 | 0.525 | 0.562 |
| Car theft | 0.350 | 0.013 | 0.000 | 0.323 | 0.376 |
| **Gender of crime victim** | | | | | |
| Female | 0.510 | 0.005 | 0.070 | 0.499 | 0.520 |
| Male | 0.490 | 0.005 | 0.070 | 0.480 | 0.501 |
| **Age of crime victim** | | | | | |
| Teenager | 0.496 | 0.010 | 0.688 | 0.477 | 0.515 |
| Adult | 0.461 | 0.008 | 0.000 | 0.445 | 0.477 |
| Child | 0.573 | 0.010 | 0.000 | 0.553 | 0.594 |
| Elderly | 0.487 | 0.008 | 0.098 | 0.471 | 0.502 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.539 | 0.010 | 0.000 | 0.519 | 0.558 |
| Gangs | 0.490 | 0.011 | 0.384 | 0.469 | 0.512 |
| Bystanders | 0.513 | 0.010 | 0.202 | 0.493 | 0.533 |
| Police | 0.468 | 0.011 | 0.002 | 0.447 | 0.488 |
| Neighbors | 0.491 | 0.010 | 0.360 | 0.470 | 0.511 |

Table 40: Marginal Means – Support for Death Penalty: Do Not Know

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.452 | 0.016 | 0.004 | 0.420 | 0.485 |
| Male | 0.536 | 0.012 | 0.003 | 0.512 | 0.560 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.521 | 0.020 | 0.294 | 0.482 | 0.560 |
| Adult | 0.508 | 0.018 | 0.660 | 0.473 | 0.543 |
| Elderly | 0.472 | 0.019 | 0.145 | 0.435 | 0.510 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.506 | 0.025 | 0.816 | 0.457 | 0.554 |
| White | 0.497 | 0.022 | 0.903 | 0.455 | 0.540 |
| Indigenous | 0.506 | 0.024 | 0.813 | 0.458 | 0.553 |
| Black | 0.491 | 0.025 | 0.715 | 0.442 | 0.539 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.487 | 0.014 | 0.368 | 0.460 | 0.515 |
| In the neighborhood | 0.513 | 0.014 | 0.369 | 0.485 | 0.541 |
| **Offense** | | | | | |
| Murder | 0.610 | 0.024 | 0.000 | 0.563 | 0.658 |
| Pick-pocketing | 0.337 | 0.024 | 0.000 | 0.290 | 0.384 |
| Rape | 0.692 | 0.038 | 0.000 | 0.618 | 0.766 |
| Molestation | 0.532 | 0.027 | 0.235 | 0.479 | 0.584 |
| Car theft | 0.350 | 0.038 | 0.000 | 0.276 | 0.424 |
| **Gender of crime victim** | | | | | |
| Female | 0.518 | 0.013 | 0.161 | 0.493 | 0.544 |
| Male | 0.481 | 0.013 | 0.161 | 0.455 | 0.507 |
| **Age of crime victim** | | | | | |
| Teenager | 0.521 | 0.023 | 0.349 | 0.477 | 0.566 |
| Adult | 0.491 | 0.020 | 0.671 | 0.452 | 0.531 |
| Child | 0.548 | 0.024 | 0.042 | 0.502 | 0.594 |
| Elderly | 0.454 | 0.023 | 0.044 | 0.409 | 0.499 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.545 | 0.029 | 0.120 | 0.488 | 0.602 |
| Gangs | 0.542 | 0.027 | 0.126 | 0.488 | 0.596 |
| Bystanders | 0.478 | 0.027 | 0.416 | 0.426 | 0.531 |
| Police | 0.462 | 0.025 | 0.120 | 0.414 | 0.510 |
| Neighbors | 0.473 | 0.027 | 0.310 | 0.421 | 0.525 |

Table 41: Marginal Means – Support for Death Penalty: Rather Not Say

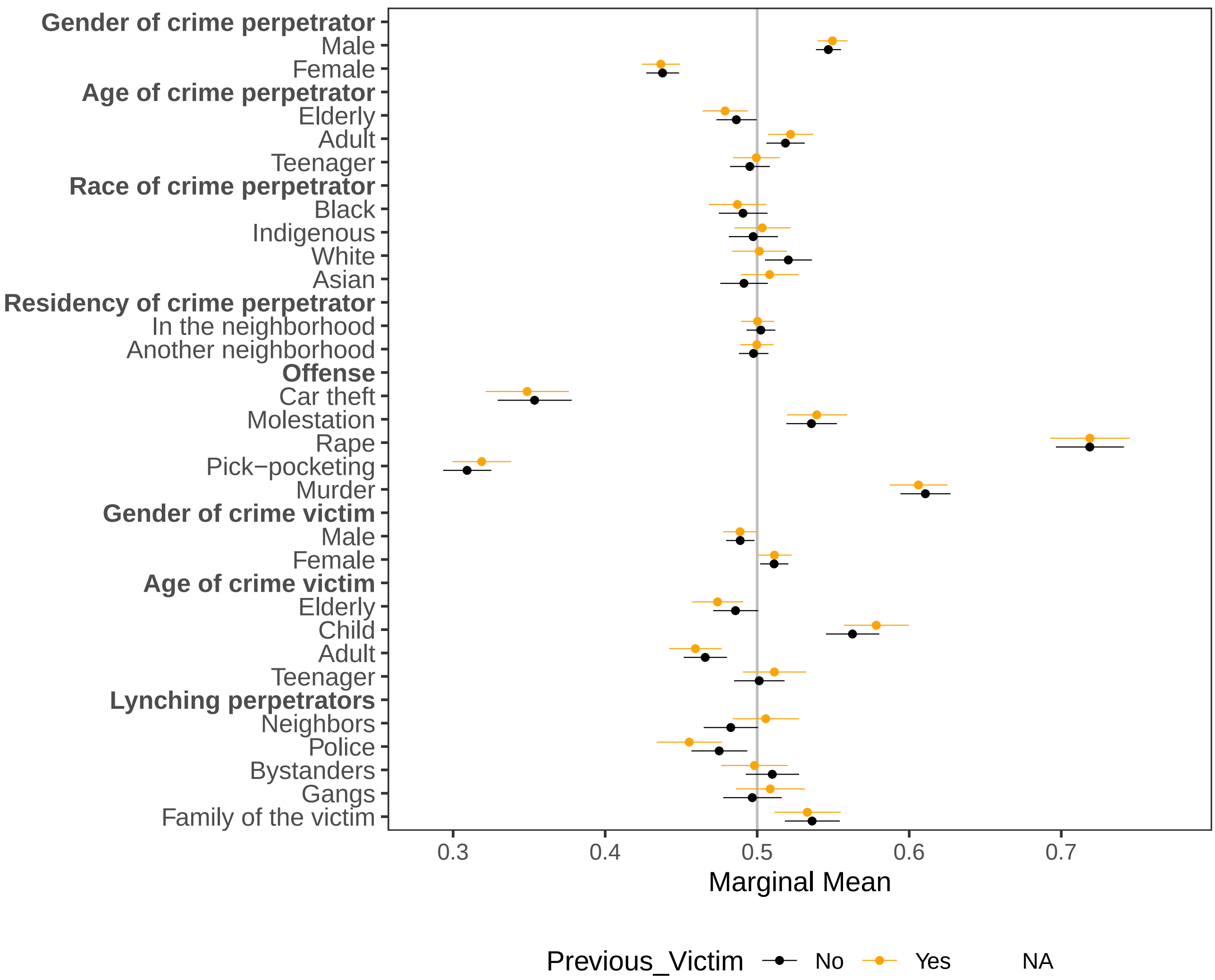
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.465 | 0.017 | 0.042 | 0.432 | 0.499 |
| Male | 0.529 | 0.014 | 0.044 | 0.501 | 0.557 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.515 | 0.024 | 0.529 | 0.469 | 0.561 |
| Adult | 0.505 | 0.022 | 0.804 | 0.462 | 0.549 |
| Elderly | 0.480 | 0.021 | 0.332 | 0.439 | 0.521 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.518 | 0.027 | 0.499 | 0.465 | 0.571 |
| White | 0.520 | 0.024 | 0.413 | 0.472 | 0.568 |
| Indigenous | 0.421 | 0.029 | 0.006 | 0.364 | 0.478 |
| Black | 0.531 | 0.023 | 0.174 | 0.486 | 0.576 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.495 | 0.016 | 0.752 | 0.465 | 0.526 |
| In the neighborhood | 0.505 | 0.015 | 0.752 | 0.476 | 0.533 |
| **Offense** | | | | | |
| Murder | 0.616 | 0.029 | 0.000 | 0.559 | 0.674 |
| Pick-pocketing | 0.313 | 0.027 | 0.000 | 0.261 | 0.366 |
| Rape | 0.662 | 0.038 | 0.000 | 0.587 | 0.737 |
| Molestation | 0.524 | 0.031 | 0.439 | 0.463 | 0.585 |
| Car theft | 0.410 | 0.049 | 0.069 | 0.314 | 0.507 |
| **Gender of crime victim** | | | | | |
| Female | 0.499 | 0.015 | 0.950 | 0.470 | 0.529 |
| Male | 0.501 | 0.015 | 0.950 | 0.471 | 0.531 |
| **Age of crime victim** | | | | | |
| Teenager | 0.505 | 0.030 | 0.878 | 0.446 | 0.564 |
| Adult | 0.502 | 0.025 | 0.942 | 0.453 | 0.551 |
| Child | 0.516 | 0.027 | 0.572 | 0.462 | 0.569 |
| Elderly | 0.482 | 0.025 | 0.457 | 0.434 | 0.530 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.541 | 0.030 | 0.166 | 0.483 | 0.600 |
| Gangs | 0.457 | 0.032 | 0.183 | 0.393 | 0.520 |
| Bystanders | 0.528 | 0.034 | 0.406 | 0.462 | 0.594 |
| Police | 0.497 | 0.037 | 0.941 | 0.425 | 0.569 |
| Neighbors | 0.471 | 0.033 | 0.389 | 0.406 | 0.537 |

### C.4.8 Previous Victimization

Respondents who had been victimized in the past 12 months also do not have different preferences towards lynchings victim profiles. The results are virtually identical for both groups, as one can see below.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  mutate(previous_victim_dummy, "Yes", "No")
cjdt$Previous_Victim <- factor(cjdt$previous_victim_dummy)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Previous_Victim)


# Plot
plot(mm_by, group = "Previous_Victim", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
# Tables
```

```r
mm_yes <- mm_by %>% filter(BY == "Yes")

table_mm_by(mm_yes, capt = "Marginal Means -- Previous Victimization (12 Months): Yes")
```

Table 42: Marginal Means – Previous Victimization (12 Months): Yes

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.437 | 0.006 | 0.000 | 0.424 | 0.449 |
| Male | 0.549 | 0.005 | 0.000 | 0.540 | 0.559 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.499 | 0.008 | 0.944 | 0.484 | 0.515 |
| Adult | 0.522 | 0.007 | 0.003 | 0.507 | 0.537 |
| Elderly | 0.479 | 0.008 | 0.005 | 0.464 | 0.494 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.508 | 0.010 | 0.391 | 0.489 | 0.527 |
| White | 0.501 | 0.009 | 0.880 | 0.483 | 0.519 |
| Indigenous | 0.503 | 0.009 | 0.719 | 0.485 | 0.522 |
| Black | 0.487 | 0.010 | 0.173 | 0.468 | 0.506 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.500 | 0.005 | 0.966 | 0.489 | 0.510 |
| In the neighborhood | 0.500 | 0.005 | 0.966 | 0.490 | 0.511 |
| **Offense** | | | | | |
| Murder | 0.606 | 0.010 | 0.000 | 0.587 | 0.625 |
| Pick-pocketing | 0.319 | 0.010 | 0.000 | 0.300 | 0.338 |
| Rape | 0.719 | 0.013 | 0.000 | 0.693 | 0.745 |
| Molestation | 0.539 | 0.010 | 0.000 | 0.520 | 0.559 |
| Car theft | 0.349 | 0.014 | 0.000 | 0.322 | 0.376 |
| **Gender of crime victim** | | | | | |
| Female | 0.511 | 0.006 | 0.044 | 0.500 | 0.522 |
| Male | 0.489 | 0.006 | 0.044 | 0.478 | 0.500 |
| **Age of crime victim** | | | | | |
| Teenager | 0.511 | 0.011 | 0.283 | 0.491 | 0.532 |
| Adult | 0.459 | 0.009 | 0.000 | 0.442 | 0.477 |
| Child | 0.578 | 0.011 | 0.000 | 0.557 | 0.599 |
| Elderly | 0.474 | 0.008 | 0.002 | 0.457 | 0.491 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.533 | 0.011 | 0.003 | 0.511 | 0.555 |
| Gangs | 0.509 | 0.011 | 0.455 | 0.486 | 0.531 |
| Bystanders | 0.498 | 0.011 | 0.874 | 0.476 | 0.520 |
| Police | 0.455 | 0.011 | 0.000 | 0.434 | 0.477 |
| Neighbors | 0.506 | 0.011 | 0.607 | 0.484 | 0.527 |

