

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

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## A Introduction

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

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.

```
# Install and load required packages

packages <- c("bartCause", "cjoint", "cregg", "estimatr", "kableExtra",
             "janitor", "quanteda", "quanteda.textmodels", "quanteda.textplots",
             "quanteda.textstats", "seededlda", "stargazer", "tidyverse")

installed_packages <- packages %in% rownames(installed.packages())

if (any(installed_packages == FALSE)) {
  install.packages(packages[!installed_packages])
}

invisible(lapply(packages, library, character.only = TRUE))

# Load the dataset, remove unused rows and columns,
# and convert variable names to snake case

df <- read_csv("../data/data.csv") %>%
  clean_names() %>%
  mutate(response_id      = as.character(response_id),
         consent          = as.factor(q1),
         progress          = as.numeric(progress),
         finished          = as.factor(finished),
         age              = as.numeric(q2),
         gender            = as.factor(q3),
         race              = as.factor(q4),
         education         = as.factor(q5),
         region            = as.factor(q6),
         household_income  = as.factor(q7),
         ideology          = as.factor(q8),
         death_penalty     = as.factor(q9),
         previous_victim    = as.character(q10),
         previous_victim_text = as.character(q10_text),
```

```

views_police      = as.factor(q11),
views_justice     = as.factor(q12),
exp01_control     = as.numeric(q18),
exp01_police      = as.numeric(q19),
exp01_slow_justice = as.numeric(q20),
exp01_small_punishment = as.numeric(q21),
exp03_control     = as.numeric(q22),
exp03_constitution = as.numeric(q23),
exp03_rights      = as.numeric(q24),
exp03_vendetta    = as.numeric(q25)) %>%

slice(-1L) %>%

select(-c(q1:q12, q18:q25)) %>%

relocate(response_id, consent, progress, finished,
          location_latitude, location_longitude) %>%

mutate(across(where(is.character), tolower)) %>%

mutate(across(where(is.factor), tolower))

# Translate factor values from Portuguese to English
df <- df %>%

mutate(consent = recode(consent,
                        concordo      = "Agree",
                        `não concordo` = "Disagree"),

gender = recode(gender,
                "feminino"      = "Female",
                "masculino"     = "Male",
                "outro"         = "Other",
                "prefiro não responder" = "Rather Not Say"),

race = recode(race,
              "amarela"      = "Asian",
              "branca"       = "White",
              "indígena"     = "Indigenous",
              "outra"        = "Other",
              "parda"        = "Mixed Race",
              "prefiro não responder" = "Rather Not Say",
              "preta"        = "Black"),

race = fct_relevel(race, "Other", "Rather Not Say", after = Inf),

education = recode(education,

```

```

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

```

```

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

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

```

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

## B Descriptive Statistics

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

### B.1 Informed Consent

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

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

Table 1: Informed Consent

Consent	N	Frequency
Agree	2406	0.98
Disagree	54	0.02

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

## B.2 Gender

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

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

Table 2: Gender

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

## B.3 Age

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

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

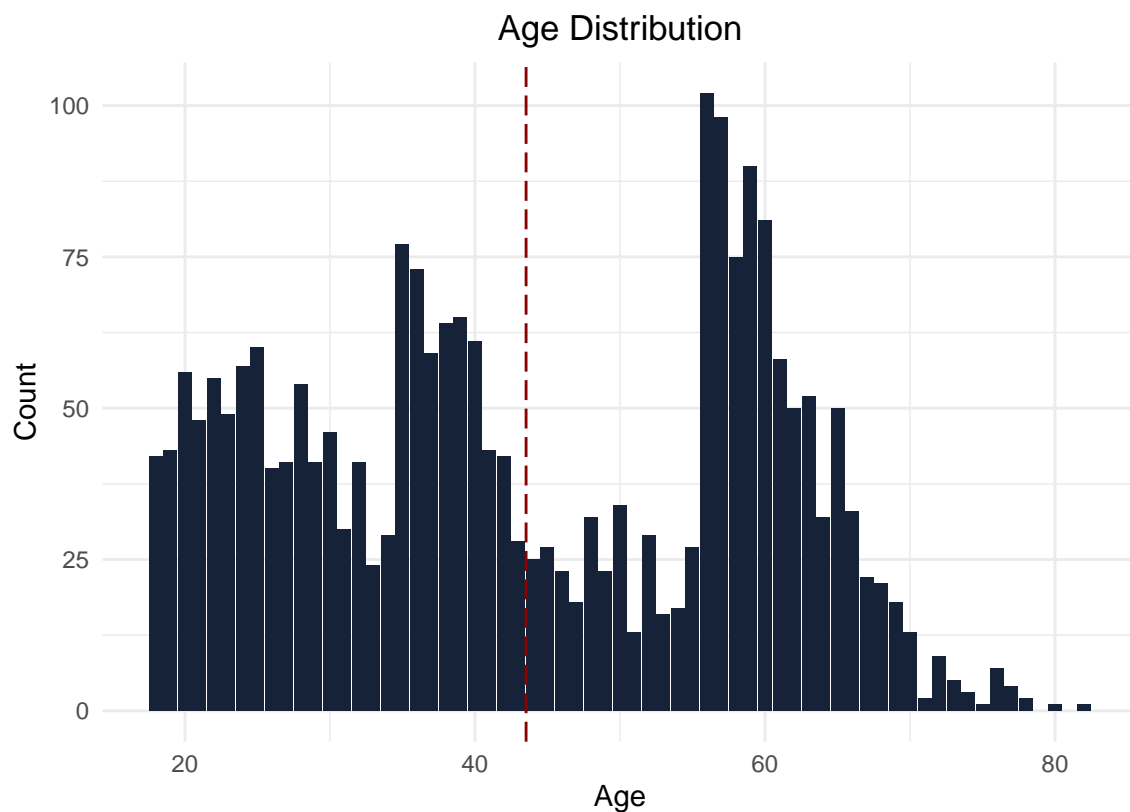


```
row_spec(0, bold = TRUE) %>%
kable_styling(latex_options = "hold_position")
```

Table 3: Age

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

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



## B.4 Race

The next demographic variable we show here is race. According to the [Brazilian Census Bureau](#), 42.7% of the Brazilian population identify as White, 46.8% as Mixed Race, 9.4% as Blacks, and 1.1% as Asians or Indigenous. As we see below, our sample includes more Whites and fewer Mixed-Race individuals. The number of Blacks roughly coincide with their actual population share.

```
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

<b>Race</b>	<b>N</b>	<b>Frequency</b>
Asian	60	0.025
Black	231	0.097
Indigenous	8	0.003
Mixed Race	652	0.274
White	1407	0.590
Other	8	0.003
Rather Not Say	17	0.007

## B.5 Education

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

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

Table 5: Education

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

## B.6 Household Income

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

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

## B.7 Political Ideology

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

Table 6: Household Income

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

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

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

Table 7: Political Ideology

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

## B.8 Support for Death Penalty

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

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

Table 8: Support for Death Penalty

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

## B.9 Previous Victimization

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

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

Table 9: Previous Victimization (12 Months)

<b>Victimization</b>	<b>N</b>	<b>Frequency</b>
Yes	934	0.401
No	1397	0.599

## B.10 Opinion on the Police

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

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

Table 10: Opinion on the Police

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

## B.11 Opinion on the Judicial System

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

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

Table 11: Opinion on the Justice System

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

## C Experiment 01

### C.1 Description

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

Table 12: **Attributes and Levels**

<b>Attribute</b>	<b>Levels</b>
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; neighbors; 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 selecting the profiles, respondents were asked to 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.<sup>1</sup>

## C.2 Marginal Means Estimator

We estimate the conjoint experiment with the `cregg` package (Leeper 2018) for the R statistical language (R Core Team 2018). We follow Leeper et al. (2020) and report marginal means as our main

<sup>1</sup>Original text in Portuguese: Linchamentos são às vezes usados como punição social no Brasil. Linchamentos são casos nos quais três ou mais pessoas agredem 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.



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,
         "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
```

