Supplementary Materials for "Vigilantism, Institutions, and Culture: Understanding Attitudes towards Lynching in Brazil"

Danilo Freire* David Skarbek†

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Contents

*School of Social and Political Sciences, University of Lincoln, danilofreire@gmail.com, http://danilofreire.github.io.

†The Department of Political Science and the Political Theory Project, Brown University, davidskarbek@brown.edu, http://davidskarbek.com.

1 Introduction

This appendix contains the R code required to replicate the results we present in "*Vigilantism, Institutions, and Culture: 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", "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),
```

```r
        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
```

2 Descriptive Statistics

We ran our survey experiments from October 30 to December 14 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.

2.1 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")
```

2.2 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

2.3 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) (CIA 2020).

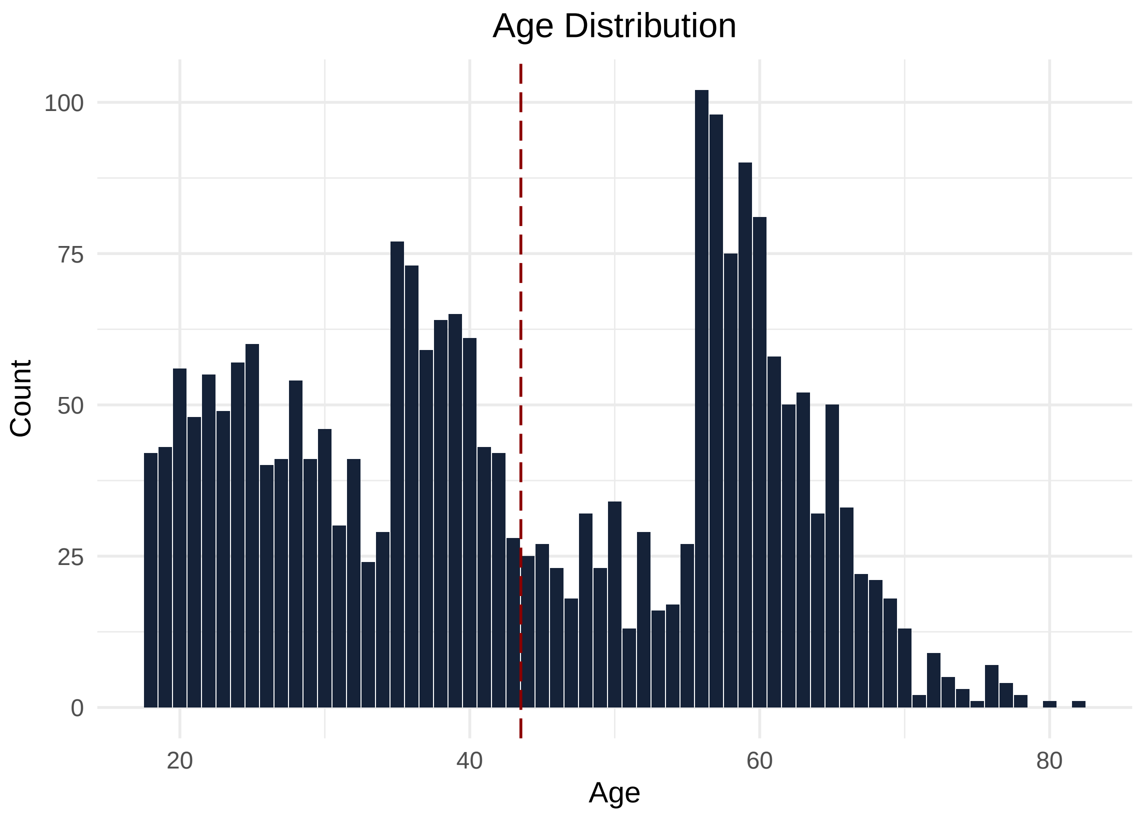
```
tibble(` `     = "Age",
       Median = round(median(df1$age, na.rm = TRUE), 2),
       Mean   = round(mean(df1$age, na.rm = TRUE), 2),
       SD     = round(sd(df1$age, na.rm = TRUE), 2),
       Min    = min(df1$age, na.rm = TRUE),
       Max    = max(df1$age, na.rm = TRUE),
       `NA`   = sum(is.na(df1$age)))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



2.4 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.

```
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

2.5 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.

```
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

2.6 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")
```

2.7 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

2.8 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

2.9 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

2.10 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

2.11 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

3 Experiment 01

3.1 Description

In our first experiment, we analyze how respondents justify their preferences towards extralegal violence. We assess the impact of three factors that have been cited as major drivers of lynchings: 1) police ineffectiveness; 2) slow criminal justice; 3) demand for harsher punishment for criminals. Below, we discuss them in further detail.

Research shows that police ineffectiveness frequently appears as a strong predictor of vigilantism (Cruz and Kloppe-Santamaría 2019; García-Ponce et al. 2019). The direct result of the weakness of police institutions is that citizens decide to take criminal matters "into their own hands", thus persecuting and punishing the criminals by themselves. A recent statistic indicates that the police solves only 10% of the homicides in Brazil, which lends support to the link between weak law enforcement and lynchings (Pearson and Magalhaes 2018).

Another possible determinant of lynching support is lack of trust in the justice system (Godoy 2004; Smith 2019). This is often due to long criminal proceedings, which cause significant anxiety for the victims. In Brazil, the penal code allows the accused to appeal each decision several times, so it can take decades before a criminal case is closed (Sousa 2005). In this respect, citizens do not believe that, even if the criminal is put to trial, he/she will be punished in a timely matter. Note that although the police is technically part of the criminal justice system, we analyze the two institutions separately in our experiment.

Lastly, we evaluate whether respondents think that the legal punishment assigned to criminals is not proportional to the severity of their crimes. In particular, we intend to gauge the demand for iron-fisted criminal justice in Brazil. Although this treatment arm is related to the previous ones, it addresses not the efficiency of the institutions, but their legitimacy (Nivette 2016). In fact, Brazilians are often vocal about their preference for repressive legal punishment. In a recent article in *The Wall Street Journal*, a bar owner justified the lynching of the local thug who killed his son by saying that "*even if he had been put behind bars for 100 years it wouldn't have been enough to pay for all his crimes*" (Pearson and Magalhaes 2018). We hypothesize that many Brazilians also share this view.

The experiment consists of three treatment conditions and one control group. Respondents read an excerpt of a news article describing a real lynching case. We have slightly edited the original text so that respondents have no prior knowledge of the crime.[1] The vignette for the control group includes no information about the reasons behind the lynching. We ask respondents to show their level of lynching support using a 0-100 slider, where 0 means no support and 100 means full support. Respondents in each of the three treatment arms read the same piece, but with one additional sentence explaining the motivations behind the lynching. The vignettes are as follows:

- *Control group*: A man was lynched last Friday in Jundiaí, São Paulo. According to the neighbours,

[1]The original article is available at the following address: https://jr.jor.br/2020/05/01/homem-e-linchado-na-vila-progresso. Access: August 2020.

he tried to break into a house but was immobilised and beaten by members of the community.[2]

- *Treatment 01 - Police ineffectiveness*: A man was lynched last Friday in Jundiaí, São Paulo. According to the neighbours, he tried to break into a house but was immobilised and beaten by members of the community. **One of the residents who took part in the lynching said they had beaten the suspect because "the police never patrols the area"**.[3]

- *Treatment 02 - Criminal justice ineffectiveness*: A man was lynched last Friday in Jundiaí, São Paulo. According to the neighbours, he tried to break into a house but was immobilised and beaten by members of the community. **One of the residents who took part in the lynching said they had beaten the suspect because "the judicial system is too slow and the perpetrator is on the street until the case is heard"**.[4]

- *Treatment 03 - Demand for harsher legal punishment*: A man was lynched last Friday in Jundiaí, São Paulo. According to the neighbours, he tried to break into a house but was immobilised and beaten by members of the community. **One of the residents who took part in the lynching said they had beaten the suspect because "the judicial punishment is not harsh enough"**.[5]

Before each vignette, respondents read the following text:

- You will be shown a news article. Please read it carefully. After you read the article, we will ask you one question about it.[6]

After the vignette, respondents were presented with this question:

[2]In Portuguese: Um homem foi linchado na última sexta-feira em Jundiaí, São Paulo. De acordo com vizinhos, ele tentou invadir uma residência mas foi imobilizado e agredido por membros da comunidade.

[3]In Portuguese: Um homem foi linchado na última sexta-feira em Jundiaí, São Paulo. De acordo com vizinhos, ele tentou invadir uma residência mas foi imobilizado e agredido por membros da comunidade. **Um dos moradores envolvidos no linchamento disse que eles agrediram o suspeito porque "a polícia nunca patrulha o local".**

[4]In Portuguese: Um homem foi linchado na última sexta-feira em Jundiaí, São Paulo. De acordo com vizinhos, ele tentou invadir uma residência mas foi imobilizado e agredido por membros da comunidade. **Um dos moradores envolvidos no linchamento disse que eles agrediram o suspeito porque "a justiça é muito lenta e os criminosos ficam soltos até o julgamento"**.

[5]In Portuguese: Um homem foi linchado na última sexta-feira em Jundiaí, São Paulo. De acordo com vizinhos, ele tentou invadir uma residência mas foi imobilizado e agredido por membros da comunidade. **Um dos moradores envolvidos no linchamento disse que eles agrediram o suspeito porque "a punição da justiça não é dura o suficiente"**.

[6]In Portuguese: Uma notícia será apresentada para você. Por favor, leia a notícia com atenção. Após você ler o artigo, faremos uma pergunta sobre ele.

- Do you think that the lynching was justified? Please use the slider below to indicate your opinion. For disagreement, use 0 to 49; for agreement, use 51 to 100. Please use 50 if you neither agree nor disagree.[7]

3.2 Main Results

Table 12 summarizes our results. As we see, none of the treatment effects are statistically significant at conventional levels. This suggests that institutional factors do not affect lynching support in our sample.

```
df_exp01 <- df1 %>%
  mutate(exp01_outcomes = coalesce(exp01_control, exp01_police,
                                   exp01_slow_justice, exp01_small_punishment),
         exp01_any_treat = case_when(!is.na(exp01_control) ~ "0",
                                     !is.na(exp01_police) ~ "1",
                                     !is.na(exp01_slow_justice) ~ "1",
                                     !is.na(exp01_small_punishment) ~ "1",
                                     TRUE ~ NA_character_),
         exp01_police_treat = case_when(!is.na(exp01_control) ~ "0",
                                        !is.na(exp01_police) ~ "1"),
         exp01_slow_justice_treat = case_when(!is.na(exp01_control) ~ "0",
                                              !is.na(exp01_slow_justice) ~ "1"),
         exp01_small_punishment_treat = case_when(!is.na(exp01_control) ~ "0",
                                                  !is.na(exp01_small_punishment) ~ "1"))

# Models
m1 <- lm(exp01_outcomes ~ exp01_police_treat, data = df_exp01)
m2 <- lm(exp01_outcomes ~ exp01_slow_justice_treat, data = df_exp01)
m3 <- lm(exp01_outcomes ~ exp01_small_punishment_treat, data = df_exp01)
m4 <- lm(exp01_outcomes ~ exp01_any_treat, data = df_exp01)

# Table
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:exp01main",
```

[7] In Portuguese: Você acha que o linchamento foi correto? Por favor, use a barra abaixo para indicar sua opinião. Para discordar, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 para não concordar nem discordar.

```
       title = "Experiment 01 -- Main Results", style = "apsr",
       dep.var.labels = "\\textbf{Lynching Support}\\vspace{.5cm}",
       covariate.labels = c("Police does not patrol area", "Justice too slow",
                            "Punishment not harsh enough", "Combined treatments"),
       column.sep.width = "3pt", notes = "Robust standard errors in parentheses.",
       keep.stat = "n", no.space = TRUE)
```

Table 12: Experiment 01 – Main Results

	Lynching Support			
	(1)	(2)	(3)	(4)
Police does not patrol area	1.115			
	(1.861)			
Justice too slow		−0.289		
		(1.927)		
Punishment not harsh enough			0.438	
			(1.921)	
Combined treatments				0.443
				(1.545)
Constant	36.300***	36.300***	36.300***	36.300***
	(1.332)	(1.332)	(1.332)	(1.332)
N	1,161	1,111	1,103	2,215

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

3.3 Determinants of Baseline Levels

Here we estimate the effect of gender, race, and political ideology on lynching support. We find that males, blacks, and mixed race individuals are more likely to endorse lynchings when compared to females and whites, respectively. Left and center-left voters, in contrast, show lower support for lynchings when compared to centrists.

```
df_exp01_group <- df_exp01 %>%
  filter(gender == c("Female", "Male"),
         race %in% c("Asian", "Black", "Mixed Race", "White"),
         ideology %in% c("Center", "Center-Left", "Center-Right",
                         "Left", "Right"))


m1 <- lm(exp01_outcomes ~ gender, data = df_exp01_group)
```

```
m2 <- lm(exp01_outcomes ~ relevel(race, ref = "White"), data = df_exp01_group)
m3 <- lm(exp01_outcomes ~ relevel(ideology, ref = "Center"), data = df_exp01_group)
m4 <- lm(exp01_outcomes ~ gender + relevel(race, ref = "White") +
         relevel(ideology, ref = "Center"), data = df_exp01_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:exp01baseline",
          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", "Black", "Mixed Race",
                               "Left", "Center-Left", "Center-Right", "Right"),
          column.sep.width = "3pt", notes = "Robust standard errors in parentheses.",
          keep.stat = "n", no.space = TRUE)
```

Table 13: Experiment 01 – Determinants of Baseline Levels of Lynching Support

	Lynching Support			
	(1)	(2)	(3)	(4)
Male	6.208***			4.945**
	(2.192)			(2.165)
Asian		4.553		3.827
		(6.455)		(6.530)
Black		8.655**		9.877***
		(3.715)		(3.672)
Mixed Race		4.974*		4.621*
		(2.561)		(2.536)
Left			−10.739***	−10.108***
			(3.233)	(3.199)
Center-Left			−17.689***	−17.484***
			(3.604)	(3.575)
Center-Right			−5.280	−5.047
			(3.816)	(3.838)
Right			2.560	2.722
			(3.234)	(3.235)
Constant	32.788***	33.897***	40.970***	35.861***
	(1.550)	(1.414)	(2.449)	(2.830)
N	838	838	838	838

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

3.4 Heterogeneous Effects

We estimate heterogeneous effects for our experiment using Bayesian Additive Regression Trees (BART) (Chipman et al. 2010; Hill 2011). BART methods allow users to detect non-linear interactions and are insensitive to the choice of tuning parameters, so they are well-suited to analyze observational and experimental data (Green and Kern 2012). More specifically, we employ the `bartCause` package, which is designed to estimate causal inference models.