```r
mm_no <- mm_by %>% filter(BY == "No")

table_mm_by(mm_no, capt = "Marginal Means -- Previous Victimization (12 Months): No")
```

Table 43: Marginal Means – Previous Victimization (12 Months): No

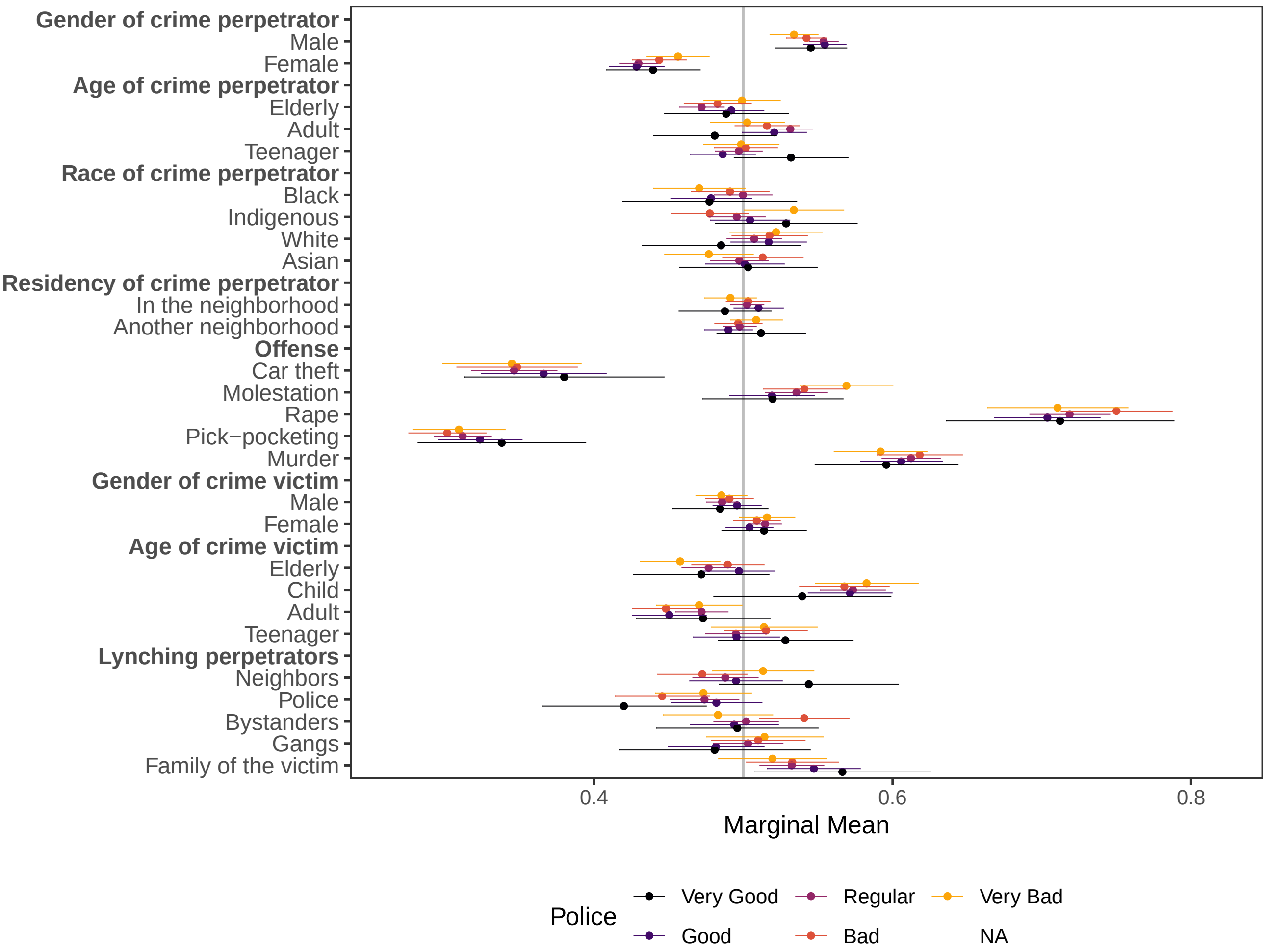
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.438 | 0.005 | 0.000 | 0.427 | 0.448 |
| Male | 0.547 | 0.004 | 0.000 | 0.539 | 0.555 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.495 | 0.007 | 0.461 | 0.482 | 0.508 |
| Adult | 0.519 | 0.006 | 0.004 | 0.506 | 0.531 |
| Elderly | 0.486 | 0.007 | 0.039 | 0.473 | 0.499 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.491 | 0.008 | 0.269 | 0.476 | 0.507 |
| White | 0.520 | 0.008 | 0.009 | 0.505 | 0.536 |
| Indigenous | 0.497 | 0.008 | 0.745 | 0.481 | 0.513 |
| Black | 0.491 | 0.008 | 0.247 | 0.475 | 0.506 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.005 | 0.617 | 0.488 | 0.507 |
| In the neighborhood | 0.502 | 0.005 | 0.617 | 0.493 | 0.512 |
| **Offense** | | | | | |
| Murder | 0.611 | 0.008 | 0.000 | 0.594 | 0.627 |
| Pick-pocketing | 0.309 | 0.008 | 0.000 | 0.293 | 0.325 |
| Rape | 0.719 | 0.011 | 0.000 | 0.696 | 0.741 |
| Molestation | 0.536 | 0.008 | 0.000 | 0.519 | 0.552 |
| Car theft | 0.354 | 0.012 | 0.000 | 0.329 | 0.378 |
| **Gender of crime victim** | | | | | |
| Female | 0.511 | 0.005 | 0.017 | 0.502 | 0.520 |
| Male | 0.489 | 0.005 | 0.017 | 0.480 | 0.498 |
| **Age of crime victim** | | | | | |
| Teenager | 0.501 | 0.008 | 0.874 | 0.485 | 0.518 |
| Adult | 0.466 | 0.007 | 0.000 | 0.452 | 0.480 |
| Child | 0.563 | 0.009 | 0.000 | 0.545 | 0.580 |
| Elderly | 0.486 | 0.007 | 0.056 | 0.471 | 0.500 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.536 | 0.009 | 0.000 | 0.518 | 0.554 |
| Gangs | 0.497 | 0.010 | 0.741 | 0.478 | 0.516 |
| Bystanders | 0.510 | 0.009 | 0.261 | 0.493 | 0.527 |
| Police | 0.475 | 0.009 | 0.007 | 0.457 | 0.493 |
| Neighbors | 0.483 | 0.009 | 0.055 | 0.465 | 0.500 |

### C.4.9 Opinion on the Police

Experimental results do not change when we break down the responses according to how subjects view the police forces.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  mutate(views_police2 = case_when(views_police == "Rather Not Say" ~ NA_character_,
                                   views_police == "Don't Know" ~ NA_character_,
                                   TRUE ~ as.character(views_police)),
         views_police2 = fct_relevel(views_police2, "Very Good", "Good",
                                     "Regular", "Bad", "Very Bad")) %>%
  drop_na(views_police2)
cjdt$Police <- factor(cjdt$views_police2)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Police)

# Plot
plot(mm_by, group = "Police", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```




```
# Tables

mm_vgood <- mm_by %>% filter(BY == "Very Good")

table_mm_by(mm_vgood, capt = "Marginal Means -- Opinion on the Police: Very Good")


mm_good <- mm_by %>% filter(BY == "Good")

table_mm_by(mm_good, capt = "Marginal Means -- Opinion on the Police: Good")


mm_regular <- mm_by %>% filter(BY == "Regular")

table_mm_by(mm_regular, capt = "Marginal Means -- Opinion on the Police: Regular")


mm_bad <- mm_by %>% filter(BY == "Bad")

table_mm_by(mm_bad, capt = "Marginal Means -- Opinion on the Police: Bad")


mm_vbad <- mm_by %>% filter(BY == "Very Bad")