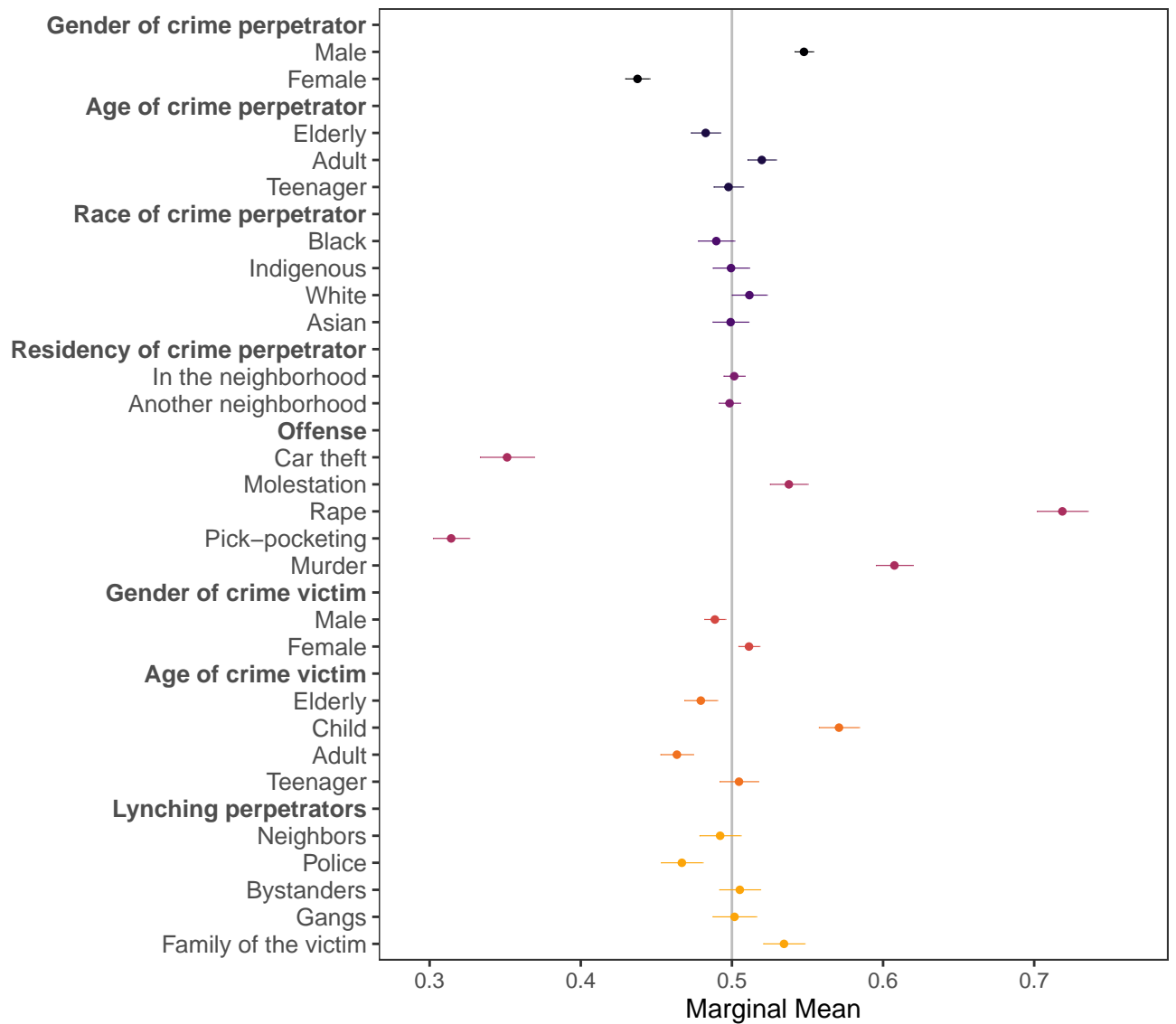
```
fm <- selected ~ `Gender of crime perpetrator` +  
  `Age of crime perpetrator` + `Race of crime perpetrator` +  
  `Residency of crime perpetrator` + `Offense` +  
  `Gender of crime victim` + `Age of crime victim` +  
  `Lynching perpetrators`
```

```
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 13: Marginal Means – Full Model

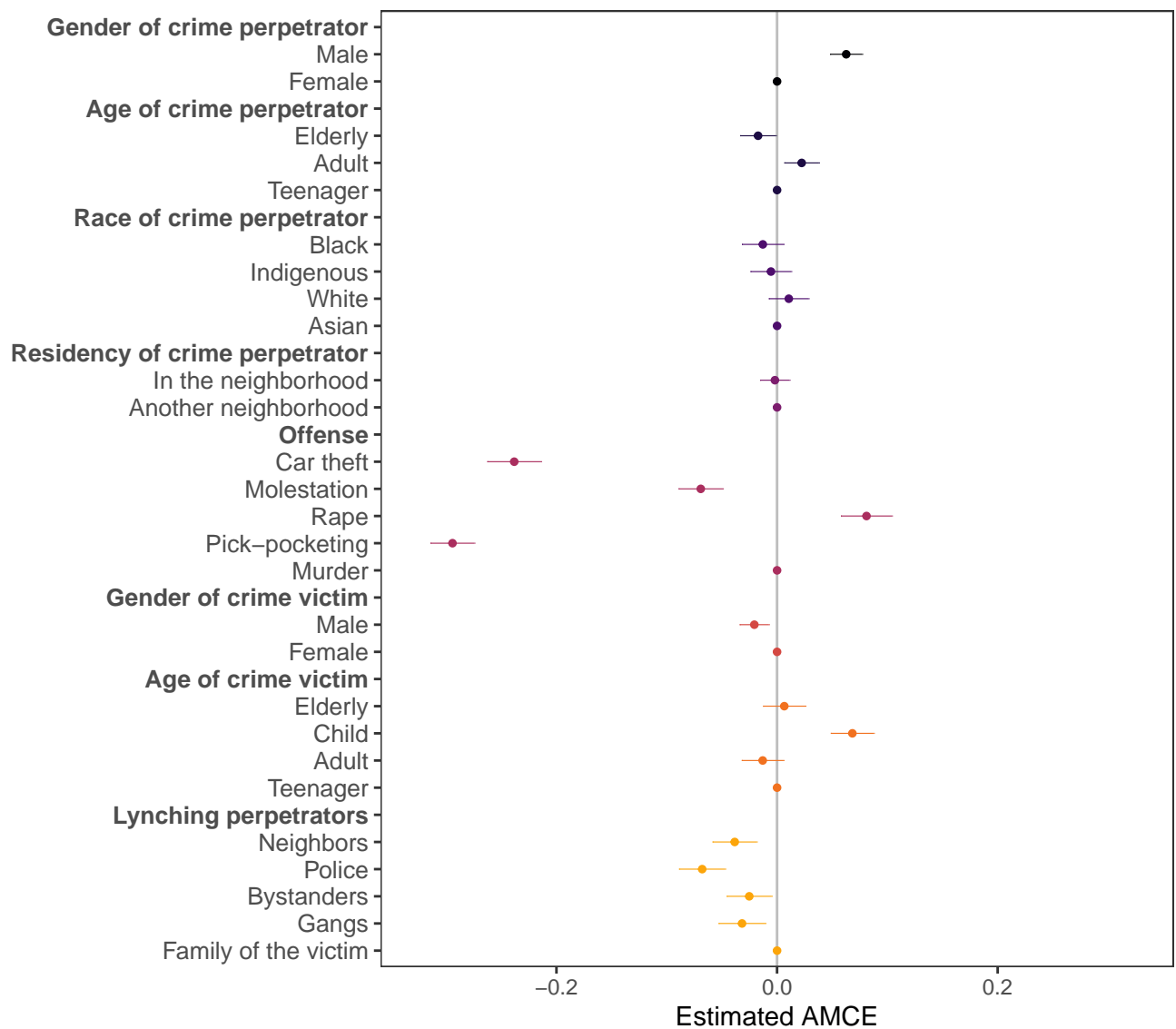
Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.438	0.004	0.000	0.429	0.446
Male	0.548	0.003	0.000	0.541	0.554
<b>Age of crime perpetrator</b>					
Teenager	0.498	0.005	0.650	0.488	0.508
Adult	0.520	0.005	0.000	0.510	0.529
Elderly	0.483	0.005	0.000	0.473	0.492
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.511	0.004	0.002	0.504	0.518
Male	0.489	0.004	0.002	0.482	0.496
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.534	0.007	0.000	0.521	0.548
Gangs	0.502	0.007	0.815	0.487	0.516
Bystanders	0.505	0.007	0.450	0.492	0.519
Police	0.467	0.007	0.000	0.453	0.481
Neighbors	0.492	0.007	0.262	0.479	0.506

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

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

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

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



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

Table 14: Average Marginal Component Effects – Full Model

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.000	NA	NA	NA	NA
Male	0.063	0.007	0.000	0.048	0.077
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
Another neighborhood	0.000	NA	NA	NA	NA
In the neighborhood	-0.002	0.007	0.776	-0.015	0.011
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.000	NA	NA	NA	NA
Male	-0.021	0.007	0.002	-0.034	-0.007
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.000	NA	NA	NA	NA
Gangs	-0.032	0.011	0.003	-0.053	-0.011
Bystanders	-0.025	0.010	0.015	-0.046	-0.005
Police	-0.068	0.011	0.000	-0.089	-0.047
Neighbors	-0.038	0.010	0.000	-0.058	-0.018

## C.4 Subgroup Analyses

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

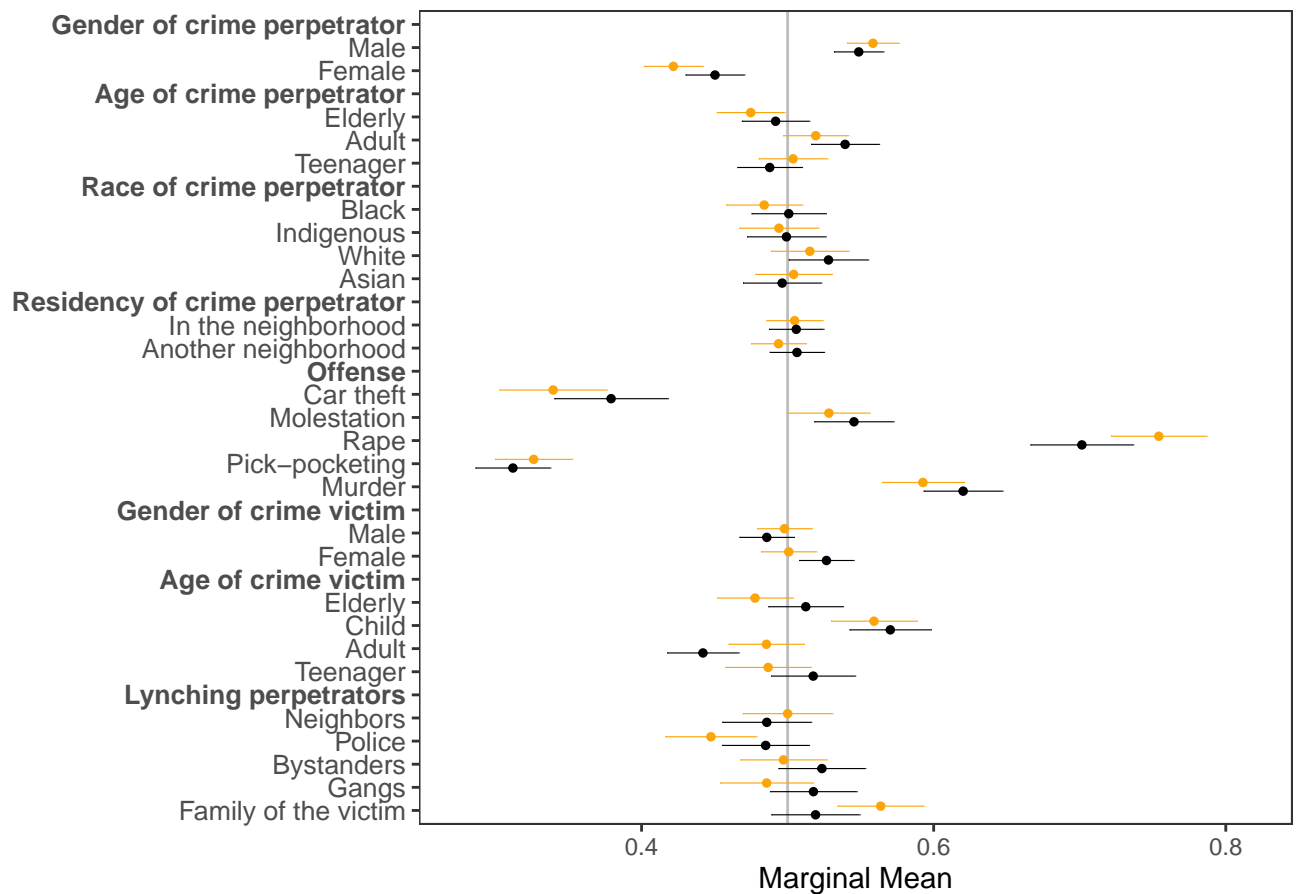
### C.4.1 Gender

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

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

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





Gender ● Female ● Male NA

# Tables

```
table_mm_by <- function(mm_by, capt) {
  dfr <- data.frame(feature = mm_by[, c(5)],
    round(mm_by[, c(6, 7, 9, 10, 11)], digits = 3))
  names(dfr) <- c("Feature", "Estimate", "Std. Error",
    "P-Value", "Lower", "Upper")
  return(kbl(dfr, "latex", caption = capt, linesep = "",
    booktabs = TRUE) %>%
    kable_styling(font_size = 12, full_width = TRUE,
      latex_options = "hold_position") %>%
    pack_rows("Gender of crime perpetrator", 1, 2) %>%
    pack_rows("Age of crime perpetrator", 3, 5) %>%
    pack_rows("Race of crime perpetrator", 6, 9) %>%
    pack_rows("Residency of crime perpetrator", 10, 11) %>%
    pack_rows("Offense", 12, 16) %>%
    pack_rows("Gender of crime victim", 17, 18) %>%
    pack_rows("Age of crime victim", 19, 22) %>%
    pack_rows("Lynching perpetrators", 23, 27) %>%
```

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

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

Table 15: Marginal Means – Females

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.450	0.010	0.000	0.430	0.470
Male	0.549	0.009	0.000	0.532	0.566
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.527	0.010	0.005	0.508	0.545
Male	0.486	0.010	0.133	0.467	0.504
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.519	0.015	0.215	0.489	0.549
Gangs	0.518	0.015	0.242	0.488	0.547
Bystanders	0.523	0.015	0.121	0.494	0.553
Police	0.485	0.015	0.322	0.455	0.515
Neighbors	0.486	0.016	0.358	0.455	0.516

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

Table 16: Marginal Means – Males

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.422	0.010	0.000	0.402	0.442
Male	0.558	0.009	0.000	0.541	0.576
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.501	0.010	0.937	0.482	0.520
Male	0.498	0.010	0.823	0.479	0.517
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.564	0.015	0.000	0.534	0.593
Gangs	0.486	0.016	0.376	0.454	0.517
Bystanders	0.497	0.015	0.851	0.468	0.527
Police	0.447	0.016	0.001	0.416	0.479
Neighbors	0.500	0.016	1.000	0.469	0.531

## C.4.2 Age

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