3.4.1 Treatment 01: Police Ineffectiveness

Our results indicate that the effects for this treatment arm is null in every model specification. We find no evidence of heterogeneous effects.

```
df_exp01_het <- df_exp01 %>%
  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_exp01_police <- df_exp01_het %>%
  mutate(exp01_police_treat = as.numeric(exp01_police_treat)) %>%
  drop_na(exp01_police_treat)
```

```r
# Gender
summary(bartc(exp01_outcomes, exp01_police_treat, gender,
              group.by = gender, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##               confounders = gender, data = df_exp01_police, 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     1.4086 3.206   -4.875    7.692  574
## 2     0.5410 3.192   -5.715    6.797  579
## tot   0.9729 2.293   -3.521    5.467 1153
## Estimates fit from 1153 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
# Age
summary(bartc(exp01_outcomes, exp01_police_treat, age2,
              group.by = age2, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##               confounders = age2, data = df_exp01_police, 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     -2.052 3.941   -9.777    5.672  358
## 2      3.156 3.797   -4.286   10.599  405
## 3      2.095 3.731   -5.217    9.407  390
## tot    1.180 2.266   -3.261    5.622 1153
## Estimates fit from 1153 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(exp01_outcomes, exp01_police_treat, race,
              group.by = race, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##             confounders = race, data = df_exp01_police, 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     1.0819  2.785   -4.376    6.540  672
## 2    -0.4764  5.552  -11.357   10.405  126
## 3     1.4095  3.849   -6.134    8.953  310
## 4     3.4156  9.777  -15.746   22.577   28
## 5     1.1299 22.987  -43.923   46.183    4
```

```
## 6     2.6390 26.417  -49.137   54.415    3
## 7     1.8004 15.027  -27.651   31.252   10
## tot   1.0668  2.261   -3.365    5.499 1153
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1153 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(exp01_outcomes, exp01_police_treat, education,
              group.by = education, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##             confounders = education, data = df_exp01_police, 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     0.55350 19.086  -36.853   37.960    6
## 2     0.14684  8.271  -16.064   16.358   43
## 3     3.25733  3.561   -3.722   10.237  409
## 4    -0.01389  3.002   -5.898    5.871  591
## 5    -0.17549  6.286  -12.495   12.144   98
## 6     0.87232 19.128  -36.618   38.363    6
## tot   1.14633  2.277   -3.316    5.609 1153
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1153 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(exp01_outcomes, exp01_police_treat, household_income,
              group.by = household_income, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##               confounders = household_income, data = df_exp01_police, 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     0.02387 6.671  -13.050   13.098   69
## 2     1.26379 4.669   -7.888   10.415  164
## 3     1.78825 4.598   -7.224   10.801  177
## 4     1.65421 3.965   -6.117    9.425  267
## 5     0.38773 3.678   -6.822    7.597  315
## 6     1.29658 5.363   -9.214   11.807  117
## 7     1.82558 8.229  -14.304   17.955   44
## tot  1.14593 2.290   -3.343    5.635 1153
## Estimates fit from 1153 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
# Political Ideology
summary(bartc(exp01_outcomes, exp01_police_treat, ideology,
              group.by = ideology, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##             confounders = ideology, data = df_exp01_police, 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     1.8492 4.550   -7.069   10.768  176
## 2     0.9579 4.513   -7.887    9.802  188
## 3     1.9992 5.492   -8.765   12.763  106
## 4     4.1745 5.857   -7.306   15.655  107
## 5    -0.5542 4.119   -8.628    7.520  258
## 6     1.0016 4.765   -8.339   10.342  152
## 7     2.4424 4.827   -7.019   11.903  166
## tot   1.3693 2.225   -2.992    5.731 1153
## Estimates fit from 1153 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(exp01_outcomes, exp01_police_treat, death_penalty,
              group.by = death_penalty, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##             confounders = death_penalty, data = df_exp01_police, 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     0.7992 3.199   -5.471    7.070  488
## 2     0.7491 3.112   -5.351    6.849  508
## 3     3.1747 6.683   -9.924   16.273   89
## 4    -1.2337 7.602  -16.133   13.666   68
## tot   0.8406 2.158   -3.390    5.071 1153
## Estimates fit from 1153 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_exp01_police2 <- df_exp01_police %>% drop_na(previous_victim_dummy)
summary(bartc(exp01_outcomes, exp01_police_treat, previous_victim_dummy,
              group.by = previous_victim_dummy, group.effects = TRUE, data = df_exp01_police2,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##               confounders = previous_victim_dummy, data = df_exp01_police2,
##               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     0.9469 3.477   -5.867    7.761  464
## 2     0.7704 2.942   -4.995    6.536  672
## tot   0.8425 2.272   -3.611    5.296 1136
## Estimates fit from 1136 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(exp01_outcomes, exp01_police_treat, views_police,
              group.by = views_police, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##               confounders = views_police, data = df_exp01_police, 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     1.1577  3.225   -5.163    7.479  449
## 2     0.5715  6.839  -12.833   13.976   67
## 3     0.8694  4.209   -7.380    9.119  235
## 4     1.2500  4.354   -7.283    9.783  220
## 5     1.1277  4.772   -8.226   10.481  162
## 6     3.4946 13.539  -23.041   30.030   13
## 7     0.8935 17.647  -33.693   35.480    7
## tot   1.1030  2.272   -3.349    5.555 1153
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1153 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(exp01_outcomes, exp01_police_treat, views_justice,
              group.by = views_police, group.effects = TRUE, data = df_exp01_police,
              n.chains = 5L, seed = 144))
```

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

## Call: bartc(response = exp01_outcomes, treatment = exp01_police_treat,
##             confounders = views_justice, data = df_exp01_police, 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      1.5215  2.886   -4.136    7.179  449
## 2      1.4107  5.879  -10.111   12.933   67
## 3      1.6034  3.584   -5.421    8.628  235
## 4      0.8333  3.711   -6.440    8.107  220
## 5      0.3218  4.314   -8.133    8.777  162
## 6      3.1625 13.019  -22.354   28.679   13
## 7      1.9862 16.994  -31.322   35.295    7
## tot    1.2532  2.250   -3.157    5.663 1153
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1153 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
```

3.4.2 Treatment 02: Criminal Justice Ineffectiveness

We do not find any evidence of heterogeneous treatment effects in this condition either.

```
# Remove "Indigenous" and "Other" from `race` as they only
# have 1 observation each. The model cannot be estimated otherwise.
df_exp01_slow_justice <- df_exp01_het %>%
  filter(race %in% c("White", "Asian", "Black", "Mixed Race", "Rather Not Say")) %>%
  mutate(exp01_slow_justice_treat = as.numeric(exp01_slow_justice_treat)) %>%
  drop_na(exp01_slow_justice_treat)
```

```r
# Gender
summary(bartc(exp01_outcomes, exp01_slow_justice_treat, gender,
              group.by = gender, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##              confounders = gender, data = df_exp01_slow_justice, 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   -0.70511 3.244   -7.064    5.654  575
## 2    0.61085 3.369   -5.992    7.213  528
## tot -0.07517 2.372   -4.725    4.574 1103
## Estimates fit from 1103 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
# Age
summary(bartc(exp01_outcomes, exp01_slow_justice_treat, age2,
              group.by = age2, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##              confounders = age2, data = df_exp01_slow_justice, 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     -4.0433 4.060  -12.002    3.915  349
## 2      1.0628 3.859   -6.501    8.627  386
## 3      1.8841 3.897   -5.754    9.522  368
## tot  -0.2788 2.379   -4.942    4.384 1103
## Estimates fit from 1103 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(exp01_outcomes, exp01_slow_justice_treat, race,
              group.by = race, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##              confounders = race, data = df_exp01_slow_justice, 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     -0.4748  2.962   -6.280    5.331  630
## 2     -4.7800  6.533  -17.585    8.024  112
## 3      1.4545  3.971   -6.329    9.238  324
## 4      1.7147  9.829  -17.550   20.980   31
## 5         NaN     NA       NA       NA    0
## 6         NaN     NA       NA       NA    0
```

```
## 7    -0.4321 19.782  -39.205   38.341    6
## tot      NaN     NA       NA       NA 1103
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1103 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(exp01_outcomes, exp01_slow_justice_treat, education,
              group.by = education, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##              confounders = education, data = df_exp01_slow_justice, 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     1.9858 16.202  -29.770   33.741    9
## 2     0.9912 10.740  -20.058   22.041   27
## 3    -1.6216  3.738   -8.948    5.705  377
## 4     1.4392  3.069   -4.575    7.454  588
## 5    -0.3693  6.249  -12.618   11.879   97
## 6    -0.1299 21.124  -41.531   41.272    5
## tot   0.2204  2.347   -4.380    4.821 1103
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1103 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(exp01_outcomes, exp01_slow_justice_treat, household_income,
              group.by = household_income, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))

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

## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##              confounders = household_income, data = df_exp01_slow_justice,
##              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   -0.11441 6.726  -13.297   13.068   67
## 2    0.76917 5.514  -10.038   11.577  132
## 3    1.22368 4.710   -8.008   10.455  187
## 4   -0.07034 4.070   -8.048    7.907  249
## 5   -0.04866 3.745   -7.389    7.292  308
## 6   -3.92074 6.182  -16.037    8.196  114
## 7    2.70008 8.290  -13.548   18.948   46
## tot -0.02953 2.331   -4.599    4.540 1103
## Estimates fit from 1103 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(exp01_outcomes, exp01_slow_justice_treat, ideology,
              group.by = ideology, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##             confounders = ideology, data = df_exp01_slow_justice, 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    3.46201 5.353   -7.029   13.953  158
## 2    1.13259 4.549   -7.783   10.048  209
## 3   -1.27098 5.887  -12.810   10.268   96
## 4   -0.18674 5.845  -11.642   11.269   98
## 5   -0.39400 4.038   -8.307    7.519  260
## 6   -1.51478 5.377  -12.054    9.025  125
## 7   -2.89689 5.120  -12.932    7.138  157
## tot -0.09357 2.339   -4.678    4.491 1103
## Estimates fit from 1103 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(exp01_outcomes, exp01_slow_justice_treat, death_penalty,
              group.by = death_penalty, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##             confounders = death_penalty, data = df_exp01_slow_justice,
##             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      2.7789 3.349   -3.785    9.343  461
## 2     -1.6507 3.167   -7.858    4.557  512
## 3      1.6431 7.285  -12.635   15.921   77
## 4     -3.2941 8.379  -19.717   13.129   53
## tot    0.3516 2.237   -4.033    4.736 1103
## Estimates fit from 1103 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_exp01_slow_justice2 <- df_exp01_slow_justice %>% drop_na(previous_victim_dummy)
summary(bartc(exp01_outcomes, exp01_slow_justice_treat, previous_victim_dummy,
              group.by = previous_victim_dummy, group.effects = TRUE, data = df_exp01_slow_justice2,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##               confounders = previous_victim_dummy, data = df_exp01_slow_justice2,
##               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    -1.02230 3.683   -8.240    6.196  424
## 2     0.02415 2.933   -5.724    5.772  661
## tot  -0.38478 2.307   -4.906    4.137 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
```

```
# Opinion on the Police
summary(bartc(exp01_outcomes, exp01_slow_justice_treat, views_police,
              group.by = views_police, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##             confounders = views_police, data = df_exp01_slow_justice,
##             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    0.49513  3.398   -6.164    7.154  417
## 2    1.28720  7.398  -13.213   15.787   58
## 3    0.74236  4.248   -7.584    9.068  229
## 4   -1.01432  4.458   -9.752    7.723  225
## 5   -1.83092  5.111  -11.849    8.187  155
## 6    1.15489 14.511  -27.286   29.596   11
## 7   -1.41815 16.694  -34.139   31.302    8
## tot -0.05397  2.360   -4.679    4.571 1103
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1103 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(exp01_outcomes, exp01_slow_justice_treat, views_justice,
```

```
              group.by = views_police, group.effects = TRUE, data = df_exp01_slow_justice,
              n.chains = 5L, seed = 144))

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

## Call: bartc(response = exp01_outcomes, treatment = exp01_slow_justice_treat,
##             confounders = views_justice, data = df_exp01_slow_justice,
##             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     0.3888  2.968   -5.428    6.205  417
## 2     0.4882  6.475  -12.203   13.179   58
## 3     0.4889  3.637   -6.639    7.616  229
## 4    -0.5745  3.842   -8.105    6.956  225
## 5    -0.4304  4.367   -8.989    8.128  155
## 6     0.4706 13.956  -26.883   27.825   11
## 7     0.1864 16.086  -31.342   31.715    8
## tot   0.1026  2.303   -4.411    4.616 1103
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1103 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
```

3.4.3 Treatment 03: Demand for Harsher Legal Punishment

As in the last two series of models, our results show no evidence of heterogeneous treatment effects.

