

# Effective Giving AI Persuasion Project - Complete Analysis Report

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## Table of contents

<b>1</b>	<b>Introduction</b>	<b>2</b>
1.1	Project Overview . . . . .	2
<b>2</b>	<b>Data and Setup</b>	<b>2</b>
<b>3</b>	<b>Sample Descriptives and Attrition Analysis</b>	<b>2</b>
3.1	Attrition Analysis . . . . .	2
3.2	Sample Characteristics . . . . .	4
<b>4</b>	<b>Charity Descriptives</b>	<b>5</b>
<b>5</b>	<b>Motivation Analysis</b>	<b>15</b>
<b>6</b>	<b>Average Treatment Effects (ATEs)</b>	<b>17</b>
<b>7</b>	<b>Categorical Heterogeneity Analysis</b>	<b>22</b>
<b>8</b>	<b>Causal Forest Analysis</b>	<b>44</b>
<b>9</b>	<b>Generalized Additive Models (GAMs)</b>	<b>46</b>
<b>10</b>	<b>Persuasive Strategies Analysis</b>	<b>47</b>
<b>11</b>	<b>AI Accuracy Assessment</b>	<b>59</b>
<b>12</b>	<b>Figures</b>	<b>64</b>
12.1	Charity Descriptive Plot . . . . .	64
12.2	Motivation Plots . . . . .	71
12.3	Main Treatment Effects Plot . . . . .	73
12.4	Categorical Heterogeneity Plot . . . . .	77
12.5	Binned Heterogeneity Plot . . . . .	83
12.6	VIP and GAM Plot . . . . .	86
12.7	Causal Forest Plots . . . . .	88
12.8	Strategy Plot . . . . .	88
12.9	Accuracy Figure . . . . .	91
<b>13</b>	<b>Tables</b>	<b>93</b>
13.1	GAM Tables . . . . .	93

13.2 Strategy Regression Table . . . . .	95
<b>14 Session Information</b>	<b>99</b>
<b>15 Appendix</b>	<b>100</b>
15.1 Additional Notes . . . . .	100
15.2 Reproducibility . . . . .	101
15.3 Alternative: R Markdown Version . . . . .	101

# 1 Introduction

This report presents the complete analysis for the Effective Giving AI Persuasion Project. The analysis examines the effectiveness of AI-powered persuasive conversations compared to static messages and control conditions in promoting charitable giving to effective charities.

## 1.1 Project Overview

The study investigates whether AI-powered conversations can be more persuasive than static messages in encouraging donations to effective charities like the Against Malaria Foundation (AMF). The analysis includes:

- Sample descriptives and attrition analysis
- Average Treatment Effects (ATEs)
- Heterogeneity analysis using causal forests
- Persuasive strategy analysis
- AI accuracy assessment
- Comprehensive visualizations

# 2 Data and Setup

```
# Download and prepare data
source("download_data.R")
#download_osf_data_dir("6ya5n")
```

# 3 Sample Descriptives and Attrition Analysis

## 3.1 Attrition Analysis

```
d_all <- readr::read_csv("data/data_ai-eg-persuasion.csv") |>
  mutate(
    condition = factor(
      condition,
      levels = c('control', "static_treatment", "conv_treatment")
    )
  )

conv_errors <- c("R_7M4lC08AvzFNtA2", "R_1DPc7kbjHlQH0VS", "R_5173KJIiwXvV5oJ")
```

```
d_treated <- d_all |> filter(!is.na(condition))
d_itt <- d_treated |> filter(attn == 5)
d <- d_itt |> filter(Finished == 1) |>
  filter(!ResponseId %in% conv_errors)

ps_final <- d$ResponseId

nrow(d_all) #Total N
```

```
[1] 2270
```

```
nrow(d_all) - nrow(d_treated) # withdrew before randomization
```

```
[1] 242
```

```
nrow(d_treated) - nrow(d_itt) # failed attention check (but were randomized)
```

```
[1] 48
```

```
nrow(d_itt) - nrow(d) #28 of ITT withdrew, 3 had technical issues with chatbot
```

```
[1] 31
```

```
nrow(d) #final
```

```
[1] 1949
```

```
## Is there differential attrition from ITT to analysis sample?
d_itt |> count(condition)
```

```
# A tibble: 3 x 2
  condition      n
  <fct>        <int>
1 control      654
2 static_treatment 660
3 conv_treatment 666
```

```
d |> count(condition)
```

```
# A tibble: 3 x 2
  condition      n
  <fct>        <int>
1 control      641
2 static_treatment 649
3 conv_treatment 659
```

```
attrition_matrix <- d_itt |> count(condition) |>
  left_join(d |> count(condition), by = "condition", suffix = c("_pre", "_post")) |>
  transmute(dropped = n_pre - n_post, stayed = n_post) |>
  as.matrix()
attrition_matrix
```

	dropped	stayed
[1,]	13	641
[2,]	11	649
[3,]	7	659

```
chisq.test(attrition_matrix)
```

Pearson's Chi-squared test

```
data: attrition_matrix
X-squared = 1.9442, df = 2, p-value = 0.3783
```

## 3.2 Sample Characteristics

```
# Gender and age for total sample
d_all |> count(gender)
```

```
# A tibble: 4 x 2
  gender      n
  <chr>   <int>
1 Man     987
2 Other    21
3 Woman  1097
4 <NA>    165
```

```
d_all |>
  summarise(
    m_age = mean(age, na.rm = TRUE),
    sd_age = sd(age, na.rm = TRUE),
    min_age = min(age, na.rm = TRUE),
    max_age = max(age, na.rm = TRUE),
  ) |>
  as.data.frame()
```

	m_age	sd_age	min_age	max_age
1	42.73707	15.13187	18	83

```
# for final sample
d |> count(gender)
```

```
# A tibble: 4 x 2
  gender      n
  <chr>   <int>
1 Man     913
2 Other    21
3 Woman  1013
4 <NA>      2
```

```
d |>
  summarise(
    m_age = mean(age, na.rm = TRUE),
    sd_age = sd(age, na.rm = TRUE),
    min_age = min(age, na.rm = TRUE),
    max_age = max(age, na.rm = TRUE),
  ) |>
  as.data.frame()
```

```
      m_age  sd_age min_age max_age
1 42.62288 15.02506      18      83
```

## 4 Charity Descriptives

```
d_candid <- read_csv("data/guidestar_data.csv") |>
  janitor::clean_names()

pcs_population <- extract_unique_pcs_labels(d_candid$population_served)
pcs_subjects <- extract_unique_pcs_labels(d_candid$subject_area)
pcs_location <- extract_unique_pcs_labels(d_candid$where_we_work)

pop_hierarchy <- parse_hierarchy("data/pcs_pop_hierarchy.html", leaves_as_vec = FALSE)
subj_hierarchy <- parse_hierarchy("data/pcs_subj_hierarchy.html", leaves_as_vec = FALSE)

pop_hierarchy_df <- hierarchy_to_df(pop_hierarchy)
subj_hierarchy_df <- hierarchy_to_df(subj_hierarchy)

find_missing_with_match(pcs_population, pop_hierarchy_df)
```

	original	closest	distance
1	American Indians	Christians	10
2	At-risk youth	Out-of-home youth	9
3	Dropouts	Orphans	5
4	Ex-offenders	Mothers	8
5	Extremely poor people	Unemployed people	11
6	LGBTQ people	LGBTQIA+ people	3
7	Multiracial people	Retired people	8
8	Offenders	Caregivers	6
9	People of African descent	Black/African people	15
10	People of Asian descent	Central Asian people	14
11	People of Middle Eastern descent	People with disabilities	21
12	People with HIV/AIDS	People living with HIV or AIDS	11
13	Seniors	Shintos	4
14	Sexual identity	Students	9
15	Substance abusers	Domestic workers	11
16	Unknown or not classified	Cross-border families	18
17	Victims and oppressed people	Refugees and displaced people	14

```
find_missing_with_match(pcs_subjects, subj_hierarchy_df)
```

	original	closest	distance
1	Abuse prevention	Crime prevention	4
2	Ethnic and racial minority rights	Ethnic and racial group rights	7
3	HIV/AIDS	HIV and AIDS	5
4	Housing for the homeless	Housing for older adults	10
5	Human rights	Humanities	5
6	Immigrant services	Human services	6
7	Individual liberties	Visual arts	12
8	Justice rights	Cultural rights	6
9	LGBTQ rights	LGBTQIA+ rights	3
10	Nursing education	Nursing Education	1
11	Public safety	Public arts	4
12	Right to life	Right to privacy	6
13	Senior assisted living	Impaired driving	13
14	Senior services	Dining services	4
15	Social rights	Voter rights	5
16	Temporary accomodations	Temporary accommodations	1

```
## replace them manually after looking at hierarchy for closest match
pop_replacements <- c(
  "American Indians" = "American Indians/Native Americans",
  "At-risk youth" = "Out-of-home youth",
  "Dropouts" = "Out-of-school youth",
  "Ex-offenders" = "Formerly incarcerated people",
  "Extremely poor people" = "People living in extreme poverty",
  "LGBTQ people" = "LGBTQIA+ people",
  "Multiracial people" = "Multi-racial/Multi-ethnic people",
  "Offenders" = "Incarcerated people",
  "People of African descent" = "Black/African people",
  "People of Asian descent" = "Asian people",
  "People of Middle Eastern descent" = "Middle Eastern/North African people",
  "People with HIV/AIDS" = "People living with HIV or AIDS",
  "Seniors" = "Older adults",
  "Sexual identity" = "LGBTQIA+ people",
  "Substance abusers" = "People with substance use disorder",
  "Victims and oppressed people" = "Victims of violence or disasters"
)

subj_replacements <- c(
  "Abuse prevention" = "Abuse prevention and services",
  "Ethnic and racial minority rights" = "Ethnic and racial group rights",
  "HIV/AIDS" = "HIV and AIDS",
  "Housing for the homeless" = "Housing for homeless people",
  "Human rights" = "International human rights",
  "Immigrant services" = "Immigrant and refugee services",
  "Individual liberties" = "International human rights",
  "Justice rights" = "Criminal justice system rights",
  "LGBTQ rights" = "LGBTQIA+ rights",
  "Nursing education" = "Nursing Education",
  "Public safety" = "Public safety and disaster management",
  "Right to life" = "Anti-abortion",
  "Senior assisted living" = "Assisted living for older adults",
  "Senior services" = "Services for older adults",
  "Social rights" = "International human rights",
  "Temporary accomodations" = "Temporary accommodations"
```

```

)

# add higher levels of categories
d_candid <- d_candid |>
  mutate(
    population_served = replace_terms_named(population_served, pop_replacements),
    subject_area = replace_terms_named(subject_area, subj_replacements),
    pop_lvl1 = replace_with_level(population_served, pop_hierarchy_df, k = 1),
    pop_lvl2 = replace_with_level(population_served, pop_hierarchy_df, k = 2),
    subj_lvl1 = replace_with_level(subject_area, subj_hierarchy_df, k = 1),
    subj_lvl2 = replace_with_level(subject_area, subj_hierarchy_df, k = 2)
  )

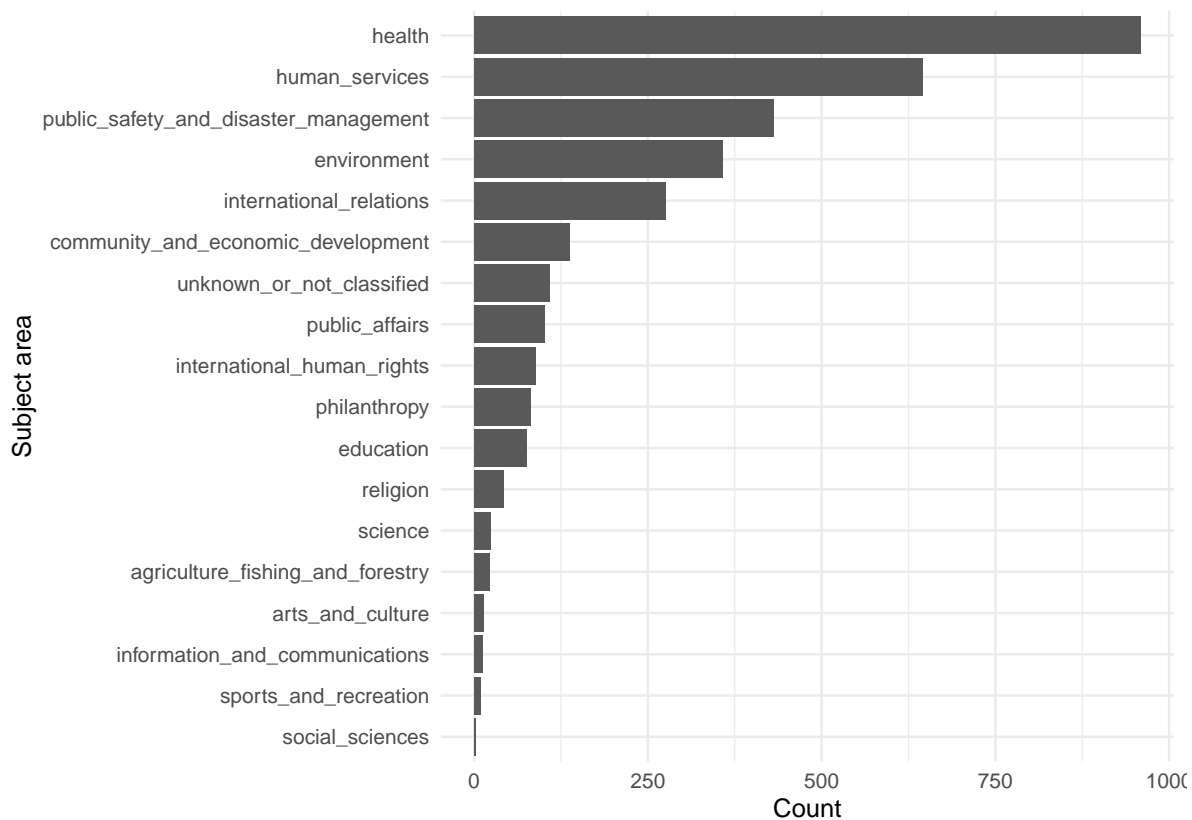
pcs_subj1_mat <- make_pcs_matrix(d_candid$subj_lvl1, "subj") |> mutate(ein = d_candid$ein)
pcs_subj2_mat <- make_pcs_matrix(d_candid$subj_lvl2, "subj") |> mutate(ein = d_candid$ein)
pcs_pop1_mat <- make_pcs_matrix(d_candid$pop_lvl1, "pop") |> mutate(ein = d_candid$ein)
pcs_pop2_mat <- make_pcs_matrix(d_candid$pop_lvl2, "pop") |> mutate(ein = d_candid$ein)

# subject 1 counts
d_subj1 <- d_all |>
  select(ResponseId, condition, starts_with("cents_to_amf"), ein) |>
  filter(ResponseId %in% ps_final) |>
  mutate(ein = format_ein(ein)) |>
  left_join(pcs_subj1_mat, by = "ein") |>
  set_unknown_on_na("subj", "subj_unknown_or_not_classified")

subj1_counts <- d_subj1 |>
  summarise(across(starts_with("subj"), ~ sum(.x))) |>
  pivot_longer(cols = everything(), names_to = "subject_area", values_to = "count") |>
  mutate(subject_area = str_remove(subject_area, "^subj_")) |>
  arrange(desc(count))

#plot
subj1_counts |>
  ggplot(aes(x = reorder(subject_area, count), y = count)) +
  geom_col() +
  coord_flip() +
  labs(x = "Subject area", y = "Count") +
  theme_minimal()