```
# Model

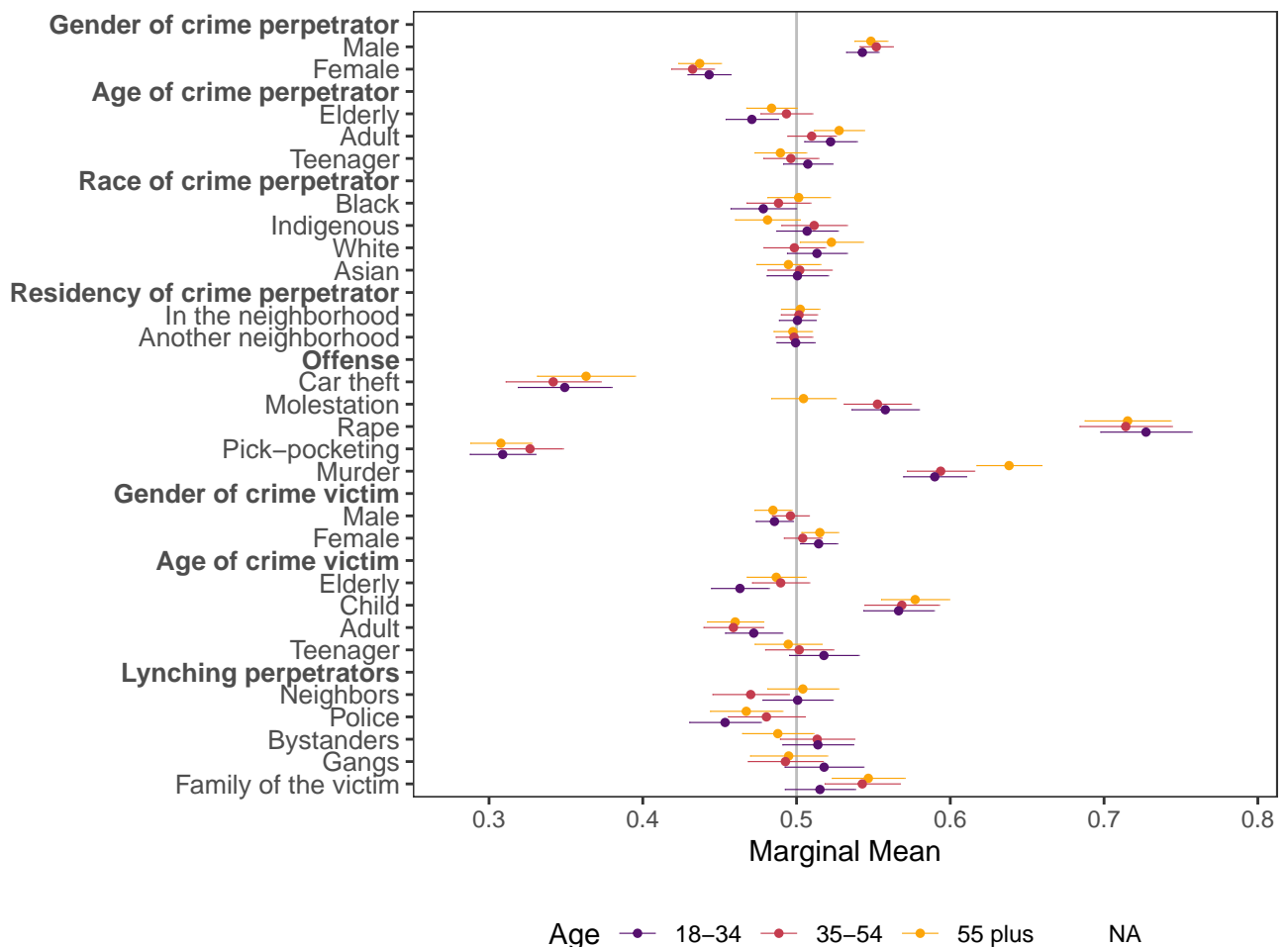
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(age) %>%
  mutate(age2 = case_when(age >= 18 & age <= 34 ~ "18-34", age >= 35 & age <= 54 ~ "35-54",
    age >= 55 ~ "55 plus", TRUE ~ as.character(age)))

cjdt$Age <- factor(cjdt$age2)

mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Age)
```

```
# Plot

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



## # Tables

```
mm_young <- mm_by %>% filter(BY == "18-34")
```

```
table_mm_by(mm_young, capt = "Marginal Means -- 18-34 Years Old")
```

Table 17: Marginal Means – 18-34 Years Old

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.443	0.007	0.000	0.429	0.457
Male	0.543	0.005	0.000	0.532	0.553
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.514	0.006	0.020	0.502	0.526
Male	0.486	0.006	0.020	0.474	0.498
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
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

```
mm_adult <- mm_by %>% filter(BY == "35-54")
```

```
table_mm_by(mm_adult, capt = "Marginal Means -- 35-54 Years Old")
```

Table 18: Marginal Means – 35-54 Years Old

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.432	0.007	0.000	0.418	0.446
Male	0.552	0.006	0.000	0.541	0.563
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.504	0.006	0.520	0.492	0.516
Male	0.496	0.006	0.520	0.484	0.508
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.543	0.013	0.001	0.518	0.567
Gangs	0.493	0.012	0.560	0.468	0.517
Bystanders	0.513	0.012	0.277	0.489	0.538
Police	0.480	0.013	0.125	0.455	0.505
Neighbors	0.470	0.013	0.019	0.445	0.495

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

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

Table 19: Marginal Means – 55+ Years Old

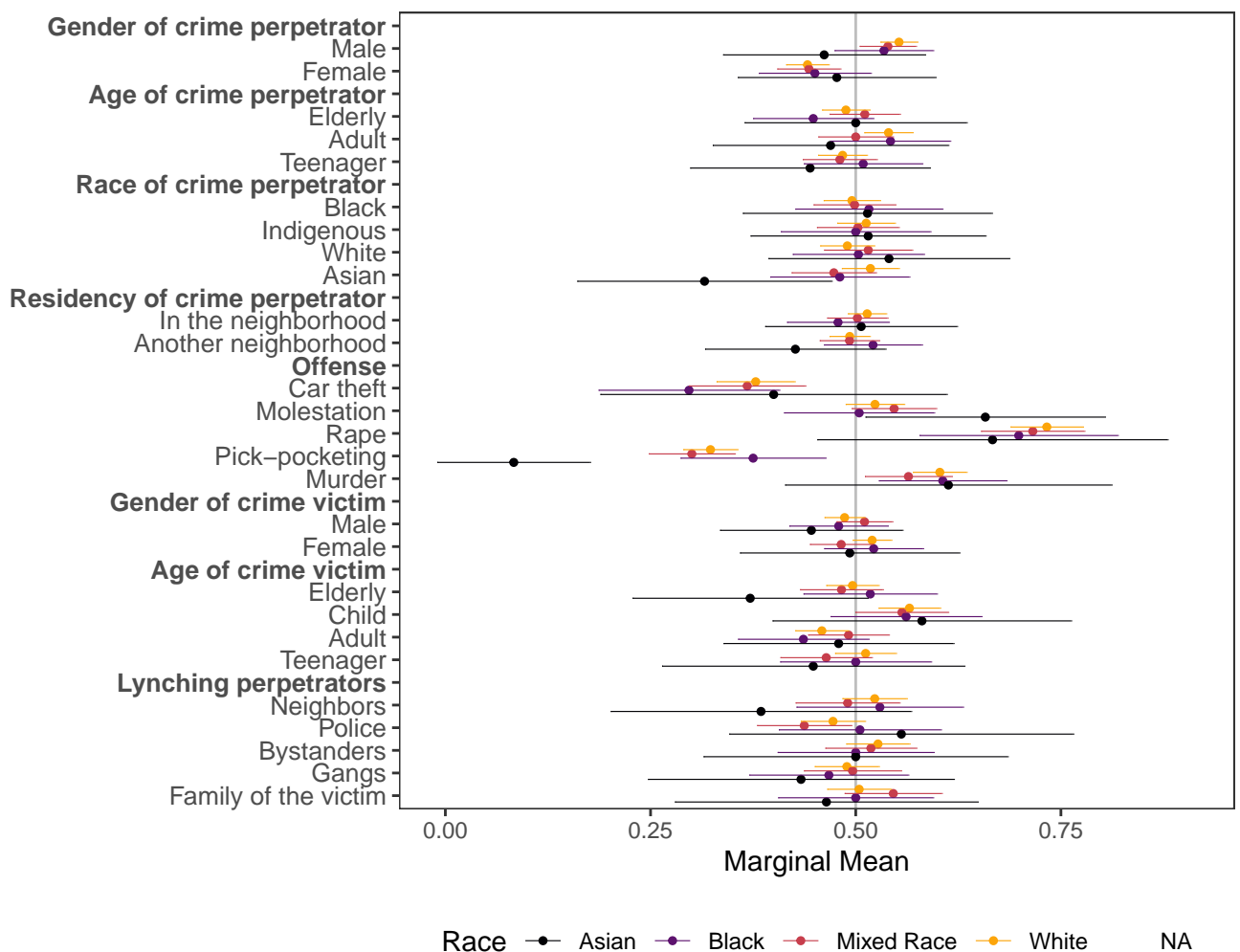
Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.437	0.007	0.000	0.423	0.451
Male	0.548	0.005	0.000	0.538	0.559
<b>Age of crime perpetrator</b>					
Teenager	0.489	0.009	0.221	0.473	0.506
Adult	0.528	0.008	0.001	0.511	0.544
Elderly	0.484	0.008	0.052	0.467	0.500
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.515	0.006	0.013	0.503	0.527
Male	0.485	0.006	0.013	0.473	0.497
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.547	0.012	0.000	0.523	0.570
Gangs	0.495	0.013	0.690	0.470	0.520
Bystanders	0.488	0.012	0.303	0.465	0.511
Police	0.467	0.012	0.006	0.444	0.491
Neighbors	0.504	0.012	0.728	0.481	0.527

### C.4.3 Race

Below are our results when we disaggregate the data by race. We find that they are almost identical in 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 = "bold", size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```



```
# Tables
```



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

Table 20: Marginal Means – Asian

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.477	0.061	0.707	0.356	0.597
Male	0.462	0.063	0.540	0.338	0.585
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.493	0.068	0.915	0.359	0.626
Male	0.446	0.057	0.341	0.335	0.557
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
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

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

mm_mixed <- mm_by %>% filter(BY == "Mixed Race")
table_mm_by(mm_mixed, capt = "Marginal Means -- Mixed Race")
```

Table 21: Marginal Means – Black

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.450	0.035	0.153	0.382	0.519
Male	0.534	0.031	0.261	0.474	0.595
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.522	0.031	0.476	0.462	0.582
Male	0.479	0.031	0.498	0.419	0.539
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.500	0.048	1.000	0.406	0.594
Gangs	0.467	0.049	0.508	0.370	0.564
Bystanders	0.500	0.049	1.000	0.405	0.595
Police	0.505	0.050	0.919	0.406	0.604
Neighbors	0.529	0.052	0.570	0.428	0.631

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

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

Table 22: Marginal Means – Mixed Race

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.443	0.020	0.004	0.404	0.481
Male	0.539	0.018	0.025	0.505	0.574
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.482	0.019	0.361	0.444	0.520
Male	0.511	0.017	0.536	0.477	0.545
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.546	0.030	0.130	0.487	0.605
Gangs	0.496	0.030	0.900	0.437	0.555
Bystanders	0.519	0.028	0.513	0.463	0.574
Police	0.437	0.029	0.032	0.380	0.495
Neighbors	0.490	0.032	0.762	0.427	0.554

Table 23: Marginal Means – White

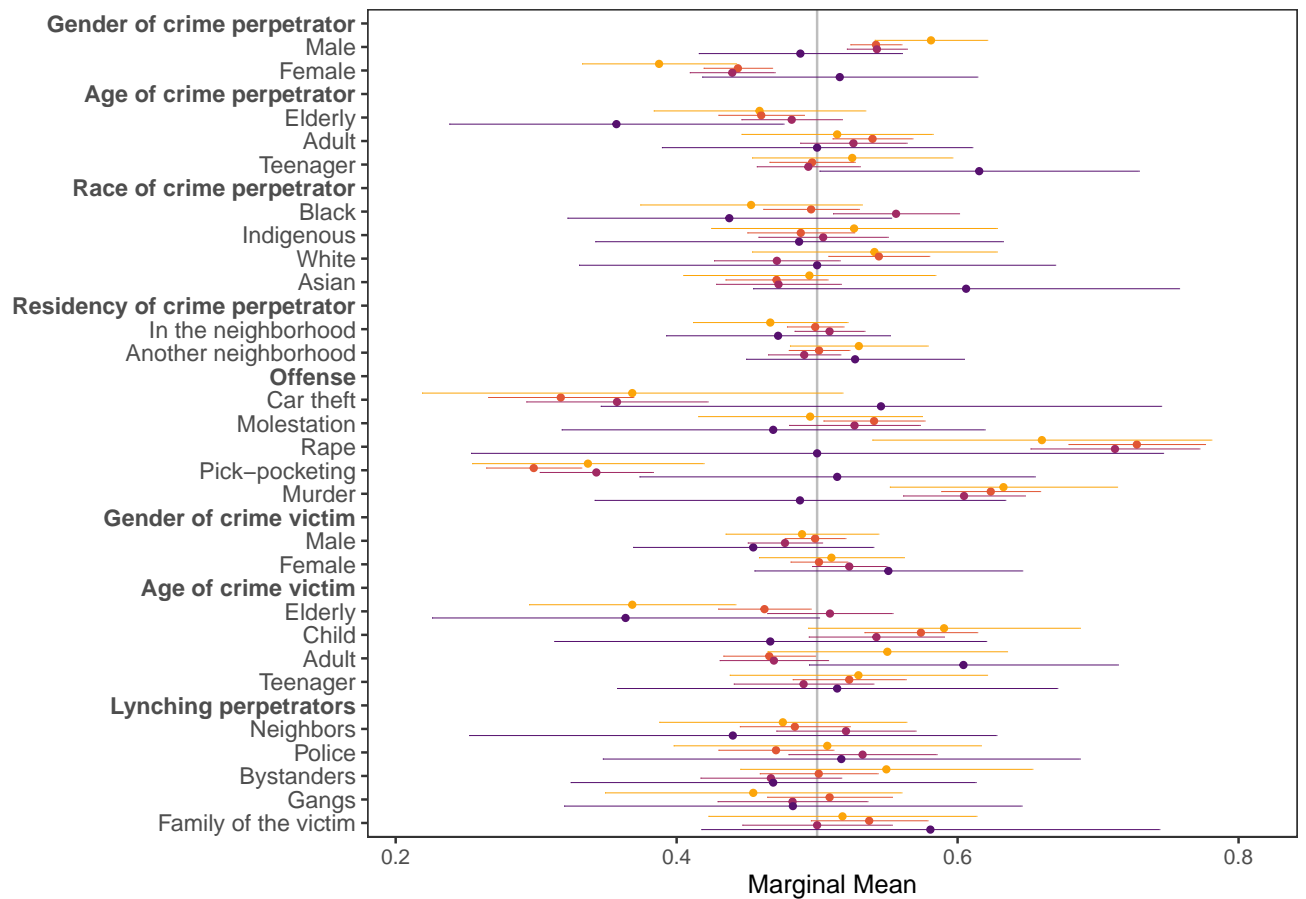
Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.441	0.013	0.000	0.415	0.467
Male	0.553	0.011	0.000	0.530	0.575
<b>Age of crime perpetrator</b>					
Teenager	0.484	0.015	0.292	0.454	0.514
Adult	0.540	0.015	0.008	0.511	0.569
Elderly	0.488	0.015	0.419	0.459	0.517
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.520	0.012	0.097	0.496	0.544
Male	0.486	0.012	0.274	0.462	0.511
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.504	0.020	0.833	0.465	0.543
Gangs	0.489	0.020	0.589	0.450	0.528
Bystanders	0.527	0.020	0.168	0.489	0.566
Police	0.472	0.020	0.166	0.433	0.512
Neighbors	0.523	0.020	0.248	0.484	0.562

### C.4.4 Education

Next, we divide our data according to respondents' level of education. As the number of interviewees with primary or secondary education is low, we merge them into a single category, while the other levels (high school, college, and graduate school) remain the same as in our questionnaire. While most results are similar across all model specifications, we find that respondents with a high school degree tend to punish Blacks more severely, but participants with a college degree believe that White criminals should be punished more harshly instead. The finding deserves attention because it indicates that individuals with lower levels of education, who are more likely to be Black and Mixed Race in Brazil, perhaps prefer to punish criminals of own race. The same is true for Whites, who are usually overrepresented in college education. The differences are not statistically significant, however, for respondents with university degrees.