```
df_exp01_small_punishment <- df_exp01_het %>%
  mutate(exp01_small_punishment_treat = as.numeric(exp01_small_punishment_treat)) %>%
  drop_na(exp01_small_punishment_treat)
```

```r
# Gender
summary(bartc(exp01_outcomes, exp01_small_punishment_treat, gender,
              group.by = gender, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))

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

## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##               confounders = gender, data = df_exp01_small_punishment, 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      1.7175 3.266   -4.684    8.119  554
## 2     -0.8986 3.255   -7.278    5.481  545
## tot    0.4202 2.331   -4.149    4.990 1099
## Estimates fit from 1099 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_exp01_small_punishment2 <- df_exp01_small_punishment %>% drop_na(age2)
summary(bartc(exp01_outcomes, exp01_small_punishment_treat, age2,
              group.by = age2, group.effects = TRUE, data = df_exp01_small_punishment2,
              n.chains = 5L, seed = 144))

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

## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##               confounders = age2, data = df_exp01_small_punishment2, 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    -4.6442 3.983  -12.450    3.162  355
## 2     5.9703 3.970   -1.810   13.751  367
## 3     0.8252 3.852   -6.725    8.376  376
## tot   0.7766 2.316   -3.763    5.317 1098
## Estimates fit from 1098 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(exp01_outcomes, exp01_small_punishment_treat, race,
              group.by = race, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##             confounders = race, data = df_exp01_small_punishment, 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    -0.1333  2.924   -5.865    5.598  646
## 2     1.4234  5.853  -10.048   12.895  111
## 3     1.7369  4.020   -6.143    9.617  296
## 4     3.8678  9.656  -15.058   22.793   30
## 5     1.6054 23.107  -43.684   46.894    4
```

```
## 6     1.2526 23.140  -44.100   46.606    4
## 7     2.4740 16.726  -30.308   35.256    8
## tot   0.6672  2.367   -3.973    5.307 1099
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1099 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(exp01_outcomes, exp01_small_punishment_treat, education,
              group.by = education, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##              confounders = education, data = df_exp01_small_punishment,
##              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    1.25526 17.847  -33.724   36.235    7
## 2   -0.30960  8.913  -17.780   17.160   36
## 3    2.75648  3.681   -4.459    9.972  391
## 4   -0.63335  3.131   -6.769    5.503  553
## 5   -1.63510  6.147  -13.683   10.413  106
## 6    0.04198 19.153  -37.498   37.582    6
## tot  0.50238  2.337   -4.078    5.082 1099
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1099 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(exp01_outcomes, exp01_small_punishment_treat, household_income,
              group.by = household_income, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##              confounders = household_income, data = df_exp01_small_punishment,
##              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     -0.3970 6.932  -13.984   13.190   63
## 2      6.8680 5.596   -4.101   17.837  155
## 3      2.6524 5.039   -7.224   12.529  170
## 4     -0.3990 4.248   -8.724    7.926  236
## 5     -1.4005 4.033   -9.305    6.504  284
## 6     -1.0526 5.489  -11.811    9.706  130
## 7     -4.1697 7.645  -19.153   10.813   61
## tot    0.5526 2.307   -3.969    5.074 1099
## Estimates fit from 1099 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(exp01_outcomes, exp01_small_punishment_treat, ideology,
              group.by = ideology, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##             confounders = ideology, data = df_exp01_small_punishment,
##             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   -0.51547 4.868  -10.056    9.025  158
## 2   -0.04112 4.659   -9.173    9.091  170
## 3    0.34180 5.707  -10.843   11.527  103
## 4   -0.24262 5.565  -11.151   10.665  104
## 5    0.43671 3.974   -7.352    8.225  252
## 6    2.59135 5.088   -7.380   12.563  156
## 7    1.50644 5.008   -8.309   11.322  156
## tot  0.61041 2.298   -3.894    5.115 1099
## Estimates fit from 1099 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(exp01_outcomes, exp01_small_punishment_treat, death_penalty,
              group.by = death_penalty, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##             confounders = death_penalty, data = df_exp01_small_punishment,
##             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     1.6220 3.276   -4.799    8.043  467
## 2    -0.3968 3.196   -6.661    5.868  502
## 3     3.0332 7.051  -10.786   16.853   78
## 4    -0.1274 8.161  -16.123   15.869   52
## tot   0.7173 2.238   -3.670    5.104 1099
## Estimates fit from 1099 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_exp01_small_punishment2 <- df_exp01_small_punishment %>% drop_na(previous_victim_dummy)
summary(bartc(exp01_outcomes, exp01_small_punishment_treat, previous_victim_dummy,
              group.by = previous_victim_dummy, group.effects = TRUE, data = df_exp01_small_punishment2,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##             confounders = previous_victim_dummy, data = df_exp01_small_punishment2,
##             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    0.130740 3.565   -6.857    7.118  446
```

```
## 2   -0.106243 3.037   -6.058    5.846  636
## tot -0.008559 2.315   -4.546    4.529 1082
## Estimates fit from 1082 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(exp01_outcomes, exp01_small_punishment_treat, views_police,
              group.by = views_police, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##              confounders = views_police, data = df_exp01_small_punishment,
##              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     3.1029  3.477   -3.711    9.917  432
## 2     2.4512  7.092  -11.449   16.352   68
## 3    -1.2224  4.635  -10.308    7.863  217
## 4    -0.2908  4.609   -9.324    8.743  199
## 5    -5.4147  5.544  -16.280    5.451  166
## 6     2.0834 14.548  -26.430   30.597   11
## 7     1.3230 19.007  -35.930   38.576    6
## tot   0.2875  2.308   -4.235    4.810 1099
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1099 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
# Opinion on the Judicial System
summary(bartc(exp01_outcomes, exp01_small_punishment_treat, views_justice,
              group.by = views_police, group.effects = TRUE, data = df_exp01_small_punishment,
              n.chains = 5L, seed = 144))
```

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

```
## Call: bartc(response = exp01_outcomes, treatment = exp01_small_punishment_treat,
##             confounders = views_justice, data = df_exp01_small_punishment,
##             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     0.8423  2.958   -4.955    6.640  432
## 2     1.2530  5.971  -10.450   12.956   68
## 3     0.4912  4.112   -7.568    8.550  217
## 4     0.5033  3.790   -6.926    7.932  199
## 5    -2.0736  4.564  -11.018    6.871  166
## 6     1.0644 14.055  -26.483   28.612   11
## 7     1.6626 18.319  -34.243   37.568    6
## tot   0.3033  2.272   -4.150    4.757 1099
##   if (n < 10) group-size estimates may be unstable
## Estimates fit from 1099 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
```

4 Experiment 02

4.1 Description

In our second 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 14 below.

Table 14: **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.[8]

4.2 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 Leeper et al. (2020) and report marginal means as our main estimates. 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,
```

[8]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.

```
        "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",
```