table_mm_by(mm_vbad, capt = "Marginal Means -- Opinion on the Police: Very Bad")
```

Table 44: Marginal Means – Opinion on the Police: Very Good

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.440 | 0.016 | 0.000 | 0.408 | 0.471 |
| Male | 0.545 | 0.012 | 0.000 | 0.521 | 0.569 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.532 | 0.020 | 0.103 | 0.494 | 0.570 |
| Adult | 0.481 | 0.021 | 0.363 | 0.440 | 0.522 |
| Elderly | 0.489 | 0.021 | 0.589 | 0.447 | 0.530 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.503 | 0.024 | 0.893 | 0.457 | 0.549 |
| White | 0.485 | 0.027 | 0.583 | 0.432 | 0.538 |
| Indigenous | 0.529 | 0.024 | 0.238 | 0.481 | 0.576 |
| Black | 0.477 | 0.030 | 0.446 | 0.419 | 0.536 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.512 | 0.015 | 0.436 | 0.482 | 0.542 |
| In the neighborhood | 0.488 | 0.016 | 0.436 | 0.457 | 0.519 |
| **Offense** | | | | | |
| Murder | 0.596 | 0.025 | 0.000 | 0.548 | 0.644 |
| Pick-pocketing | 0.338 | 0.029 | 0.000 | 0.282 | 0.394 |
| Rape | 0.712 | 0.039 | 0.000 | 0.636 | 0.789 |
| Molestation | 0.520 | 0.024 | 0.416 | 0.472 | 0.567 |
| Car theft | 0.380 | 0.034 | 0.000 | 0.313 | 0.447 |
| **Gender of crime victim** | | | | | |
| Female | 0.514 | 0.015 | 0.340 | 0.485 | 0.542 |
| Male | 0.484 | 0.016 | 0.342 | 0.452 | 0.517 |
| **Age of crime victim** | | | | | |
| Teenager | 0.528 | 0.023 | 0.223 | 0.483 | 0.574 |
| Adult | 0.473 | 0.023 | 0.239 | 0.428 | 0.518 |
| Child | 0.539 | 0.030 | 0.194 | 0.480 | 0.599 |
| Elderly | 0.472 | 0.023 | 0.227 | 0.426 | 0.517 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.566 | 0.030 | 0.028 | 0.507 | 0.625 |
| Gangs | 0.481 | 0.033 | 0.557 | 0.417 | 0.545 |
| Bystanders | 0.496 | 0.028 | 0.884 | 0.442 | 0.550 |
| Police | 0.420 | 0.028 | 0.004 | 0.365 | 0.475 |
| Neighbors | 0.544 | 0.031 | 0.153 | 0.484 | 0.604 |

Table 45: Marginal Means – Opinion on the Police: Good

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.428 | 0.009 | 0.000 | 0.410 | 0.447 |
| Male | 0.555 | 0.007 | 0.000 | 0.540 | 0.569 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.486 | 0.011 | 0.217 | 0.464 | 0.508 |
| Adult | 0.521 | 0.011 | 0.060 | 0.499 | 0.542 |
| Elderly | 0.492 | 0.011 | 0.469 | 0.470 | 0.514 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.501 | 0.014 | 0.943 | 0.474 | 0.528 |
| White | 0.517 | 0.013 | 0.192 | 0.491 | 0.542 |
| Indigenous | 0.505 | 0.014 | 0.740 | 0.478 | 0.531 |
| Black | 0.478 | 0.014 | 0.117 | 0.451 | 0.505 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.490 | 0.008 | 0.231 | 0.474 | 0.506 |
| In the neighborhood | 0.510 | 0.009 | 0.232 | 0.493 | 0.527 |
| **Offense** | | | | | |
| Murder | 0.606 | 0.014 | 0.000 | 0.578 | 0.633 |
| Pick-pocketing | 0.324 | 0.014 | 0.000 | 0.295 | 0.352 |
| Rape | 0.704 | 0.018 | 0.000 | 0.668 | 0.739 |
| Molestation | 0.519 | 0.015 | 0.190 | 0.491 | 0.548 |
| Car theft | 0.366 | 0.021 | 0.000 | 0.324 | 0.408 |
| **Gender of crime victim** | | | | | |
| Female | 0.504 | 0.008 | 0.613 | 0.488 | 0.520 |
| Male | 0.496 | 0.008 | 0.613 | 0.479 | 0.512 |
| **Age of crime victim** | | | | | |
| Teenager | 0.495 | 0.015 | 0.758 | 0.466 | 0.524 |
| Adult | 0.450 | 0.013 | 0.000 | 0.425 | 0.475 |
| Child | 0.571 | 0.014 | 0.000 | 0.543 | 0.600 |
| Elderly | 0.497 | 0.012 | 0.812 | 0.473 | 0.521 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.547 | 0.016 | 0.003 | 0.516 | 0.579 |
| Gangs | 0.482 | 0.016 | 0.265 | 0.449 | 0.514 |
| Bystanders | 0.494 | 0.015 | 0.686 | 0.464 | 0.524 |
| Police | 0.482 | 0.016 | 0.246 | 0.451 | 0.512 |
| Neighbors | 0.495 | 0.016 | 0.759 | 0.464 | 0.526 |

Table 46: Marginal Means – Opinion on the Police: Regular

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.430 | 0.007 | 0.000 | 0.417 | 0.443 |
| Male | 0.554 | 0.005 | 0.000 | 0.544 | 0.564 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.497 | 0.008 | 0.710 | 0.481 | 0.513 |
| Adult | 0.531 | 0.008 | 0.000 | 0.517 | 0.546 |
| Elderly | 0.472 | 0.008 | 0.000 | 0.457 | 0.487 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.497 | 0.010 | 0.783 | 0.478 | 0.517 |
| White | 0.507 | 0.009 | 0.439 | 0.489 | 0.526 |
| Indigenous | 0.496 | 0.010 | 0.654 | 0.476 | 0.515 |
| Black | 0.500 | 0.010 | 0.980 | 0.480 | 0.519 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.006 | 0.668 | 0.486 | 0.509 |
| In the neighborhood | 0.502 | 0.006 | 0.668 | 0.491 | 0.514 |
| **Offense** | | | | | |
| Murder | 0.612 | 0.010 | 0.000 | 0.593 | 0.632 |
| Pick-pocketing | 0.312 | 0.010 | 0.000 | 0.293 | 0.331 |
| Rape | 0.719 | 0.014 | 0.000 | 0.692 | 0.745 |
| Molestation | 0.536 | 0.011 | 0.001 | 0.515 | 0.556 |
| Car theft | 0.346 | 0.015 | 0.000 | 0.318 | 0.375 |
| **Gender of crime victim** | | | | | |
| Female | 0.515 | 0.006 | 0.010 | 0.504 | 0.526 |
| Male | 0.486 | 0.006 | 0.010 | 0.475 | 0.497 |
| **Age of crime victim** | | | | | |
| Teenager | 0.495 | 0.011 | 0.638 | 0.474 | 0.516 |
| Adult | 0.472 | 0.009 | 0.002 | 0.454 | 0.490 |
| Child | 0.573 | 0.011 | 0.000 | 0.552 | 0.595 |
| Elderly | 0.477 | 0.009 | 0.012 | 0.459 | 0.495 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.532 | 0.011 | 0.003 | 0.511 | 0.554 |
| Gangs | 0.503 | 0.012 | 0.791 | 0.480 | 0.527 |
| Bystanders | 0.502 | 0.011 | 0.869 | 0.480 | 0.524 |
| Police | 0.474 | 0.012 | 0.027 | 0.451 | 0.497 |
| Neighbors | 0.488 | 0.011 | 0.281 | 0.466 | 0.510 |

Table 47: Marginal Means – Opinion on the Police: Bad

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.444 | 0.009 | 0.000 | 0.426 | 0.462 |
| Male | 0.542 | 0.007 | 0.000 | 0.529 | 0.556 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.502 | 0.011 | 0.873 | 0.481 | 0.523 |
| Adult | 0.516 | 0.011 | 0.152 | 0.494 | 0.537 |
| Elderly | 0.483 | 0.012 | 0.133 | 0.460 | 0.505 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.513 | 0.014 | 0.346 | 0.486 | 0.540 |
| White | 0.518 | 0.013 | 0.175 | 0.492 | 0.543 |
| Indigenous | 0.478 | 0.013 | 0.093 | 0.451 | 0.504 |
| Black | 0.491 | 0.013 | 0.505 | 0.465 | 0.517 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.497 | 0.008 | 0.676 | 0.481 | 0.513 |
| In the neighborhood | 0.503 | 0.008 | 0.676 | 0.488 | 0.518 |
| **Offense** | | | | | |
| Murder | 0.618 | 0.015 | 0.000 | 0.590 | 0.647 |
| Pick-pocketing | 0.302 | 0.013 | 0.000 | 0.276 | 0.328 |
| Rape | 0.750 | 0.019 | 0.000 | 0.713 | 0.787 |
| Molestation | 0.541 | 0.014 | 0.004 | 0.513 | 0.568 |
| Car theft | 0.348 | 0.021 | 0.000 | 0.308 | 0.389 |
| **Gender of crime victim** | | | | | |
| Female | 0.509 | 0.008 | 0.261 | 0.493 | 0.525 |
| Male | 0.491 | 0.008 | 0.261 | 0.475 | 0.507 |
| **Age of crime victim** | | | | | |
| Teenager | 0.515 | 0.014 | 0.285 | 0.487 | 0.543 |
| Adult | 0.448 | 0.012 | 0.000 | 0.425 | 0.471 |
| Child | 0.568 | 0.015 | 0.000 | 0.537 | 0.598 |
| Elderly | 0.490 | 0.012 | 0.401 | 0.465 | 0.514 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.533 | 0.016 | 0.037 | 0.502 | 0.564 |
| Gangs | 0.510 | 0.016 | 0.536 | 0.478 | 0.541 |
| Bystanders | 0.541 | 0.015 | 0.008 | 0.511 | 0.571 |
| Police | 0.446 | 0.016 | 0.001 | 0.414 | 0.477 |
| Neighbors | 0.473 | 0.015 | 0.073 | 0.442 | 0.503 |

Table 48: Marginal Means – Opinion on the Police: Very Bad

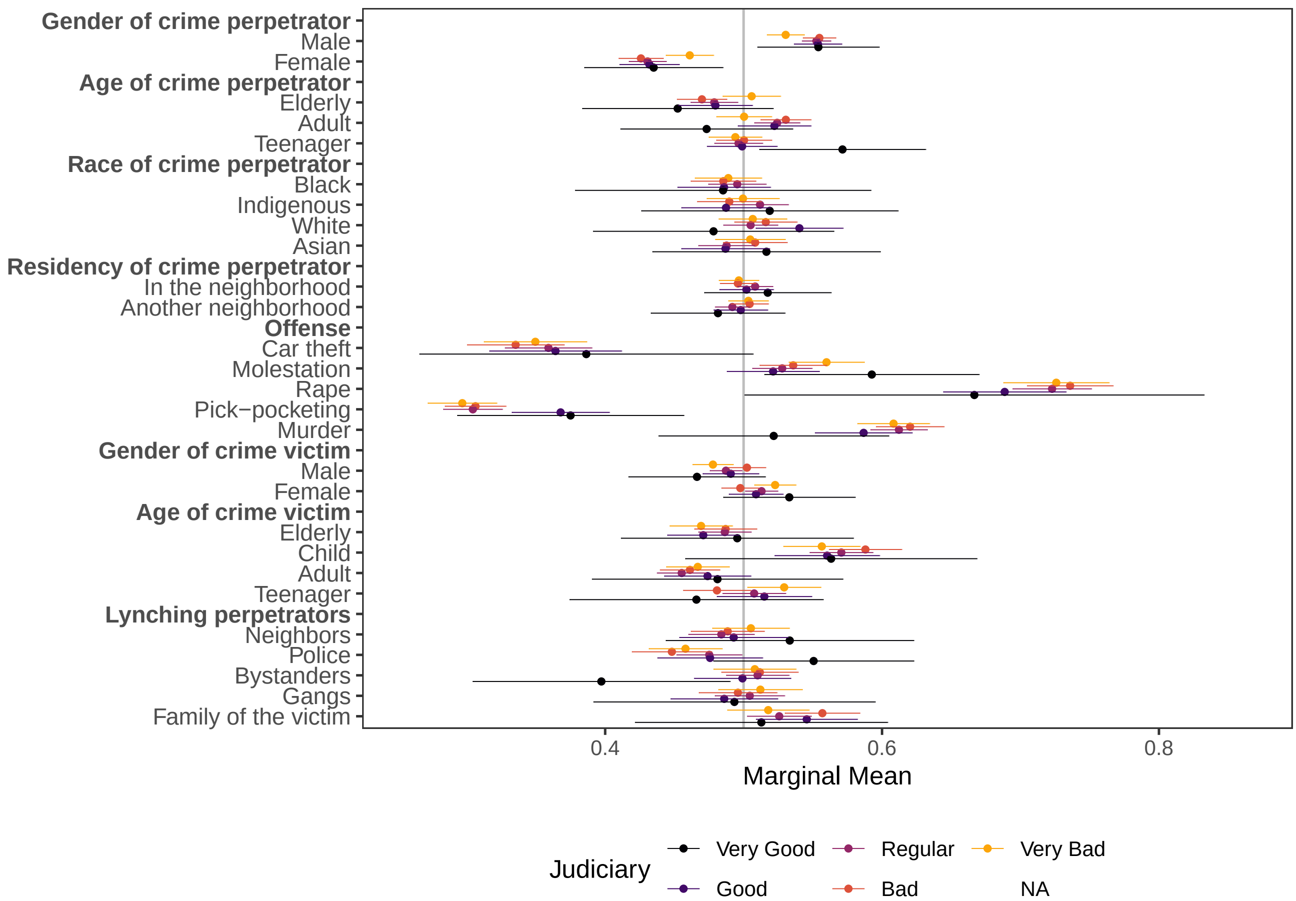
| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.456 | 0.011 | 0.000 | 0.435 | 0.477 |
| Male | 0.534 | 0.008 | 0.000 | 0.518 | 0.550 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.499 | 0.013 | 0.908 | 0.473 | 0.524 |
| Adult | 0.503 | 0.013 | 0.840 | 0.478 | 0.527 |
| Elderly | 0.499 | 0.013 | 0.941 | 0.473 | 0.525 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.477 | 0.015 | 0.128 | 0.447 | 0.507 |
| White | 0.522 | 0.016 | 0.167 | 0.491 | 0.553 |
| Indigenous | 0.534 | 0.017 | 0.048 | 0.500 | 0.567 |
| Black | 0.470 | 0.016 | 0.060 | 0.440 | 0.501 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.509 | 0.009 | 0.337 | 0.491 | 0.526 |
| In the neighborhood | 0.491 | 0.009 | 0.336 | 0.474 | 0.509 |
| **Offense** | | | | | |
| Murder | 0.592 | 0.016 | 0.000 | 0.561 | 0.623 |
| Pick-pocketing | 0.309 | 0.016 | 0.000 | 0.278 | 0.341 |
| Rape | 0.711 | 0.024 | 0.000 | 0.663 | 0.758 |
| Molestation | 0.569 | 0.016 | 0.000 | 0.538 | 0.600 |
| Car theft | 0.345 | 0.024 | 0.000 | 0.298 | 0.392 |
| **Gender of crime victim** | | | | | |
| Female | 0.516 | 0.010 | 0.095 | 0.497 | 0.535 |
| Male | 0.485 | 0.009 | 0.095 | 0.468 | 0.503 |
| **Age of crime victim** | | | | | |
| Teenager | 0.514 | 0.018 | 0.447 | 0.478 | 0.550 |
| Adult | 0.470 | 0.015 | 0.043 | 0.442 | 0.499 |
| Child | 0.583 | 0.018 | 0.000 | 0.548 | 0.617 |
| Elderly | 0.458 | 0.014 | 0.002 | 0.431 | 0.485 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.520 | 0.019 | 0.292 | 0.483 | 0.556 |
| Gangs | 0.514 | 0.020 | 0.478 | 0.475 | 0.553 |
| Bystanders | 0.483 | 0.019 | 0.363 | 0.446 | 0.520 |
| Police | 0.473 | 0.016 | 0.104 | 0.441 | 0.506 |
| Neighbors | 0.513 | 0.017 | 0.445 | 0.479 | 0.547 |

### C.4.10 Opinion on the Judicial System

Lastly, we analyze whether personal beliefs about the judicial system affect the type of lynching victim respondents select.

```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  mutate(views_justice2 = case_when(views_justice == "Rather Not Say" ~ NA_character_,
                                    views_justice == "Don't Know" ~ NA_character_,
                                   TRUE ~ as.character(views_justice)),
         views_justice2 = fct_relevel(views_justice2, "Very Good", "Good",
                                      "Regular", "Bad", "Very Bad")) %>%
  drop_na(views_justice2)
cjdt$Judiciary <- factor(cjdt$views_justice2)
mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Judiciary)


# Plot
plot(mm_by, group = "Judiciary", vline = 0.5, header_fmt = "%s") +
  theme(legend.position = "bottom", axis.text.y = element_text(face = faces, size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```



```r
# Tables

mm_vgood <- mm_by %>% filter(BY == "Very Good")

table_mm_by(mm_vgood, capt = "Marginal Means -- Opinion on the Judicial System: Very Good")
```

Table 49: Marginal Means – Opinion on the Judicial System: Very Good

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.435 | 0.026 | 0.011 | 0.385 | 0.485 |
| Male | 0.554 | 0.022 | 0.016 | 0.510 | 0.598 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.571 | 0.031 | 0.020 | 0.511 | 0.631 |
| Adult | 0.473 | 0.032 | 0.400 | 0.411 | 0.535 |
| Elderly | 0.452 | 0.035 | 0.176 | 0.383 | 0.521 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.516 | 0.042 | 0.695 | 0.434 | 0.599 |
| White | 0.478 | 0.044 | 0.624 | 0.391 | 0.565 |
| Indigenous | 0.519 | 0.047 | 0.690 | 0.426 | 0.612 |
| Black | 0.485 | 0.055 | 0.785 | 0.378 | 0.592 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.481 | 0.025 | 0.454 | 0.433 | 0.530 |
| In the neighborhood | 0.517 | 0.023 | 0.456 | 0.472 | 0.563 |
| **Offense** | | | | | |
| Murder | 0.522 | 0.042 | 0.608 | 0.439 | 0.605 |
| Pick-pocketing | 0.375 | 0.042 | 0.003 | 0.293 | 0.457 |
| Rape | 0.667 | 0.085 | 0.049 | 0.501 | 0.833 |
| Molestation | 0.593 | 0.040 | 0.019 | 0.515 | 0.670 |
| Car theft | 0.386 | 0.061 | 0.065 | 0.266 | 0.507 |
| **Gender of crime victim** | | | | | |
| Female | 0.533 | 0.024 | 0.175 | 0.485 | 0.581 |
| Male | 0.466 | 0.025 | 0.182 | 0.417 | 0.516 |
| **Age of crime victim** | | | | | |
| Teenager | 0.466 | 0.047 | 0.466 | 0.374 | 0.558 |
| Adult | 0.481 | 0.046 | 0.683 | 0.391 | 0.572 |
| Child | 0.563 | 0.054 | 0.240 | 0.458 | 0.669 |
| Elderly | 0.495 | 0.043 | 0.915 | 0.411 | 0.579 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.513 | 0.047 | 0.783 | 0.422 | 0.604 |
| Gangs | 0.493 | 0.052 | 0.898 | 0.392 | 0.595 |
| Bystanders | 0.397 | 0.047 | 0.030 | 0.304 | 0.490 |
| Police | 0.551 | 0.037 | 0.171 | 0.478 | 0.623 |
| Neighbors | 0.533 | 0.046 | 0.466 | 0.444 | 0.623 |

```r
mm_good <- mm_by %>% filter(BY == "Good")

table_mm_by(mm_good, capt = "Marginal Means -- Opinion on the Judicial System: Good")
```