```

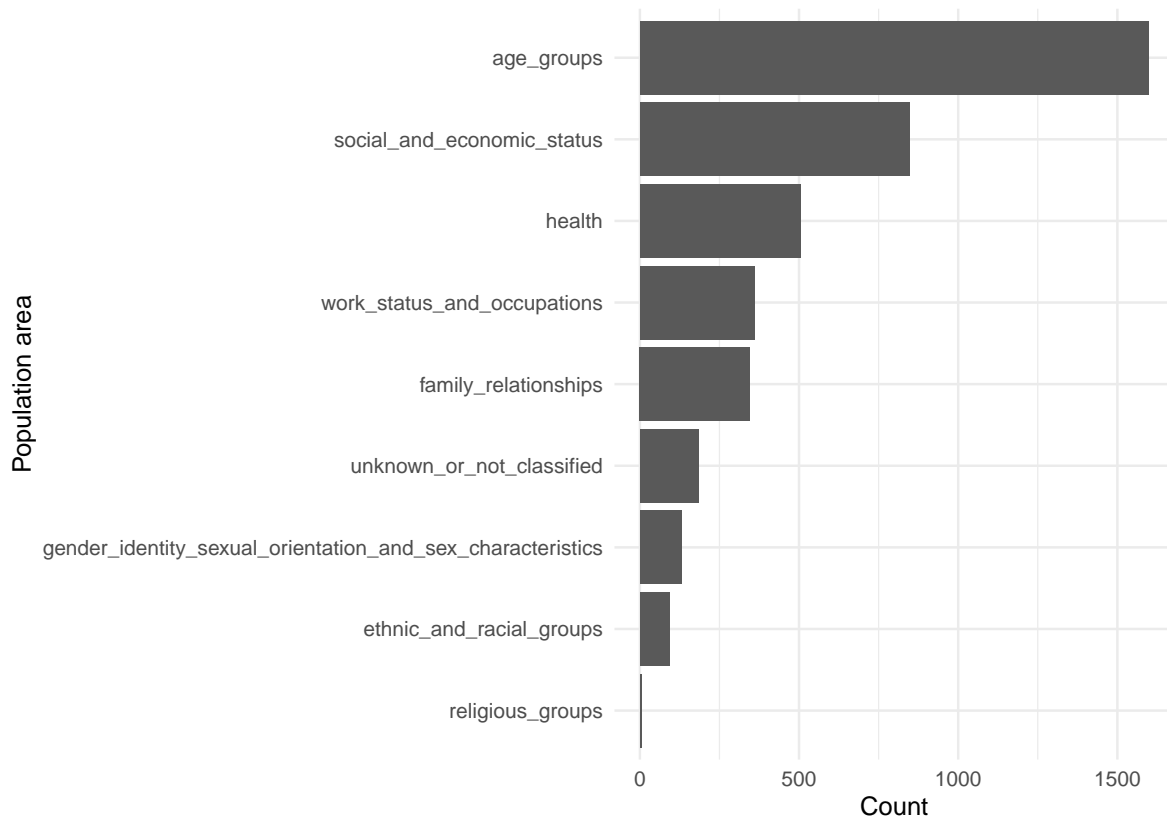


```
# population 1 counts
d_pop1 <- d_all |>
  select(ResponseId, condition, starts_with("cents_to_amf"), ein) |>
  filter(ResponseId %in% ps_final) |>
  mutate(ein = format_ein(ein)) |>
  left_join(pcs_pop1_mat, by = "ein") |>
  set_unknown_on_na("pop", "pop_unknown_or_not_classified")

pop1_counts <- d_pop1 |>
  summarise(across(starts_with("pop"), ~ sum(.x))) |>
  pivot_longer(cols = everything(), names_to = "population_area", values_to = "count") |>
  mutate(population_area = str_remove(population_area, "^pop_")) |>
  arrange(desc(count))

#plot
pop1_counts |>
  ggplot(aes(x = reorder(population_area, count), y = count)) +
  geom_col() +
  coord_flip() +
  labs(x = "Population area", y = "Count") +
  theme_minimal()
```

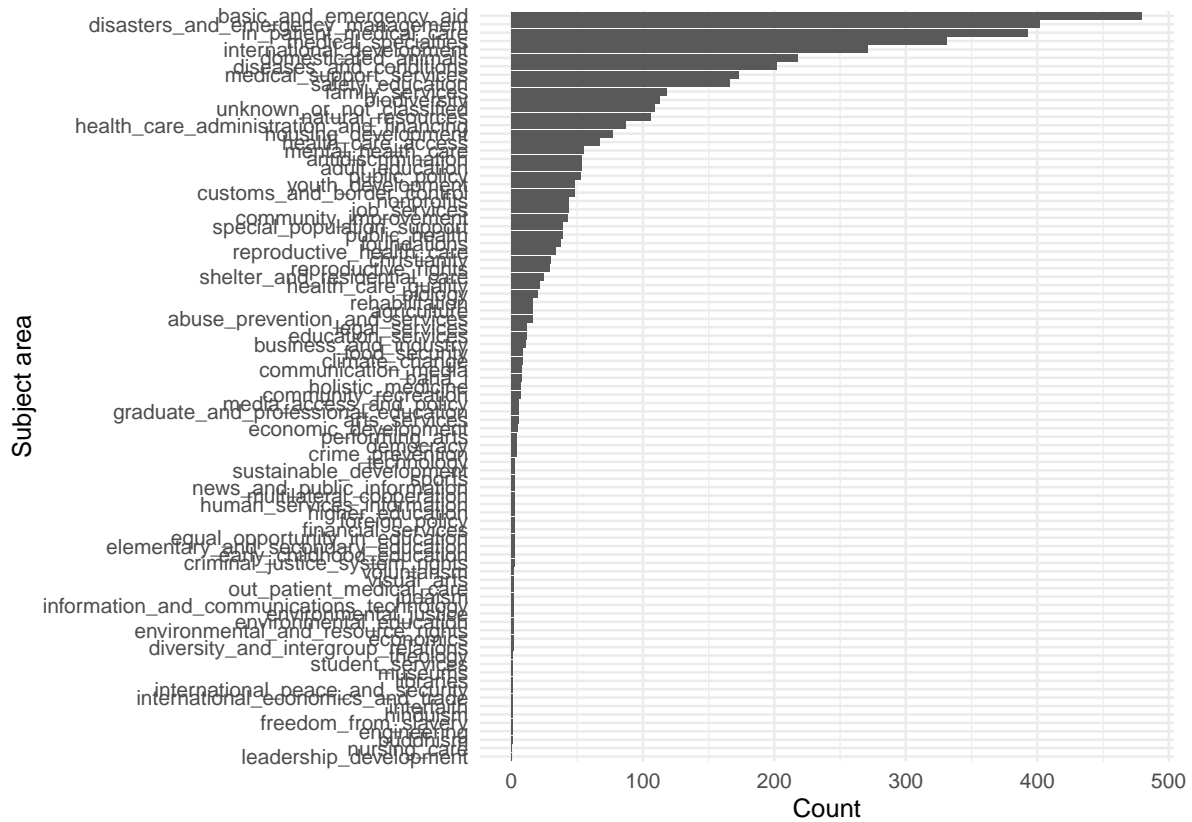




```
# subject 2 counts
d_subj2 <- d_all |>
  select(ResponseId, condition, starts_with("cents_to_amf"), ein) |>
  filter(ResponseId %in% ps_final) |>
  mutate(ein = format_ein(ein)) |>
  left_join(pcs_subj2_mat, by = "ein") |>
  set_unknown_on_na("subj", "subj_unknown_or_not_classified")

subj2_counts <- d_subj2 |>
  summarise(across(starts_with("subj"), ~ sum(.x))) |>
  pivot_longer(cols = everything(), names_to = "subject_area", values_to = "count") |>
  mutate(subject_area = str_remove(subject_area, "^subj_")) |>
  arrange(desc(count))

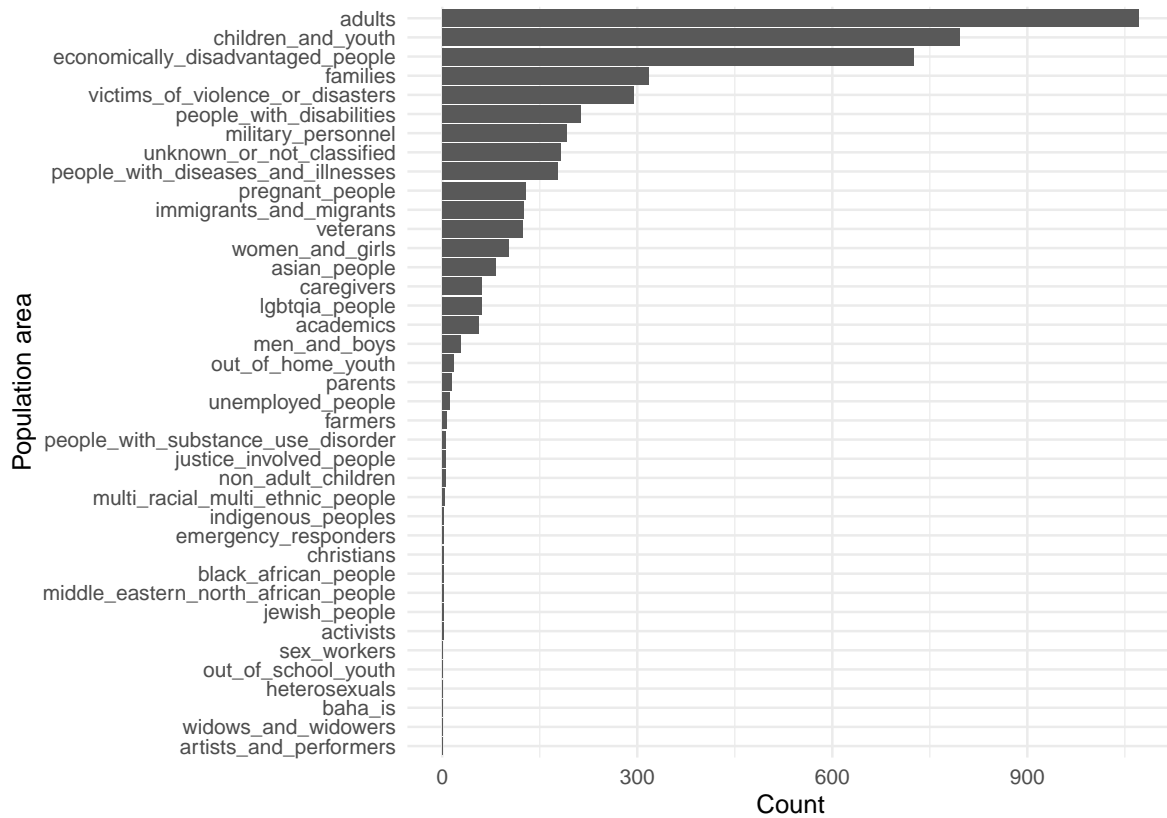
#plot
subj2_counts |>
  ggplot(aes(x = reorder(subject_area, count), y = count)) +
  geom_col() +
  coord_flip() +
  labs(x = "Subject area", y = "Count") +
  theme_minimal()
```



```
# population 2 counts
d_pop2 <- d_all |>
  select(ResponseId, condition, starts_with("cents_to_amf"), ein) |>
  filter(ResponseId %in% ps_final) |>
  mutate(ein = format_ein(ein)) |>
  left_join(pcs_pop2_mat, by = "ein") |>
  set_unknown_on_na("pop", "pop_unknown_or_not_classified")

pop2_counts <- d_pop2 |>
  summarise(across(starts_with("pop"), ~ sum(.x))) |>
  pivot_longer(cols = everything(), names_to = "population_area", values_to = "count") |>
  mutate(population_area = str_remove(population_area, "^pop_")) |>
  arrange(desc(count))

#plot
pop2_counts |>
  ggplot(aes(x = reorder(population_area, count), y = count)) +
  geom_col() +
  coord_flip() +
  labs(x = "Population area", y = "Count") +
  theme_minimal()
```



```
## NOW lets look at the location data
d_where_orig <- read_csv("data/location_categories.csv") |>
  janitor::clean_names() |>
  mutate(
    location_cat = str_to_lower(category)
  )

## summarizi
d_where_mod_agreement <- d_where_orig %>%
  group_by(ein) %>%
  summarise(
    # total non-NA location_cat responses
    n_responses = sum(!is.na(location_cat)),
    n_unique = length(unique(location_cat)),
    # largest count of any single location_cat value
    max_same = max(table(location_cat)),
    all_valid = n_responses == 3,
    perf_agreement = max_same == 3,
    all_agreement = n_responses == max_same,
    majority_cat = names(which.max(table(location_cat))),
    minority_cat = names(which.min(table(location_cat))),
    .groups = "drop"
  )
```

```
## now lets get proportions of all of these, first for the whole dataset
d_where_mod_agreement |>
```

```
  summarise(
    n_total = n(),
    n_valid = sum(all_valid),
    n_perf_agreement = sum(perf_agreement),
    n_all_agreement = sum(all_agreement),
    n_complete_disagreement = sum(n_unique == 3),
    prop_valid = n_valid / n_total,
    prop_perf_agreement = n_perf_agreement / n_total,
    prop_all_agreement = n_all_agreement / n_total
  )
```

```
# A tibble: 1 x 8
  n_total n_valid n_perf_agreement n_all_agreement n_complete_disagreement
  <int>   <int>         <int>         <int>             <int>
1     327     327             298             298                 0
# i 3 more variables: prop_valid <dbl>, prop_perf_agreement <dbl>,
#   prop_all_agreement <dbl>
```

```
# now by majority answer
```

```
d_where_mod_agreement |>
```

```
  group_by(majority_cat) %>%
  summarise(
    n_total = n(),
    n_valid = sum(all_valid),
    n_perf_agreement = sum(perf_agreement),
    n_all_agreement = sum(all_agreement),
    n_complete_disagreement = sum(n_unique == 3),
    prop_valid = n_valid / n_total,
    prop_perf_agreement = n_perf_agreement / n_total,
    prop_all_agreement = n_all_agreement / n_total
  )
```

```
# A tibble: 4 x 9
  majority_cat n_total n_valid n_perf_agreement n_all_agreement
  <chr>         <int>   <int>         <int>             <int>
1 international    118     118             114             114
2 local             75      75              67              67
3 national         95      95              91              91
4 state            39      39              26              26
# i 4 more variables: n_complete_disagreement <int>, prop_valid <dbl>,
#   prop_perf_agreement <dbl>, prop_all_agreement <dbl>
```

```
# now lets look at when there is disagreement, what is the majority and minority answers, what proportion of the total
```

```
↪ category
```

```
d_where_mod_agreement |>
```

```
  count(majority_cat, minority_cat)
```