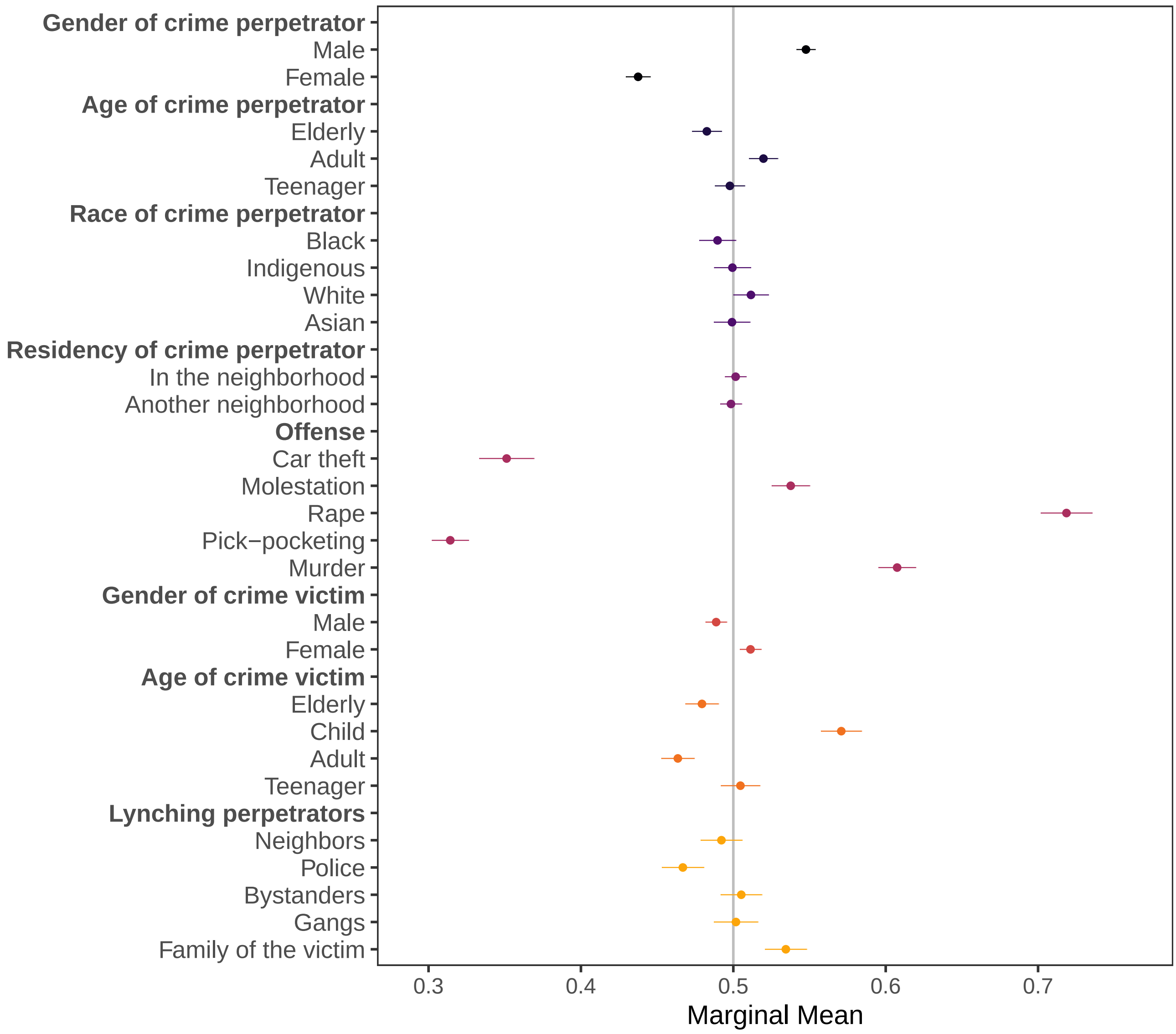
```
                                            " Child"     = "Criança",
                                            " Adult"     = "Adulto(a)",
                                            " Elderly"   = "Idoso(a)"),
         `Lynching perpetrators` = fct_recode(`Lynching perpetrators`,
                                              "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))


# 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 15: Marginal Means – Full Model

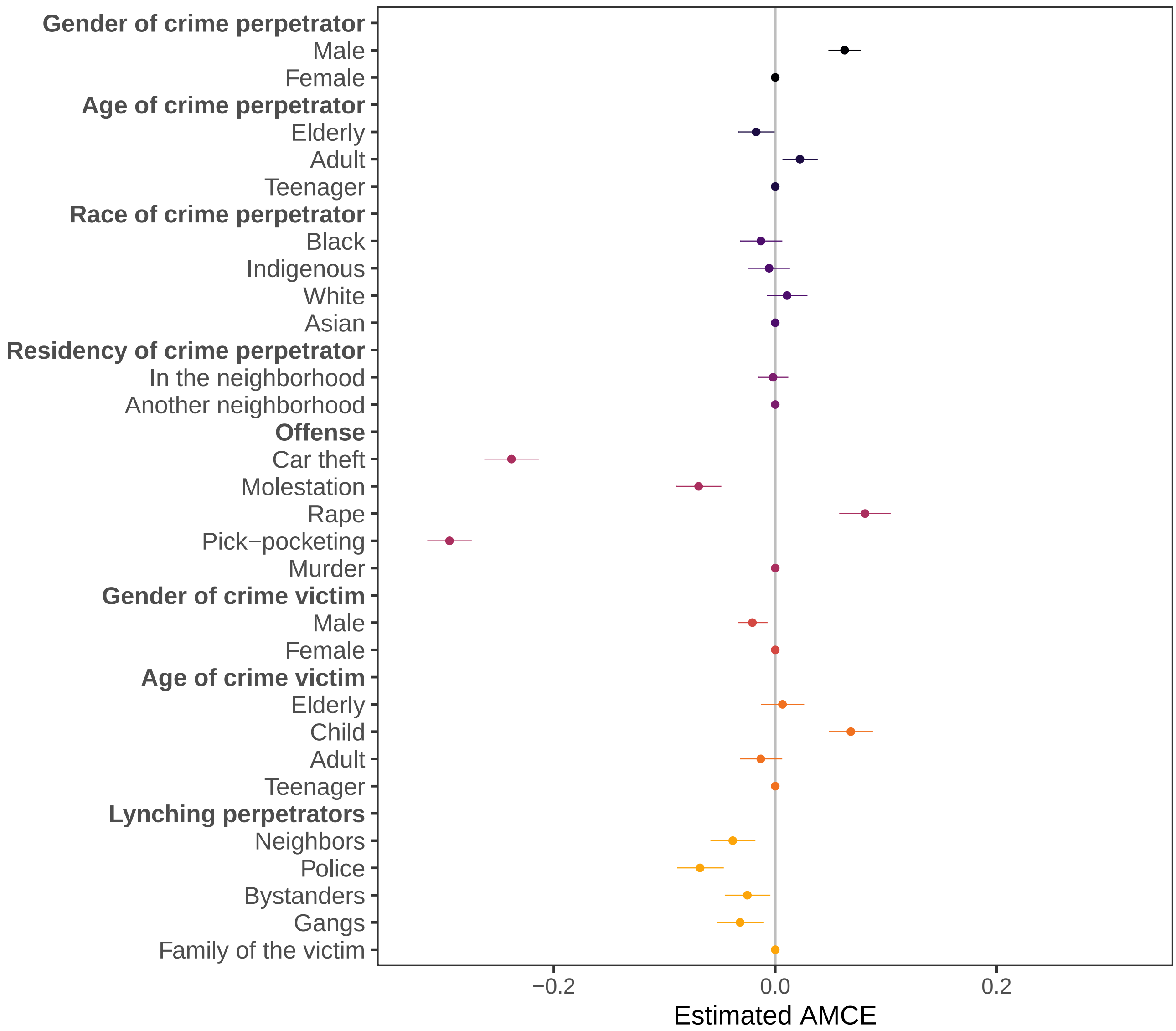
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.438	0.004	0.000	0.429	0.446
Male	0.548	0.003	0.000	0.541	0.554
Age of crime perpetrator					
Teenager	0.498	0.005	0.650	0.488	0.508
Adult	0.520	0.005	0.000	0.510	0.529
Elderly	0.483	0.005	0.000	0.473	0.492
Race 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

4.3 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 16: 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

4.4 Subgroup Analyses

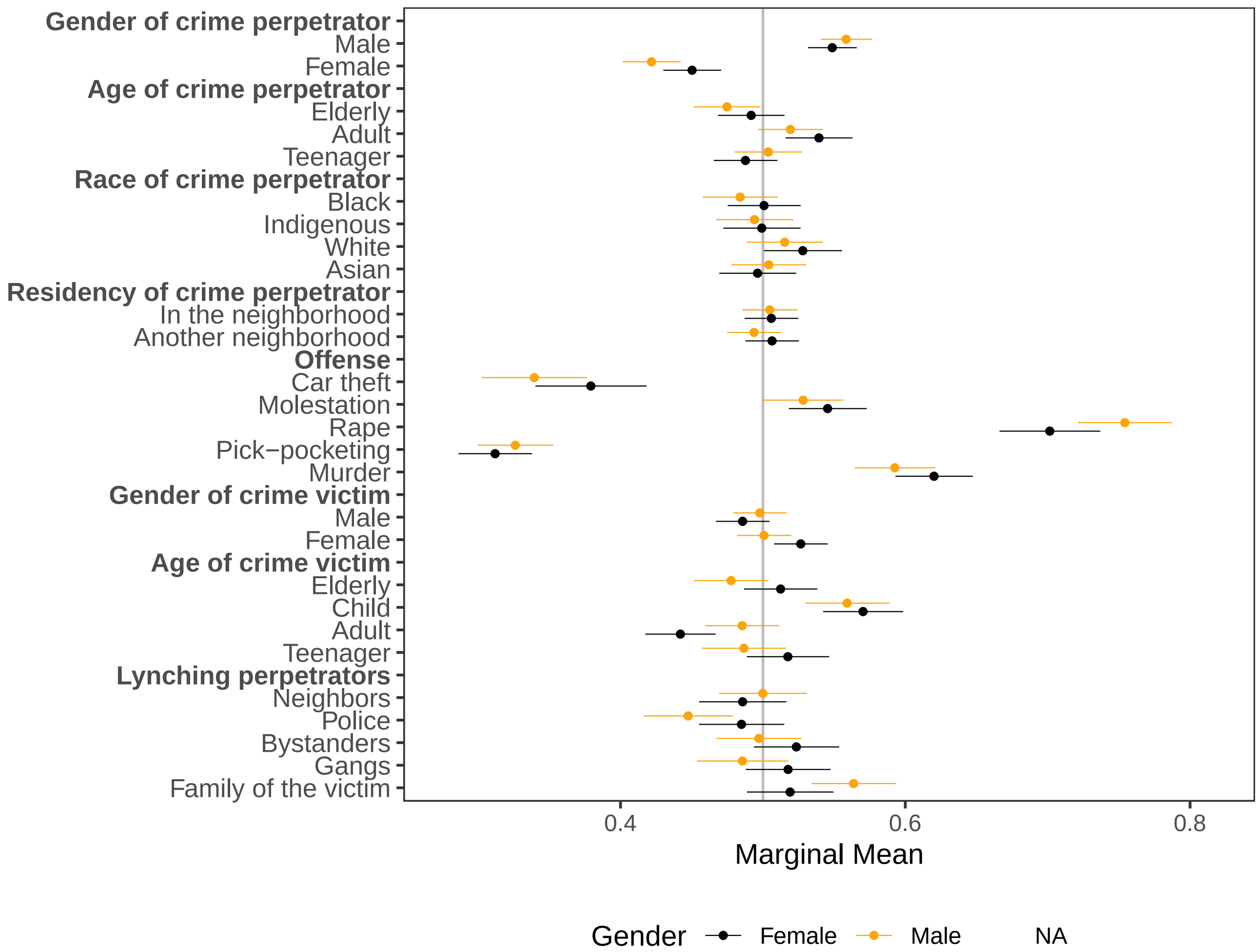
In this subsection, we test whether our results vary according to individual characteristics, such as gender, age, race, income, support for death penalty, and the respondents' opinions on the judicial system and the police forces. All models report marginal means. As we shall see, the results are very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

4.4.1 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.

```r
# 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 17: 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 18: Marginal Means – Males

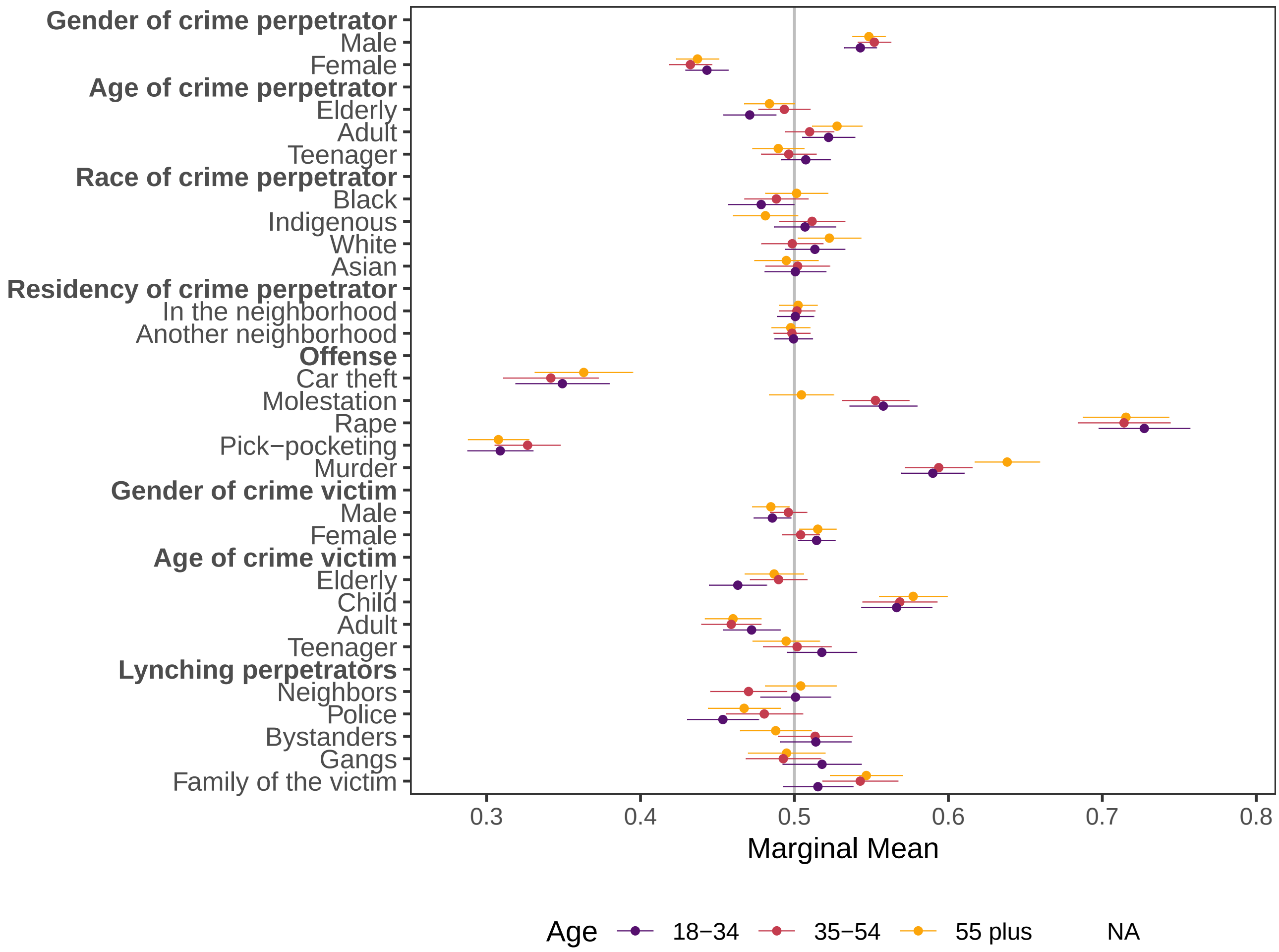
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.422	0.010	0.000	0.402	0.442
Male	0.558	0.009	0.000	0.541	0.576
Age of crime perpetrator					
Teenager	0.504	0.012	0.754	0.480	0.527
Adult	0.519	0.011	0.091	0.497	0.542
Elderly	0.475	0.012	0.033	0.452	0.498
Race 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

4.4.2 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 19: 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 20: 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 21: Marginal Means – 55+ Years Old

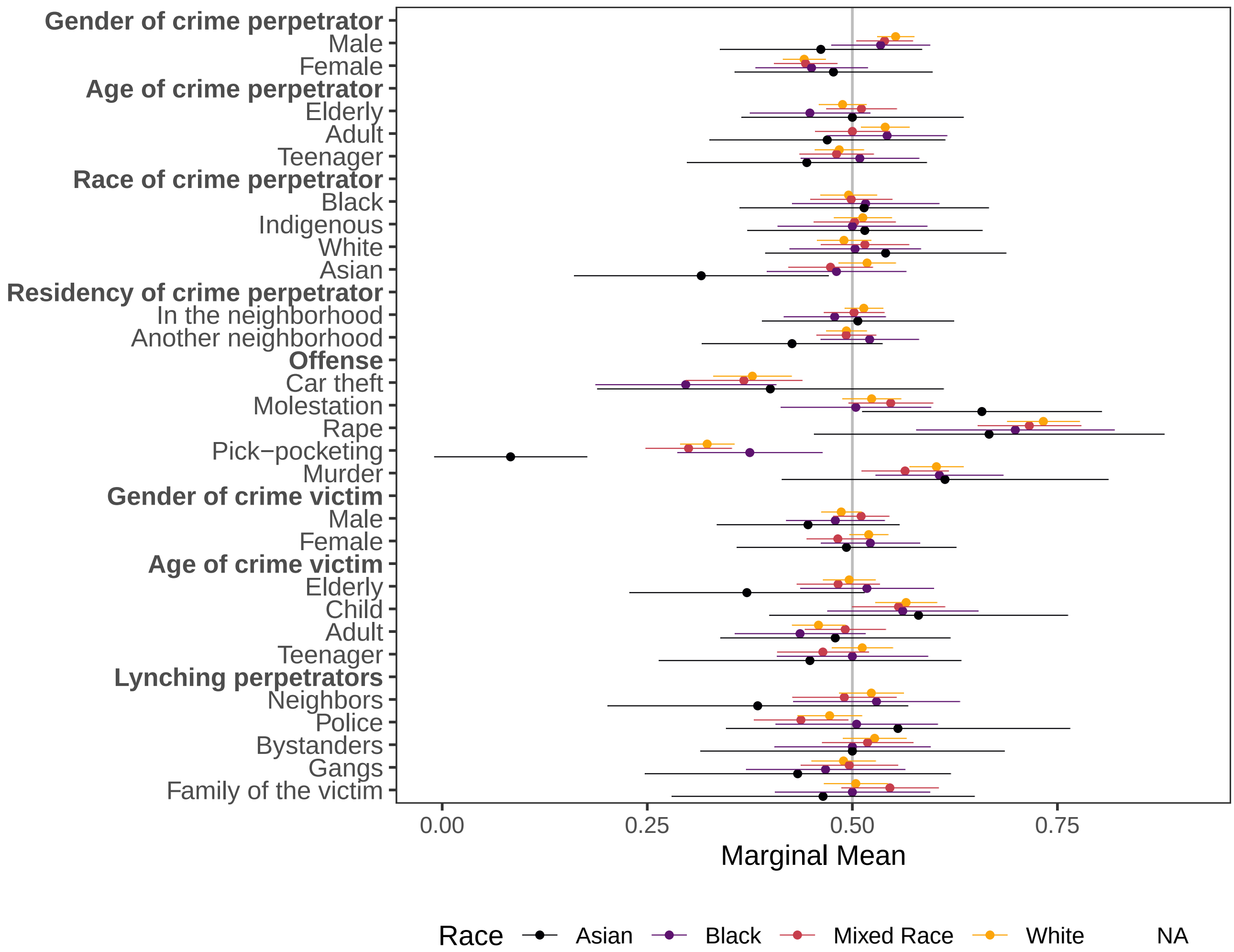
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.437	0.007	0.000	0.423	0.451
Male	0.548	0.005	0.000	0.538	0.559
Age of crime perpetrator					
Teenager	0.489	0.009	0.221	0.473	0.506
Adult	0.528	0.008	0.001	0.511	0.544
Elderly	0.484	0.008	0.052	0.467	0.500
Race 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