Table 50: Marginal Means – Opinion on the Judicial System: Good

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.432 | 0.011 | 0.000 | 0.410 | 0.454 |
| Male | 0.554 | 0.009 | 0.000 | 0.536 | 0.571 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.499 | 0.013 | 0.933 | 0.474 | 0.524 |
| Adult | 0.522 | 0.013 | 0.099 | 0.496 | 0.549 |
| Elderly | 0.480 | 0.014 | 0.136 | 0.453 | 0.506 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.487 | 0.016 | 0.421 | 0.455 | 0.519 |
| White | 0.540 | 0.016 | 0.012 | 0.509 | 0.572 |
| Indigenous | 0.487 | 0.016 | 0.439 | 0.455 | 0.519 |
| Black | 0.486 | 0.017 | 0.410 | 0.452 | 0.519 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.498 | 0.010 | 0.832 | 0.478 | 0.517 |
| In the neighborhood | 0.502 | 0.010 | 0.832 | 0.483 | 0.522 |
| **Offense** | | | | | |
| Murder | 0.587 | 0.018 | 0.000 | 0.552 | 0.622 |
| Pick-pocketing | 0.368 | 0.018 | 0.000 | 0.333 | 0.403 |
| Rape | 0.689 | 0.023 | 0.000 | 0.644 | 0.733 |
| Molestation | 0.521 | 0.017 | 0.211 | 0.488 | 0.555 |
| Car theft | 0.364 | 0.024 | 0.000 | 0.316 | 0.412 |
| **Gender of crime victim** | | | | | |
| Female | 0.509 | 0.010 | 0.369 | 0.489 | 0.529 |
| Male | 0.491 | 0.010 | 0.369 | 0.470 | 0.511 |
| **Age of crime victim** | | | | | |
| Teenager | 0.515 | 0.017 | 0.393 | 0.481 | 0.549 |
| Adult | 0.474 | 0.016 | 0.103 | 0.443 | 0.505 |
| Child | 0.560 | 0.019 | 0.002 | 0.522 | 0.598 |
| Elderly | 0.471 | 0.013 | 0.028 | 0.445 | 0.497 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.546 | 0.019 | 0.015 | 0.509 | 0.582 |
| Gangs | 0.486 | 0.020 | 0.478 | 0.447 | 0.525 |
| Bystanders | 0.499 | 0.018 | 0.963 | 0.464 | 0.534 |
| Police | 0.476 | 0.019 | 0.211 | 0.438 | 0.514 |
| Neighbors | 0.493 | 0.020 | 0.721 | 0.454 | 0.532 |

```r
mm_regular <- mm_by %>% filter(BY == "Regular")

table_mm_by(mm_regular, capt = "Marginal Means -- Opinion on the Judicial System: Regular")
```

```r
mm_bad <- mm_by %>% filter(BY == "Bad")

table_mm_by(mm_bad, capt = "Marginal Means -- Opinion on the Judicial System: Bad")
```

```r
mm_vbad <- mm_by %>% filter(BY == "Very Bad")

table_mm_by(mm_vbad, capt = "Marginal Means -- Opinion on the Judicial System: Very Bad")
```

Table 51: Marginal Means – Opinion on the Judicial System: Regular

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.431 | 0.007 | 0.000 | 0.417 | 0.444 |
| Male | 0.553 | 0.005 | 0.000 | 0.542 | 0.563 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.496 | 0.009 | 0.683 | 0.479 | 0.514 |
| Adult | 0.524 | 0.008 | 0.004 | 0.508 | 0.541 |
| Elderly | 0.479 | 0.009 | 0.015 | 0.462 | 0.496 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.488 | 0.010 | 0.235 | 0.467 | 0.508 |
| White | 0.505 | 0.010 | 0.614 | 0.485 | 0.525 |
| Indigenous | 0.512 | 0.010 | 0.256 | 0.491 | 0.532 |
| Black | 0.495 | 0.011 | 0.665 | 0.475 | 0.516 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.492 | 0.006 | 0.204 | 0.479 | 0.504 |
| In the neighborhood | 0.508 | 0.007 | 0.204 | 0.495 | 0.521 |
| **Offense** | | | | | |
| Murder | 0.612 | 0.010 | 0.000 | 0.592 | 0.633 |
| Pick-pocketing | 0.304 | 0.011 | 0.000 | 0.283 | 0.326 |
| Rape | 0.723 | 0.015 | 0.000 | 0.694 | 0.751 |
| Molestation | 0.528 | 0.011 | 0.011 | 0.506 | 0.549 |
| Car theft | 0.359 | 0.016 | 0.000 | 0.328 | 0.390 |
| **Gender of crime victim** | | | | | |
| Female | 0.513 | 0.006 | 0.031 | 0.501 | 0.525 |
| Male | 0.487 | 0.006 | 0.031 | 0.476 | 0.499 |
| **Age of crime victim** | | | | | |
| Teenager | 0.508 | 0.012 | 0.512 | 0.485 | 0.530 |
| Adult | 0.455 | 0.009 | 0.000 | 0.437 | 0.473 |
| Child | 0.571 | 0.012 | 0.000 | 0.548 | 0.593 |
| Elderly | 0.486 | 0.010 | 0.162 | 0.467 | 0.505 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.526 | 0.012 | 0.029 | 0.503 | 0.549 |
| Gangs | 0.504 | 0.013 | 0.729 | 0.479 | 0.530 |
| Bystanders | 0.510 | 0.012 | 0.382 | 0.487 | 0.533 |
| Police | 0.475 | 0.012 | 0.040 | 0.452 | 0.499 |
| Neighbors | 0.484 | 0.012 | 0.185 | 0.460 | 0.508 |

Table 52: Marginal Means – Opinion on the Judicial System: Bad

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.426 | 0.008 | 0.000 | 0.410 | 0.442 |
| Male | 0.555 | 0.006 | 0.000 | 0.543 | 0.567 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.500 | 0.010 | 0.977 | 0.480 | 0.520 |
| Adult | 0.531 | 0.009 | 0.001 | 0.512 | 0.549 |
| Elderly | 0.470 | 0.009 | 0.001 | 0.452 | 0.488 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.508 | 0.012 | 0.479 | 0.485 | 0.532 |
| White | 0.516 | 0.012 | 0.165 | 0.493 | 0.539 |
| Indigenous | 0.490 | 0.012 | 0.381 | 0.466 | 0.513 |
| Black | 0.485 | 0.012 | 0.222 | 0.462 | 0.509 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.504 | 0.007 | 0.531 | 0.491 | 0.518 |
| In the neighborhood | 0.496 | 0.007 | 0.530 | 0.483 | 0.509 |
| **Offense** | | | | | |
| Murder | 0.620 | 0.013 | 0.000 | 0.596 | 0.645 |
| Pick-pocketing | 0.306 | 0.011 | 0.000 | 0.284 | 0.328 |
| Rape | 0.736 | 0.016 | 0.000 | 0.705 | 0.767 |
| Molestation | 0.536 | 0.012 | 0.004 | 0.512 | 0.560 |
| Car theft | 0.335 | 0.018 | 0.000 | 0.300 | 0.370 |
| **Gender of crime victim** | | | | | |
| Female | 0.498 | 0.007 | 0.729 | 0.484 | 0.511 |
| Male | 0.502 | 0.007 | 0.729 | 0.489 | 0.516 |
| **Age of crime victim** | | | | | |
| Teenager | 0.481 | 0.012 | 0.122 | 0.456 | 0.505 |
| Adult | 0.461 | 0.011 | 0.000 | 0.440 | 0.483 |
| Child | 0.588 | 0.013 | 0.000 | 0.562 | 0.614 |
| Elderly | 0.487 | 0.012 | 0.258 | 0.464 | 0.510 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.557 | 0.014 | 0.000 | 0.530 | 0.584 |
| Gangs | 0.496 | 0.014 | 0.776 | 0.468 | 0.524 |
| Bystanders | 0.512 | 0.014 | 0.407 | 0.484 | 0.539 |
| Police | 0.448 | 0.015 | 0.000 | 0.419 | 0.477 |
| Neighbors | 0.488 | 0.014 | 0.395 | 0.462 | 0.515 |

Table 53: Marginal Means – Opinion on the Judicial System: Very Bad

| Feature | Estimate | Std. Error | P-Value | Lower | Upper |
|---|---|---|---|---|---|
| **Gender of crime perpetrator** | | | | | |
| Female | 0.461 | 0.009 | 0.000 | 0.444 | 0.478 |
| Male | 0.530 | 0.007 | 0.000 | 0.517 | 0.544 |
| **Age of crime perpetrator** | | | | | |
| Teenager | 0.494 | 0.010 | 0.542 | 0.475 | 0.513 |
| Adult | 0.500 | 0.010 | 0.974 | 0.480 | 0.520 |
| Elderly | 0.506 | 0.011 | 0.587 | 0.485 | 0.527 |
| **Race of crime perpetrator** | | | | | |
| Asian | 0.505 | 0.013 | 0.711 | 0.479 | 0.530 |
| White | 0.507 | 0.013 | 0.599 | 0.482 | 0.531 |
| Indigenous | 0.500 | 0.013 | 0.973 | 0.473 | 0.526 |
| Black | 0.489 | 0.012 | 0.369 | 0.465 | 0.513 |
| **Residency of crime perpetrator** | | | | | |
| Another neighborhood | 0.503 | 0.007 | 0.639 | 0.489 | 0.518 |
| In the neighborhood | 0.497 | 0.007 | 0.639 | 0.482 | 0.511 |
| **Offense** | | | | | |
| Murder | 0.608 | 0.013 | 0.000 | 0.582 | 0.634 |
| Pick-pocketing | 0.297 | 0.013 | 0.000 | 0.272 | 0.322 |
| Rape | 0.726 | 0.019 | 0.000 | 0.688 | 0.764 |
| Molestation | 0.560 | 0.014 | 0.000 | 0.533 | 0.587 |
| Car theft | 0.350 | 0.019 | 0.000 | 0.312 | 0.387 |
| **Gender of crime victim** | | | | | |
| Female | 0.523 | 0.008 | 0.003 | 0.508 | 0.538 |
| Male | 0.478 | 0.007 | 0.003 | 0.463 | 0.493 |
| **Age of crime victim** | | | | | |
| Teenager | 0.529 | 0.014 | 0.030 | 0.503 | 0.556 |
| Adult | 0.467 | 0.012 | 0.004 | 0.444 | 0.490 |
| Child | 0.556 | 0.014 | 0.000 | 0.529 | 0.584 |
| Elderly | 0.469 | 0.012 | 0.008 | 0.447 | 0.492 |
| **Lynching perpetrators** | | | | | |
| Family of the victim | 0.518 | 0.015 | 0.238 | 0.488 | 0.547 |
| Gangs | 0.512 | 0.015 | 0.433 | 0.482 | 0.542 |
| Bystanders | 0.508 | 0.015 | 0.594 | 0.478 | 0.538 |
| Police | 0.458 | 0.014 | 0.002 | 0.432 | 0.485 |
| Neighbors | 0.505 | 0.014 | 0.712 | 0.477 | 0.533 |

## C.5 Text Analysis

In addition to the conjoint experiments, we also asked respondents to justify their profile choices. We added a text box after each conjoint and informed subjects that their responses were optional. However, we obtained 8297 responses in our survey, which we analyze here.