```
# Model
cjdtt <- 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"))
cjdtt$Education <- factor(cjdtt$education2)
mm_by <- cj(cjdtt, 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 = "bold", size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8, begin = 0.25)
```



Education — Primary or Secondary School — High School — College — Graduate School

#### # Tables

```
mm_pri_sec <- mm_by %>% filter(BY == "Primary or Secondary School")
table_mm_by(mm_pri_sec, capt = "Marginal Means -- Primary or Secondary School Degree")

mm_high <- mm_by %>% filter(BY == "High School")
table_mm_by(mm_high, capt = "Marginal Means -- High School Degree")

mm_college <- mm_by %>% filter(BY == "College")
table_mm_by(mm_college, capt = "Marginal Means -- College Degree")

mm_grad <- mm_by %>% filter(BY == "Graduate School")
table_mm_by(mm_grad, capt = "Marginal Means -- Graduate School Degree")
```

Table 24: Marginal Means – Primary or Secondary School Degree

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.516	0.050	0.747	0.418	0.614
Male	0.488	0.037	0.747	0.416	0.560
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.551	0.049	0.297	0.455	0.646
Male	0.455	0.044	0.297	0.369	0.540
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.581	0.083	0.332	0.418	0.744
Gangs	0.483	0.083	0.836	0.320	0.646
Bystanders	0.469	0.074	0.671	0.325	0.613
Police	0.517	0.087	0.842	0.347	0.687
Neighbors	0.440	0.096	0.531	0.252	0.628

Table 25: Marginal Means – High School Degree

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.440	0.015	0.000	0.409	0.470
Male	0.543	0.011	0.000	0.521	0.564
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.523	0.013	0.090	0.496	0.549
Male	0.477	0.013	0.090	0.451	0.504
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.500	0.027	1.000	0.447	0.553
Gangs	0.483	0.027	0.520	0.429	0.536
Bystanders	0.467	0.026	0.198	0.417	0.517
Police	0.532	0.027	0.228	0.480	0.585
Neighbors	0.521	0.025	0.416	0.471	0.570



Table 26: Marginal Means – College Degree

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.444	0.012	0.000	0.419	0.468
Male	0.542	0.009	0.000	0.524	0.560
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.501	0.010	0.897	0.481	0.521
Male	0.499	0.011	0.897	0.477	0.520
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.537	0.021	0.080	0.496	0.579
Gangs	0.509	0.023	0.694	0.464	0.553
Bystanders	0.501	0.021	0.957	0.459	0.543
Police	0.471	0.021	0.160	0.430	0.512
Neighbors	0.484	0.020	0.427	0.445	0.523

Table 27: Marginal Means – Graduate School Degree

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.387	0.028	0.000	0.333	0.442
Male	0.581	0.020	0.000	0.541	0.621
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.510	0.026	0.698	0.459	0.562
Male	0.489	0.028	0.698	0.435	0.544
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.518	0.049	0.710	0.423	0.613
Gangs	0.455	0.054	0.399	0.349	0.560
Bystanders	0.549	0.053	0.353	0.445	0.653
Police	0.507	0.056	0.897	0.398	0.617
Neighbors	0.476	0.045	0.587	0.388	0.564

### C.4.5 Household Income

We also disaggregate the results by monthly household income. As some categories have few respondents, we group them into three categories: (i) up to R\$3,000 (US\$550); (ii) from R\$3,001 to R\$5,000 (US\$550-915); and (iii) above R\$5,000 (US\$915+). The levels roughly represent low, middle, and high-income households. We find no considerable differences among them, except the fact that respondents with lower incomes are more likely to select profiles that include White criminals.

```
# Model

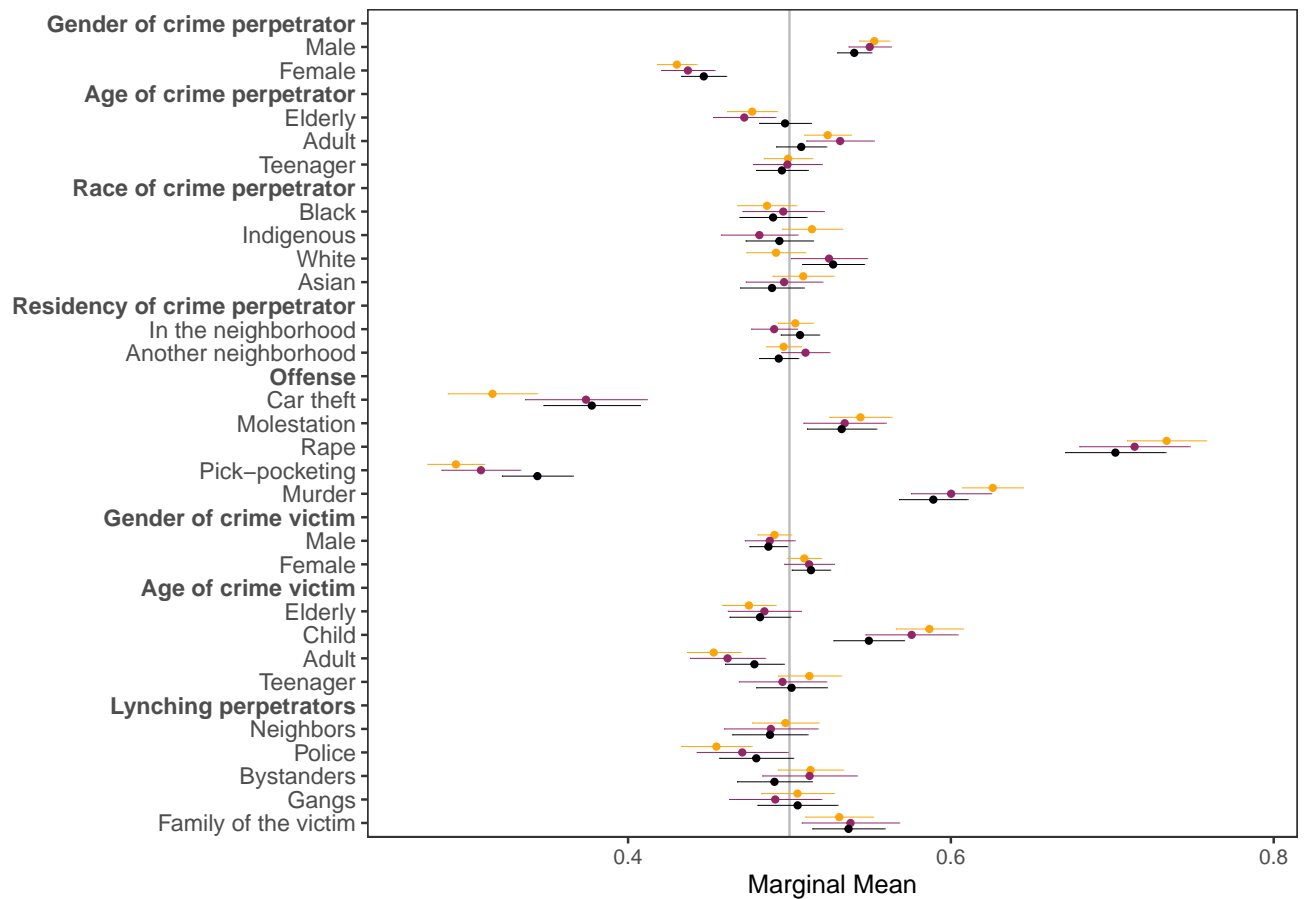
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(household_income) %>%
  mutate(household_income2 = case_when(household_income == "Up to R$1,000" ~ "Up to R$3,000",
                                       household_income == "From R$1,001 to R$2,000" ~ "Up to R$3,000",
                                       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 = "bold", size = 10)) +
  scale_colour_viridis_d(option = "inferno", end = 0.8)
```



Income —●— Up to R\$3,000 —●— From R\$3,001 to R\$5,000 —●— Above R\$5,000 NA

#### # Tables

```
mm_3k <- mm_by %>% filter(BY == "Up to R$3,000")
table_mm_by(mm_3k, capt = "Marginal Means -- Up to 3,000 BRL")

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

mm_abv5k <- mm_by %>% filter(BY == "Above R$5,000")
table_mm_by(mm_abv5k, capt = "Marginal Means -- Above 5,000 BRL")
```

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.447	0.007	0.000	0.433	0.461
Male	0.540	0.005	0.000	0.530	0.551
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.513	0.006	0.028	0.501	0.525
Male	0.487	0.006	0.029	0.475	0.499
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.537	0.011	0.001	0.514	0.559
Gangs	0.505	0.013	0.689	0.480	0.530
Bystanders	0.491	0.012	0.432	0.468	0.514
Police	0.479	0.012	0.078	0.457	0.502
Neighbors	0.488	0.012	0.309	0.465	0.511

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.437	0.008	0.000	0.421	0.454
Male	0.550	0.007	0.000	0.537	0.563
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.512	0.008	0.121	0.497	0.528
Male	0.488	0.008	0.121	0.472	0.503
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.538	0.015	0.014	0.508	0.568
Gangs	0.491	0.015	0.547	0.463	0.520
Bystanders	0.512	0.015	0.404	0.483	0.542
Police	0.471	0.014	0.042	0.443	0.499
Neighbors	0.488	0.015	0.435	0.460	0.517

Table 30: Marginal Means – Above 5,000 BRL

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.430	0.006	0.000	0.418	0.442
Male	0.553	0.005	0.000	0.543	0.562
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.509	0.005	0.081	0.499	0.520
Male	0.491	0.005	0.081	0.480	0.501
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.531	0.011	0.004	0.510	0.552
Gangs	0.505	0.012	0.667	0.482	0.528
Bystanders	0.513	0.010	0.205	0.493	0.533
Police	0.455	0.011	0.000	0.433	0.477
Neighbors	0.498	0.011	0.813	0.477	0.518

## C.4.6 Political Ideology

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