4.4.3 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 22: 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 23: 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

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

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

Table 24: 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 25: Marginal Means – White

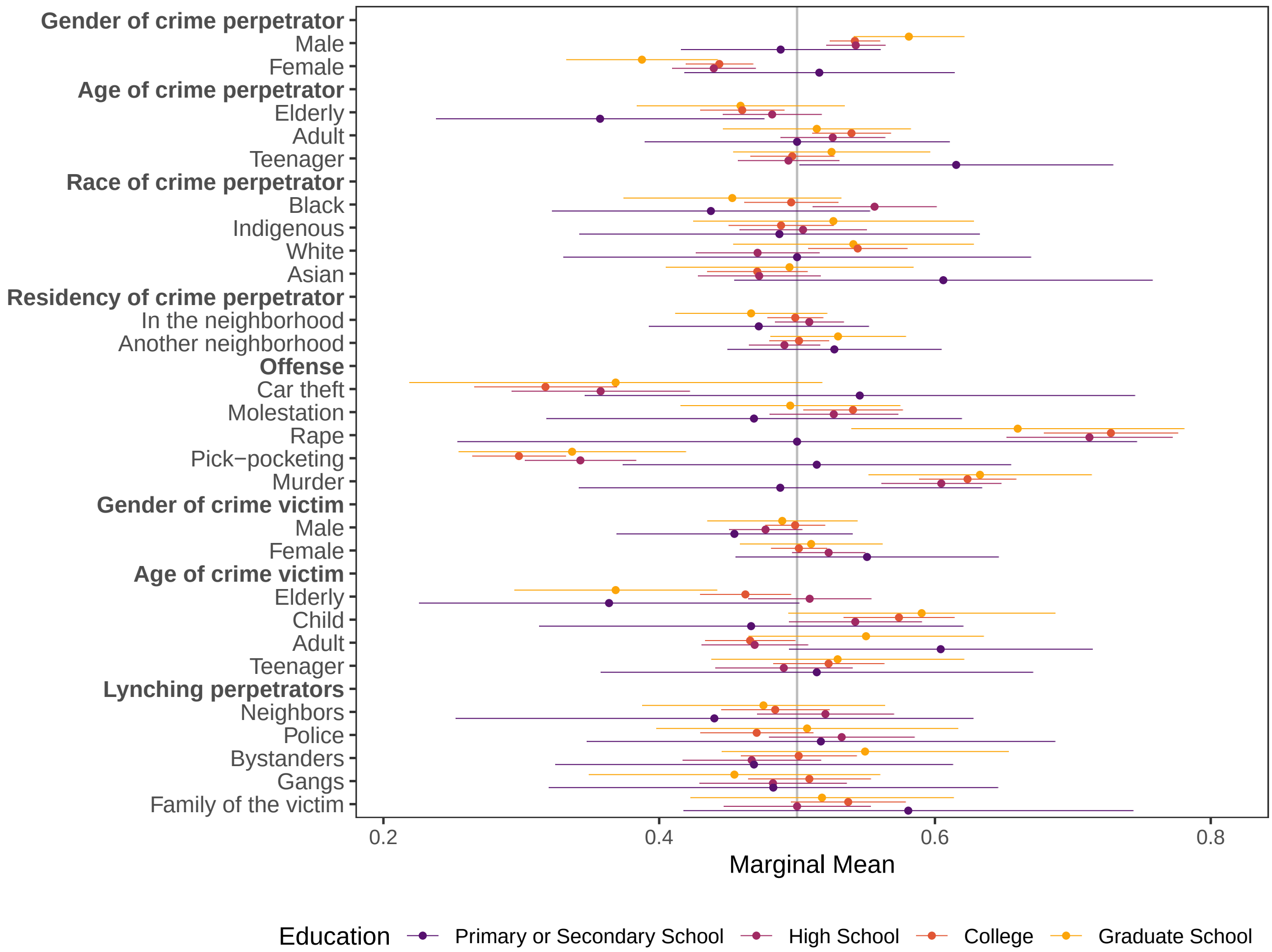
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.441	0.013	0.000	0.415	0.467
Male	0.553	0.011	0.000	0.530	0.575
Age of crime perpetrator					
Teenager	0.484	0.015	0.292	0.454	0.514
Adult	0.540	0.015	0.008	0.511	0.569
Elderly	0.488	0.015	0.419	0.459	0.517
Race 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

4.4.4 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 26: 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 27: 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 28: 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 29: Marginal Means – Graduate School Degree

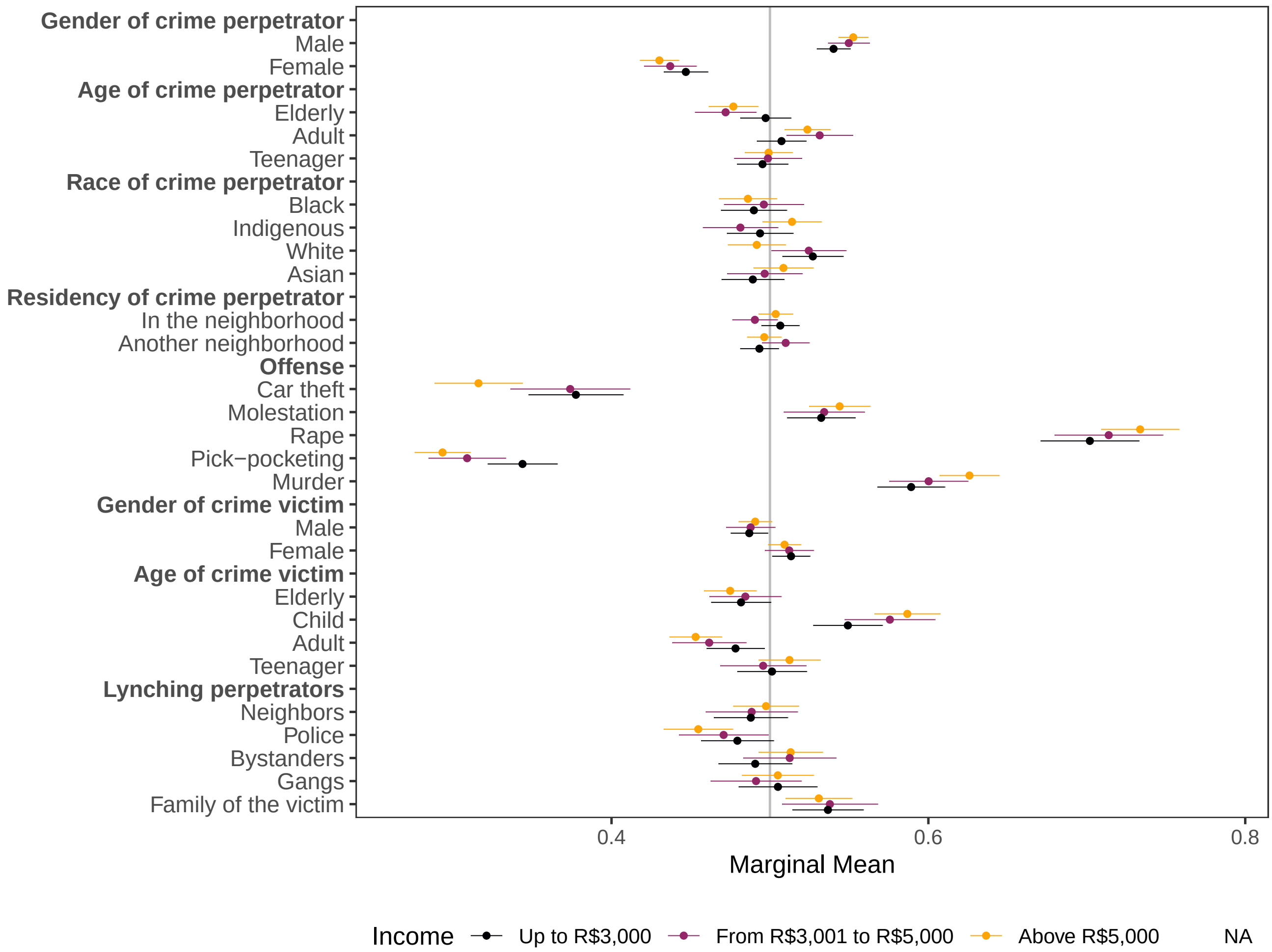
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.387	0.028	0.000	0.333	0.442
Male	0.581	0.020	0.000	0.541	0.621
Age of crime perpetrator					
Teenager	0.525	0.036	0.492	0.454	0.596
Adult	0.514	0.035	0.681	0.446	0.582
Elderly	0.459	0.038	0.286	0.384	0.534
Race 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