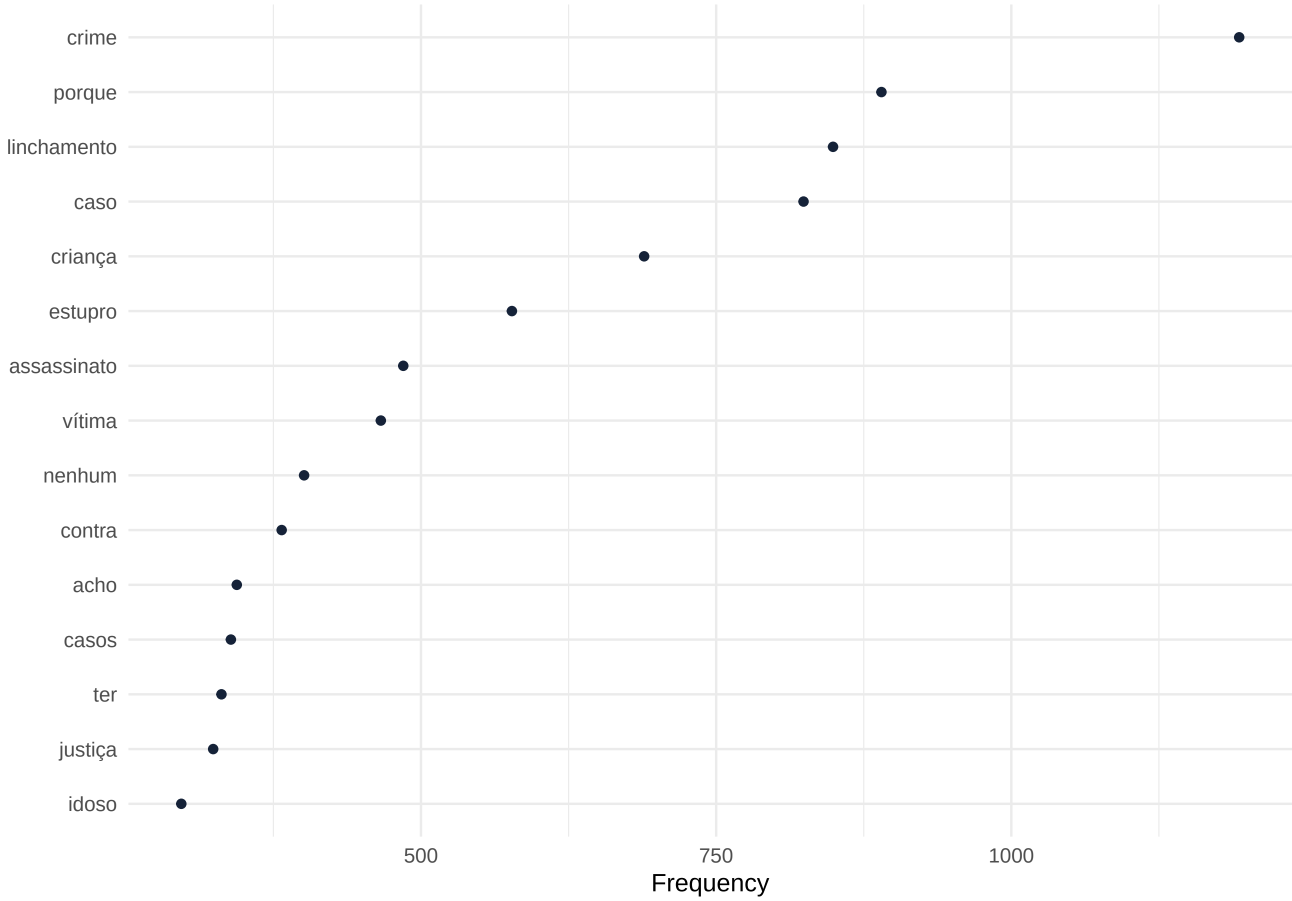
First, we concatenate all text responses into a single vector. Then we tokenize the sentences, remove Portuguese stop words and punctuation, and select the words that appear most frequently in the texts.

The graphs shows that *crime* (same as in English), *porque* (because), *linchamento* (lynching), and *caso* (case) are the words respondents use most often. This is expected as subjects were asked to justify their choices. The next words in the list are related to victim or crime characteristics, such as *criança* (child), *estupro* (rape), *assassinato* (murder), and *vítima* (victim). Indeed, they provide evidence for our previous findings and confirm that respondents select lynching victim profiles according to these two factors. Criminal characteristics, such as age or race, do not seem to be particularly relevant, as respondents do not mention them as much. The following terms are *nenhum* (none), *contra* (against), *acho* (I think), *casos* (cases), *ter* (have to), and *justiça* (justice). We believe these words correspond to cases where respondents wanted to affirm that they do not have any preference regarding the lynching profiles, or that they would rather not have chosen any of the alternatives.

```
dfmat <- df1 %>%
  select(q13_text, q14_text, q15_text, q16_text, q17_text) %>%
  gather() %>%
  corpus(text_field = "value") %>%
  tokens(remove_punct = TRUE, remove_numbers = TRUE,
         remove_symbol = TRUE) %>%
  dfm() %>%
  dfm_remove(., pattern = c(stopwords("pt", source = "snowball"),
                            "é", "ser"))


# Plot
dfmat %>%
  textstat_frequency(n = 15) %>%
  ggplot(aes(x = reorder(feature, frequency), y = frequency)) +
  geom_point(colour = "#152238") +
  coord_flip() +
```

```r
labs(x = NULL, y = "Frequency") +
theme_minimal()
```




We also construct a feature co-occurrence matrix (FCM) that shows which words appear together in the responses we collected. Again, the results confirm the findings of the conjoint experiment. As suggested in the previous graph, we see a central cluster that describes crime and victim characteristics and includes the words *linchamentos* (lynchings), *caso* (case), *estupro* (rape), *criança* (child), *assassinato* (murder), and *vítima* (victim). This highlights that these are the most important reasons why respondents choose lynching profiles.

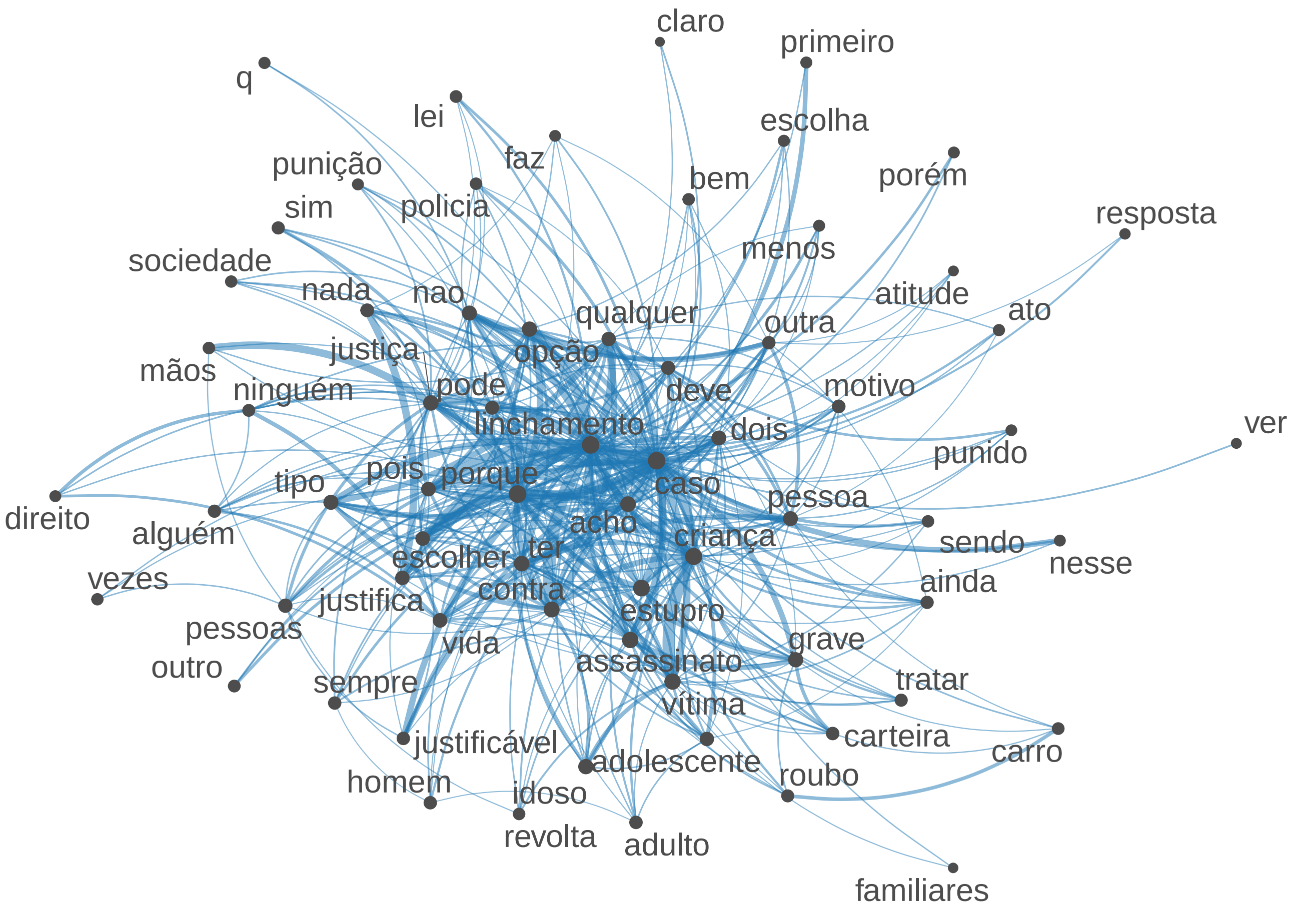
We note that there is another word cluster on the left. It contains words that indicate that some respondents do not support lynchings, such as *não* (no), *opção* (choice), *nada* (nothing), *justifica* (justifies), *justificável* (justifiable), and *escolher* (choose).

```r
fcmat <- fcm(dfmat)
feat <- names(topfeatures(fcmat, 70))
fcmat_select <- fcm_select(fcmat, pattern = feat, selection = "keep")
size <- log(colSums(dfm_select(dfmat, feat, selection = "keep")))


# Plot
```

```r
set.seed(144)

textplot_network(fcmat_select, min_freq = 0.8, vertex_size = size / max(size) * 3, max.overlaps = 30)
```




We estimate a latent Dirichlet allocation (LDA) model to identify the three most important topics in our corpus. The first topic includes words that refer to victim and crime characteristics, many of which have also appeared in our previous estimations. Some of the most common words in this group are *crime* (crime), *criança* (child), *estupro* (rape), *vítima* (victim), *porque* (because), *idoso* (elderly), *grave* (serious), and *molestar* (molest). When we count the number of topics in the corpus, we see that this is the predominant one. The second topic identified by the model describes lynching perpetrators, as it contains the words like *polícia* (police), *pessoas* (people), and *família* (family). The third topic identifies the same words we associate with respondents who are against lynchings, such as *nenhum* (none), *opção* (choice), *não* (no), and *contra* (against). As our results show, respondents decide which individual deserves punishment based on factors related to the crime he/she committed, especially the crime victim. There is also a group of respondents that oppose lynchings in principle, who affirm that lynchings are never justified.

```r
# Unsupervized LDA

tmod_lda <- textmodel_lda(dfmat, k = 3)

terms(tmod_lda, 10)
```

```
##       topic1    topic2
##  [1,] "porque"  "crime"
##  [2,] "justiça" "criança"
##  [3,] "vida"    "estupro"
##  [4,] "família" "vítima"
##  [5,] "polícia" "assassinato"
##  [6,] "pessoas" "porque"
##  [7,] "fazer"   "idoso"
##  [8,] "pessoa"  "grave"
##  [9,] "deve"    "molestar"
## [10,] "pode"    "vitima"
##       topic3
##  [1,] "linchamento"
##  [2,] "caso"
##  [3,] "nenhum"
##  [4,] "casos"
##  [5,] "opção"
##  [6,] "concordo"
##  [7,] "acho"
##  [8,] "nao"
##  [9,] "dois"
## [10,] "contra"
```

```
table(topics(tmod_lda))
```

```
##
## topic1 topic2 topic3
##   2278   3500   2482
```

Our last model is a semisupervized LDA, in which we include a series of keywords to measure how frequently some pre-defined topics appear often in the responses. We adopt a conservative approach and only include words that we have a high degree of confidence that are not ambiguous. There are four pre-defined topics in this estimation. The first refers to victims, and include the Portuguese words for *children*, *life*, and *victim* (along with possible variations). The second topic describes crime characteristics with words such as *murder*, *rape*, *kill*, *molest*, and *steal*. The next group has four keywords that describe lynching perpetrators, and they are *gangs*, *family*, *bystanders*, and *police*. The fourth topic includes terms to identify respondents who are against lynchings, and we added *against*, *none*, *do not agree*, and *choice* as seed terms. We see that the topic describing crime characteristics is the one that appears more often.

```r
# Semisupervized LDA
keywords <- dictionary(list(victim      = c("crian*", "vida*", "v*tima*"),
                            crime       = c("assassin*", "estupr*", "mata*", "molest*", "roub*"),
                            perpetrator = c("gang*", "fam*lia*", "pedestr*", "pol*cia*"),
                            against     = c("contra", "escolha", "nenhum*", "n*o concord*", "op**o")))

slda <- textmodel_seededlda(dfmat, keywords, residual = TRUE)
terms(slda, 10)
```

```
##       victim        crime
##  [1,] "criança"     "crime"
##  [2,] "vítima"      "estupro"
##  [3,] "vida"        "assassinato"
##  [4,] "vitima"      "molestar"
##  [5,] "crianças"    "molestou"
##  [6,] "crianca"     "assassinou"
##  [7,] "vítimas"     "roubo"
##  [8,] "criancas"    "assassino"
##  [9,] "vitimas"     "roubar"
## [10,] "criança.mas" "estuprou"
##       perpetrator  against       other
##  [1,] "família"    "linchamento" "porque"
##  [2,] "polícia"    "nenhum"      "sei"
##  [3,] "gangues"    "contra"      "pq"
##  [4,] "policia"    "opção"       "crimes"
##  [5,] "familia"    "caso"        "morte"
##  [6,] "policiais"  "nenhuma"     "sim"
##  [7,] "gangue"     "escolha"     "pra"
##  [8,] "familiares" "opinião"     "pessoas"
##  [9,] "pedestres"  "opcao"       "mesma"
## [10,] "policial"   "opçao"       "nao"
```

```r
table(topics(slda))
```

```
##
##      victim       crime perpetrator
```

```
##        1696        2161        1198
##     against       other
##        1669        1536
```

# D Experiment 02

## D.1 Description

Our second experiment measures the effect of information provision on attitudes about lynching. In particular, we test whether reminding respondents about the legal and social consequences of vigilante justice reduces the subjects' level of support for such practice.