```
# Model

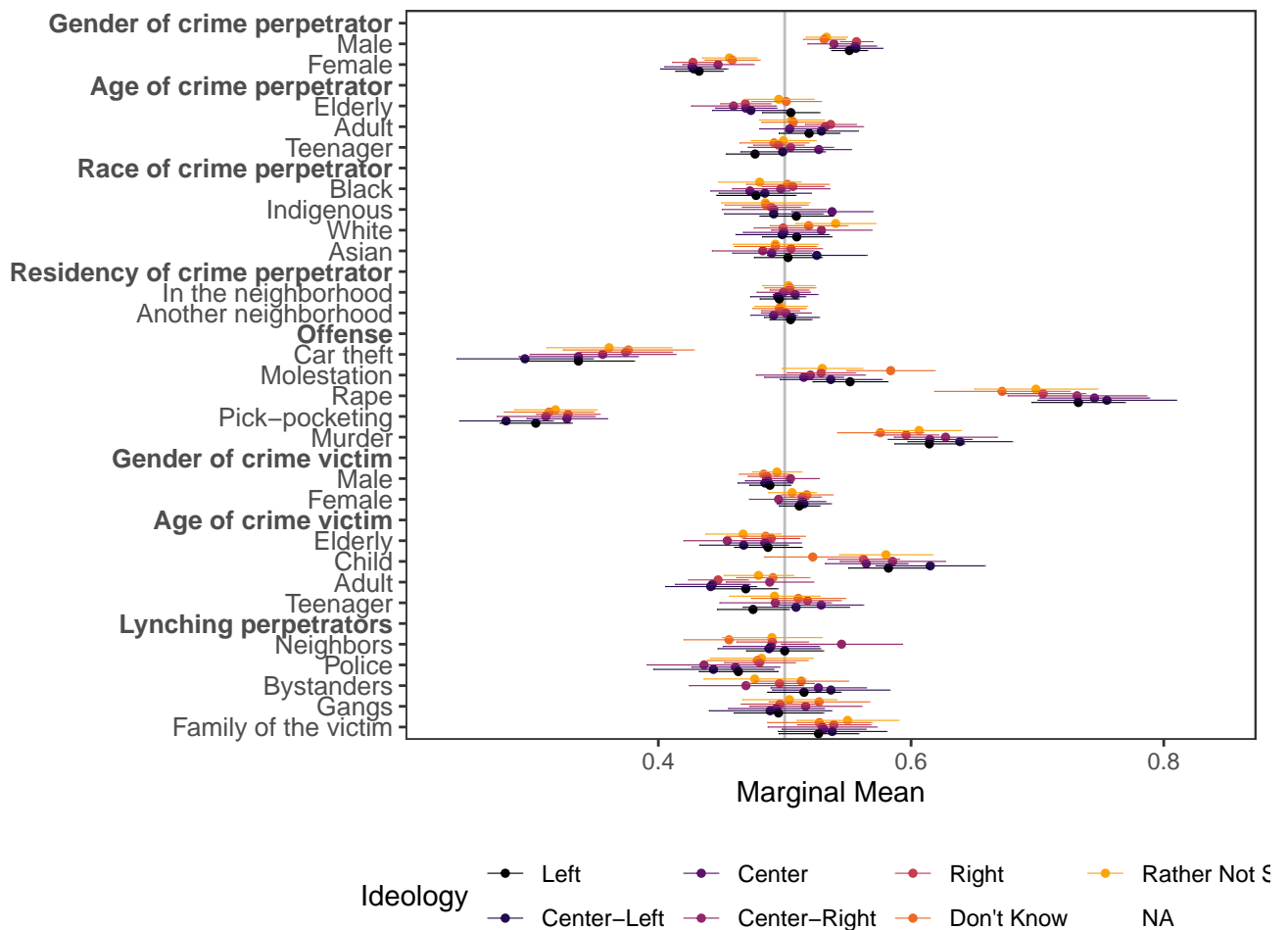
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(ideology)

cjdt$Ideology <- factor(cjdt$ideology)

mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by =
  ~Ideology)
```

```
# Plot

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



```
# Tables

mm_left <- mm_by %>% filter(BY == "Left")

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



Table 31: Marginal Means – Left

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

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

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

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

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

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

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

Table 32: Marginal Means – Center-Left

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

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

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

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

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

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

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

Table 33: Marginal Means – Center

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

Table 34: Marginal Means – Center-Right

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

Table 35: Marginal Means – Right

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

Table 36: Marginal Means – Don't Know

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

Table 37: Marginal Means – Rather Not Say

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

### C.4.7 Support for Death Penalty

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

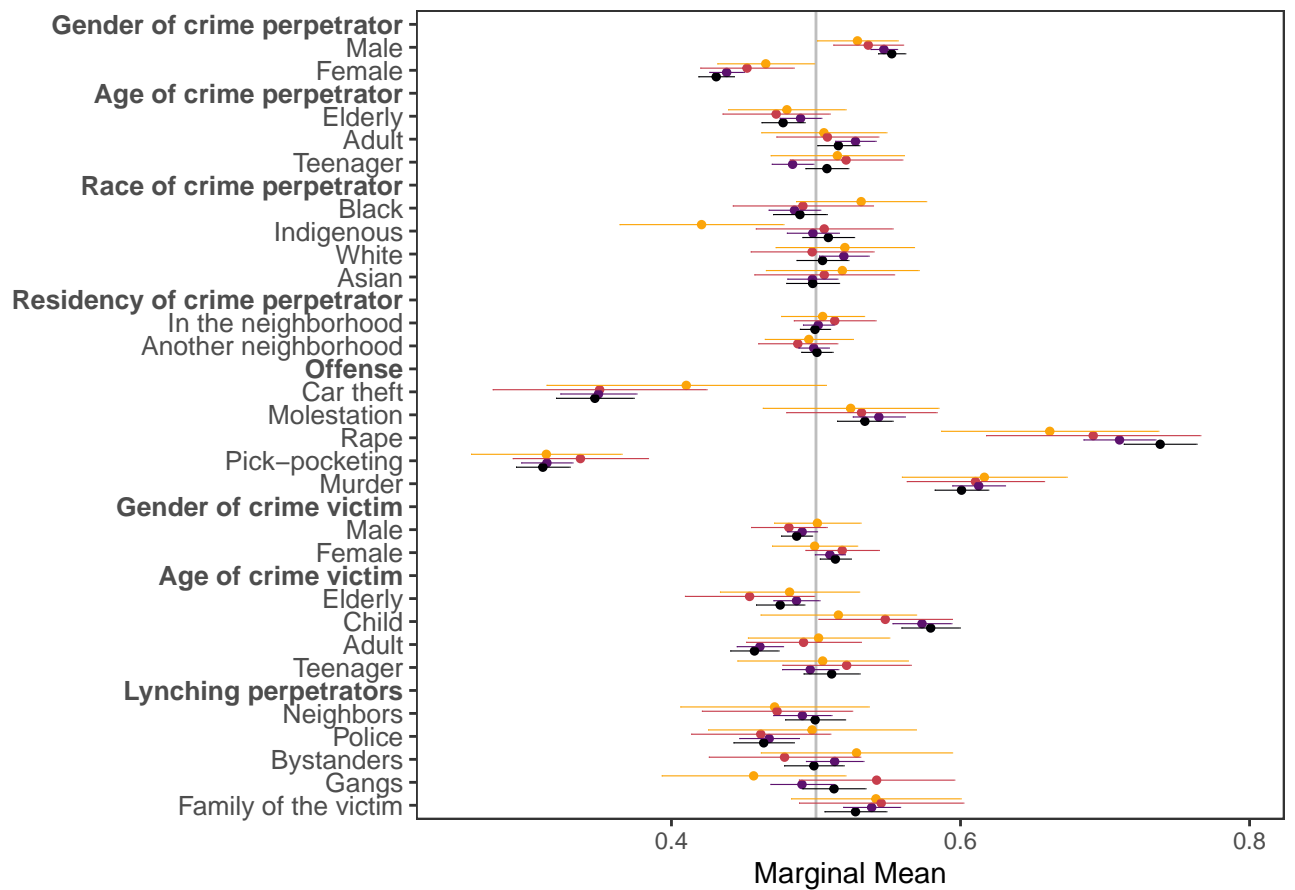
```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  drop_na(death_penalty) %>%
  mutate(death_penalty = fct_relevel(death_penalty, "Yes", "No",
                                     "Don't Know", "Rather Not Say"))

cjdt$Death_Penalty <- factor(cjdt$death_penalty)

mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Death_Penalty)

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





Death\_Penalty —●— Yes —●— No —●— Don't Know —●— Rather Not Say

# Tables

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

```
table_mm_by(mm_yes, capt = "Marginal Means -- Support for Death Penalty: Yes")
```

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

```
table_mm_by(mm_no, capt = "Marginal Means -- Support for Death Penalty: No")
```

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

```
table_mm_by(mm_dk, capt = "Marginal Means -- Support for Death Penalty: Do Not Know")
```

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

```
table_mm_by(mm_rns, capt = "Marginal Means -- Support for Death Penalty: Rather Not Say")
```

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.431	0.006	0.000	0.419	0.443
Male	0.552	0.005	0.000	0.543	0.562
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.513	0.005	0.015	0.503	0.524
Male	0.487	0.005	0.015	0.476	0.497
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.527	0.011	0.012	0.506	0.549
Gangs	0.512	0.011	0.261	0.491	0.534
Bystanders	0.499	0.011	0.893	0.478	0.519
Police	0.464	0.011	0.001	0.443	0.485
Neighbors	0.499	0.011	0.957	0.479	0.520

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.438	0.006	0.000	0.426	0.450
Male	0.547	0.005	0.000	0.538	0.556
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.510	0.005	0.070	0.499	0.520
Male	0.490	0.005	0.070	0.480	0.501
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.539	0.010	0.000	0.519	0.558
Gangs	0.490	0.011	0.384	0.469	0.512
Bystanders	0.513	0.010	0.202	0.493	0.533
Police	0.468	0.011	0.002	0.447	0.488
Neighbors	0.491	0.010	0.360	0.470	0.511

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.452	0.016	0.004	0.420	0.485
Male	0.536	0.012	0.003	0.512	0.560
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.518	0.013	0.161	0.493	0.544
Male	0.481	0.013	0.161	0.455	0.507
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.545	0.029	0.120	0.488	0.602
Gangs	0.542	0.027	0.126	0.488	0.596
Bystanders	0.478	0.027	0.416	0.426	0.531
Police	0.462	0.025	0.120	0.414	0.510
Neighbors	0.473	0.027	0.310	0.421	0.525