4.4.5 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.

```r
# 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)
```




```r
# 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 30: 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 31: 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 32: Marginal Means – Above 5,000 BRL

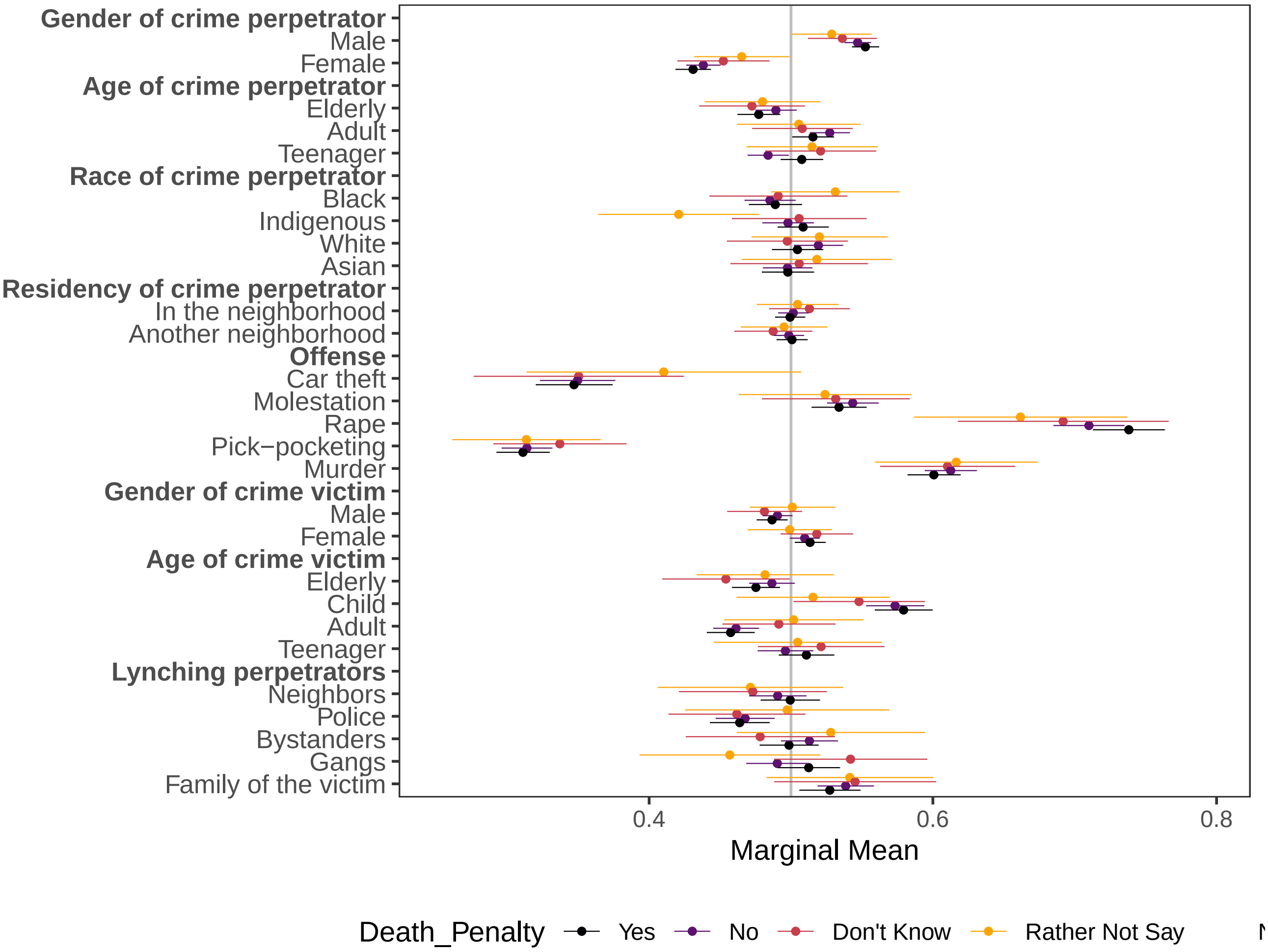
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.430	0.006	0.000	0.418	0.442
Male	0.553	0.005	0.000	0.543	0.562
Age of crime perpetrator					
Teenager	0.499	0.008	0.912	0.484	0.514
Adult	0.524	0.007	0.001	0.509	0.538
Elderly	0.477	0.008	0.004	0.461	0.492
Race 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

4.4.6 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 33: 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 34: 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 35: 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 36: Marginal Means – Support for Death Penalty: Rather Not Say

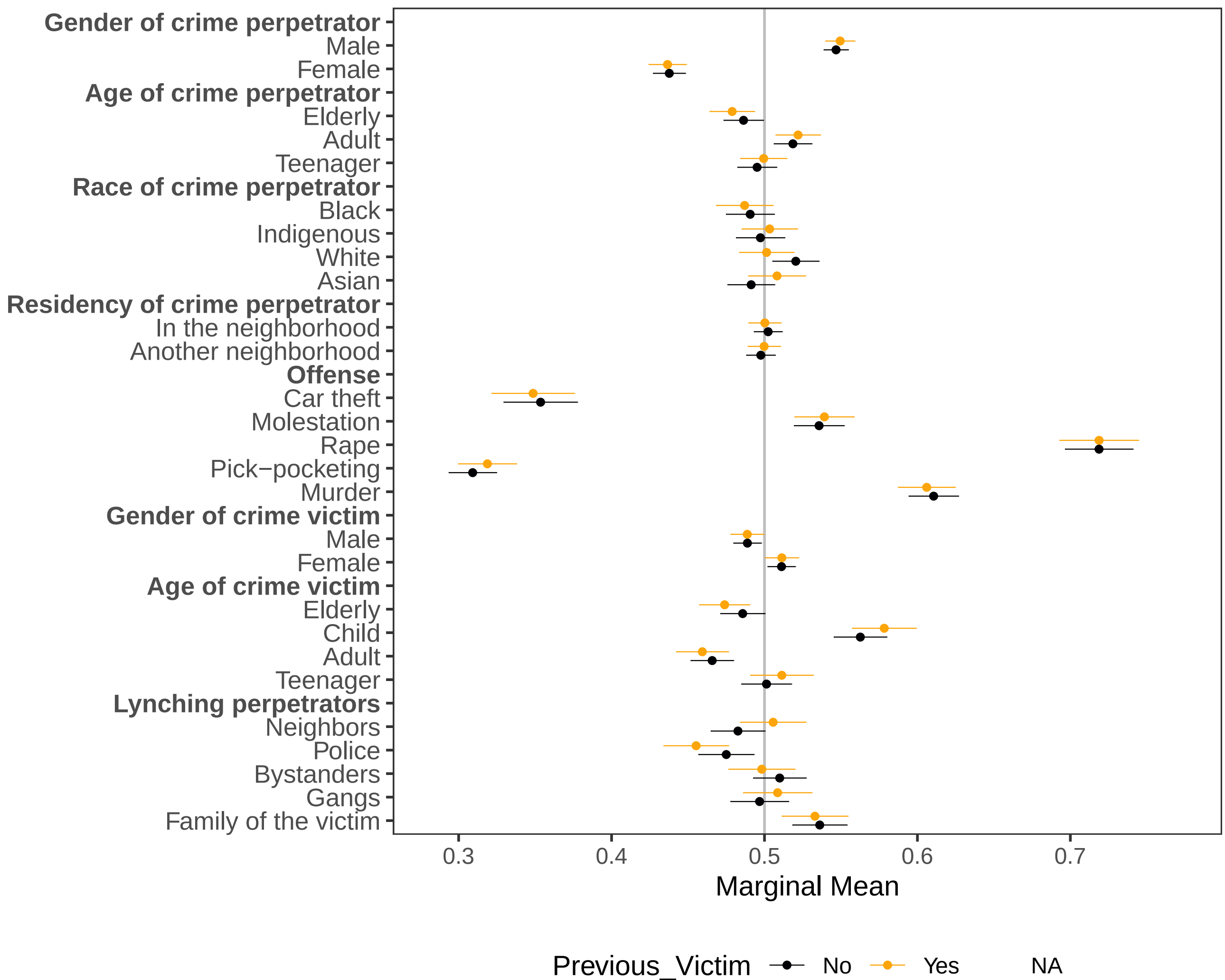
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.465	0.017	0.042	0.432	0.499
Male	0.529	0.014	0.044	0.501	0.557
Age of crime perpetrator					
Teenager	0.515	0.024	0.529	0.469	0.561
Adult	0.505	0.022	0.804	0.462	0.549
Elderly	0.480	0.021	0.332	0.439	0.521
Race 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

4.4.7 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 37: 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 38: Marginal Means – Previous Victimization (12 Months): No

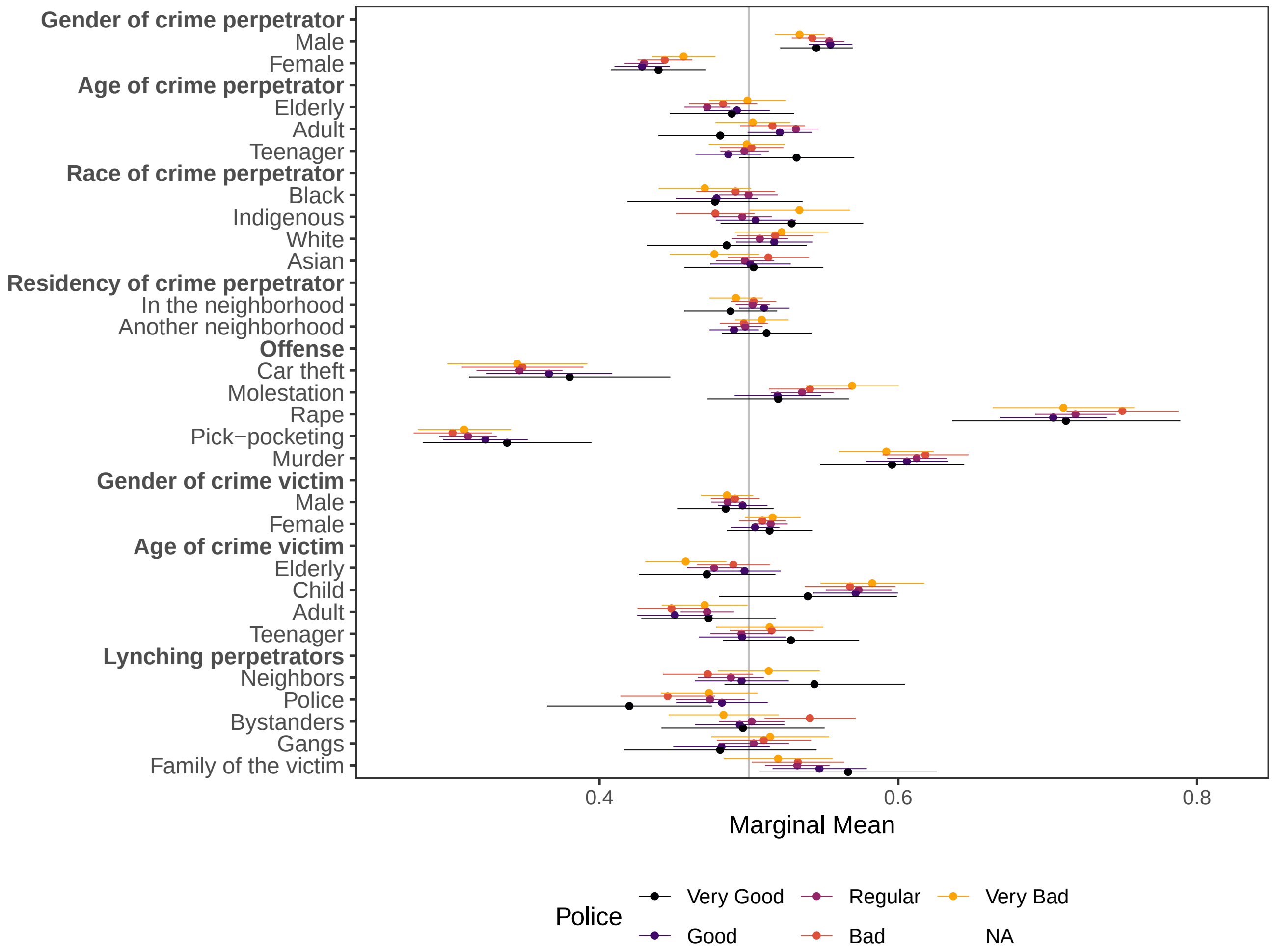
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.438	0.005	0.000	0.427	0.448
Male	0.547	0.004	0.000	0.539	0.555
Age of crime perpetrator					
Teenager	0.495	0.007	0.461	0.482	0.508
Adult	0.519	0.006	0.004	0.506	0.531
Elderly	0.486	0.007	0.039	0.473	0.499
Race 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

4.4.8 Opinion on the Police

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

```r
# 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)
```




```r
# 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 39: 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 40: 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 41: 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 42: 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 43: Marginal Means – Opinion on the Police: Very Bad

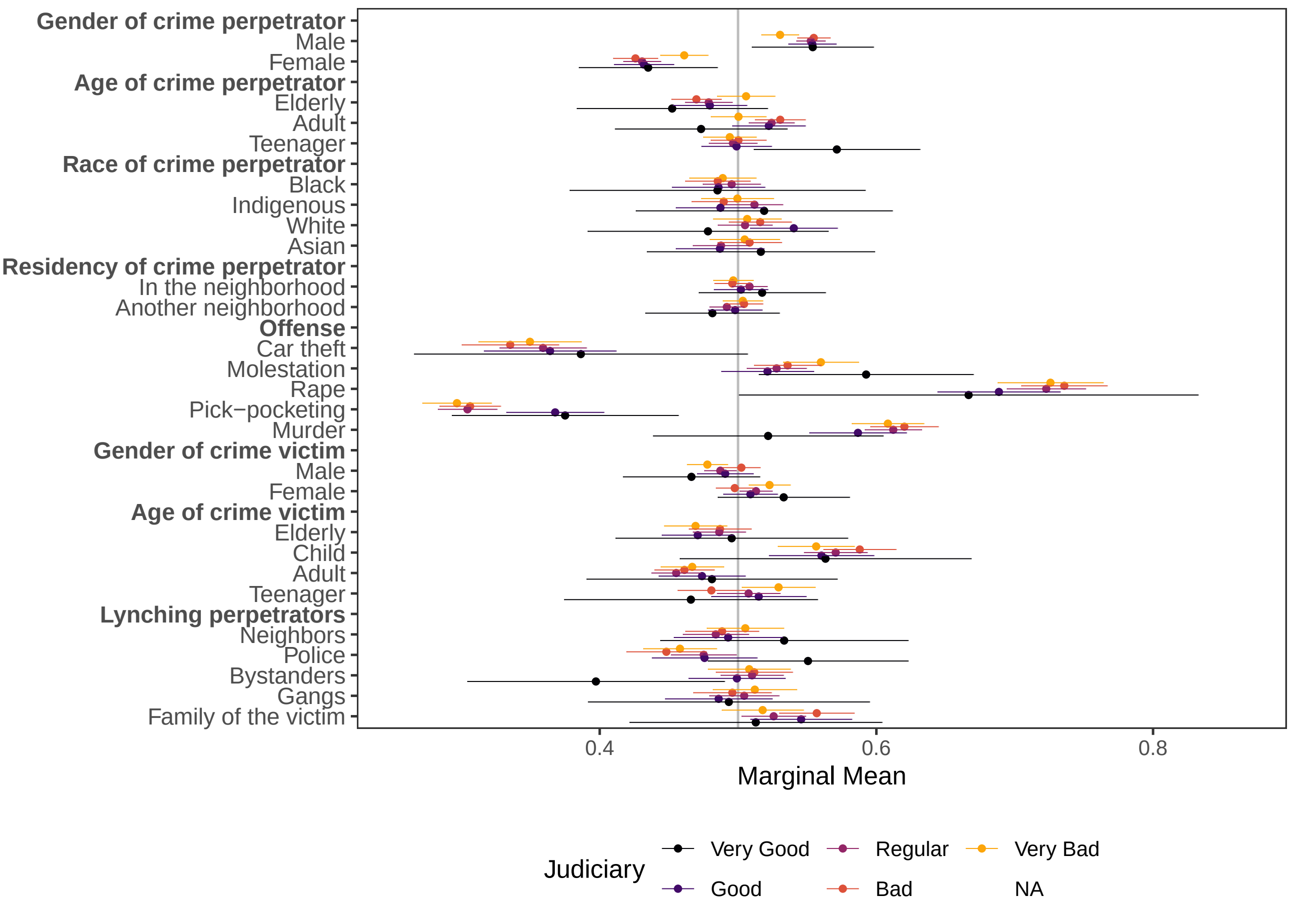
Feature	Estimate	Std. Error	P-Value	Lower	Upper
Gender of crime perpetrator					
Female	0.456	0.011	0.000	0.435	0.477
Male	0.534	0.008	0.000	0.518	0.550
Age of crime perpetrator					
Teenager	0.499	0.013	0.908	0.473	0.524
Adult	0.503	0.013	0.840	0.478	0.527
Elderly	0.499	0.013	0.941	0.473	0.525
Race 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

4.4.9 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 44: 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 45: 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 46: 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 47: 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 48: 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

4.5 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.