The experiment has three treatment conditions and a control group. In all of them we present respondents with a short statement affirming that some Brazilians support vigilantism under certain conditions. Respondents were asked to use 0 to 49 if they disagree, 50 if they neither agree nor disagree, and 50-100 if they agree with the sentence.

Each of the three treatment groups received a different message about the legal or social consequences of lynching in Brazil. In the first treatment arm, we informed subjects about how the Brazilian constitution and penal code punishes civilian violence. The second treatment group was notified about the human rights guarantees enshrined in Brazil's legal framework. The last group read a vignette that mentions how lynchings can spark *vendettas* and initiate a cycle of violence in the community. Subjects in the control group received no information about the consequences of lynchings. The text shown to the control and treatment groups can be read below.

- *Control group*: In Brazil, some people believe that lynching may be justified under certain conditions. To what degree do you agree or disagree that lynching can be justified? Please use the slider below to indicate your preference. For disagreement, use 0 to 49; for agreement, use 51 to 100. Please use 50 if you neither agree nor disagree.[2]

- *Treatment 01 - Legal punishment for lynching perpetrators*: In Brazil, some people believe that lynching may be justified under certain conditions. **However, the Brazilian constitution**

[2]In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições. O quanto você concorda ou discorda que linchamentos podem ser justificados? Por favor, use a barra abaixo para indicar sua preferência. Para indicar que discorda, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 caso você não concorde nem discorde.

**and penal code strictly forbid lynching and those involved can be accused of torture or murder**. To what degree do you agree or disagree that lynching can be justified? Please use the slider below to indicate your preference. For disagreement, use 0 to 49; for agreement, use 51 to 100. Please use 50 if you neither agree nor disagree.[3]

- *Treatment 02 - Human rights*: In Brazil, some people believe that lynching may be justified under certain conditions. **However, the Brazilian constitution states that all individuals have the right of not being tortured, including criminals**. To what degree do you agree or disagree that lynching can be justified? Please use the slider below to indicate your preference. For disagreement, use 0 to 49; for agreement, use 51 to 100. Please use 50 if you neither agree nor disagree.[4]

- *Treatment 03 - Vendettas*: In Brazil, some people believe that lynching may be justified under certain conditions. **However, lynchings can trigger a new cycle of violence as the family or friends of the victim may retaliate the community**. To what degree do you agree or disagree that lynching can be justified? Please use the slider below to indicate your preference. For disagreement, use 0 to 49; for agreement, use 51 to 100. Please use 50 if you neither agree nor disagree.[5]

## D.2 Main Results

Our results are available in table 54. Reminding respondents of the legal consequences of lynchings has a strong, negative effect on individual levels of lynching support. We see a reduction of about 4.5%, which corresponds to an 11% change when compared to the baseline levels. Our second treatment condition, reminding subjects of human rights guarantees, has no statistically significant effect.

[3]In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições. **Entretanto, a constituição e o código penal do Brasil proíbem estritamente os linchamentos e os envolvidos podem ser acusados de tortura ou assassinato.** O quanto você concorda ou discorda que linchamentos podem ser justificados? Por favor, use a barra abaixo para indicar sua preferência. Para indicar que discorda, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 caso você não concorde nem discorde.

[4]In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições. **Entretanto, a constituição do Brasil afirma que todos os indivíduos têm o direito de não serem torturados, inclusive criminosos**. O quanto você concorda ou discorda que linchamentos podem ser justificados? Por favor, use a barra abaixo para indicar sua preferência. Para indicar que discorda, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 caso você não concorde nem discorde.

[5]In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições. **Entretanto, linchamentos podem iniciar um ciclo de violência pois a família ou amigos da vítima podem retaliar a comunidade**. O quanto você concorda ou discorda que linchamentos podem ser justificados? Por favor, use a barra abaixo para indicar sua preferência. Para indicar que discorda, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 caso você não concorde nem discorde.

Informing respondents that lynchings can trigger a cycle of violence also has a large negative effect. It decreases lynching support by 3%, which is an 8% reduction in comparison with the control group. When we combine all treatments, we still detect a negative impact of the treatment conditions.

```
df_exp03 <- df1 %>%
  mutate(exp03_outcomes = coalesce(exp03_control, exp03_constitution, exp03_rights, exp03_vendetta),
         exp03_any_treat = case_when(!is.na(exp03_control) ~ "0", !is.na(exp03_constitution) ~ "1",
                                     !is.na(exp03_rights) ~ "1", !is.na(exp03_vendetta) ~ "1",
                                     TRUE ~ NA_character_),
         exp03_constitution_treat = case_when(!is.na(exp03_control) ~ "0",
                                              !is.na(exp03_constitution) ~ "1"),
         exp03_rights_treat = case_when(!is.na(exp03_control) ~ "0",
                                        !is.na(exp03_rights) ~ "1"),
         exp03_vendetta_treat = case_when(!is.na(exp03_control) ~ "0",
                                          !is.na(exp03_vendetta) ~ "1"))

m1 <- lm(exp03_outcomes ~ exp03_constitution_treat, data = df_exp03)
m2 <- lm(exp03_outcomes ~ exp03_rights_treat, data = df_exp03)
m3 <- lm(exp03_outcomes ~ exp03_vendetta_treat, data = df_exp03)
m4 <- lm(exp03_outcomes ~ exp03_any_treat, data = df_exp03)

stargazer(m1, m2, m3, m4, se = starprep(m1, m2, m3, m4), header = FALSE,
          p = starprep(m1, m2, m3, m4, stat = "p.value"), align = TRUE,
          title = "Experiment 03 -- Main Results", style = "apsr", label = "tab:exp03main",
          dep.var.labels = "\\textbf{Lynching Support}\\vspace{.5cm}",
          covariate.labels = c("Constitution and penal code", "Human rights",
                               "Vendettas", "Combined treatments"),
          column.sep.width = "3pt", notes = "Robust standard errors in parentheses.",
          keep.stat = "n", no.space = TRUE)
```

## D.3 Determinants of Baseline Levels

We also evaluate how individual characteristics impact lynching support. We find that the coefficient for white respondents is negative in two estimations, and the coefficient for male does not reach statistical significance in the last model ($p$-value = 0.11). Political ideology is strongly correlated with support for lynchings.

Table 54: Experiment 03 – Main Results

| | Lynching Support | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constitution and penal code | $-4.509^{**}$ | | | |
| | (1.805) | | | |
| Human rights | | $-1.571$ | | |
| | | (1.801) | | |
| Vendettas | | | $-3.156^{*}$ | |
| | | | (1.879) | |
| Combined treatments | | | | $-3.023^{**}$ |
| | | | | (1.493) |
| Constant | $40.823^{***}$ | $40.823^{***}$ | $40.823^{***}$ | $40.823^{***}$ |
| | (1.293) | (1.293) | (1.293) | (1.293) |
| N | 1,114 | 1,173 | 1,092 | 2,215 |

$^{*}$p < .1; $^{**}$p < .05; $^{***}$p < .01
Robust standard errors in parentheses.

```
df_exp03_group <- df_exp03 %>%
  filter(gender == c("Female", "Male"),
         race %in% c("Asian", "Black", "Mixed Race", "White"),
         ideology %in% c("Center", "Center-Left", "Center-Right", "Left", "Right")) %>%
  mutate(race = fct_relevel(race, "Black"), ideology = fct_relevel(ideology, "Center"))

df_exp03_gender <- df_exp03 %>% filter(gender == c("Female", "Male"))
df_exp03_race <- df_exp03 %>% filter(race %in% c("Asian", "Black", "Mixed Race", "White")) %>%
  mutate(race = fct_relevel(race, "Black"))
df_exp03_ideology <- df_exp03 %>%
         filter(ideology %in% c("Center", "Center-Left", "Center-Right", "Left", "Right")) %>%
         mutate(ideology = fct_relevel(ideology, "Center"))

m1 <- lm(exp03_outcomes ~ gender, data = df_exp03_gender)
m2 <- lm(exp03_outcomes ~ race, data = df_exp03_race)
m3 <- lm(exp03_outcomes ~ ideology, data = df_exp03_ideology)
m4 <- lm(exp03_outcomes ~ gender + race + ideology, data = df_exp03_group)

stargazer(m1, m2, m3, m4, se = starprep(m1, m2, m3, m4), p = starprep(m1, m2, m3, m4, stat = "p.value"),
          header = FALSE, align = TRUE, label = "tab:exp03baseline",
          title = "Experiment 01 -- Determinants of Baseline Levels of
```

```
Lynching Support", style = "apsr", dep.var.labels = "\\textbf{Lynching Support}\\vspace{.5cm}",
covariate.labels = c("Male", "Asian", "Mixed Race", "White",
                     "Left", "Center-Left", "Center-Right", "Right"),
column.sep.width = "3pt", notes = "Robust standard errors in parentheses.",
keep.stat = "n", no.space = TRUE)
```

Table 55: Experiment 01 – Determinants of Baseline Levels of Lynching Support

| | **Lynching Support** | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Male | 4.825*** | | | 3.329 |
| | (1.809) | | | (2.089) |
| Asian | | 1.584 | | 1.487 |
| | | (4.729) | | (8.218) |
| Mixed Race | | −0.422 | | −4.205 |
| | | (2.393) | | (4.126) |
| White | | −3.873* | | −8.962** |
| | | (2.247) | | (3.883) |
| Left | | | −10.475*** | −12.049*** |
| | | | (2.268) | (3.058) |
| Center-Left | | | −14.893*** | −16.576*** |
| | | | (2.525) | (3.639) |
| Center-Right | | | −2.564 | −5.600 |
| | | | (2.745) | (3.813) |
| Right | | | 0.887 | 2.194 |
| | | | (2.179) | (3.109) |
| Constant | 36.063*** | 40.898*** | 43.358*** | 48.833*** |
| | (1.223) | (2.079) | (1.679) | (4.275) |
| N | 1,141 | 2,185 | 1,625 | 831 |

*p < .1; **p < .05; ***p < .01
Robust standard errors in parentheses.

## D.4 Heterogeneous Effects

In this section, we explore whether our pre-treatment covariates impact the treatment effect. We use the same flexible approach we employed in the previous experiment, and estimate all models using Bayesian Additive Regression Trees (BART). The algorithm produces average treatment effects for each category in the moderator variables.