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

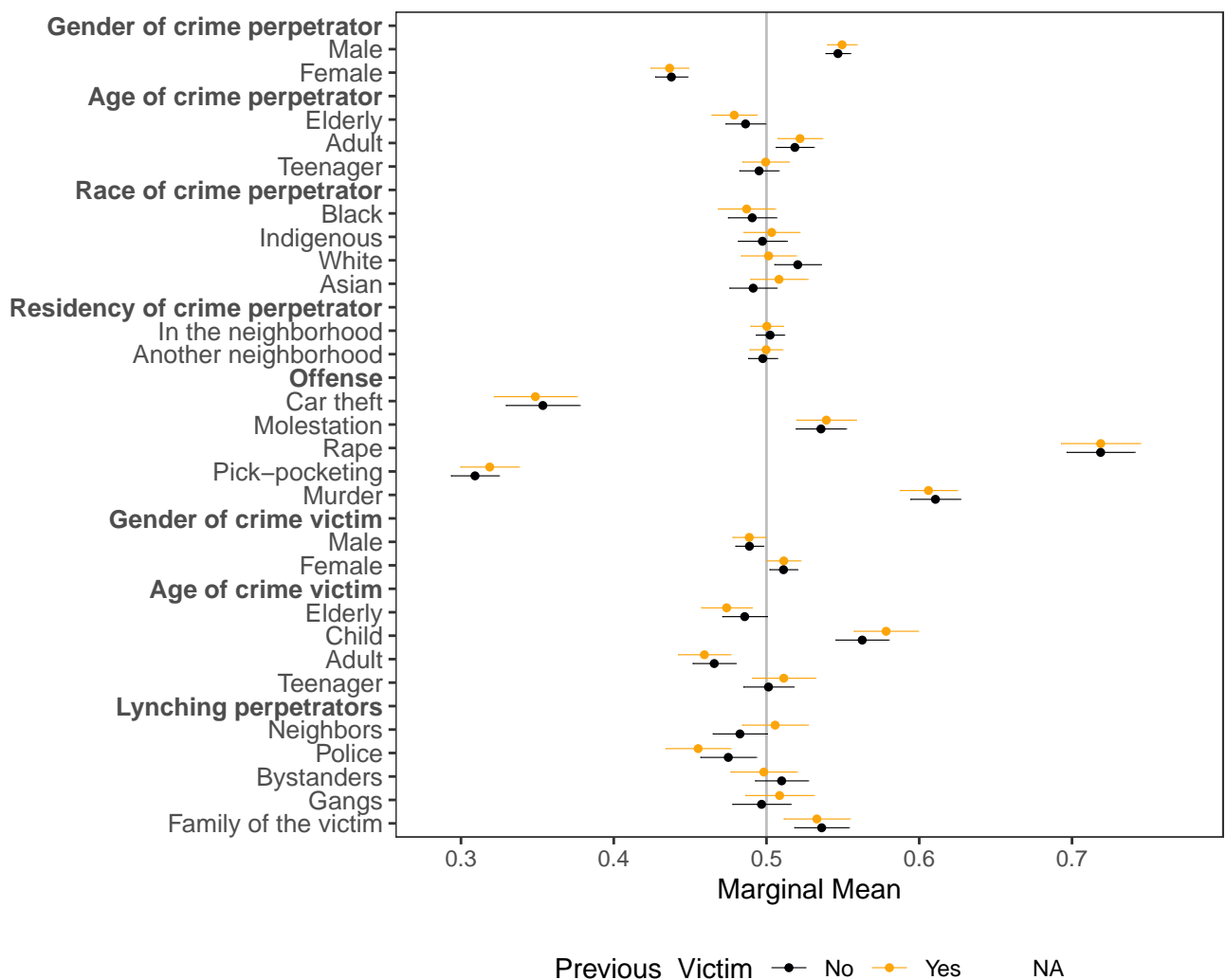
Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.465	0.017	0.042	0.432	0.499
Male	0.529	0.014	0.044	0.501	0.557
<b>Age of crime perpetrator</b>					
Teenager	0.515	0.024	0.529	0.469	0.561
Adult	0.505	0.022	0.804	0.462	0.549
Elderly	0.480	0.021	0.332	0.439	0.521
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.499	0.015	0.950	0.470	0.529
Male	0.501	0.015	0.950	0.471	0.531
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.541	0.030	0.166	0.483	0.600
Gangs	0.457	0.032	0.183	0.393	0.520
Bystanders	0.528	0.034	0.406	0.462	0.594
Police	0.497	0.037	0.941	0.425	0.569
Neighbors	0.471	0.033	0.389	0.406	0.537

### C.4.8 Previous Victimization

Respondents who had been victimized in the past 12 months also do not have different preferences towards lynchings victim profiles. The results are virtually identical for both groups, as one can see below. The only exception is that respondents who had not been victimized one year prior to the research are slightly more likely to support the lynching of White criminals.

```
# 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 = "bold", 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 -- Previous Victimization (12 Months): Yes")
```

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.437	0.006	0.000	0.424	0.449
Male	0.549	0.005	0.000	0.540	0.559
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.511	0.006	0.044	0.500	0.522
Male	0.489	0.006	0.044	0.478	0.500
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
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

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

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

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.438	0.005	0.000	0.427	0.448
Male	0.547	0.004	0.000	0.539	0.555
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.511	0.005	0.017	0.502	0.520
Male	0.489	0.005	0.017	0.480	0.498
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.536	0.009	0.000	0.518	0.554
Gangs	0.497	0.010	0.741	0.478	0.516
Bystanders	0.510	0.009	0.261	0.493	0.527
Police	0.475	0.009	0.007	0.457	0.493
Neighbors	0.483	0.009	0.055	0.465	0.500

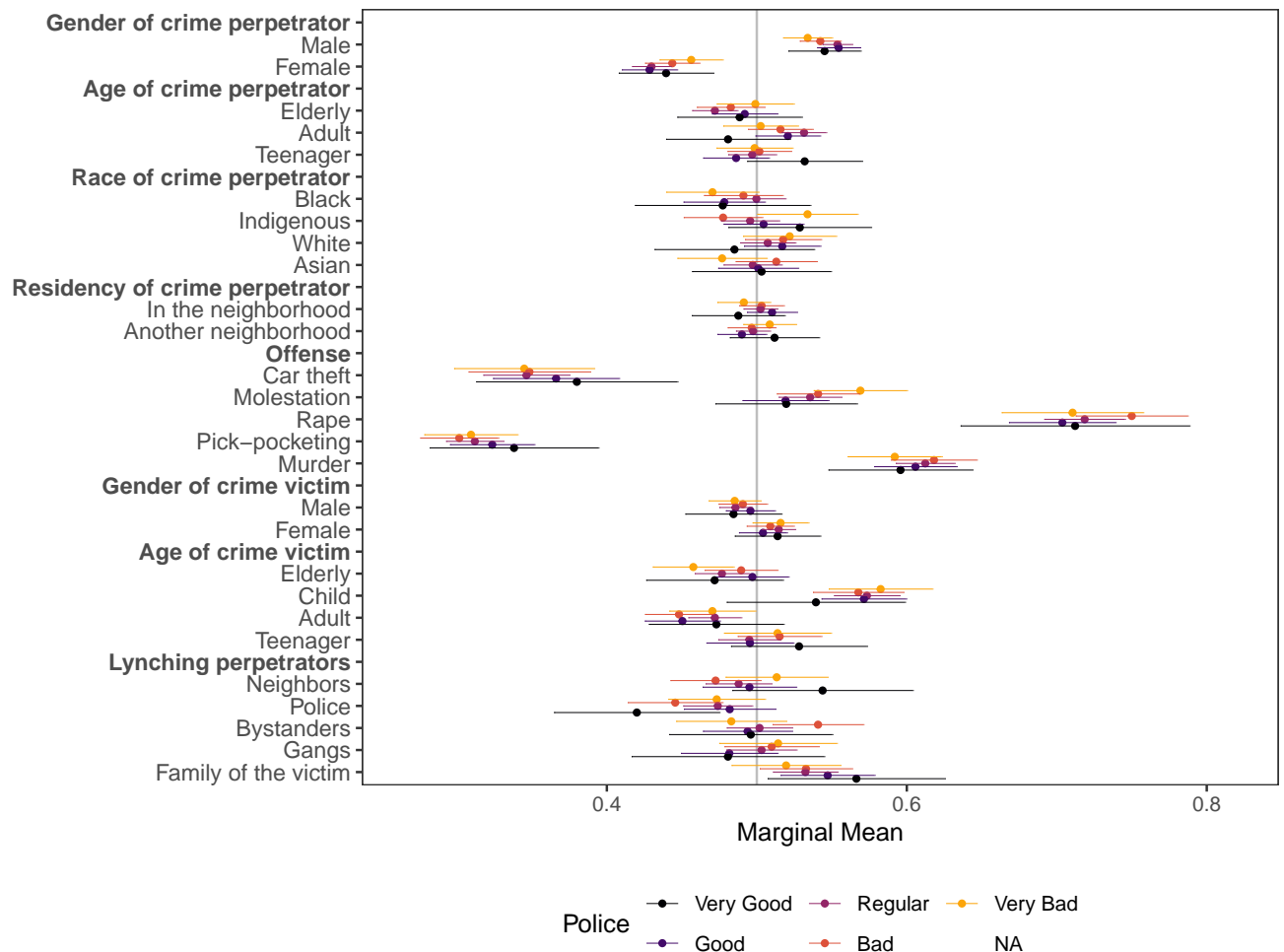


### C.4.9 Opinion on the Police

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

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

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



#### # Tables

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

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

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

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

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

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

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

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

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

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

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.440	0.016	0.000	0.408	0.471
Male	0.545	0.012	0.000	0.521	0.569
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.514	0.015	0.340	0.485	0.542
Male	0.484	0.016	0.342	0.452	0.517
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.566	0.030	0.028	0.507	0.625
Gangs	0.481	0.033	0.557	0.417	0.545
Bystanders	0.496	0.028	0.884	0.442	0.550
Police	0.420	0.028	0.004	0.365	0.475
Neighbors	0.544	0.031	0.153	0.484	0.604

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.428	0.009	0.000	0.410	0.447
Male	0.555	0.007	0.000	0.540	0.569
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.504	0.008	0.613	0.488	0.520
Male	0.496	0.008	0.613	0.479	0.512
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.547	0.016	0.003	0.516	0.579
Gangs	0.482	0.016	0.265	0.449	0.514
Bystanders	0.494	0.015	0.686	0.464	0.524
Police	0.482	0.016	0.246	0.451	0.512
Neighbors	0.495	0.016	0.759	0.464	0.526

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.430	0.007	0.000	0.417	0.443
Male	0.554	0.005	0.000	0.544	0.564
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.515	0.006	0.010	0.504	0.526
Male	0.486	0.006	0.010	0.475	0.497
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.532	0.011	0.003	0.511	0.554
Gangs	0.503	0.012	0.791	0.480	0.527
Bystanders	0.502	0.011	0.869	0.480	0.524
Police	0.474	0.012	0.027	0.451	0.497
Neighbors	0.488	0.011	0.281	0.466	0.510

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.444	0.009	0.000	0.426	0.462
Male	0.542	0.007	0.000	0.529	0.556
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.509	0.008	0.261	0.493	0.525
Male	0.491	0.008	0.261	0.475	0.507
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.533	0.016	0.037	0.502	0.564
Gangs	0.510	0.016	0.536	0.478	0.541
Bystanders	0.541	0.015	0.008	0.511	0.571
Police	0.446	0.016	0.001	0.414	0.477
Neighbors	0.473	0.015	0.073	0.442	0.503

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.456	0.011	0.000	0.435	0.477
Male	0.534	0.008	0.000	0.518	0.550
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.516	0.010	0.095	0.497	0.535
Male	0.485	0.009	0.095	0.468	0.503
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.520	0.019	0.292	0.483	0.556
Gangs	0.514	0.020	0.478	0.475	0.553
Bystanders	0.483	0.019	0.363	0.446	0.520
Police	0.473	0.016	0.104	0.441	0.506
Neighbors	0.513	0.017	0.445	0.479	0.547