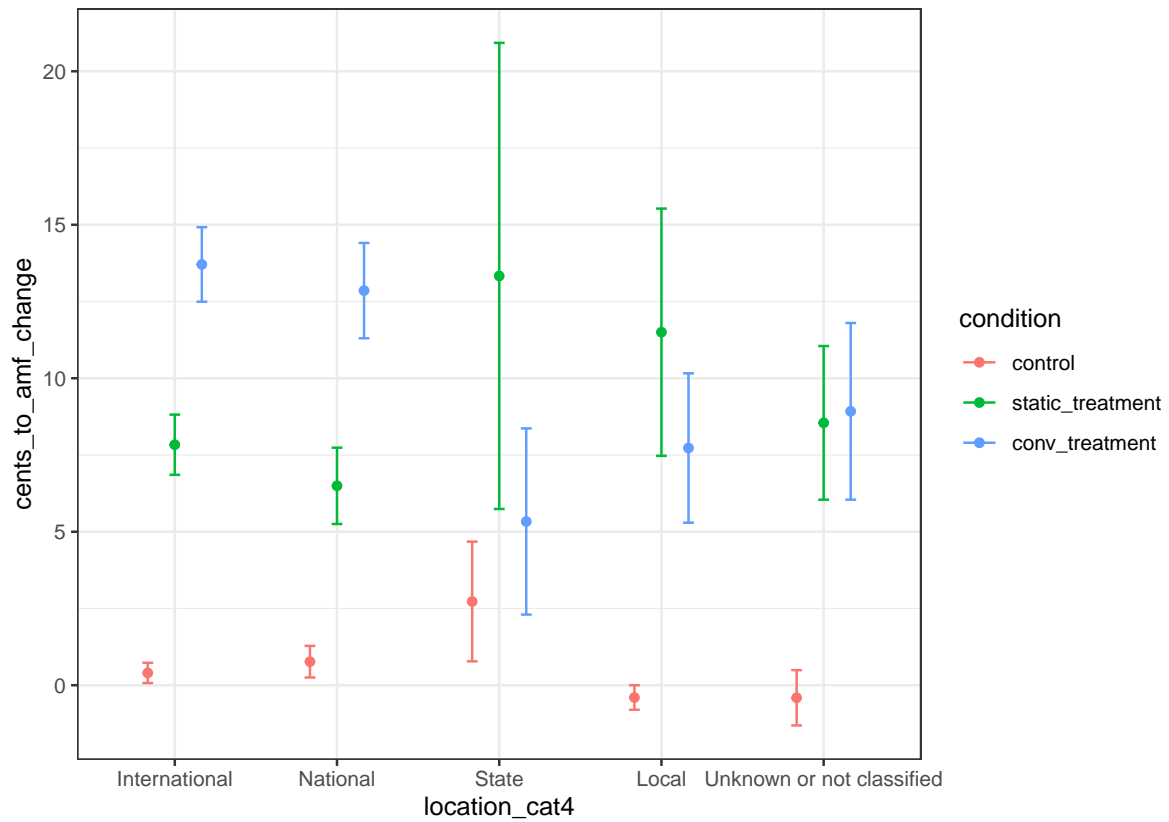
```
# A tibble: 9 x 3
  majority_cat minority_cat    n
  <chr>         <chr>    <int>
1 international international  114
```

2	international	national	4
3	local	local	67
4	local	state	8
5	national	international	4
6	national	national	91
7	state	local	7
8	state	national	6
9	state	state	26

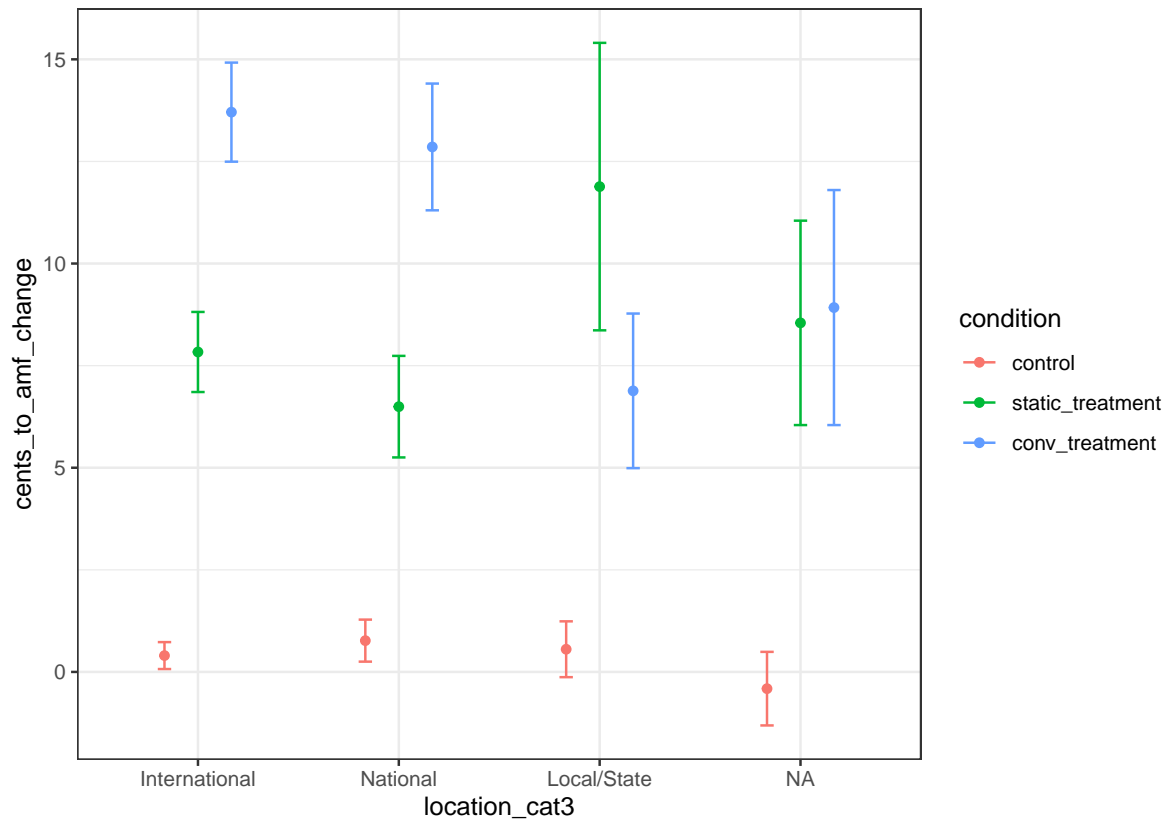
```
## lets look at results with cat4, and cat3 (collapsing local and state)
d_where_agg <- d_where_orig |>
  group_by(ein) |>
  summarise(
    location_cat4 = names(which.max(table(location_cat))),
    location_cat3 = case_when(
      location_cat4 %in% c("local", "state") ~ "local/state",
      TRUE ~ location_cat4
    ),
  )

d_where <- d_all |>
  select(ResponseId, condition, starts_with("cents_to_amf"), ein) |>
  filter(ResponseId %in% ps_final) |>
  mutate(ein = format_ein(ein)) |>
  left_join(d_where_agg, by = "ein") |>
  mutate(
    location_cat4 = replace_na(location_cat4, "Unknown or not classified"),
    location_cat3 = replace_na(location_cat3, "Unknown or not classified"),
    location_cat4 = factor(
      location_cat4,
      levels = c("international", "national", "state", "local", "Unknown or not classified"),
      labels = c("International", "National", "State", "Local", "Unknown or not classified")
    ),
    location_cat3 = factor(
      location_cat3,
      levels = c("international", "national", "local/state", "Unknown or not classified"),
      labels = c("International", "National", "Local/State", "NA")
    ),
    is_international = if_else(location_cat3 == "International", 1L, 0L),
  )

# plot cents_to_amf_change by location cats
d_where |>
  ggplot(aes(x = location_cat4, y = cents_to_amf_change, col = condition)) +
  #geom_jitter(position = position_dodge(width = 0.5), alpha = 0.5) +
  stat_summary(fun = mean, geom = "point", position = position_dodge(width = 0.5)) +
  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.2, position = position_dodge(width = 0.5))
```



```
d_where |>
  ggplot(aes(x = location_cat3, y = cents_to_amf_change, col = condition)) +
  #geom_jitter(position = position_dodge(width = 0.5), alpha = 0.5) +
  stat_summary(fun = mean, geom = "point", position = position_dodge(width = 0.5)) +
  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.2, position = position_dodge(width = 0.5))
```



## 5 Motivation Analysis

```

m_dat1 <- read_csv("data/motivation_ratings_GPT4oSonnet3Deepseek.csv") # original 3, accidentally with earlier version of
↳ sonnet
m_dat_3.7 <- read_csv("data/motivation_ratings_Sonnet3.7.csv") # sonnet 3.7

m_dat_all <- m_dat1 |>
  bind_rows(m_dat_3.7) |>
  filter(model != "anthropic/claude-3-sonnet") |>
  arrange(ResponseId)

m_dat_all_long <- m_dat_all |>
  pivot_longer(AwarenessOfNeed:DoesntGive, names_to = "variable", values_to = "value")

#1. ICCs for agreement 2k (agreement)
d_ratings_wide <- m_dat_all_long |>
  filter(ResponseId %in% ps_final) |>
  filter(variable != "DoesntGive") |>
  pivot_wider(names_from = model, values_from = value) |>
  select(-charity_reasons, -why_charity_general, -ResponseId) |>
  rename_with(~ str_remove(.x, "^.*"/))

```

```
agreement_analysis_by_group(d_ratings_wide, group_var = "variable")
```

Grand ICC:

Call: psych::ICC(x = select(d, -!!group\_sym))