### D.4.1 Treatment 01: Legal Punishment for Lynching Perpetrators

We find no evidence of heterogeneous effects in this treatment condition. All coefficients are largely similar across all model specifications.

```
df_exp03_het <- df_exp03 %>%
  filter(gender %in% c("Female", "Male")) %>%
  mutate(race = fct_relevel(race, "White", "Black", "Mixed Race", "Asian",
                            "Indigenous"),
         education = fct_relevel(education, "Primary School", "Secondary School",
                                 "High School", "College", "Graduate School"),
         views_police = fct_relevel(views_police, "Regular", "Very Good", "Good",
                                    "Bad", "Very Bad"),
         views_justice = fct_relevel(views_justice, "Regular", "Very Good", "Good",
                                     "Bad", "Very Bad"),
         ideology = fct_relevel(ideology, "Center", "Left", "Center-Left",
                                "Center-Right", "Right", "Don't Know", "Rather Not Say"),
         household_income = fct_relevel(household_income, "Up to R$1,000", "From R$1,001 to R$2,000",
                                        "From R$2,001 to R$3,000", "From R$3,001 to R$5,000",
                                        "From R$5,001 to R$10,000", "From R$10,001 to R$20,000",
                                        "Above R$20,000"),
         previous_victim_dummy = fct_relevel(previous_victim_dummy, "Yes", "No"),
         death_penalty = fct_relevel(death_penalty, "Yes", "No"),
         age2 = case_when(age >= 18 & age <= 34 ~ "18-34", age >= 35 & age <= 54 ~ "35-54",
                          age >= 55 ~ "55 plus", TRUE ~ as.character(age)))

df_exp03_constitution <- df_exp03_het %>%
  mutate(exp03_constitution_treat = as.numeric(exp03_constitution_treat)) %>%
  drop_na(exp03_constitution_treat)

# Gender
summary(bartc(exp03_outcomes, exp03_constitution_treat, gender,
              group.by = gender, group.effects = TRUE, data = df_exp03_constitution,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
```

```
##              confounders = gender, data = df_exp03_constitution, group.by = gender,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -4.280 3.039  -10.237  1.67709  567
## 2     -4.567 3.145  -10.732  1.59724  542
## tot   -4.420 2.205   -8.743 -0.09788 1109
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Age
df_exp03_constitution2 <- df_exp03_constitution %>% drop_na(age2)
summary(bartc(exp03_outcomes, exp03_constitution_treat, age2,
              group.by = age2, group.effects = TRUE, data = df_exp03_constitution2,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##              confounders = age2, data = df_exp03_constitution2, group.by = age2,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -5.616 3.648  -12.765   1.5332  378
## 2     -5.062 3.768  -12.446   2.3232  353
```

```
## 3     -2.695 3.603   -9.757   4.3675  377
## tot   -4.445 2.179   -8.716  -0.1743 1108
## Estimates fit from 1108 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Race
summary(bartc(exp03_outcomes, exp03_constitution_treat, race,
              group.by = race, group.effects = TRUE, data = df_exp03_constitution,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##              confounders = race, data = df_exp03_constitution, group.by = race,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1   -5.59879  2.749  -10.986 -0.21148  661
## 2   -3.28618  5.768  -14.592  8.01956  102
## 3   -2.19340  3.885   -9.807  5.42070  306
## 4   -0.01751 11.365  -22.292 22.25740   20
## 5   -3.05695 25.120  -52.292 46.17802    3
## 6   -4.47984 20.095  -43.866 34.90646    5
## 7   -2.66272 13.461  -29.045 23.72005   12
## tot -4.30211  2.213   -8.640  0.03587 1109
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```r
# Education
summary(bartc(exp03_outcomes, exp03_constitution_treat, education,
              group.by = education, group.effects = TRUE, data = df_exp03_constitution,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##              confounders = education, data = df_exp03_constitution, group.by = education,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1     -3.667 17.188  -37.355  30.0205    7
## 2     -4.393  8.487  -21.028  12.2421   39
## 3     -5.243  3.425  -11.957   1.4709  385
## 4     -4.363  2.875   -9.997   1.2713  570
## 5     -2.634  5.949  -14.294   9.0267  103
## 6     -2.697 19.941  -41.780  36.3864    5
## tot   -4.497  2.179   -8.768  -0.2258 1109
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```r
# Household Income
summary(bartc(exp03_outcomes, exp03_constitution_treat, household_income,
              group.by = household_income, group.effects = TRUE, data = df_exp03_constitution,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##             confounders = household_income, data = df_exp03_constitution,
##             group.by = household_income, group.effects = TRUE, n.chains = 5L,
##             seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -5.075 6.150  -17.129   6.9799   77
## 2     -2.096 5.299  -12.482   8.2905  134
## 3     -6.680 4.693  -15.879   2.5192  173
## 4     -5.962 3.914  -13.633   1.7094  267
## 5     -2.185 3.890   -9.809   5.4381  296
## 6     -6.108 5.520  -16.927   4.7118  110
## 7     -5.365 7.437  -19.942   9.2127   52
## tot   -4.524 2.222   -8.879  -0.1676 1109
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Political Ideology
summary(bartc(exp03_outcomes, exp03_constitution_treat, ideology,
              group.by = ideology, group.effects = TRUE, data = df_exp03_constitution,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##             confounders = ideology, data = df_exp03_constitution, group.by = ideology,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
```

```
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1    -2.1798 4.984  -11.947   7.5879  144
## 2    -5.8330 4.533  -14.717   3.0513  191
## 3    -1.9474 5.757  -13.230   9.3356   99
## 4    -2.1615 5.556  -13.052   8.7287  104
## 5    -9.5717 4.199  -17.802  -1.3418  271
## 6    -0.6526 5.072  -10.593   9.2879  150
## 7    -3.6067 4.830  -13.074   5.8605  150
## tot  -4.5793 2.180   -8.851  -0.3072 1109
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Support for Death Penalty
summary(bartc(exp03_outcomes, exp03_constitution_treat, death_penalty,
              group.by = death_penalty, group.effects = TRUE, data = df_exp03_constitution,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##             confounders = death_penalty, data = df_exp03_constitution,
##             group.by = death_penalty, group.effects = TRUE, n.chains = 5L,
##             seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -6.917 3.142  -13.076  -0.7591  465
## 2     -2.281 3.048   -8.255   3.6919  518
```

```
## 3      -4.284 7.137  -18.272   9.7042   72
## 4      -2.179 7.744  -17.358  12.9991   54
## tot    -4.350 2.142   -8.548  -0.1530 1109
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Previous Victimization
df_exp03_constitution2 <- df_exp03_constitution %>% drop_na(previous_victim_dummy)
summary(bartc(exp03_outcomes, exp03_constitution_treat, previous_victim_dummy,
              group.by = previous_victim_dummy, group.effects = TRUE, data = df_exp03_constitution2,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##             confounders = previous_victim_dummy, data = df_exp03_constitution2,
##             group.by = previous_victim_dummy, group.effects = TRUE, n.chains = 5L,
##             seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##      estimate    sd ci.lower ci.upper    n
## 1      -5.152 3.472  -11.958   1.6534  428
## 2      -3.377 2.777   -8.821   2.0664  669
## tot    -4.070 2.187   -8.356   0.2165 1097
## Estimates fit from 1097 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Opinion on the Police
summary(bartc(exp03_outcomes, exp03_constitution_treat, views_police,
```

```
             group.by = views_police, group.effects = TRUE, data = df_exp03_constitution,
             n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##             confounders = views_police, data = df_exp03_constitution,
##             group.by = views_police, group.effects = TRUE, n.chains = 5L,
##             seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1     -2.775  3.388   -9.416  3.86511  409
## 2     -3.637  6.959  -17.275 10.00182   62
## 3     -3.820  4.155  -11.964  4.32308  229
## 4     -4.991  4.314  -13.447  3.46462  219
## 5     -8.787  5.121  -18.823  1.24996  168
## 6     -2.863 12.649  -27.655 21.92779   14
## 7     -6.332 15.998  -37.689 25.02391    8
## tot   -4.414  2.237   -8.798 -0.03023 1109
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Opinion on the Judicial System
summary(bartc(exp03_outcomes, exp03_constitution_treat, views_justice,
             group.by = views_police, group.effects = TRUE, data = df_exp03_constitution,
             n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_constitution_treat,
##             confounders = views_justice, data = df_exp03_constitution,
##             group.by = views_police, group.effects = TRUE, n.chains = 5L,
##             seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1     -3.619  2.963   -9.427   2.1879  409
## 2     -3.786  6.011  -15.568   7.9963   62
## 3     -3.175  3.581  -10.194   3.8446  229
## 4     -5.623  3.801  -13.073   1.8266  219
## 5     -4.714  4.155  -12.857   3.4292  168
## 6     -2.355 12.055  -25.982  21.2715   14
## 7     -4.171 15.310  -34.179  25.8365    8
## tot   -4.086  2.188   -8.375   0.2019 1109
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1109 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

### D.4.2 Treatment 02: Human Rights

Our results show no presence of heterogeneous effects.

```
df_exp03_rights <- df_exp03_het %>%
  mutate(exp03_rights_treat = as.numeric(exp03_rights_treat)) %>%
  drop_na(exp03_rights_treat)


# Gender
summary(bartc(exp03_outcomes, exp03_rights_treat, gender,
              group.by = gender, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
```

```
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##              confounders = gender, data = df_exp03_rights, group.by = gender,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -1.912 3.083   -7.955    4.130  589
## 2     -1.249 3.127   -7.378    4.880  579
## tot   -1.583 2.201   -5.897    2.731 1168
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Age
df_exp03_rights2 <- df_exp03_rights %>% drop_na(age2)
summary(bartc(exp03_outcomes, exp03_rights_treat, age2,
              group.by = age2, group.effects = TRUE, data = df_exp03_rights2,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##              confounders = age2, data = df_exp03_rights2, group.by = age2,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
```

```
## 1    -2.4767 3.687   -9.703    4.749  380
## 2    -2.3180 3.654   -9.479    4.843  394
## 3     0.1441 3.629   -6.969    7.258  393
## tot  -1.5405 2.204   -5.861    2.780 1167
## Estimates fit from 1167 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Race
summary(bartc(exp03_outcomes, exp03_rights_treat, race,
              group.by = race, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##              confounders = race, data = df_exp03_rights, group.by = race,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1    -2.0425  2.647   -7.230    3.145  689
## 2    -1.5909  5.296  -11.971    8.789  117
## 3    -0.6657  3.611   -7.744    6.412  314
## 4     0.5013  9.084  -17.302   18.305   31
## 5    -0.5564 17.166  -34.201   33.089    7
## 6    -1.3067 25.705  -51.687   49.074    3
## 7    -1.2059 17.083  -34.687   32.275    7
## tot  -1.5438  2.173   -5.803    2.716 1168
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
```

```
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```r
# Education
summary(bartc(exp03_outcomes, exp03_rights_treat, education,
              group.by = education, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##              confounders = education, data = df_exp03_rights, group.by = education,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1    -1.9759 18.531  -38.296   34.344    6
## 2    -2.1842  9.510  -20.824   16.455   32
## 3    -3.1628  3.413   -9.852    3.526  417
## 4    -0.7388  2.848   -6.321    4.843  606
## 5     0.8754  5.955  -10.796   12.547  103
## 6    -1.7446 22.515  -45.874   42.385    4
## tot  -1.5113  2.170   -5.764    2.741 1168
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```r
# Household Income
summary(bartc(exp03_outcomes, exp03_rights_treat, household_income,
              group.by = household_income, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##             confounders = household_income, data = df_exp03_rights, group.by = household_income,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1    -1.0876 6.767  -14.350   12.175   68
## 2    -1.3837 4.972  -11.129    8.362  153
## 3    -2.9467 4.492  -11.751    5.857  193
## 4    -1.9882 3.850   -9.534    5.558  275
## 5     0.9273 3.924   -6.764    8.619  304
## 6    -3.0499 5.176  -13.194    7.094  133
## 7    -1.2901 7.886  -16.747   14.167   42
## tot  -1.3519 2.216   -5.696    2.992 1168
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Political Ideology
summary(bartc(exp03_outcomes, exp03_rights_treat, ideology,
              group.by = ideology, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##             confounders = ideology, data = df_exp03_rights, group.by = ideology,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
```

```
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1    -1.7231 4.558  -10.657    7.211  177
## 2    -3.2659 4.449  -11.985    5.453  204
## 3    -0.3674 5.662  -11.466   10.731  100
## 4    -0.2013 5.408  -10.801   10.399  112
## 5    -4.0126 4.207  -12.258    4.233  253
## 6     3.2825 5.260   -7.027   13.591  158
## 7    -1.2508 4.634  -10.333    7.831  164
## tot  -1.4830 2.158   -5.714    2.747 1168
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Support for Death Penalty
summary(bartc(exp03_outcomes, exp03_rights_treat, death_penalty,
              group.by = death_penalty, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##              confounders = death_penalty, data = df_exp03_rights, group.by = death_penalty,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1    -4.0531 3.197  -10.319    2.213  486
## 2    -0.8195 3.029   -6.756    5.117  538
```

```
## 3     5.5199 6.854   -7.913   18.953   86
## 4     3.5583 7.751  -11.634   18.750   58
## tot  -1.4808 2.113   -5.623    2.661 1168
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Previous Victimization
df_exp03_rights2 <- df_exp03_rights %>% drop_na(previous_victim_dummy)
summary(bartc(exp03_outcomes, exp03_rights_treat, previous_victim_dummy,
              group.by = previous_victim_dummy, group.effects = TRUE, data = df_exp03_rights2,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##              confounders = previous_victim_dummy, data = df_exp03_rights2,
##              group.by = previous_victim_dummy, group.effects = TRUE, n.chains = 5L,
##              seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1    -4.0969 3.388  -10.737    2.543  482
## 2    -0.2471 2.842   -5.817    5.323  674
## tot  -1.8523 2.195   -6.155    2.450 1156
## Estimates fit from 1156 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Opinion on the Police
summary(bartc(exp03_outcomes, exp03_rights_treat, views_police,
```

```
              group.by = views_police, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
##               confounders = views_police, data = df_exp03_rights, group.by = views_police,
##               group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1   -1.21331  3.129   -7.347    4.920  464
## 2    0.34947  6.901  -13.176   13.875   65
## 3   -0.06316  4.246   -8.386    8.260  234
## 4   -2.97000  4.189  -11.181    5.241  223
## 5   -3.52328  4.883  -13.094    6.047  165
## 6   -0.66005 15.343  -30.732   29.412    9
## 7   -1.55562 16.123  -33.157   30.046    8
## tot -1.55571  2.217   -5.902    2.790 1168
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Opinion on the Judicial System
summary(bartc(exp03_outcomes, exp03_rights_treat, views_justice,
              group.by = views_police, group.effects = TRUE, data = df_exp03_rights,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_rights_treat,
```

```
##             confounders = views_justice, data = df_exp03_rights, group.by = views_police,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##      estimate     sd ci.lower ci.upper    n
## 1     -1.7887  2.822   -7.319    3.741  464
## 2      1.3945  5.992  -10.349   13.138   65
## 3     -0.3203  3.829   -7.824    7.184  234
## 4     -2.9825  3.575   -9.990    4.025  223
## 5     -2.5000  4.319  -10.965    5.965  165
## 6     -1.1552 14.777  -30.117   27.807    9
## 7     -0.6518 15.613  -31.252   29.949    8
## tot   -1.6331  2.164   -5.875    2.609 1168
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1168 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