### C.4.10 Opinion on the Judicial System

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

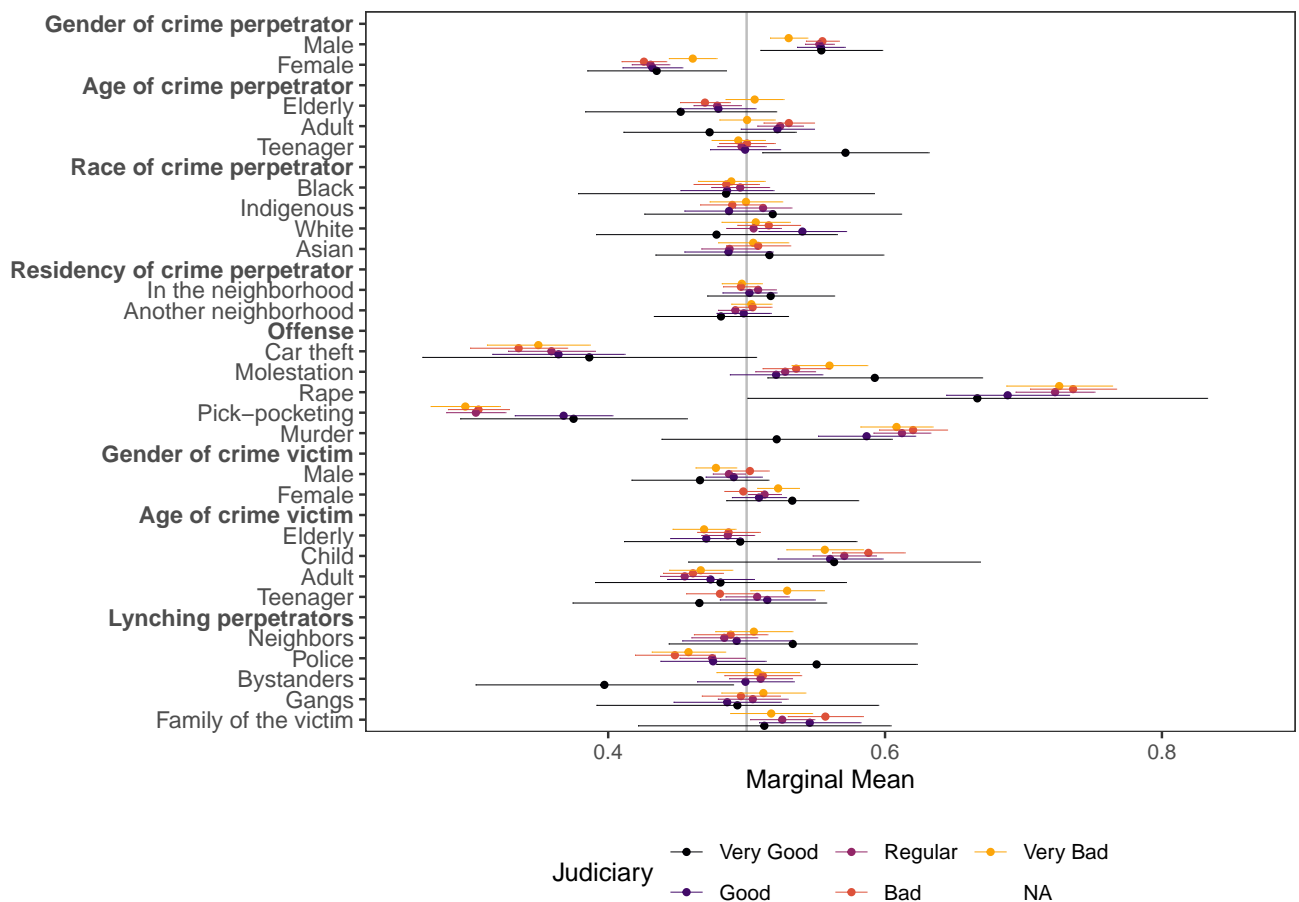
```
# Model
cjdt <- full_join(conjoint_data, df1, by = "response_id") %>%
  mutate(views_justice2 = case_when(views_justice == "Rather Not Say" ~ NA_character_,
    views_justice == "Don't Know" ~ NA_character_,
    TRUE ~ as.character(views_justice)),
  views_justice2 = fct_relevel(views_justice2, "Very Good", "Good",
    "Regular", "Bad", "Very Bad")) %>%

  drop_na(views_justice2)

cjdt$Judiciary <- factor(cjdt$views_justice2)

mm_by <- cj(cjdt, fm, id = ~response_id, estimate = "mm", h0 = 0.5, by = ~Judiciary)

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





## # Tables

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

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

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.435	0.026	0.011	0.385	0.485
Male	0.554	0.022	0.016	0.510	0.598
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.533	0.024	0.175	0.485	0.581
Male	0.466	0.025	0.182	0.417	0.516
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
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

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

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

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.432	0.011	0.000	0.410	0.454
Male	0.554	0.009	0.000	0.536	0.571
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.509	0.010	0.369	0.489	0.529
Male	0.491	0.010	0.369	0.470	0.511
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
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

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

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

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

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

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

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

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.431	0.007	0.000	0.417	0.444
Male	0.553	0.005	0.000	0.542	0.563
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.513	0.006	0.031	0.501	0.525
Male	0.487	0.006	0.031	0.476	0.499
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.526	0.012	0.029	0.503	0.549
Gangs	0.504	0.013	0.729	0.479	0.530
Bystanders	0.510	0.012	0.382	0.487	0.533
Police	0.475	0.012	0.040	0.452	0.499
Neighbors	0.484	0.012	0.185	0.460	0.508

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.426	0.008	0.000	0.410	0.442
Male	0.555	0.006	0.000	0.543	0.567
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.498	0.007	0.729	0.484	0.511
Male	0.502	0.007	0.729	0.489	0.516
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.557	0.014	0.000	0.530	0.584
Gangs	0.496	0.014	0.776	0.468	0.524
Bystanders	0.512	0.014	0.407	0.484	0.539
Police	0.448	0.015	0.000	0.419	0.477
Neighbors	0.488	0.014	0.395	0.462	0.515

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

Feature	Estimate	Std. Error	P-Value	Lower	Upper
<b>Gender of crime perpetrator</b>					
Female	0.461	0.009	0.000	0.444	0.478
Male	0.530	0.007	0.000	0.517	0.544
<b>Age of crime perpetrator</b>					
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
<b>Race of crime perpetrator</b>					
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
<b>Residency of crime perpetrator</b>					
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
<b>Offense</b>					
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
<b>Gender of crime victim</b>					
Female	0.523	0.008	0.003	0.508	0.538
Male	0.478	0.007	0.003	0.463	0.493
<b>Age of crime victim</b>					
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
<b>Lynching perpetrators</b>					
Family of the victim	0.518	0.015	0.238	0.488	0.547
Gangs	0.512	0.015	0.433	0.482	0.542
Bystanders	0.508	0.015	0.594	0.478	0.538
Police	0.458	0.014	0.002	0.432	0.485
Neighbors	0.505	0.014	0.712	0.477	0.533

## C.5 Text Analysis

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

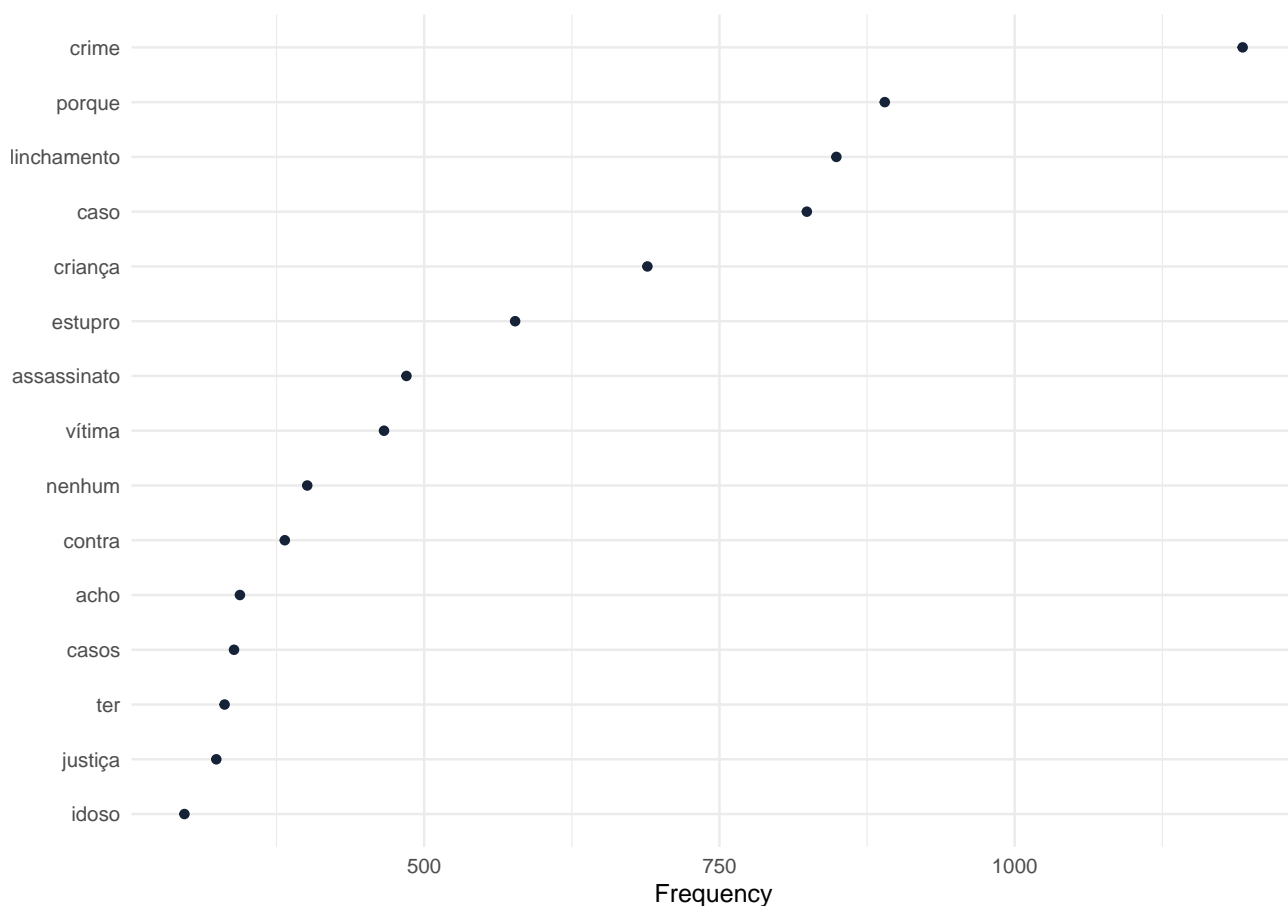
First, we concatenate all text responses into a single vector. Then we tokenize the sentences, remove Portuguese stop words and punctuation, and select the words that appear most frequently in the texts.

The graphs shows that *crime* (same as in English), *porque* (because), *linchamento* (lynching), and *caso* (case) are the words respondents use most often. This is expected as subjects were asked to justify their choices. The next words in the list are related to victim or crime characteristics, such as *criança* (child), *estupro* (rape), *assassinato* (murder), and *vítima* (victim). Indeed, they provide evidence for our previous findings and confirm that respondents select lynching victim profiles according to these two factors. Criminal characteristics, such as age or race, do not seem to be particularly relevant, as respondents do not mention them as much. Then respondents mention terms like *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()
```

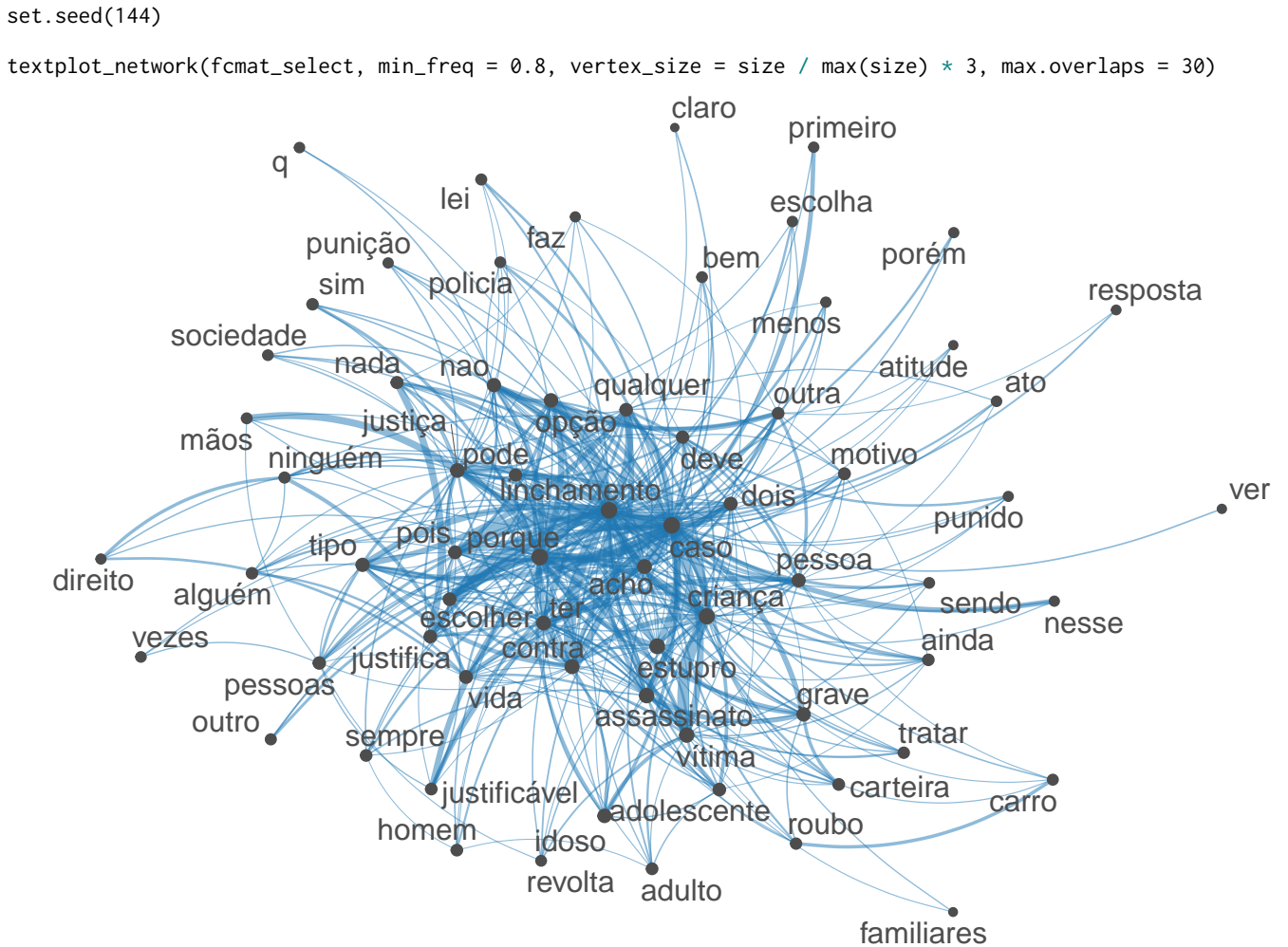


We also construct a feature co-occurrence matrix (FCM) that shows which words appear together in the responses we collected. Again, the results confirm the findings of the conjoint experiment. As suggested in the previous graph, we see a central cluster that describes crime and victim characteristics 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(dfmat_select(dfmat, feat, selection = "keep")))
```