Intraclass correlation coefficients

	type	ICC	F	df1	df2	p	lower bound	upper bound
Single_raters_absolute	ICC1	0.85	17	15591	31184	0	0.84	0.85
Single_random_raters	ICC2	0.85	19	15591	31182	0	0.82	0.87
Single_fixed_raters	ICC3	0.86	19	15591	31182	0	0.85	0.86
Average_raters_absolute	ICC1k	0.94	17	15591	31184	0	0.94	0.94
Average_random_raters	ICC2k	0.94	19	15591	31182	0	0.93	0.95
Average_fixed_raters	ICC3k	0.95	19	15591	31182	0	0.95	0.95

Number of subjects = 15592      Number of Judges = 3

See the help file for a discussion of the other 4 McGraw and Wong estimates,

Individual ICCs (ICC2k):

# A tibble: 8 x 10

# Groups:    variable [8]

	variable	icc_name	type	ICC	F	df1	df2	p	lower bound
<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	AwarenessOfNeed	Average~	ICC2k	0.902	11.1	1948	3896	0	0.882
2	Solicitation	Average~	ICC2k	0.908	10.9	1948	3896	0	0.901
3	CostsAndBenefi~	Average~	ICC2k	0.920	13.0	1948	3896	0	0.911
4	Altruism	Average~	ICC2k	0.855	9.49	1948	3896	0	0.738
5	Reputation	Average~	ICC2k	0.749	4.05	1948	3896	8.45e-301	0.728
6	PsychologicalB~	Average~	ICC2k	0.765	5.82	1948	3896	0	0.590
7	Values	Average~	ICC2k	0.877	8.20	1948	3896	0	0.867
8	Efficacy	Average~	ICC2k	0.822	6.70	1948	3896	0	0.750

# i 1 more variable: `upper bound` <dbl>

mean ICCs (ICC):

# A tibble: 1 x 3

	mean_icc2k	min_icc2k	max_icc2k
<dbl>	<dbl>	<dbl>	<dbl>
1	0.850	0.749	0.920

Cronbach's Alpha:

# A tibble: 8 x 10

# Groups:    variable [8]

	variable	raw_alpha	std.alpha	G6(smc)	average_r	S/N	ase	mean	sd
<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	AwarenessOf~	0.910	0.912	0.874	0.775	10.3	0.00348	3.77	1.07
2	Solicitation	0.909	0.910	0.879	0.771	10.1	0.00348	1.11	0.495
3	CostsAndBen~	0.923	0.937	0.910	0.833	14.9	0.00254	1.56	0.980
4	Altruism	0.895	0.896	0.853	0.741	8.57	0.00410	3.73	0.922
5	Reputation	0.753	0.790	0.718	0.556	3.75	0.00880	1.06	0.262
6	Psychologic~	0.828	0.836	0.773	0.629	5.08	0.00657	2.72	0.925
7	Values	0.878	0.884	0.836	0.717	7.61	0.00462	3.49	0.994
8	Efficacy	0.851	0.857	0.802	0.666	5.99	0.00563	2.79	0.948

# i 1 more variable: median\_r <dbl>



```
## final data for use in analysis
m_dat <- d |>
  select(AwarenessOfNeed:Efficacy, DoesntGive)
```

## 6 Average Treatment Effects (ATEs)

```
## T-tests

## For the conversation group
t.test(
  d$cents_to_amf_post[d$condition == "conv_treatment"],
  d$cents_to_amf_pre[d$condition == "conv_treatment"], paired = TRUE
)
```

Paired t-test

```
data: d$cents_to_amf_post[d$condition == "conv_treatment"] and d$cents_to_amf_pre[d$condition == "conv_treatment"]
t = 14.457, df = 658, p-value < 2.2e-16
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 10.69006 14.05045
sample estimates:
mean difference
 12.37026
```

```
## for the static treatment group
t.test(
  d$cents_to_amf_post[d$condition == "static_treatment"],
  d$cents_to_amf_pre[d$condition == "static_treatment"], paired = TRUE
)
```

Paired t-test

```
data: d$cents_to_amf_post[d$condition == "static_treatment"] and d$cents_to_amf_pre[d$condition == "static_treatment"]
t = 10.627, df = 648, p-value < 2.2e-16
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 6.299472 9.155073
sample estimates:
mean difference
 7.727273
```

```
## for the control treatment group
t.test(
  d$cents_to_amf_post[d$condition == "control"],
  d$cents_to_amf_pre[d$condition == "control"], paired = TRUE
)
```

# Paired t-test

```
data: d$cents_to_amf_post[d$condition == "control"] and d$cents_to_amf_pre[d$condition == "control"]
t = 1.7076, df = 640, p-value = 0.0882
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.06574601  0.94250108
sample estimates:
mean difference
      0.4383775
```

```
## get means and SDs
d |>
  group_by(condition) |>
  summarise(
    mean_pre = mean(cents_to_amf_pre),
    sd_pre = sd(cents_to_amf_pre),
    mean_post = mean(cents_to_amf_post),
    sd_post = sd(cents_to_amf_post),
    mean_change = mean(cents_to_amf_change),
    sd_change = sd(cents_to_amf_change)
  )
```

```
# A tibble: 3 x 7
  condition mean_pre sd_pre mean_post sd_post mean_change sd_change
  <fct>      <dbl> <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
1 control      27.4  26.3     27.8     26.6      0.438     6.50
2 static_treatment 26.9  26.2     34.6     29.1      7.73     18.5
3 conv_treatment  26.5  27.5     38.9     32.4     12.4     22.0
```

```
# standardizers
pooled_pre_mean <- mean(d$cents_to_amf_pre) # for percent change
pooled_pre_sd <- sd(d$cents_to_amf_pre) # for cohens d

## get percentage increase for each from pre-treatment
mean(d$cents_to_amf_change[d$condition == "conv_treatment"])/pooled_pre_mean
```

```
[1] 0.4595024
```

```
mean(d$cents_to_amf_change[d$condition == "static_treatment"])/pooled_pre_mean
```

```
[1] 0.2870353
```

```
mean(d$cents_to_amf_change[d$condition == "control"])/pooled_pre_mean
```

```
[1] 0.01628386
```

```
## get cohens d (mean change in donation amount / SD pre donation amount (pooled))
mean(d$cents_to_amf_change[d$condition == "conv_treatment"])/pooled_pre_sd
```

```
[1] 0.4635142
```

```
mean(d$cents_to_amf_change[d$condition == "static_treatment"])/pooled_pre_sd
```

```
[1] 0.2895413
```

```
mean(d$cents_to_amf_change[d$condition == "control"])/pooled_pre_sd
```

```
[1] 0.01642603
```

```
### ATEs
d_cov_scaled <- d |>
select(cents_to_amf_change, charity_wrong_change, trust_ai_change,
       cents_to_amf_pre, charity_wrong_pre, trust_ai_pre, condition) |>
mutate(
  cents_to_amf_pre_c = cents_to_amf_pre - mean(cents_to_amf_pre),
  charity_wrong_pre_c = charity_wrong_pre - mean(charity_wrong_pre),
  trust_ai_pre_c = trust_ai_pre - mean(trust_ai_pre)
)

## All relevant comparisons treatments
## same as preregistered
## estimatr::lm_lin(cents_to_amf_change ~ condition, covariates = ~ cents_to_amf_pre, data = d)
lh_mod <- estimatr::lh_robust(
  cents_to_amf_change ~ condition*cents_to_amf_pre_c, data = d_cov_scaled,
  linear_hypothesis = "conditionconv_treatment = conditionstatic_treatment"
)
lh_mod
```

```
$lm_robust
```

	Estimate	Std. Error	t value
(Intercept)	0.44787003	0.255466443	1.753146
conditionstatic_treatment	7.27192285	0.758443190	9.587960
conditionconv_treatment	11.87239317	0.877621966	13.527913
cents_to_amf_pre_c	-0.02051145	0.007594457	-2.700845
conditionstatic_treatment:cents_to_amf_pre_c	-0.11169191	0.028064319	-3.979855
conditionconv_treatment:cents_to_amf_pre_c	-0.10624057	0.029053268	-3.656751
	Pr(> t )	CI Lower	
(Intercept)	7.973459e-02	-0.05314709	
conditionstatic_treatment	2.638291e-21	5.78447494	
conditionconv_treatment	6.465496e-40	10.15121355	
cents_to_amf_pre_c	6.976419e-03	-0.03540559	
conditionstatic_treatment:cents_to_amf_pre_c	7.149085e-05	-0.16673125	
conditionconv_treatment:cents_to_amf_pre_c	2.622265e-04	-0.16321942	
	CI Upper	DF	
(Intercept)	0.948887160	1943	
conditionstatic_treatment	8.759370758	1943	
conditionconv_treatment	13.593572787	1943	
cents_to_amf_pre_c	-0.005617309	1943	
conditionstatic_treatment:cents_to_amf_pre_c	-0.056652573	1943	
conditionconv_treatment:cents_to_amf_pre_c	-0.049261716	1943	

```
$lh
```

	Estimate	Std. Error	t value
conditionconv_treatment = conditionstatic_treatment	4.6	1.102	4.174
	Pr(> t )	CI Lower	CI Upper

```

conditionconv_treatment = conditionstatic_treatment 3.128e-05    2.439    6.762
                        DF
conditionconv_treatment = conditionstatic_treatment 1943

```

```

# Cohens d
lh_mod$lm_robust$coefficients["conditionconv_treatment"]/pooled_pre_sd #conv v control

```

```

conditionconv_treatment
0.4448592

```

```

lh_mod$lm_robust$coefficients["conditionstatic_treatment"]/pooled_pre_sd #static v control

```

```

conditionstatic_treatment
0.2724793

```

```

coef(lh_mod$lh)/pooled_pre_sd # conv v static

```

```

[1] 0.1723799

```

```

# percent change
lh_mod$lm_robust$coefficients["conditionconv_treatment"]/pooled_pre_mean #conv v control

```

```

conditionconv_treatment
0.4410089

```

```

lh_mod$lm_robust$coefficients["conditionstatic_treatment"]/pooled_pre_mean #static v control

```

```

conditionstatic_treatment
0.270121

```

```

coef(lh_mod$lh)/pooled_pre_mean # conv v static

```

```

[1] 0.1708879

```

```

## click-through

#preregistered analysis
d %>%
  group_by(condition) %>%
  summarise(
    mean_clicked = mean(link_clicked)
  )

```

```

# A tibble: 3 x 2
  condition      mean_clicked
  <fct>          <dbl>
1 control        0.0686
2 static_treatment 0.0940
3 conv_treatment  0.0910

```

```
logreg <- glm(link_clicked ~ condition, data = d, family = binomial)

logreg |> summary()
```

Call:

```
glm(formula = link_clicked ~ condition, family = binomial, data = d)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-2.6077	0.1562	-16.694	<2e-16 ***
conditionstatic_treatment	0.3419	0.2061	1.658	0.0972 .
conditionconv_treatment	0.3068	0.2067	1.484	0.1378

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1130.4 on 1948 degrees of freedom

Residual deviance: 1127.1 on 1946 degrees of freedom

AIC: 1133.1

Number of Fisher Scoring iterations: 5

```
exp(logreg$coefficients)
```

(Intercept)	conditionstatic_treatment	conditionconv_treatment
0.07370184	1.40758349	1.35908332

```
## Moral Belief change
```

```
#Now lets do a comparison of the conditions
```

```
d_cov_scaled <- d |>
```

```
  select(cents_to_amf_change, charity_wrong_change, trust_ai_change,
         cents_to_amf_pre, charity_wrong_pre, trust_ai_pre, condition) |>
```

```
  mutate(
    cents_to_amf_pre_c = cents_to_amf_pre - mean(cents_to_amf_pre),
    charity_wrong_pre_c = charity_wrong_pre - mean(charity_wrong_pre),
    trust_ai_pre_c = trust_ai_pre - mean(trust_ai_pre)
  )
```

```
## All relevant comparisons treatments
```

```
lh_mod <- estimatr::lh_robust(
  charity_wrong_change ~ condition*charity_wrong_pre_c, data = d_cov_scaled,
  linear_hypothesis = "conditionconv_treatment = conditionstatic_treatment"
)
lh_mod
```

```
$lm_robust
```

	Estimate	Std. Error
(Intercept)	-0.463390206	0.39607144
conditionstatic_treatment	0.168173854	0.63248675
conditionconv_treatment	1.277104066	0.61148999
charity_wrong_pre_c	-0.072136652	0.01657080

```

conditionstatic_treatment:charity_wrong_pre_c -0.014642163 0.02684760
conditionconv_treatment:charity_wrong_pre_c 0.004258065 0.02373923
      t value      Pr(>|t|)
(Intercept) -1.1699662 2.421580e-01
conditionstatic_treatment 0.2658931 7.903498e-01
conditionconv_treatment 2.0885118 3.688157e-02
charity_wrong_pre_c -4.3532390 1.411133e-05
conditionstatic_treatment:charity_wrong_pre_c -0.5453808 5.855542e-01
conditionconv_treatment:charity_wrong_pre_c 0.1793683 8.576672e-01
      CI Lower      CI Upper      DF
(Intercept) -1.24015983 0.31337942 1943
conditionstatic_treatment -1.07225010 1.40859781 1943
conditionconv_treatment 0.07785867 2.47634946 1943
charity_wrong_pre_c -0.10463507 -0.03963824 1943
conditionstatic_treatment:charity_wrong_pre_c -0.06729528 0.03801096 1943
conditionconv_treatment:charity_wrong_pre_c -0.04229897 0.05081510 1943

$lh
      Estimate Std. Error t value
conditionconv_treatment = conditionstatic_treatment 1.109 0.6784 1.635
      Pr(>|t|) CI Lower CI Upper
conditionconv_treatment = conditionstatic_treatment 0.1023 -0.2215 2.439
      DF
conditionconv_treatment = conditionstatic_treatment 1943