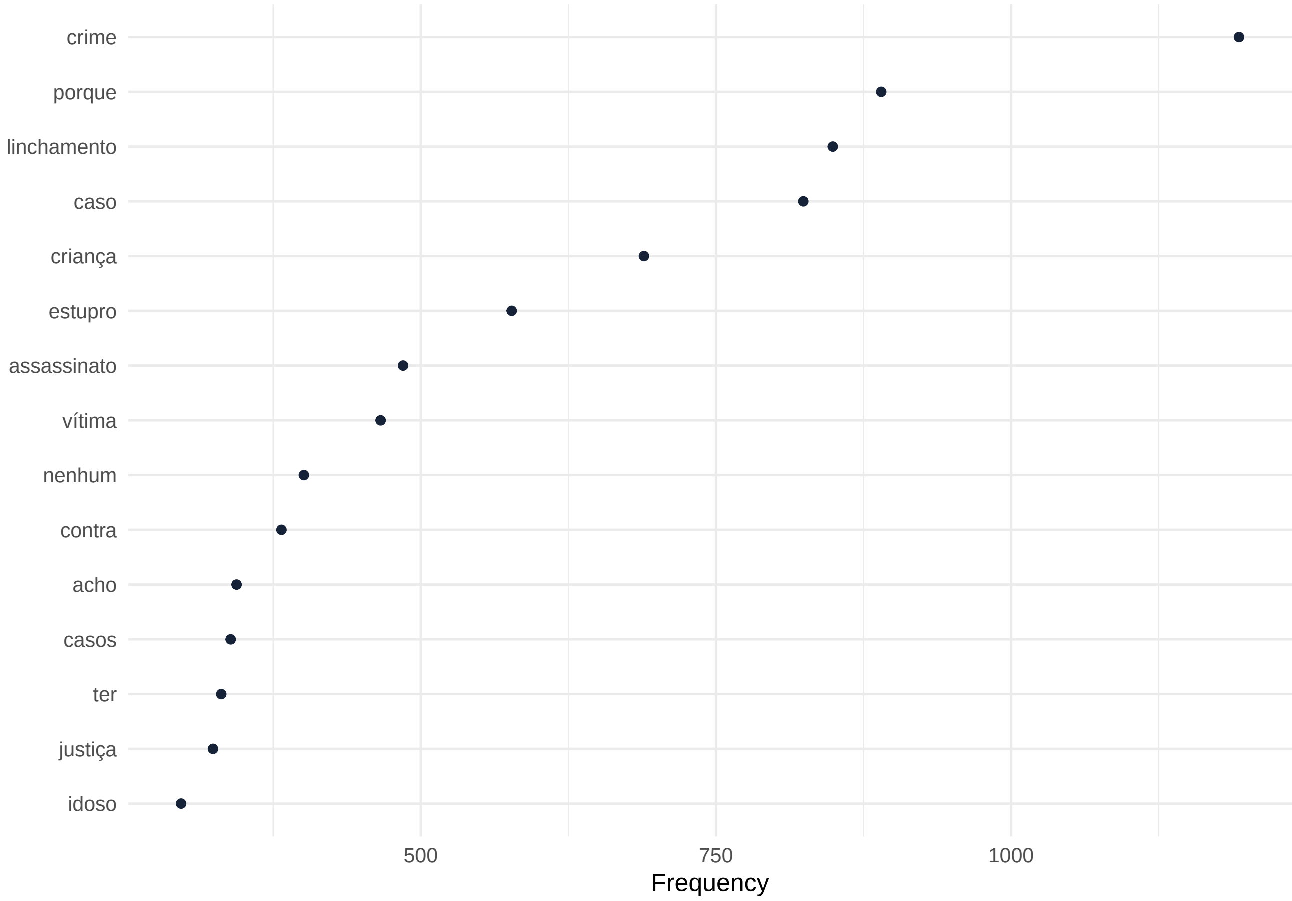
First, we concatenate all text responses into a single vector. Then we tokenize the sentences, remove Portuguese stop words and punctuation, and select the words that appear most frequently in the texts.

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() +
```

```
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.

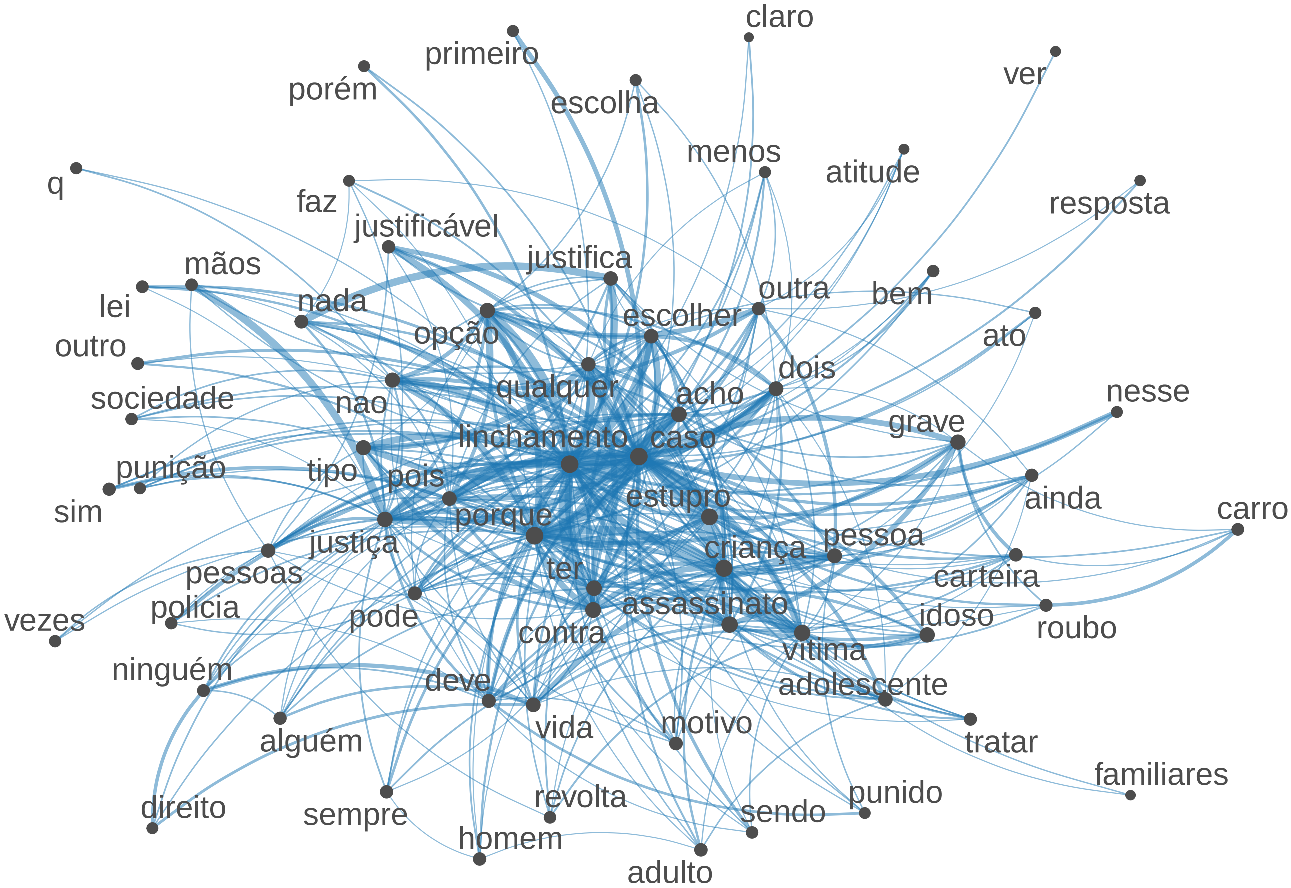
We note that there is another word cluster on the left. It contains words that indicate that some respondents do not support lynchings, such as *não* (no), *opção* (choice), *nada* (nothing), *justifica* (justifies), *justificável* (justifiable), and *escolher* (choose).

```
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
```

```
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.

```
# Unsupervised LDA

tmod_lda <- textmodel_lda(dfmat, k = 3)

terms(tmod_lda, 10)
```

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

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

```
##
## topic1 topic2 topic3
##   3495   2339   2426
```

Our last model is a semisupervised 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.

```
# Semisupervised 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
##  [1,] "família"    "nenhum"
##  [2,] "polícia"    "contra"
##  [3,] "gangues"    "linchamento"
##  [4,] "policia"    "opção"
##  [5,] "familia"    "caso"
##  [6,] "policiais"  "nenhuma"
##  [7,] "gangue"     "escolha"
##  [8,] "familiares" "opinião"
##  [9,] "pedestres"  "opcao"
## [10,] "policial"   "opçao"
##       other
##  [1,] "porque"
##  [2,] "sei"
##  [3,] "crimes"
```

```
##  [4,] "pq"
##  [5,] "pessoas"
##  [6,] "pra"
##  [7,] "sim"
##  [8,] "mesma"
##  [9,] "sempre"
## [10,] "vezes"
```

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

```
##
##      victim       crime perpetrator
##        1699        2247        1172
##     against       other
##        1680        1462
```

5 Experiment 03

5.1 Description

Our last 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.[9]

- *Treatment 01 - Legal punishment for lynching perpetrators*: In Brazil, some people believe that lynching may be justified under certain conditions. **However, the Brazilian constitution 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.[10]

- *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.[11]

- *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.[12]

[9] 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.

[10] 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.

[11] 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.

[12] In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições.

5.2 Main Results

Our results are available in table 49. 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. 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)


# Table
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"),
```

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.

```
    column.sep.width = "3pt", notes = "Robust standard errors in parentheses.",
    keep.stat = "n", no.space = TRUE)
```

Table 49: 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.

5.3 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.

5.3.1 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     -4.324 3.045  -10.292  1.64464  567
```

```
## 2     -4.591 3.168  -10.801  1.61847  542
## tot   -4.454 2.234   -8.832 -0.07629 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     -5.564 3.619  -12.657   1.5283  378
## 2     -5.059 3.783  -12.473   2.3559  353
## 3     -2.788 3.624   -9.890   4.3139  377
## tot   -4.459 2.208   -8.787  -0.1304 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
## 1    -5.6730  2.769  -11.101 -0.24493
## 2    -3.0775  5.758  -14.363  8.20825
## 3    -2.1744  3.819   -9.660  5.31151
## 4     0.4951 11.394  -21.837 22.82763
## 5    -2.3681 25.187  -51.734 46.99792
## 6    -4.0899 19.913  -43.119 34.93878
## 7    -2.4672 13.440  -28.809 23.87497
## tot  -4.3069  2.220   -8.657  0.04335
##        n
## 1    661
## 2    102
## 3    306
## 4     20
## 5      3
## 6      5
## 7     12
## tot 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

# 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
## 1      -4.235 17.005  -37.565  29.0949
## 2      -4.520  8.324  -20.834  11.7941
## 3      -5.273  3.373  -11.884   1.3377
## 4      -4.252  2.877   -9.891   1.3878
## 5      -2.921  5.920  -14.524   8.6822
## 6      -2.954 19.792  -41.745  35.8382
## tot    -4.486  2.190   -8.779  -0.1939
##         n
## 1       7
## 2      39
## 3     385
## 4     570
## 5     103
## 6       5
## tot 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

# 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      -5.079 6.187  -17.206   7.0485   77
## 2      -2.254 5.269  -12.582   8.0740  134
## 3      -6.630 4.695  -15.832   2.5722  173
## 4      -5.934 3.899  -13.576   1.7077  267
## 5      -2.131 3.880   -9.735   5.4732  296
## 6      -6.221 5.605  -17.207   4.7653  110
## 7      -5.253 7.378  -19.715   9.2081   52
## tot    -4.520 2.206   -8.844  -0.1959 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    -2.2621 4.947  -11.958   7.4335  144
## 2    -5.6883 4.456  -14.421   3.0444  191
## 3    -2.0756 5.840  -13.522   9.3712   99
## 4    -2.0208 5.600  -12.997   8.9550  104
## 5    -9.4915 4.226  -17.774  -1.2094  271
## 6    -0.6939 5.042  -10.575   9.1875  150
## 7    -3.7738 4.795  -13.172   5.6242  150
## tot  -4.5719 2.175   -8.835  -0.3083 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     -6.932 3.196  -13.195  -0.6689  465
## 2     -2.269 3.007   -8.162   3.6248  518
## 3     -4.152 7.135  -18.136   9.8323   72
## 4     -2.251 7.548  -17.046  12.5434   54
## tot   -4.345 2.115   -8.491  -0.2001 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     -5.199 3.503  -12.064   1.6663  428
## 2     -3.356 2.799   -8.842   2.1295  669
## tot   -4.075 2.205   -8.396   0.2457 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
## 1     -2.894  3.313   -9.387  3.59959
## 2     -3.644  6.919  -17.204  9.91657
## 3     -3.759  4.152  -11.896  4.37825
## 4     -4.831  4.287  -13.235  3.57169
## 5     -8.575  5.070  -18.511  1.36176
## 6     -2.778 12.600  -27.473 21.91682
## 7     -6.469 16.001  -37.830 24.89167
## tot   -4.382  2.215   -8.722 -0.04129
##         n
## 1     409
## 2      62
## 3     229
## 4     219
## 5     168
## 6      14
## 7       8
```