```
# Plot
```



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

table(topics(tmod_lda))

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

```

Our last model is a 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"))))
```

```
sllda <- textmodel_seededlda(dfmat, keywords, residual = TRUE)
```

```
terms(sllda, 10)
```

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

```
table(topics(sllda))
```

```
##
```

```
##      victim      crime perpetrator
```

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

## D Experiment 02

### D.1 Description

Our second experiment measures the effect of information provision on attitudes about lynching. In particular, we test whether reminding respondents about the legal and social consequences of vigilante justice reduces the subjects' level of support for such practice.<sup>2</sup>

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.<sup>3</sup>
- *Treatment 01 - Legal punishment for lynching perpetrators*: In Brazil, some people believe that lynching may be justified under certain conditions. **However, the Brazilian constitution**

<sup>2</sup>To prevent eventual carryover effects caused by the conjoint, we randomized the order of the conjoint and the information provision experiments.

<sup>3</sup>In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições. O quanto você concorda ou discorda que linchamentos podem ser justificados? Por favor, use a barra abaixo para indicar sua preferência. Para indicar que discorda, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 caso você não concorde nem discorde.

**and penal code strictly forbid lynching and those involved can be accused of torture or murder.** To what degree do you agree or disagree that lynching can be justified? Please use the slider below to indicate your preference. For disagreement, use 0 to 49; for agreement, use 51 to 100. Please use 50 if you neither agree nor disagree.<sup>4</sup>

- *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.<sup>5</sup>
- *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.<sup>6</sup>

## D.2 Main Results

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

<sup>4</sup>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.

<sup>5</sup>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.

<sup>6</sup>In Portuguese: No Brasil, algumas pessoas acreditam que linchamentos são justificados sob certas condições. **Entretanto, linchamentos podem iniciar um ciclo de violência pois a família ou amigos da vítima podem retaliar a comunidade.** O quanto você concorda ou discorda que linchamentos podem ser justificados? Por favor, use a barra abaixo para indicar sua preferência. Para indicar que discorda, use de 0 a 49; para concordar, use de 51 a 100. Por favor, use 50 caso você não concorde nem discorde.

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

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

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

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

### D.3 Determinants of Baseline Levels

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

Table 54: Experiment 03 – Main Results

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

\*p < .1; \*\*p < .05; \*\*\*p < .01

Robust standard errors in parentheses.

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

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

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

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

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

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

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

\*p < .1; \*\*p < .05; \*\*\*p < .01

Robust standard errors in parentheses.

## D.4 Heterogeneous Effects

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

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

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

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

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

# Gender

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

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

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



```

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

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

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

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

```

```

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

# Race

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

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

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

```

```

# Education

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

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

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

# Household Income

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

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

```

```

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

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

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

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

```

```

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

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

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

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

```

```

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

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

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

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

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

```

```

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

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

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

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

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

```

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

## D.4.2 Treatment 02: Human Rights

Our results show no presence of heterogeneous effects.

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

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

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



```

## fitting response model via method 'bart'

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

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

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

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

```

```

## 1    -2.4767 3.687   -9.703    4.749  380
## 2    -2.3180 3.654   -9.479    4.843  394
## 3      0.1441 3.629   -6.969    7.258  393
## tot  -1.5405 2.204   -5.861    2.780 1167

## Estimates fit from 1167 total observations

## 95% credible interval calculated by: normal approximation

## population TE approximated by: posterior predictive distribution

## Result based on 800 posterior samples times 5 chains

# Race

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

## fitting treatment model via method 'bart'

## fitting response model via method 'bart'

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

## if (n < 10) group-size estimates may be unstable

## Estimates fit from 1168 total observations

## 95% credible interval calculated by: normal approximation

```

```

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

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

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

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

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

```

```

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

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

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

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

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

```

```

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

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

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

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

```

```

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

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

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

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

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

```

```

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

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

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

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

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

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

```

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

### D.4.3 Treatment 03: Vendettas

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

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

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

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



```

## fitting response model via method 'bart'

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

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

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

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

```

```

## 1    -1.1651 3.945   -8.896    6.566  342
## 2    -5.8445 3.877  -13.443    1.754  347
## 3    -0.9202 3.658   -8.091    6.250  396
## tot  -2.5722 2.269   -7.020    1.875 1085

## Estimates fit from 1085 total observations
## 95% credible interval calculated by: normal approximation
## population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

# Race

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

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

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

## if (n < 10) group-size estimates may be unstable
## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation

```

```

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

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

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

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

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

```

```

## fitting treatment model via method 'bart'

## fitting response model via method 'bart'

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

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

## fitting treatment model via method 'bart'

## fitting response model via method 'bart'

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

```

```

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

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

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

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

```

```

## 2      -2.682 3.183   -8.921   3.5566  493
## 3      -1.334 7.130  -15.308  12.6405   74
## 4      -2.549 8.165  -18.551  13.4537   59
## tot    -3.309 2.195   -7.612   0.9927 1086

## Estimates fit from 1086 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

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

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

## Call: bartc(response = exp03_outcomes, treatment = exp03_vendetta_treat,
##             confounders = previous_victim_dummy, data = df_exp03_vendetta2,
##             group.by = previous_victim_dummy, group.effects = TRUE, n.chains = 5L,
##             seed = 144)
##
## Causal inference model fit by:
##   model.rsp: bart
##   model.trt: bart
##
## Treatment effect (pate):
##      estimate    sd ci.lower ci.upper    n
## 1      -4.522 3.624  -11.625    2.581  427
## 2      -1.821 2.942   -7.587    3.944  648
## tot    -2.894 2.302   -7.405    1.617 1075

## Estimates fit from 1075 total observations
## 95% credible interval calculated by: normal approximation
##   population TE approximated by: posterior predictive distribution
## Result based on 800 posterior samples times 5 chains

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

```

```

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

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

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

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

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

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

```

```

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

```

## E Ethics Statement

We adhered to the ethical guidelines provided by the Institutional Review Board at Brown University and APSA's Principles and Guidance. To facilitate transparency, we comment here on a few aspects of our research design. First, we worked with Brown University's IRB to reduce the risk of harm for participants taking the survey. This included consultation with a cultural expert to inform the phrasing of the survey. Second, respondents received compensation via Qualtrics, which paid respondents directly after they completed the questionnaire. Each subject in Qualtrics' online panel received the equivalent of 2.5 USD in Brazilian Reals (local currency). Respondents who did not finish the survey did not receive compensation. The compensation was appropriate for the participant population. As of August 17, 2020, Brazil's monthly minimum wage was BRL 1039, which amounted



to 191 US dollars. Assuming 40 working hours per week, the hourly minimum wage equals 1.19 US dollars. Our survey took about 20 minutes to complete and respondents received 2.5 USD, therefore subjects received a monetary compensation that was 6 times higher than the local minimum wage. Third, we do not see any potential or perceived conflicts of interest in carrying out this research. We received a grant of USD 10,000 to conduct this research from the Centre for the Study of Governance & Society at King's College London, which in turn receives support from the Templeton Foundation. We are not aware of any conflicts of interest from either source. All of the code and data used in this article have already been made publicly available.

## F Session Information

```
sessionInfo()

## R version 4.2.1 (2022-06-23)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Monterey 12.6
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.2/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.2/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] grid      stats    graphics grDevices
## [5] utils     datasets methods  base
##
## other attached packages:
## [1] forcats_0.5.1
## [2] stringr_1.4.1
## [3] dplyr_1.0.10
## [4] purrr_0.3.5
## [5] readr_2.1.2
## [6] tidyr_1.2.1
## [7] tibble_3.1.8
```

```

## [8] tidyverse_1.3.1
## [9] stargazer_5.2.3
## [10] seededlda_0.8.1
## [11] proxyC_0.3.2
## [12] quanteda.textstats_0.95
## [13] quanteda.textplots_0.94.2
## [14] quanteda.textmodels_0.9.5
## [15] quanteda_3.2.3
## [16] janitor_2.1.0
## [17] kableExtra_1.3.4
## [18] estimatr_1.0.0
## [19] cregg_0.4.0
## [20] cjoint_2.1.0
## [21] survey_4.1-1
## [22] survival_3.3-1
## [23] Matrix_1.5-1
## [24] ggplot2_3.3.6
## [25] lmtest_0.9-40
## [26] zoo_1.8-11
## [27] sandwich_3.0-2
## [28] bartCause_1.0-4
## [29] rmarkdown_2.17
## [30] nvimcom_0.9-132
##
## loaded via a namespace (and not attached):
## [1] colorspace_2.0-3
## [2] ellipsis_0.3.2
## [3] ggstance_0.3.5
## [4] snakecase_0.11.0
## [5] fs_1.5.2
## [6] rstudioapi_0.14
## [7] farver_2.1.1
## [8] ggrepel_0.9.1
## [9] bit64_4.0.5
## [10] fansi_1.0.3
## [11] lubridate_1.8.0
## [12] xml2_1.3.3

```

```
## [13] codetools_0.2-18
## [14] splines_4.2.1
## [15] dbarts_0.9-22
## [16] knitr_1.40
## [17] Formula_1.2-4
## [18] jsonlite_1.8.3
## [19] broom_1.0.1
## [20] dbplyr_2.2.1
## [21] shiny_1.7.2
## [22] compiler_4.2.1
## [23] httr_1.4.4
## [24] backports_1.4.1
## [25] assertthat_0.2.1
## [26] fastmap_1.1.0
## [27] cli_3.4.1
## [28] later_1.3.0
## [29] htmltools_0.5.3
## [30] tools_4.2.1
## [31] coda_0.19-4
## [32] gtable_0.3.1
## [33] glue_1.6.2
## [34] LiblineaR_2.10-12
## [35] tinytex_0.42
## [36] fastmatch_1.1-3
## [37] Rcpp_1.0.9
## [38] statnet.common_4.6.0
## [39] cellranger_1.1.0
## [40] vctrs_0.5.0
## [41] svglite_2.1.0
## [42] iterators_1.0.14
## [43] xfun_0.34
## [44] network_1.17.2
## [45] stopwords_2.3
## [46] rvest_1.0.2
## [47] nsyllable_1.0.1
## [48] mime_0.12
## [49] lifecycle_1.0.3
```

```
## [50] scales_1.2.1
## [51] vroom_1.5.7
## [52] hms_1.1.2
## [53] promises_1.2.0.1
## [54] parallel_4.2.1
## [55] SparseM_1.81
## [56] yaml_2.3.6
## [57] stringi_1.7.8
## [58] highr_0.9
## [59] foreach_1.5.2
## [60] shape_1.4.6
## [61] rlang_1.0.6
## [62] pkgconfig_2.0.3
## [63] systemfonts_1.0.4
## [64] evaluate_0.17
## [65] lattice_0.20-45
## [66] labeling_0.4.2
## [67] bit_4.0.4
## [68] tidyselect_1.2.0
## [69] plyr_1.8.7
## [70] magrittr_2.0.3
## [71] R6_2.5.1
## [72] generics_0.1.3
## [73] sna_2.7
## [74] DBI_1.1.3
## [75] pillar_1.8.1
## [76] haven_2.5.0
## [77] withr_2.5.0
## [78] modelr_0.1.8
## [79] crayon_1.5.2
## [80] utf8_1.2.2
## [81] tzdb_0.3.0
## [82] readxl_1.4.1
## [83] reprex_2.0.1
## [84] digest_0.6.30
## [85] webshot_0.5.3
## [86] xtable_1.8-4
```

```
## [87] httpuv_1.6.5
## [88] RcppParallel_5.1.5
## [89] munsell_0.5.0
## [90] glmnet_4.1-4
## [91] viridisLite_0.4.1
## [92] mitools_2.4
```

## References

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- Leeper, T. J., Hobolt, S. B., and Tilley, J. (2020). Measuring Subgroup Preferences in Conjoint Experiments. *Political Analysis*, 28(2):207–221.
- R Core Team (2018). R: A Language and Environment for Statistical Computing. <https://www.R-project.org>. Access: June, 2020.