# Cohens d
lh_mod$lm_robust$coefficients["conditionconv_treatment"]/pooled_pre_sd #conv v control

conditionconv_treatment
0.04785315

lh_mod$lm_robust$coefficients["conditionstatic_treatment"]/pooled_pre_sd #static v control

conditionstatic_treatment
0.006301483

coef(lh_mod$lh)/pooled_pre_sd # conv v static

[1] 0.04155167

```

## 7 Categorical Heterogeneity Analysis

```

d <- d %>%
  mutate(
    charity_fct = charity_name_final %>%
      fct_na_value_to_level("Other") %>%
      fct_lump_min(min = 40, other_level = "Other") %>%
      fct_infreq()
  )

```

```
# CHARITY
char_het <- het_by_cat("charity_fct", d, control_var = "cents_to_amf_pre_cat")
char_het
```

```
$lm_mod
```

	Estimate
(Intercept)	0.76093183
conditionstatic_treatment	10.37586104
conditionconv_treatment	11.53936473
charity_fctALSAC - St. Jude Children's Research Hospital	
-0.83400005	
charity_fctAmerican Red Cross	-0.52137413
charity_fctFeeding America	-0.78899147
charity_fctDoctors Without Borders, USA	0.17907413
charity_fctAmerican Society for the Prevention of Cruelty to Animals	
-1.06984773	
charity_fctMake-A-Wish America	1.73665999
charity_fctHabitat for Humanity International	
-0.73783655	
charity_fctSalvation Army World Service Office Sawso	
-0.72396864	
charity_fctGoodwill Industries International Inc.	
-2.77807281	
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
0.70887050	
cents_to_amf_pre_cat10-Jan	2.60700407
cents_to_amf_pre_cat20-Nov	1.92243542
cents_to_amf_pre_cat21-30	2.08673635
cents_to_amf_pre_cat31-40	1.09887188
cents_to_amf_pre_cat41-50	-0.79422706
cents_to_amf_pre_cat51-100	-2.76481085
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
0.68473817	
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
6.38725181	
conditionstatic_treatment:charity_fctAmerican Red Cross	
1.84934750	
conditionconv_treatment:charity_fctAmerican Red Cross	
-2.03837479	
conditionstatic_treatment:charity_fctFeeding America	
1.91639635	
conditionconv_treatment:charity_fctFeeding America	
2.98102153	
conditionstatic_treatment:charity_fctDoctors Without Borders, USA	
4.98463168	
conditionconv_treatment:charity_fctDoctors Without Borders, USA	
12.88840160	
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
-0.73846905	
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
3.79747875	
conditionstatic_treatment:charity_fctMake-A-Wish America	
3.09780794	

conditionconv_treatment:charity_fctMake-A-Wish America	
0.57303661	
conditionstatic_treatment:charity_fctHabitat for Humanity International	
-3.81083500	
conditionconv_treatment:charity_fctHabitat for Humanity International	
-0.88608691	
conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso	
-0.25080335	
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso	
4.74763425	
conditionstatic_treatment:charity_fctGoodwill Industries International Inc.	
0.22384660	
conditionconv_treatment:charity_fctGoodwill Industries International Inc.	
9.13676961	
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
-9.16454122	
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
3.28822015	
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	
-3.41503962	
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	
15.39017932	
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	
-0.09251329	
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	
7.14365234	
conditionstatic_treatment:cents_to_amf_pre_cat21-30	
-7.42417308	
conditionconv_treatment:cents_to_amf_pre_cat21-30	
-4.55486053	
conditionstatic_treatment:cents_to_amf_pre_cat31-40	
-8.25098647	
conditionconv_treatment:cents_to_amf_pre_cat31-40	
-1.25451109	
conditionstatic_treatment:cents_to_amf_pre_cat41-50	
-5.25410091	
conditionconv_treatment:cents_to_amf_pre_cat41-50	
-3.76263759	
conditionstatic_treatment:cents_to_amf_pre_cat51-100	
-9.50413670	
conditionconv_treatment:cents_to_amf_pre_cat51-100	
-11.88997615	
(Intercept)	Std. Error
conditionstatic_treatment	0.3882843
conditionconv_treatment	1.6842528
charity_fctALSAC - St. Jude Children's Research Hospital	1.8710822
charity_fctAmerican Red Cross	0.6965570
charity_fctFeeding America	0.9875902
charity_fctDoctors Without Borders, USA	1.0181702
charity_fctAmerican Society for the Prevention of Cruelty to Animals	0.8001465
0.6222916	
charity_fctMake-A-Wish America	2.2750533
charity_fctHabitat for Humanity International	0.5542797



charity_fctSalvation Army World Service Office Sawso	0.5538398
charity_fctGoodwill Industries International Inc.	2.0160888
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
1.0304684	
cents_to_amf_pre_cat10-Jan	2.3739880
cents_to_amf_pre_cat20-Nov	1.7746405
cents_to_amf_pre_cat21-30	1.5003331
cents_to_amf_pre_cat31-40	1.4756224
cents_to_amf_pre_cat41-50	0.4504887
cents_to_amf_pre_cat51-100	1.6371878
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
2.2198698	
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
2.5200890	
conditionstatic_treatment:charity_fctAmerican Red Cross	2.7414511
conditionconv_treatment:charity_fctAmerican Red Cross	2.6635370
conditionstatic_treatment:charity_fctFeeding America	3.0157198
conditionconv_treatment:charity_fctFeeding America	3.5539742
conditionstatic_treatment:charity_fctDoctors Without Borders, USA	
4.4201166	
conditionconv_treatment:charity_fctDoctors Without Borders, USA	
4.5257846	
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
3.5929801	
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
4.3322236	
conditionstatic_treatment:charity_fctMake-A-Wish America	5.1433961
conditionconv_treatment:charity_fctMake-A-Wish America	4.3728241
conditionstatic_treatment:charity_fctHabitat for Humanity International	
1.9992260	
conditionconv_treatment:charity_fctHabitat for Humanity International	
3.6390021	
conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso	
3.4881687	
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso	
4.5777873	
conditionstatic_treatment:charity_fctGoodwill Industries International Inc.	
3.0044665	
conditionconv_treatment:charity_fctGoodwill Industries International Inc.	
4.9797730	
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
4.7696789	
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
8.4931685	
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	4.7431254
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	7.1087433
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	4.3776218
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	4.7274614
conditionstatic_treatment:cents_to_amf_pre_cat21-30	2.5836268
conditionconv_treatment:cents_to_amf_pre_cat21-30	3.1877262
conditionstatic_treatment:cents_to_amf_pre_cat31-40	2.8388055
conditionconv_treatment:cents_to_amf_pre_cat31-40	4.4448459
conditionstatic_treatment:cents_to_amf_pre_cat41-50	1.8313148
conditionconv_treatment:cents_to_amf_pre_cat41-50	1.9136479

conditionstatic_treatment:cents_to_amf_pre_cat51-100	3.0924704
conditionconv_treatment:cents_to_amf_pre_cat51-100	2.8633876
	t value
(Intercept)	1.95972864
conditionstatic_treatment	6.16051269
conditionconv_treatment	6.16721425
charity_fctALSAC - St. Jude Children's Research Hospital	
-1.19731780	
charity_fctAmerican Red Cross	-0.52792560
charity_fctFeeding America	-0.77491121
charity_fctDoctors Without Borders, USA	0.22380168
charity_fctAmerican Society for the Prevention of Cruelty to Animals	
-1.71920651	
charity_fctMake-A-Wish America	0.76334914
charity_fctHabitat for Humanity International	-1.33116281
charity_fctSalvation Army World Service Office Sawso	-1.30718064
charity_fctGoodwill Industries International Inc.	-1.37795162
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
0.68791092	
cents_to_amf_pre_cat10-Jan	1.09815386
cents_to_amf_pre_cat20-Nov	1.08328164
cents_to_amf_pre_cat21-30	1.39084867
cents_to_amf_pre_cat31-40	0.74468365
cents_to_amf_pre_cat41-50	-1.76303449
cents_to_amf_pre_cat51-100	-1.68875611
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
0.30845871	
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
2.53453420	
conditionstatic_treatment:charity_fctAmerican Red Cross	
0.67458707	
conditionconv_treatment:charity_fctAmerican Red Cross	
-0.76528872	
conditionstatic_treatment:charity_fctFeeding America	
0.63546896	
conditionconv_treatment:charity_fctFeeding America	0.83878536
conditionstatic_treatment:charity_fctDoctors Without Borders, USA	
1.12771496	
conditionconv_treatment:charity_fctDoctors Without Borders, USA	
2.84777175	
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
-0.20553107	
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
0.87656573	
conditionstatic_treatment:charity_fctMake-A-Wish America	
0.60228842	
conditionconv_treatment:charity_fctMake-A-Wish America	
0.13104497	
conditionstatic_treatment:charity_fctHabitat for Humanity International	
-1.90615515	
conditionconv_treatment:charity_fctHabitat for Humanity International	
-0.24349722	
conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso	
-0.07190115	

conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso	
1.03710241	
conditionstatic_treatment:charity_fctGoodwill Industries International Inc.	
0.07450461	
conditionconv_treatment:charity_fctGoodwill Industries International Inc.	
1.83477632	
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
-1.92141682	
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
0.38716059	
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	
-0.71999775	
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	
2.16496484	
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	
-0.02113323	
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	
1.51109693	
conditionstatic_treatment:cents_to_amf_pre_cat21-30	
-2.87354703	
conditionconv_treatment:cents_to_amf_pre_cat21-30	
-1.42887446	
conditionstatic_treatment:cents_to_amf_pre_cat31-40	
-2.90649941	
conditionconv_treatment:cents_to_amf_pre_cat31-40	
-0.28223950	
conditionstatic_treatment:cents_to_amf_pre_cat41-50	
-2.86903206	
conditionconv_treatment:cents_to_amf_pre_cat41-50	
-1.96621207	
conditionstatic_treatment:cents_to_amf_pre_cat51-100	
-3.07331533	
conditionconv_treatment:cents_to_amf_pre_cat51-100	
-4.15241586	
	Pr(> t )
(Intercept)	5.017367e-02
conditionstatic_treatment	8.829997e-10
conditionconv_treatment	8.470951e-10
charity_fctALSAC - St. Jude Children's Research Hospital	
2.313322e-01	
charity_fctAmerican Red Cross	5.976127e-01
charity_fctFeeding America	4.384887e-01
charity_fctDoctors Without Borders, USA	8.229357e-01
charity_fctAmerican Society for the Prevention of Cruelty to Animals	
8.573982e-02	
charity_fctMake-A-Wish America	4.453501e-01
charity_fctHabitat for Humanity International	
1.832953e-01	
charity_fctSalvation Army World Service Office Sawso	
1.913097e-01	
charity_fctGoodwill Industries International Inc.	
1.683807e-01	
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
4.915929e-01	

cents_to_amf_pre_cat10-Jan	2.722766e-01
cents_to_amf_pre_cat20-Nov	2.788210e-01
cents_to_amf_pre_cat21-30	1.644344e-01
cents_to_amf_pre_cat31-40	4.565552e-01
cents_to_amf_pre_cat41-50	7.805557e-02
cents_to_amf_pre_cat51-100	9.143044e-02
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
7.577672e-01	
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
1.133945e-02	
conditionstatic_treatment:charity_fctAmerican Red Cross	
5.000203e-01	
conditionconv_treatment:charity_fctAmerican Red Cross	
4.441948e-01	
conditionstatic_treatment:charity_fctFeeding America	
5.251992e-01	
conditionconv_treatment:charity_fctFeeding America	
4.016954e-01	
conditionstatic_treatment:charity_fctDoctors Without Borders, USA	
2.595829e-01	
conditionconv_treatment:charity_fctDoctors Without Borders, USA	
4.450043e-03	
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
8.371793e-01	
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
3.808335e-01	
conditionstatic_treatment:charity_fctMake-A-Wish America	
5.470541e-01	
conditionconv_treatment:charity_fctMake-A-Wish America	
8.957536e-01	
conditionstatic_treatment:charity_fctHabitat for Humanity International	
5.678099e-02	
conditionconv_treatment:charity_fctHabitat for Humanity International	
8.076465e-01	
conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso	
9.426881e-01	
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso	
2.998202e-01	
conditionstatic_treatment:charity_fctGoodwill Industries International Inc.	
9.406167e-01	
conditionconv_treatment:charity_fctGoodwill Industries International Inc.	
6.669527e-02	
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
5.482878e-02	
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
6.986807e-01	
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	
4.716150e-01	
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	
3.051464e-02	
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	
9.831416e-01	
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	
1.309302e-01	

conditionstatic_treatment:cents_to_amf_pre_cat21-30	
4.104055e-03	
conditionconv_treatment:cents_to_amf_pre_cat21-30	
1.532049e-01	
conditionstatic_treatment:cents_to_amf_pre_cat31-40	
3.697355e-03	
conditionconv_treatment:cents_to_amf_pre_cat31-40	
7.777906e-01	
conditionstatic_treatment:cents_to_amf_pre_cat41-50	
4.162837e-03	
conditionconv_treatment:cents_to_amf_pre_cat41-50	
4.941966e-02	
conditionstatic_treatment:cents_to_amf_pre_cat51-100	
2.147062e-03	
conditionconv_treatment:cents_to_amf_pre_cat51-100	
3.435614e-05	
	CI Lower
(Intercept)	-5.769927e-04
conditionstatic_treatment	7.072680e+00
conditionconv_treatment	7.869771e+00
charity_fctALSAC - St. Jude Children's Research Hospital	
-2.200098e+00	
charity_fctAmerican Red Cross	-2.458250e+00
charity_fctFeeding America	-2.785842e+00
charity_fctDoctors Without Borders, USA	
-1.390185e+00	
charity_fctAmerican Society for the Prevention of Cruelty to Animals	
-2.290295e+00	
charity_fctMake-A-Wish America	-2.725208e+00
charity_fctHabitat for Humanity International	
-1.824898e+00	
charity_fctSalvation Army World Service Office Sawso	
-1.810167e+00	
charity_fctGoodwill Industries International Inc.	
-6.732056e+00	
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
-1.312099e+00	
cents_to_amf_pre_cat10-Jan	-2.048896e+00
cents_to_amf_pre_cat20-Nov	-1.558015e+00
cents_to_amf_pre_cat21-30	-8.557390e-01
cents_to_amf_pre_cat31-40	-1.795140e+00
cents_to_amf_pre_cat41-50	-1.677732e+00
cents_to_amf_pre_cat51-100	-5.975687e+00
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
-3.668903e+00	
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
1.444816e+00	
conditionstatic_treatment:charity_fctAmerican Red Cross	
-3.527227e+00	
conditionconv_treatment:charity_fctAmerican Red Cross	
-7.262143e+00	
conditionstatic_treatment:charity_fctFeeding America	
-3.998078e+00	

conditionconv\_treatment:charity\_fctFeeding America  
 -3.989085e+00  
 conditionstatic\_treatment:charity\_fctDoctors Without Borders, USA  
 -3.684166e+00  
 conditionconv\_treatment:charity\_fctDoctors Without Borders, USA  
 4.012367e+00  
 conditionstatic\_treatment:charity\_fctAmerican Society for the Prevention of Cruelty to Animals  
 -7.785074e+00  
 conditionconv\_treatment:charity\_fctAmerican Society for the Prevention of Cruelty to Animals  
 -4.698942e+00  
 conditionstatic\_treatment:charity\_fctMake-A-Wish America  
 -6.989496e+00  
 conditionconv\_treatment:charity\_fctMake-A-Wish America  
 -8.003010e+00  
 conditionstatic\_treatment:charity\_fctHabitat for Humanity International  
 -7.731746e+00  
 conditionconv\_treatment:charity\_fctHabitat for Humanity International  
 -8.022951e+00  
 conditionstatic\_treatment:charity\_fctSalvation Army World Service Office Sawso  
 -7.091851e+00  
 conditionconv\_treatment:charity\_fctSalvation Army World Service Office Sawso  
 -4.230389e+00  
 conditionstatic\_treatment:charity\_fctGoodwill Industries International Inc.  
 -5.668557e+00  
 conditionconv\_treatment:charity\_fctGoodwill Industries International Inc.  
 -6.296342e-01  
 conditionstatic\_treatment:charity\_fctHumane World for Animals (formerly known as the Humane Society of the United States)  
 -1.851891e+01  
 conditionconv\_treatment:charity\_fctHumane World for Animals (formerly known as the Humane Society of the United States)  
 -1.336871e+01  
 conditionstatic\_treatment:cents\_to\_amf\_pre\_cat10-Jan  
 -1.271733e+01  
 conditionconv\_treatment:cents\_to\_amf\_pre\_cat10-Jan  
 1.448408e+00  
 conditionstatic\_treatment:cents\_to\_amf\_pre\_cat20-Nov  
 -8.677969e+00  
 conditionconv\_treatment:cents\_to\_amf\_pre\_cat20-Nov  
 -2.127914e+00  
 conditionstatic\_treatment:cents\_to\_amf\_pre\_cat21-30  
 -1.249122e+01  
 conditionconv\_treatment:cents\_to\_amf\_pre\_cat21-30  
 -1.080668e+01  
 conditionstatic\_treatment:cents\_to\_amf\_pre\_cat31-40  
 -1.381849e+01  
 conditionconv\_treatment:cents\_to\_amf\_pre\_cat31-40  
 -9.971808e+00  
 conditionstatic\_treatment:cents\_to\_amf\_pre\_cat41-50  
 -8.845702e+00  
 conditionconv\_treatment:cents\_to\_amf\_pre\_cat41-50  
 -7.515712e+00  
 conditionstatic\_treatment:cents\_to\_amf\_pre\_cat51-100  
 -1.556913e+01  
 conditionconv\_treatment:cents\_to\_amf\_pre\_cat51-100  
 -1.750569e+01

(Intercept)	CI Upper
conditionstatic_treatment	1.522440660
conditionconv_treatment	13.679042388
charity_fctALSAC - St. Jude Children's Research Hospital	15.208958518
0.532097665	
charity_fctAmerican Red Cross	1.415502162
charity_fctFeeding America	1.207858759
charity_fctDoctors Without Borders, USA	1.748333190
charity_fctAmerican Society for the Prevention of Cruelty to Animals	
0.150599625	
charity_fctMake-A-Wish America	6.198527861
charity_fctHabitat for Humanity International	
0.349224956	
charity_fctSalvation Army World Service Office Sawso	
0.362230052	
charity_fctGoodwill Industries International Inc.	
1.175910058	
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
2.729840315	
cents_to_amf_pre_cat10-Jan	7.262904114
cents_to_amf_pre_cat20-Nov	5.402886272
cents_to_amf_pre_cat21-30	5.029211665
cents_to_amf_pre_cat31-40	3.992884165
cents_to_amf_pre_cat41-50	0.089277917
cents_to_amf_pre_cat51-100	0.446065788
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
5.038379338	
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	
11.329687310	
conditionstatic_treatment:charity_fctAmerican Red Cross	
7.225921641	
conditionconv_treatment:charity_fctAmerican Red Cross	
3.185392941	
conditionstatic_treatment:charity_fctFeeding America	
7.830870296	
conditionconv_treatment:charity_fctFeeding America	
9.951127846	
conditionstatic_treatment:charity_fctDoctors Without Borders, USA	
13.653429189	
conditionconv_treatment:charity_fctDoctors Without Borders, USA	
21.764436680	
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
6.308136122	
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	
12.293899188	
conditionstatic_treatment:charity_fctMake-A-Wish America	
13.185111775	
conditionconv_treatment:charity_fctMake-A-Wish America	
9.149083359	
conditionstatic_treatment:charity_fctHabitat for Humanity International	
0.110076386	
conditionconv_treatment:charity_fctHabitat for Humanity International	
6.250777346	

conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso	
6.590244184	
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso	
13.725657729	
conditionstatic_treatment:charity_fctGoodwill Industries International Inc.	
6.116250227	
conditionconv_treatment:charity_fctGoodwill Industries International Inc.	
18.903173392	
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
0.189822873	
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	
19.945146569	
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	
5.887247363	
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	
29.331950852	
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	
8.492942764	
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	
16.415218819	
conditionstatic_treatment:cents_to_amf_pre_cat21-30	
-2.357126379	
conditionconv_treatment:cents_to_amf_pre_cat21-30	
1.696954775	
conditionstatic_treatment:cents_to_amf_pre_cat31-40	
-2.683479567	
conditionconv_treatment:cents_to_amf_pre_cat31-40	
7.462785878	
conditionstatic_treatment:cents_to_amf_pre_cat41-50	
-1.662499476	
conditionconv_treatment:cents_to_amf_pre_cat41-50	
-0.009563307	
conditionstatic_treatment:cents_to_amf_pre_cat51-100	
-3.439138448	
conditionconv_treatment:cents_to_amf_pre_cat51-100	
-6.274258410	
	DF
(Intercept)	1898
conditionstatic_treatment	1898
conditionconv_treatment	1898
charity_fctALSAC - St. Jude Children's Research Hospital	1898
charity_fctAmerican Red Cross	1898
charity_fctFeeding America	1898
charity_fctDoctors Without Borders, USA	1898
charity_fctAmerican Society for the Prevention of Cruelty to Animals	1898
charity_fctMake-A-Wish America	1898
charity_fctHabitat for Humanity International	1898
charity_fctSalvation Army World Service Office Sawso	1898
charity_fctGoodwill Industries International Inc.	1898
charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	1898
cents_to_amf_pre_cat10-Jan	1898
cents_to_amf_pre_cat20-Nov	1898
cents_to_amf_pre_cat21-30	1898
cents_to_amf_pre_cat31-40	1898



cents_to_amf_pre_cat41-50	1898
cents_to_amf_pre_cat51-100	1898
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	1898
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital	1898
conditionstatic_treatment:charity_fctAmerican Red Cross	1898
conditionconv_treatment:charity_fctAmerican Red Cross	1898
conditionstatic_treatment:charity_fctFeeding America	1898
conditionconv_treatment:charity_fctFeeding America	1898
conditionstatic_treatment:charity_fctDoctors Without Borders, USA	1898
conditionconv_treatment:charity_fctDoctors Without Borders, USA	1898
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	1898
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals	1898
conditionstatic_treatment:charity_fctMake-A-Wish America	1898
conditionconv_treatment:charity_fctMake-A-Wish America	1898
conditionstatic_treatment:charity_fctHabitat for Humanity International	1898
conditionconv_treatment:charity_fctHabitat for Humanity International	1898
conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso	1898
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso	1898
conditionstatic_treatment:charity_fctGoodwill Industries International Inc.	1898
conditionconv_treatment:charity_fctGoodwill Industries International Inc.	1898
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	1898
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)	1898
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	1898
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	1898
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	1898
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	1898
conditionstatic_treatment:cents_to_amf_pre_cat21-30	1898
conditionconv_treatment:cents_to_amf_pre_cat21-30	1898
conditionstatic_treatment:cents_to_amf_pre_cat31-40	1898
conditionconv_treatment:cents_to_amf_pre_cat31-40	1898
conditionstatic_treatment:cents_to_amf_pre_cat41-50	1898
conditionconv_treatment:cents_to_amf_pre_cat41-50	1898
conditionstatic_treatment:cents_to_amf_pre_cat51-100	1898
conditionconv_treatment:cents_to_amf_pre_cat51-100	1898

\$omnibus\_tests  
\$omnibus\_tests\$all  
Linear hypothesis test

Hypothesis:

conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital = 0
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital = 0
conditionstatic_treatment:charity_fctAmerican Red Cross = 0
conditionconv_treatment:charity_fctAmerican Red Cross = 0
conditionstatic_treatment:charity_fctFeeding America = 0
conditionconv_treatment:charity_fctFeeding America = 0
conditionstatic_treatment:charity_fctDoctors Without Borders, USA = 0
conditionconv_treatment:charity_fctDoctors Without Borders, USA = 0
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals = 0
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals = 0
conditionstatic_treatment:charity_fctMake-A-Wish America = 0
conditionconv_treatment:charity_fctMake-A-Wish America = 0
conditionstatic_treatment:charity_fctHabitat for Humanity International = 0
conditionconv_treatment:charity_fctHabitat for Humanity International = 0