### D.4.3 Treatment 03: Vendettas

We do not find considerable heterogeneity in the results. Overall, the three treatment conditions are very stable, thus we are confident that the main results are not driven by any particular group.

```
df_exp03_vendetta <- df_exp03_het %>%
  mutate(exp03_vendetta_treat = as.numeric(exp03_vendetta_treat)) %>%
  drop_na(exp03_vendetta_treat)

# Gender
summary(bartc(exp03_outcomes, exp03_vendetta_treat, gender,
              group.by = gender, group.effects = TRUE, data = df_exp03_vendetta,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
```

```
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##             confounders = gender, data = df_exp03_vendetta, group.by = gender,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -2.601 3.218   -8.909    3.707  553
## 2     -3.596 3.239   -9.945    2.753  533
## tot   -3.089 2.303   -7.603    1.425 1086
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Age
df_exp03_vendetta2 <- df_exp03_vendetta %>% drop_na(age2)
summary(bartc(exp03_outcomes, exp03_vendetta_treat, age2,
              group.by = age2, group.effects = TRUE, data = df_exp03_vendetta2,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##             confounders = age2, data = df_exp03_vendetta2, group.by = age2,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
```

```
## 1    -1.1651 3.945   -8.896    6.566  342
## 2    -5.8445 3.877  -13.443    1.754  347
## 3    -0.9202 3.658   -8.091    6.250  396
## tot  -2.5722 2.269   -7.020    1.875 1085
## Estimates fit from 1085 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Race
summary(bartc(exp03_outcomes, exp03_vendetta_treat, race,
              group.by = race, group.effects = TRUE, data = df_exp03_vendetta,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##               confounders = race, data = df_exp03_vendetta, group.by = race,
##               group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1     -4.361  2.833   -9.915    1.192  636
## 2     -2.070  5.700  -13.241    9.101  108
## 3     -0.693  3.944   -8.424    7.038  297
## 4     -1.279  9.444  -19.789   17.231   30
## 5     -3.042 22.515  -47.170   41.086    4
## 6     -2.546 25.861  -53.233   48.140    3
## 7     -2.243 16.459  -34.502   30.017    8
## tot   -3.020  2.262   -7.452    1.413 1086
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
```

```
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Education
summary(bartc(exp03_outcomes, exp03_vendetta_treat, education,
              group.by = education, group.effects = TRUE, data = df_exp03_vendetta,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##              confounders = education, data = df_exp03_vendetta, group.by = education,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##      estimate     sd ci.lower ci.upper    n
## 1      -1.426 16.824  -34.400   31.547    8
## 2      -3.506  8.970  -21.088   14.075   34
## 3      -6.280  3.737  -13.604    1.045  377
## 4      -1.251  3.037   -7.204    4.701  571
## 5      -1.305  6.174  -13.405   10.796   92
## 6      -2.500 22.660  -46.912   41.912    4
## tot    -3.078  2.300   -7.585    1.429 1086
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Household Income
summary(bartc(exp03_outcomes, exp03_vendetta_treat, household_income,
              group.by = household_income, group.effects = TRUE, data = df_exp03_vendetta,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##              confounders = household_income, data = df_exp03_vendetta,
##              group.by = household_income, group.effects = TRUE, n.chains = 5L,
##              seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -1.561 6.906  -15.096   11.973   65
## 2     -1.667 5.177  -11.814    8.481  129
## 3     -2.994 4.471  -11.757    5.769  186
## 4     -4.792 4.297  -13.214    3.629  235
## 5     -1.914 3.780   -9.323    5.495  285
## 6     -2.206 5.022  -12.049    7.637  141
## 7     -3.094 7.786  -18.354   12.166   45
## tot   -2.758 2.269   -7.206    1.689 1086
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Political Ideology
summary(bartc(exp03_outcomes, exp03_vendetta_treat, ideology,
              group.by = ideology, group.effects = TRUE, data = df_exp03_vendetta,
              n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##              confounders = ideology, data = df_exp03_vendetta, group.by = ideology,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
```

```
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -1.009 4.858  -10.530    8.511  162
## 2     -3.477 4.431  -12.162    5.208  189
## 3     -3.168 5.553  -14.052    7.717  105
## 4     -1.065 5.890  -12.609   10.478   98
## 5     -6.209 4.390  -14.812    2.395  241
## 6      1.024 5.243   -9.252   11.301  149
## 7     -3.577 4.979  -13.336    6.181  142
## tot   -2.863 2.256   -7.286    1.559 1086
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Support for Death Penalty
summary(bartc(exp03_outcomes, exp03_vendetta_treat, death_penalty,
              group.by = death_penalty, group.effects = TRUE, data = df_exp03_vendetta,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##             confounders = death_penalty, data = df_exp03_vendetta, group.by = death_penalty,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -4.397 3.233  -10.734   1.9404  460
```

```
## 2     -2.682 3.183   -8.921   3.5566  493
## 3     -1.334 7.130  -15.308  12.6405   74
## 4     -2.549 8.165  -18.551  13.4537   59
## tot   -3.309 2.195   -7.612   0.9927 1086
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Previous Victimization
df_exp03_vendetta2 <- df_exp03_vendetta %>% drop_na(previous_victim_dummy)
summary(bartc(exp03_outcomes, exp03_vendetta_treat, previous_victim_dummy,
              group.by = previous_victim_dummy, group.effects = TRUE, data = df_exp03_vendetta2,
              n.chains = 5L, seed = 144))
```

```
## fitting treatment model via method 'bart'
## fitting response model via method 'bart'
```

```
## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##              confounders = previous_victim_dummy, data = df_exp03_vendetta2,
##              group.by = previous_victim_dummy, group.effects = TRUE, n.chains = 5L,
##              seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate    sd ci.lower ci.upper    n
## 1     -4.522 3.624  -11.625    2.581  427
## 2     -1.821 2.942   -7.587    3.944  648
## tot   -2.894 2.302   -7.405    1.617 1075
## Estimates fit from 1075 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

```
# Opinion on the Police
summary(bartc(exp03_outcomes, exp03_vendetta_treat, views_police,
```

```
             group.by = views_police, group.effects = TRUE, data = df_exp03_vendetta,
             n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##              confounders = views_police, data = df_exp03_vendetta, group.by = views_police,
##              group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1    -4.2021  3.329  -10.726    2.322  422
## 2    -1.0617  7.248  -15.268   13.144   58
## 3    -1.8649  4.352  -10.394    6.664  220
## 4    -1.9935  4.400  -10.617    6.630  213
## 5    -3.7645  4.916  -13.400    5.871  154
## 6    -0.9266 14.164  -28.688   26.835   11
## 7    -2.5307 16.317  -34.512   29.451    8
## tot  -3.0202  2.274   -7.477    1.437 1086
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Opinion on the Judicial System
summary(bartc(exp03_outcomes, exp03_vendetta_treat, views_justice,
             group.by = views_police, group.effects = TRUE, data = df_exp03_vendetta,
             n.chains = 5L, seed = 144))

## fitting treatment model via method 'bart'
## fitting response model via method 'bart'

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
```

```
##             confounders = views_justice, data = df_exp03_vendetta, group.by = views_police,
##             group.effects = TRUE, n.chains = 5L, seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##     estimate     sd ci.lower ci.upper    n
## 1     -3.192  2.936   -8.946    2.561  422
## 2     -1.024  6.337  -13.445   11.397   58
## 3     -1.644  3.888   -9.263    5.976  220
## 4     -3.415  3.872  -11.005    4.174  213
## 5     -4.126  4.410  -12.770    4.518  154
## 6     -1.524 13.547  -28.076   25.028   11
## 7     -1.917 15.776  -32.837   29.004    8
## tot   -2.913  2.266   -7.354    1.528 1086
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains
```

# E Ethics Statement

We adhered to the ethical guidelines provided by the Institutional Review Board at Brown University and APSA's Principles and Guidance. To facilitate transparency, we comment here on a few aspects of our research design. First, we worked with the Brown University IRB to reduce the risk of harm for participants taking the survey. This included consultation with a cultural expert to inform the phrasing of the survey. Second, respondents received compensation via Qualtrics, which paid respondents directly after they completed the questionnaire. Each subject in Qualtrics' online panel received the equivalent of 2.5 USD in Brazilian Reals (local currency). Respondents who do not finish the survey will not receive compensation. The compensation is appropriate for the participant population. As of August 17, 2020, Brazil's monthly minimum wage is BRL1039, which amounts to

191 US dollars. Assuming 40 working hours per week, the hourly minimum wage equals 1.19 US dollars. Our survey takes about 20 minutes to complete and respondents received 2.5 USD, therefore subjects will receive a monetary compensation that is 6 times higher than the local minimum wage. Third, we do not see any potential or perceived conflicts of interest in carrying out this research. We received a grant of $10,000 to conduct this research from the Centre for the Study of Governance & Society at King's College London, which receives support from the Templeton Foundation. We are aware of no conflicts of interest from either source. All of the code and data will be made publicly available.

# F Session Information

```
sessionInfo()
```

```
## R version 4.2.1 (2022-06-23)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Monterey 12.5.1
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.2/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.2/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] grid      stats     graphics  grDevices
## [5] utils     datasets  methods   base
##
## other attached packages:
##  [1] forcats_0.5.1
##  [2] stringr_1.4.0
##  [3] dplyr_1.0.9
##  [4] purrr_0.3.4
##  [5] readr_2.1.2
##  [6] tidyr_1.2.0
##  [7] tibble_3.1.7
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##  [8] tidyverse_1.3.1
##  [9] stargazer_5.2.3
## [10] seededlda_0.8.1
## [11] proxyC_0.3.2
## [12] quanteda.textplots_0.94.2
## [13] quanteda.textstats_0.95
## [14] quanteda.textmodels_0.9.5
## [15] quanteda_3.2.3
## [16] janitor_2.1.0
## [17] kableExtra_1.3.4
## [18] estimatr_1.0.0
## [19] cregg_0.4.0
## [20] cjoint_2.1.0
## [21] survey_4.1-1
## [22] survival_3.3-1
## [23] Matrix_1.4-1
## [24] ggplot2_3.3.6
## [25] lmtest_0.9-40
## [26] zoo_1.8-10
## [27] sandwich_3.0-2
## [28] bartCause_1.0-4
## [29] rmarkdown_2.14
## [30] nvimcom_0.9-131
##
## loaded via a namespace (and not attached):
##  [1] colorspace_2.0-3
##  [2] ellipsis_0.3.2
##  [3] ggstance_0.3.5
##  [4] snakecase_0.11.0
##  [5] fs_1.5.2
##  [6] rstudioapi_0.13
##  [7] farver_2.1.0
##  [8] ggrepel_0.9.1
##  [9] bit64_4.0.5
## [10] fansi_1.0.3
## [11] lubridate_1.8.0
## [12] xml2_1.3.3
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## [13] codetools_0.2-18
## [14] splines_4.2.1
## [15] dbarts_0.9-22
## [16] knitr_1.39
## [17] Formula_1.2-4
## [18] jsonlite_1.8.0
## [19] broom_1.0.0
## [20] dbplyr_2.2.1
## [21] shiny_1.7.2
## [22] compiler_4.2.1
## [23] httr_1.4.3
## [24] backports_1.4.1
## [25] assertthat_0.2.1
## [26] fastmap_1.1.0
## [27] cli_3.3.0
## [28] later_1.3.0
## [29] htmltools_0.5.2
## [30] tools_4.2.1
## [31] coda_0.19-4
## [32] gtable_0.3.0
## [33] glue_1.6.2
## [34] LiblineaR_2.10-12
## [35] tinytex_0.40
## [36] fastmatch_1.1-3
## [37] Rcpp_1.0.8.3
## [38] statnet.common_4.6.0
## [39] cellranger_1.1.0
## [40] vctrs_0.4.1
## [41] svglite_2.1.0
## [42] iterators_1.0.14
## [43] xfun_0.31
## [44] network_1.17.2
## [45] stopwords_2.3
## [46] rvest_1.0.2
## [47] nsyllable_1.0.1
## [48] mime_0.12
## [49] lifecycle_1.0.1
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## [50] scales_1.2.0
## [51] vroom_1.5.7
## [52] hms_1.1.1
## [53] promises_1.2.0.1
## [54] parallel_4.2.1
## [55] SparseM_1.81
## [56] yaml_2.3.5
## [57] stringi_1.7.6
## [58] highr_0.9
## [59] foreach_1.5.2
## [60] shape_1.4.6
## [61] rlang_1.0.3
## [62] pkgconfig_2.0.3
## [63] systemfonts_1.0.4
## [64] evaluate_0.15
## [65] lattice_0.20-45
## [66] labeling_0.4.2
## [67] bit_4.0.4
## [68] tidyselect_1.1.2
## [69] plyr_1.8.7
## [70] magrittr_2.0.3
## [71] R6_2.5.1
## [72] generics_0.1.2
## [73] sna_2.7
## [74] DBI_1.1.3
## [75] pillar_1.7.0
## [76] haven_2.5.0
## [77] withr_2.5.0
## [78] modelr_0.1.8
## [79] crayon_1.5.1
## [80] utf8_1.2.2
## [81] tzdb_0.3.0
## [82] readxl_1.4.0
## [83] reprex_2.0.1
## [84] digest_0.6.29
## [85] webshot_0.5.3
## [86] xtable_1.8-4
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## [87] httpuv_1.6.5
## [88] RcppParallel_5.1.5
## [89] munsell_0.5.0
## [90] glmnet_4.1-4
## [91] viridisLite_0.4.0
## [92] mitools_2.4
```

# References


Leeper, Thomas J. (2018). cregg: Simple Conjoint Analyses and Visualization. https://thomasleeper.com/cregg. Access: June, 2020. R package version 0.3.0.

R Core Team (2018). R: A Language and Environment for Statistical Computing. https://www.R-project.org. Access: June, 2020.