```
## tot 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
## 1     -3.674  2.895   -9.348   2.0007
## 2     -3.642  5.962  -15.327   8.0423
## 3     -3.221  3.505  -10.092   3.6486
## 4     -5.582  3.741  -12.914   1.7495
## 5     -4.558  4.122  -12.636   3.5207
## 6     -2.268 11.986  -25.759  21.2240
## 7     -3.737 15.268  -33.661  26.1870
## tot   -4.072  2.168   -8.321   0.1769
##        n
## 1    409
## 2     62
## 3    229
```

```
## 4     219
## 5     168
## 6      14
## 7       8
## tot 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
```

5.3.2 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     -1.921 3.086   -7.970    4.128  589
## 2     -1.266 3.111   -7.364    4.832  579
```

```
## tot   -1.596 2.201   -5.909    2.717 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
```

```r
# 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    -2.4808 3.695   -9.723    4.762  380
## 2    -2.3191 3.639   -9.451    4.813  394
## 3     0.1382 3.623   -6.962    7.239  393
## tot  -1.5442 2.177   -5.812    2.723 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
```

```r
# 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
## 1    -2.0473  2.713   -7.365    3.271
## 2    -1.6922  5.451  -12.375    8.991
## 3    -0.5886  3.725   -7.889    6.712
## 4     1.1343  9.268  -17.031   19.299
## 5    -0.3368 17.289  -34.222   33.549
## 6    -1.5526 25.740  -52.002   48.896
## 7    -1.1994 17.172  -34.856   32.457
## tot  -1.5186  2.232   -5.893    2.856
##        n
## 1    689
## 2    117
## 3    314
## 4     31
## 5      7
## 6      3
## 7      7
## tot 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
```

```
# 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
## 1    -1.8273 18.540  -38.165   34.511
## 2    -1.9057  9.398  -20.326   16.514
## 3    -2.9937  3.438   -9.732    3.745
## 4    -0.7837  2.868   -6.405    4.837
## 5     0.3865  5.840  -11.059   11.832
## 6    -1.6881 22.487  -45.762   42.386
## tot  -1.5088  2.197   -5.815    2.797
##        n
## 1      6
## 2     32
## 3    417
## 4    606
## 5    103
## 6      4
## tot 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

# 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    -1.0932 6.805  -14.431   12.244   68
## 2    -1.3330 4.933  -11.001    8.335  153
## 3    -2.9555 4.553  -11.878    5.967  193
## 4    -2.0103 3.789   -9.437    5.416  275
## 5     0.9204 3.906   -6.735    8.576  304
## 6    -3.1108 5.175  -13.254    7.032  133
## 7    -1.0472 7.959  -16.647   14.553   42
## tot  -1.3523 2.195   -5.655    2.950 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   -1.78447 4.516  -10.636    7.068  177
## 2   -3.24770 4.433  -11.937    5.442  204
## 3   -0.40809 5.676  -11.533   10.717  100
## 4   -0.07573 5.476  -10.808   10.656  112
## 5   -3.93323 4.161  -12.089    4.222  253
## 6    3.40039 5.287   -6.962   13.762  158
## 7   -1.33668 4.682  -10.513    7.840  164
## tot -1.45953 2.166   -5.705    2.786 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    -3.9852 3.243  -10.341    2.370  486
## 2    -0.8778 3.002   -6.761    5.005  538
## 3     5.3145 6.832   -8.077   18.706   86
## 4     3.7067 7.965  -11.905   19.318   58
## tot  -1.4872 2.110   -5.623    2.649 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     -4.090 3.437  -10.826    2.645  482
## 2     -0.262 2.860   -5.867    5.343  674
## tot   -1.858 2.223   -6.214    2.498 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
```

```r
# 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
## 1    -1.1262  3.132   -7.264    5.012
## 2     0.6241  7.073  -13.240   14.488
## 3    -0.1301  4.334   -8.625    8.364
## 4    -2.9943  4.306  -11.434    5.446
## 5    -3.6729  4.954  -13.382    6.036
## 6    -0.3938 15.448  -30.672   29.884
## 7    -1.7832 16.219  -33.571   30.005
## tot  -1.5445  2.210   -5.876    2.787
##        n
## 1    464
## 2     65
## 3    234
## 4    223
## 5    165
## 6      9
## 7      8
## tot 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
## 1    -1.8655  2.797   -7.347    3.616
## 2     1.1422  5.956  -10.531   12.815
## 3    -0.3862  3.754   -7.744    6.972
## 4    -2.9995  3.588  -10.031    4.032
## 5    -2.4987  4.246  -10.821    5.824
## 6    -1.2132 14.800  -30.220   27.794
## 7    -0.4667 15.574  -30.991   30.057
## tot  -1.6931  2.181   -5.967    2.581
##         n
## 1     464
## 2      65
## 3     234
## 4     223
## 5     165
## 6       9
## 7       8
## tot  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
```

5.3.3 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     -2.635 3.184   -8.875    3.605  553
## 2     -3.585 3.230   -9.916    2.746  533
## tot   -3.101 2.291   -7.592    1.389 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     -1.2215 3.906   -8.877    6.434  342
## 2     -5.8392 3.884  -13.452    1.774  347
## 3     -0.8722 3.673   -8.072    6.328  396
## tot  -2.5708 2.272   -7.024    1.883 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
## 1     -4.4377  2.896  -10.114    1.239
## 2     -2.1347  5.752  -13.408    9.139
## 3     -0.5801  3.999   -8.418    7.258
## 4     -1.2165  9.696  -20.220   17.787
## 5     -3.4842 22.653  -47.884   40.916
## 6     -2.6938 25.972  -53.599   48.211
## 7     -2.3391 16.747  -35.162   30.484
## tot  -3.0409  2.296   -7.541    1.459
##        n
## 1    636
## 2    108
## 3    297
## 4     30
## 5      4
## 6      3
## 7      8
## tot 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
## 1     -1.340 16.865  -34.395  31.7158
## 2     -3.369  9.044  -21.096  14.3571
## 3     -6.404  3.708  -13.672   0.8633
## 4     -1.211  3.050   -7.189   4.7670
## 5     -1.159  6.293  -13.493  11.1759
## 6     -2.884 22.613  -47.206  41.4371
## tot   -3.084  2.297   -7.586   1.4174
##        n
## 1      8
## 2     34
## 3    377
## 4    571
## 5     92
## 6      4
## tot 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     -1.570 6.854  -15.003   11.864   65
## 2     -1.735 5.091  -11.713    8.242  129
## 3     -2.990 4.445  -11.703    5.723  186
## 4     -4.658 4.257  -13.001    3.685  235
## 5     -1.938 3.796   -9.378    5.502  285
## 6     -2.280 4.904  -11.892    7.333  141
## 7     -3.241 7.616  -18.167   11.685   45
## tot   -2.759 2.263   -7.194    1.676 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    -0.9716 4.883  -10.543    8.600  162
## 2    -3.5146 4.452  -12.240    5.211  189
## 3    -3.2283 5.600  -14.203    7.747  105
## 4    -0.9681 5.967  -12.664   10.728   98
## 5    -6.4920 4.404  -15.124    2.140  241
## 6     1.2539 5.293   -9.120   11.628  149
## 7    -3.6372 5.029  -13.494    6.220  142
## tot  -2.9003 2.252   -7.314    1.513 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     -4.385 3.221  -10.698   1.9275  460
## 2     -2.643 3.118   -8.754   3.4681  493
```

```
## 3     -1.523 6.862  -14.972  11.9254   74
## 4     -2.619 7.776  -17.859  12.6212   59
## tot   -3.303 2.178   -7.573   0.9657 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     -4.539 3.591   -11.58    2.499  427
## 2     -1.804 2.968    -7.62    4.013  648
## tot   -2.890 2.301    -7.40    1.620 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
## 1     -4.1341  3.359   -10.72    2.449
## 2     -1.2975  7.181   -15.37   12.777
## 3     -1.7814  4.354   -10.31    6.751
## 4     -2.1449  4.373   -10.71    6.425
## 5     -3.7332  4.925   -13.39    5.919
## 6     -0.5239 14.428   -28.80   27.754
## 7     -2.5825 16.284   -34.50   29.334
## tot   -3.0110  2.306    -7.53    1.508
##         n
## 1     422
## 2      58
## 3     220
## 4     213
## 5     154
## 6      11
## 7       8
## tot 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
```

```r
# 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
## 1     -3.158  2.923   -8.888    2.571
## 2     -1.078  6.316  -13.458   11.302
## 3     -1.659  3.834   -9.173    5.855
## 4     -3.546  3.785  -10.964    3.873
## 5     -4.080  4.341  -12.588    4.427
## 6     -1.596 13.537  -28.128   24.936
## 7     -1.946 15.755  -32.824   28.933
## tot   -2.925  2.281   -7.396    1.545
##        n
## 1    422
## 2     58
## 3    220
## 4    213
## 5    154
## 6     11
## 7      8
## tot 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
```

6 Session Information

```
sessionInfo()
```

```
## R version 4.0.2 (2020-06-22)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS  10.16
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRblas.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.0/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
## [4] grDevices utils     datasets
## [7] methods   base
##
## other attached packages:
##  [1] keyATM_0.4.0     bartCause_1.0-4
##  [3] seededlda_0.5.1  quanteda_2.1.2
##  [5] policytree_1.0.3 grf_1.2.0
##  [7] estimatr_0.30.2  forcats_0.5.1
##  [9] stringr_1.4.0    dplyr_1.0.4
## [11] purrr_0.3.4      readr_1.4.0
## [13] tidyr_1.1.2      tibble_3.1.0
## [15] tidyverse_1.3.0  stargazer_5.2.2
## [17] janitor_2.1.0    kableExtra_1.3.4
## [19] cregg_0.4.0      cjoint_2.1.0
## [21] survey_4.0       survival_3.2-7
## [23] Matrix_1.3-2     ggplot2_3.3.3
## [25] lmtest_0.9-38    zoo_1.8-8
```

```
## [27] sandwich_3.0-0   rmarkdown_2.7
## [29] nvimcom_0.9-115
##
## loaded via a namespace (and not attached):
##  [1] colorspace_2.0-0
##  [2] ellipsis_0.3.1
##  [3] ggstance_0.3.5
##  [4] snakecase_0.11.0
##  [5] fs_1.5.0
##  [6] rstudioapi_0.13
##  [7] farver_2.1.0
##  [8] ggrepel_0.9.1
##  [9] fansi_0.4.2
## [10] lubridate_1.7.9.2
## [11] xml2_1.3.2
## [12] codetools_0.2-18
## [13] splines_4.0.2
## [14] dbarts_0.9-19
## [15] knitr_1.31
## [16] texreg_1.37.5
## [17] Formula_1.2-4
## [18] jsonlite_1.7.2
## [19] broom_0.7.5.9000
## [20] dbplyr_2.1.0
## [21] shiny_1.6.0
## [22] compiler_4.0.2
## [23] httr_1.4.2
## [24] backports_1.2.1
## [25] assertthat_0.2.1
## [26] fastmap_1.1.0
## [27] cli_2.4.0
## [28] later_1.1.0.1
## [29] htmltools_0.5.1.1
## [30] tools_4.0.2
## [31] coda_0.19-4
## [32] gtable_0.3.0
## [33] glue_1.4.2
```

```
## [34] fastmatch_1.1-0
## [35] Rcpp_1.0.6
## [36] rle_0.9.2
## [37] cellranger_1.1.0
## [38] statnet.common_4.4.1
## [39] vctrs_0.3.7
## [40] svglite_1.2.3.2
## [41] xfun_0.22
## [42] stopwords_2.2
## [43] ps_1.6.0
## [44] network_1.16.1
## [45] rvest_0.3.6
## [46] mime_0.10
## [47] lifecycle_1.0.0
## [48] scales_1.1.1
## [49] hms_1.0.0
## [50] promises_1.2.0.1
## [51] parallel_4.0.2
## [52] yaml_2.2.1
## [53] gdtools_0.2.3
## [54] stringi_1.5.3
## [55] highr_0.8
## [56] rlang_0.4.10
## [57] pkgconfig_2.0.3
## [58] systemfonts_1.0.1
## [59] evaluate_0.14
## [60] lattice_0.20-41
## [61] labeling_0.4.2
## [62] tidyselect_1.1.0
## [63] plyr_1.8.6
## [64] magrittr_2.0.1
## [65] R6_2.5.0
## [66] generics_0.1.0
## [67] sna_2.6
## [68] DBI_1.1.1
## [69] pillar_1.5.1
## [70] haven_2.3.1
```

```
## [71] withr_2.4.1
## [72] modelr_0.1.8
## [73] crayon_1.4.1
## [74] utf8_1.2.1
## [75] readxl_1.3.1
## [76] data.table_1.14.0
## [77] reprex_1.0.0
## [78] digest_0.6.27
## [79] webshot_0.5.2
## [80] xtable_1.8-4
## [81] httpuv_1.5.5
## [82] RcppParallel_5.0.2
## [83] munsell_0.5.0
## [84] viridisLite_0.3.0
## [85] mitools_2.4
```

References

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