```

conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso = 0
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso = 0
conditionstatic_treatment:charity_fctGoodwill Industries International Inc. = 0
conditionconv_treatment:charity_fctGoodwill Industries International Inc. = 0
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States) = 0
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States) = 0

```

Model 1: restricted model

Model 2: cents\_to\_amf\_change ~ condition \* charity\_fct + condition \* cents\_to\_amf\_pre\_cat

```

      Res.Df Df      F Pr(>F)
1      1918
2      1898 20 1.6428 0.03612 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

\$omnibus\_tests\$static\_only

Linear hypothesis test

Hypothesis:

```

conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital = 0
conditionstatic_treatment:charity_fctAmerican Red Cross = 0
conditionstatic_treatment:charity_fctFeeding America = 0
conditionstatic_treatment:charity_fctDoctors Without Borders, USA = 0
conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals = 0
conditionstatic_treatment:charity_fctMake-A-Wish America = 0
conditionstatic_treatment:charity_fctHabitat for Humanity International = 0
conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso = 0
conditionstatic_treatment:charity_fctGoodwill Industries International Inc. = 0
conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States) = 0

```

Model 1: restricted model

Model 2: cents\_to\_amf\_change ~ condition \* charity\_fct + condition \* cents\_to\_amf\_pre\_cat

```

      Res.Df Df      F Pr(>F)
1      1908
2      1898 10 1.2523 0.2525

```

\$omnibus\_tests\$conv\_only

Linear hypothesis test

Hypothesis:

```

conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital = 0
conditionconv_treatment:charity_fctAmerican Red Cross = 0
conditionconv_treatment:charity_fctFeeding America = 0
conditionconv_treatment:charity_fctDoctors Without Borders, USA = 0
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals = 0
conditionconv_treatment:charity_fctMake-A-Wish America = 0
conditionconv_treatment:charity_fctHabitat for Humanity International = 0
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso = 0
conditionconv_treatment:charity_fctGoodwill Industries International Inc. = 0
conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States) = 0

```

Model 1: restricted model

Model 2: cents\_to\_amf\_change ~ condition \* charity\_fct + condition \* cents\_to\_amf\_pre\_cat

```

      Res.Df Df      F Pr(>F)
1      1908
2      1898 10 1.9729 0.03255 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$omnibus_tests$conv_vs_static
Linear hypothesis test

Hypothesis:
conditionconv_treatment:charity_fctALSAC - St. Jude Children's Research Hospital =
conditionstatic_treatment:charity_fctALSAC - St. Jude Children's Research Hospital
- conditionstatic_treatment:charity_fctAmerican Red Cross + conditionconv_treatment:charity_fctAmerican Red Cross = 0
- conditionstatic_treatment:charity_fctFeeding America + conditionconv_treatment:charity_fctFeeding America = 0
- conditionstatic_treatment:charity_fctDoctors Without Borders, USA + conditionconv_treatment:charity_fctDoctors Without
Borders, USA = 0
- conditionstatic_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals +
conditionconv_treatment:charity_fctAmerican Society for the Prevention of Cruelty to Animals = 0
conditionconv_treatment:charity_fctMake-A-Wish America = conditionstatic_treatment:charity_fctMake-A-Wish America
- conditionstatic_treatment:charity_fctHabitat for Humanity International + conditionconv_treatment:charity_fctHabitat for
Humanity International = 0
- conditionstatic_treatment:charity_fctSalvation Army World Service Office Sawso +
conditionconv_treatment:charity_fctSalvation Army World Service Office Sawso = 0
- conditionstatic_treatment:charity_fctGoodwill Industries International Inc. + conditionconv_treatment:charity_fctGoodwill
Industries International Inc. = 0
- conditionstatic_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States)
+ conditionconv_treatment:charity_fctHumane World for Animals (formerly known as the Humane Society of the United States) = 0

Model 1: restricted model
Model 2: cents_to_amf_change ~ condition * charity_fct + condition * cents_to_amf_pre_cat

      Res.Df Df      F Pr(>F)
1      1908
2      1898 10 1.2245 0.2699

$comparisons

      Term                                Contrast
condition mean(conv_treatment) - mean(control)
condition mean(conv_treatment) - mean(control)
condition mean(conv_treatment) - mean(control)
condition mean(conv_treatment) - mean(control)
condition mean(conv_treatment) - mean(control)
charity_fct
Other
ALSAC - St. Jude Children's Research Hospital
American Red Cross
Feeding America
Doctors Without Borders, USA
Estimate Std. Error      z Pr(>|z|)      S    2.5 % 97.5 %
11.69     1.80  6.498 <0.001 33.5    8.1659 15.22
18.08     2.29  7.897 <0.001 48.3   13.5925 22.57
9.65      2.56  3.776 <0.001 12.6    4.6429 14.67

```

```

14.67      3.54  4.145   <0.001 14.8   7.7348  21.61
24.58      4.48  5.488   <0.001 24.6  15.8025  33.36
--- 23 rows omitted. See ?print.marginaleffects ---
condition mean(static_treatment) - mean(control)
condition mean(static_treatment) - mean(control)
condition mean(static_treatment) - mean(control)
condition mean(static_treatment) - mean(control)
condition mean(static_treatment) - mean(control)

charity_fct

Make-A-Wish America
Habitat for Humanity International
Salvation Army World Service Office Sawso
Goodwill Industries International Inc.
Humane World for Animals (formerly known as the Humane Society of the United States)
Estimate Std. Error      z Pr(>|z|)    S    2.5 % 97.5 %
      8.62      5.07  1.700   0.0892 3.5   -1.3215  18.57
      1.72      1.83  0.939   0.3477 1.5   -1.8658   5.30
      5.28      3.32  1.589   0.1120 3.2   -1.2311  11.78
      5.75      2.92  1.972   0.0486 4.4    0.0365  11.47
     -3.64      4.77 -0.763   0.4455 1.2  -12.9817   5.71
Columns: term, contrast, charity_fct, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, predicted_lo,
predicted_hi, predicted
Type: response

$preds

      condition
control
conv_treatment
static_treatment
control
conv_treatment

charity_fct

Other
Other
Other
ALSAC - St. Jude Children's Research Hospital
ALSAC - St. Jude Children's Research Hospital
Estimate Std. Error      z Pr(>|z|)    S    2.5 % 97.5 %
      1.355      0.684  1.981   0.04763 4.4    0.0142   2.70
     13.047      1.664  7.840   < 0.001 47.7   9.7852  16.31
      6.882      1.307  5.264   < 0.001 22.8   4.3197   9.44
      0.521      0.623  0.835   0.40346 1.3   -0.7008   1.74
     18.600      2.203  8.443   < 0.001 54.8  14.2826  22.92
--- 23 rows omitted. See ?print.marginaleffects ---
conv_treatment
static_treatment
control
conv_treatment
static_treatment

charity_fct

Make-A-Wish America
Make-A-Wish America
Humane World for Animals (formerly known as the Humane Society of the United States)

```

Humane World for Animals (formerly known as the Humane Society of the United States)

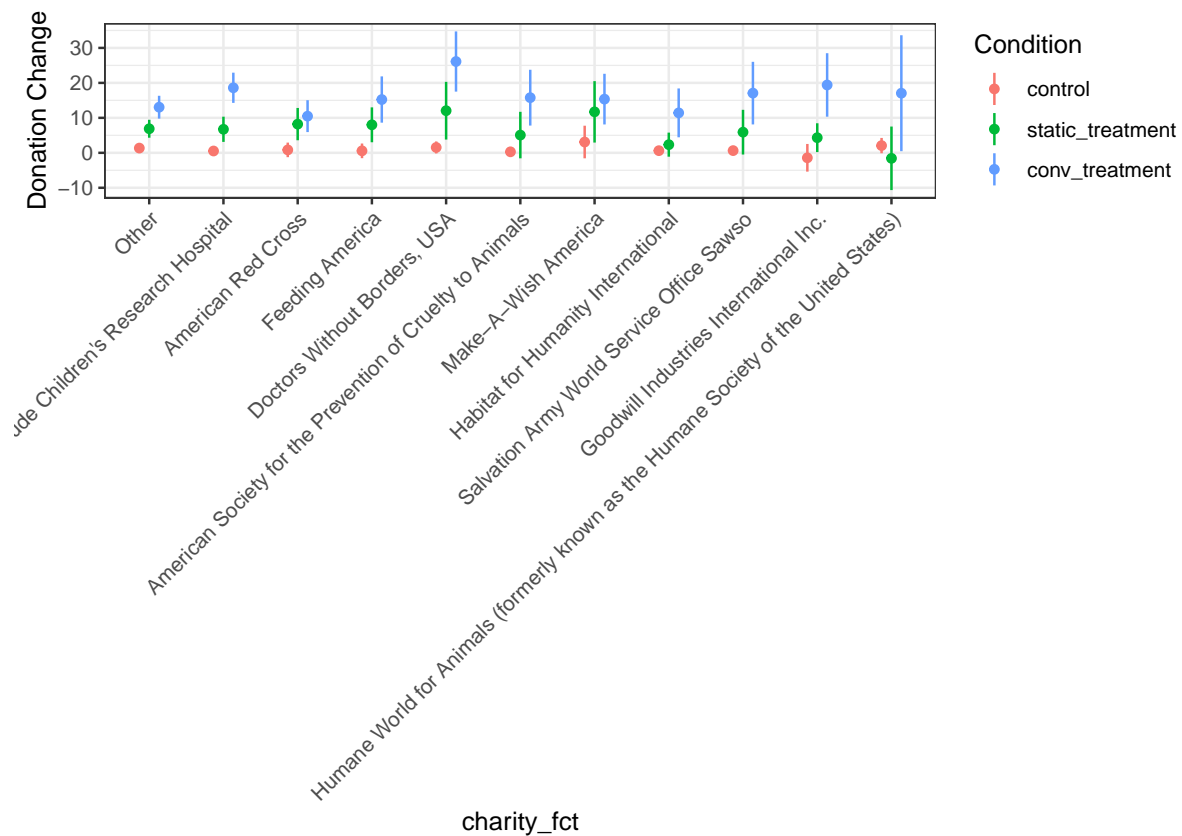
Humane World for Animals (formerly known as the Humane Society of the United States)

Estimate	Std. Error	z	Pr(> z )	S	2.5 %	97.5 %
15.357	3.697	4.154	< 0.001	14.9	8.1107	22.60
11.716	4.482	2.614	0.00895	6.8	2.9310	20.50
2.064	1.118	1.846	0.06493	3.9	-0.1277	4.25
17.044	8.459	2.015	0.04392	4.5	0.4644	33.62
-1.574	4.635	-0.340	0.73417	0.4	-10.6576	7.51

Columns: charity\_fct, condition, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high

Type: response

\$marg\_plot



```
# look at comparisons between everything here
char_cate_comparisons <- margineffects::avg_comparisons(
  char_het$lm_mod,
  variables = list("condition" = "minmax"), # just conv v control
  newdata = "balanced",
  by = c("charity_fct"),
  hypothesis = "pairwise",
  p_adjust = "holm"
)
```

```
char_cate_comparisons
```

Term

```
(Other) - (ALSAC - St. Jude Children's Research Hospital)
(Other) - (American Red Cross)
(Other) - (Feeding America)
(Other) - (Doctors Without Borders, USA)
(Other) - (American Society for the Prevention of Cruelty to Animals)
Estimate Std. Error      z Pr(>|z|)      S
    -6.39      2.52 -2.535    0.586  0.8
     2.04      2.66  0.765    1.000 -0.0
    -2.98      3.55 -0.839    1.000 -0.0
   -12.89      4.53 -2.848    0.238  2.1
    -3.80      4.33 -0.877    1.000 -0.0
--- 45 rows omitted. See ?print.marginaleffects ---
(Habitat for Humanity International) - (Goodwill Industries International Inc.)
(Habitat for Humanity International) - (Humane World for Animals (formerly known as the Humane Society of the United States))
(Salvation Army World Service Office Sawso) - (Goodwill Industries International Inc.)
(Salvation Army World Service Office Sawso) - (Humane World for Animals (formerly known as the Humane Society of the United States))
(Goodwill Industries International Inc.) - (Humane World for Animals (formerly known as the Humane Society of the United States))
Estimate Std. Error      z Pr(>|z|)      S
   -10.02      5.88 -1.705    1.000 -0.0
    -4.17      9.11 -0.458    1.000 -0.0
    -4.39      6.43 -0.683    1.000 -0.0
     1.46      9.43  0.155    1.000 -0.0
     5.85      9.66  0.605    1.000 -0.0
Columns: term, estimate, std.error, statistic, p.value, s.value
Type: response
```

```
# none less than .05 after holm
char_cate_comparisons |>
  arrange(desc(abs(estimate))) |>
  as_tibble() |>
  filter(p.value < .05) |>
  print(n = Inf)
```

```
# A tibble: 0 x 6
#   i 6 variables: term <chr>, estimate <dbl>, std.error <dbl>, statistic <dbl>,
#   p.value <dbl>, s.value <dbl>
```

```
# Location
loc_het <- het_by_cat("location_cat3", d_where, control_var = "cents_to_amf_pre_cat")
loc_het
```

```
$lm_mod

              Estimate Std. Error
(Intercept)    0.51014110  0.3222713
conditionstatic_treatment 10.68038942  1.6393500
conditionconv_treatment  15.22551381  1.9911330
location_cat3National    0.35576073  0.5772829
```

location_cat3Local/State	0.06129221	0.8137751
location_cat3NA	-0.67291051	1.0034828
cents_to_amf_pre_cat10-Jan	2.43566936	2.3418576
cents_to_amf_pre_cat20-Nov	1.68676647	1.7362111
cents_to_amf_pre_cat21-30	1.91799040	1.5784050
cents_to_amf_pre_cat31-40	1.18806585	1.4056573
cents_to_amf_pre_cat41-50	-0.81534523	0.4365163
cents_to_amf_pre_cat51-100	-2.91580386	1.7295912
conditionstatic_treatment:location_cat3National	-1.72970151	1.6737089
conditionconv_treatment:location_cat3National	-1.43602645	2.0343851
conditionstatic_treatment:location_cat3Local/State	2.48128268	3.7630918
conditionconv_treatment:location_cat3Local/State	-8.26681595	2.6000816
conditionstatic_treatment:location_cat3NA	2.10572727	2.8893636
conditionconv_treatment:location_cat3NA	-4.24862281	3.0830886
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	-2.91748530	4.7764732
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	14.18931172	7.1758359
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	0.27710480	4.2817385
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	7.58979816	5.0043078
conditionstatic_treatment:cents_to_amf_pre_cat21-30	-6.59206627	2.5819111
conditionconv_treatment:cents_to_amf_pre_cat21-30	-4.85482012	3.2657923
conditionstatic_treatment:cents_to_amf_pre_cat31-40	-8.20604791	2.7874358
conditionconv_treatment:cents_to_amf_pre_cat31-40	-1.43215591	4.7712631
conditionstatic_treatment:cents_to_amf_pre_cat41-50	-5.17095316	1.7894872
conditionconv_treatment:cents_to_amf_pre_cat41-50	-3.86631343	1.9682235
conditionstatic_treatment:cents_to_amf_pre_cat51-100	-8.84720425	3.0992842
conditionconv_treatment:cents_to_amf_pre_cat51-100	-11.78220842	2.8844315
	t value	Pr(> t )
(Intercept)	1.58295560	1.135964e-01
conditionstatic_treatment	6.51501455	9.259491e-11
conditionconv_treatment	7.64665828	3.239640e-14
location_cat3National	0.61626759	5.377910e-01
location_cat3Local/State	0.07531836	9.399693e-01
location_cat3NA	-0.67057500	5.025720e-01
cents_to_amf_pre_cat10-Jan	1.04005869	2.984437e-01
cents_to_amf_pre_cat20-Nov	0.97152153	3.314111e-01
cents_to_amf_pre_cat21-30	1.21514466	2.244604e-01
cents_to_amf_pre_cat31-40	0.84520305	3.981028e-01
cents_to_amf_pre_cat41-50	-1.86784586	6.193587e-02
cents_to_amf_pre_cat51-100	-1.68583414	9.199032e-02
conditionstatic_treatment:location_cat3National	-1.03345419	3.015216e-01
conditionconv_treatment:location_cat3National	-0.70587739	4.803501e-01
conditionstatic_treatment:location_cat3Local/State	0.65937342	5.097351e-01
conditionconv_treatment:location_cat3Local/State	-3.17944480	1.499108e-03
conditionstatic_treatment:location_cat3NA	0.72878583	4.662216e-01
conditionconv_treatment:location_cat3NA	-1.37804111	1.683513e-01
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	-0.61080323	5.414022e-01
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	1.97737407	4.814226e-02
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	0.06471782	9.484054e-01
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	1.51665293	1.295190e-01
conditionstatic_treatment:cents_to_amf_pre_cat21-30	-2.55317323	1.075140e-02
conditionconv_treatment:cents_to_amf_pre_cat21-30	-1.48656734	1.372934e-01
conditionstatic_treatment:cents_to_amf_pre_cat31-40	-2.94394149	3.279552e-03
conditionconv_treatment:cents_to_amf_pre_cat31-40	-0.30016284	7.640855e-01
conditionstatic_treatment:cents_to_amf_pre_cat41-50	-2.88962851	3.900275e-03
conditionconv_treatment:cents_to_amf_pre_cat41-50	-1.96436708	4.963166e-02

conditionstatic_treatment:cents_to_amf_pre_cat51-100	-2.85459603	4.355439e-03
conditionconv_treatment:cents_to_amf_pre_cat51-100	-4.08475929	4.593704e-05
	CI Lower	CI Upper
(Intercept)	-0.1218976	1.142179800
conditionstatic_treatment	7.4652945	13.895484299
conditionconv_treatment	11.3205018	19.130525792
location_cat3National	-0.7764070	1.487928444
location_cat3Local/State	-1.5346843	1.657268737
location_cat3NA	-2.6409420	1.295120993
cents_to_amf_pre_cat10-Jan	-2.1571840	7.028522760
cents_to_amf_pre_cat20-Nov	-1.7182924	5.091825326
cents_to_amf_pre_cat21-30	-1.1775790	5.013559768
cents_to_amf_pre_cat31-40	-1.5687106	3.944842328
cents_to_amf_pre_cat41-50	-1.6714415	0.040751022
cents_to_amf_pre_cat51-100	-6.3078797	0.476272004
conditionstatic_treatment:location_cat3National	-5.0121811	1.552778056
conditionconv_treatment:location_cat3National	-5.4258644	2.553811545
conditionstatic_treatment:location_cat3Local/State	-4.8988965	9.861461858
conditionconv_treatment:location_cat3Local/State	-13.3660985	-3.167533418
conditionstatic_treatment:location_cat3NA	-3.5608955	7.772349999
conditionconv_treatment:location_cat3NA	-10.2951791	1.797933474
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	-12.2851092	6.450138562
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	0.1160556	28.262567839
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	-8.1202448	8.674454424
conditionconv_treatment:cents_to_amf_pre_cat20-Nov	-2.2246551	17.404251450
conditionstatic_treatment:cents_to_amf_pre_cat21-30	-11.6557128	-1.528419776
conditionconv_treatment:cents_to_amf_pre_cat21-30	-11.2596950	1.550054783
conditionstatic_treatment:cents_to_amf_pre_cat31-40	-13.6727697	-2.739326156
conditionconv_treatment:cents_to_amf_pre_cat31-40	-10.7895617	7.925249842
conditionstatic_treatment:cents_to_amf_pre_cat41-50	-8.6804971	-1.661409205
conditionconv_treatment:cents_to_amf_pre_cat41-50	-7.7263952	-0.006231652
conditionstatic_treatment:cents_to_amf_pre_cat51-100	-14.9255233	-2.768885198
conditionconv_treatment:cents_to_amf_pre_cat51-100	-17.4391583	-6.125258580
	DF	
(Intercept)	1919	
conditionstatic_treatment	1919	
conditionconv_treatment	1919	
location_cat3National	1919	
location_cat3Local/State	1919	
location_cat3NA	1919	
cents_to_amf_pre_cat10-Jan	1919	
cents_to_amf_pre_cat20-Nov	1919	
cents_to_amf_pre_cat21-30	1919	
cents_to_amf_pre_cat31-40	1919	
cents_to_amf_pre_cat41-50	1919	
cents_to_amf_pre_cat51-100	1919	
conditionstatic_treatment:location_cat3National	1919	
conditionconv_treatment:location_cat3National	1919	
conditionstatic_treatment:location_cat3Local/State	1919	
conditionconv_treatment:location_cat3Local/State	1919	
conditionstatic_treatment:location_cat3NA	1919	
conditionconv_treatment:location_cat3NA	1919	
conditionstatic_treatment:cents_to_amf_pre_cat10-Jan	1919	
conditionconv_treatment:cents_to_amf_pre_cat10-Jan	1919	
conditionstatic_treatment:cents_to_amf_pre_cat20-Nov	1919	



```

conditionconv_treatment:cents_to_amf_pre_cat20-Nov 1919
conditionstatic_treatment:cents_to_amf_pre_cat21-30 1919
conditionconv_treatment:cents_to_amf_pre_cat21-30 1919
conditionstatic_treatment:cents_to_amf_pre_cat31-40 1919
conditionconv_treatment:cents_to_amf_pre_cat31-40 1919
conditionstatic_treatment:cents_to_amf_pre_cat41-50 1919
conditionconv_treatment:cents_to_amf_pre_cat41-50 1919
conditionstatic_treatment:cents_to_amf_pre_cat51-100 1919
conditionconv_treatment:cents_to_amf_pre_cat51-100 1919

$omnibus_tests
$omnibus_tests$all
Linear hypothesis test

Hypothesis:
conditionstatic_treatment:location_cat3National = 0
conditionconv_treatment:location_cat3National = 0
conditionstatic_treatment:location_cat3Local/State = 0
conditionconv_treatment:location_cat3Local/State = 0
conditionstatic_treatment:location_cat3NA = 0
conditionconv_treatment:location_cat3NA = 0

Model 1: restricted model
Model 2: cents_to_amf_change ~ condition * location_cat3 + condition *
cents_to_amf_pre_cat

Res.Df Df    F Pr(>F)
1 1925
2 1919 6 2.357 0.02849 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$omnibus_tests$static_only
Linear hypothesis test

Hypothesis:
conditionstatic_treatment:location_cat3National = 0
conditionstatic_treatment:location_cat3Local/State = 0
conditionstatic_treatment:location_cat3NA = 0

Model 1: restricted model
Model 2: cents_to_amf_change ~ condition * location_cat3 + condition *
cents_to_amf_pre_cat

Res.Df Df    F Pr(>F)
1 1922
2 1919 3 0.8974 0.4417

$omnibus_tests$conv_only
Linear hypothesis test

Hypothesis:
conditionconv_treatment:location_cat3National = 0
conditionconv_treatment:location_cat3Local/State = 0
conditionconv_treatment:location_cat3NA = 0

```

```

Model 1: restricted model
Model 2: cents_to_amf_change ~ condition * location_cat3 + condition *
      cents_to_amf_pre_cat

      Res.Df Df      F Pr(>F)
1      1922
2      1919  3 3.5932 0.01314 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$omnibus_tests$conv-vs-static
Linear hypothesis test

Hypothesis:
- conditionstatic_treatment:location_cat3National + conditionconv_treatment:location_cat3National = 0
conditionconv_treatment:location_cat3Local/State = conditionstatic_treatment:location_cat3Local/State
- conditionstatic_treatment:location_cat3NA + conditionconv_treatment:location_cat3NA = 0

Model 1: restricted model
Model 2: cents_to_amf_change ~ condition * location_cat3 + condition *
      cents_to_amf_pre_cat

      Res.Df Df      F Pr(>F)
1      1922
2      1919  3 2.8388 0.03674 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$comparisons

      Term                                     Contrast location_cat3 Estimate
condition mean(conv_treatment) - mean(control)      International    15.20
condition mean(conv_treatment) - mean(control)      National          13.77
condition mean(conv_treatment) - mean(control)      Local/State         6.94
condition mean(conv_treatment) - mean(control)      NA                 10.95
condition mean(conv_treatment) - mean(static_treatment) International     9.02
condition mean(conv_treatment) - mean(static_treatment) National          9.31
condition mean(conv_treatment) - mean(static_treatment) Local/State       -1.73
condition mean(conv_treatment) - mean(static_treatment) NA                 2.66
condition mean(static_treatment) - mean(control)      International     6.19
condition mean(static_treatment) - mean(control)      National          4.46
condition mean(static_treatment) - mean(control)      Local/State         8.67
condition mean(static_treatment) - mean(control)      NA                 8.29
Std. Error      z Pr(>|z|)      S 2.5 % 97.5 %
      1.64  9.261 < 0.001 65.4 11.99 18.42
      2.04  6.757 < 0.001 36.0  9.77 17.76
      2.57  2.700 0.00694  7.2  1.90 11.97
      3.19  3.434 < 0.001 10.7  4.70 17.21
      1.88  4.794 < 0.001 19.2  5.33 12.70
      2.38  3.917 < 0.001 13.4  4.65 13.97
      4.29 -0.404 0.68633  0.5 -10.14  6.67
      3.96  0.673 0.50096  1.0 -5.09 10.42
      1.30  4.749 < 0.001 18.9  3.63  8.74

```

1.57	2.831	0.00464	7.8	1.37	7.54
3.62	2.392	0.01677	5.9	1.56	15.77
2.71	3.060	0.00222	8.8	2.98	13.60

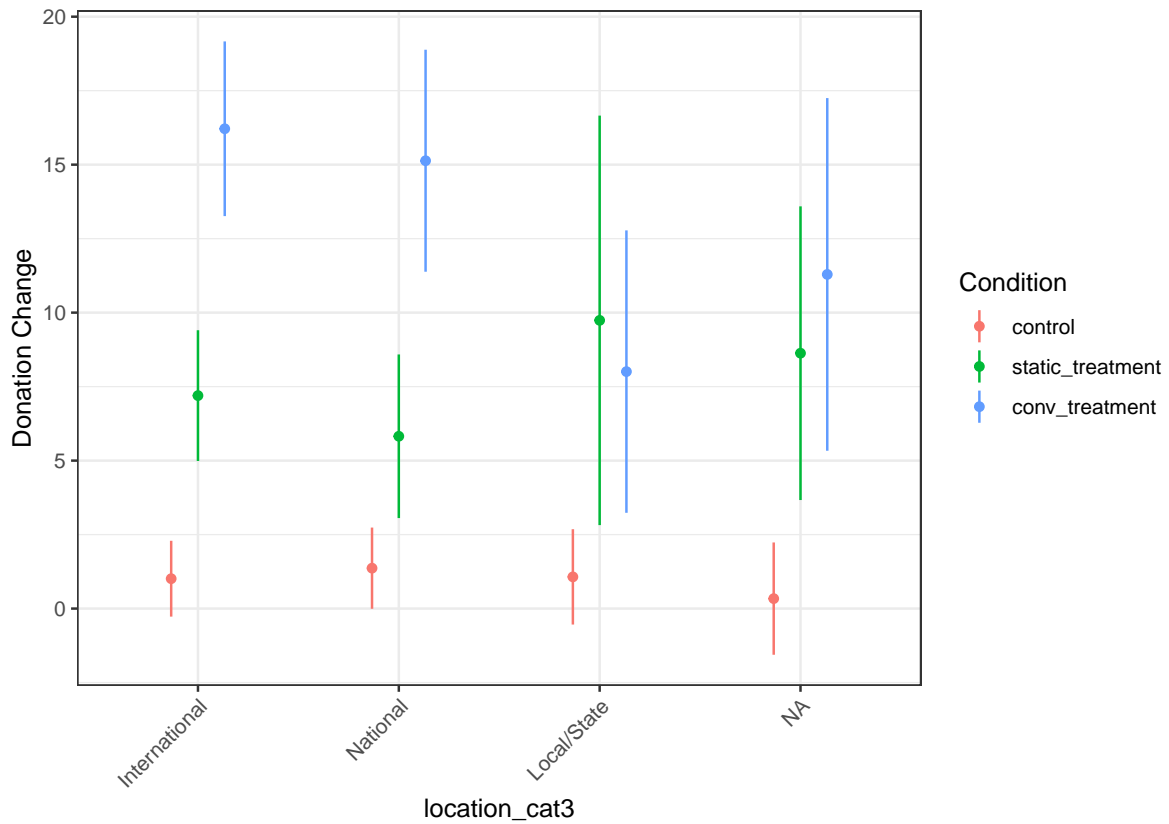
Columns: term, contrast, location\_cat3, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, predicted\_lo, predicted\_hi, predicted  
Type: response

\$preds

	condition	location_cat3	Estimate	Std. Error	z	Pr(> z )	S
control		National	1.366	0.700	1.951	0.05109	4.3
conv_treatment		National	15.133	1.914	7.908	< 0.001	48.4
static_treatment		National	5.822	1.410	4.129	< 0.001	14.7
control		NA	0.337	0.968	0.348	0.72788	0.5
conv_treatment		NA	11.291	3.040	3.714	< 0.001	12.3
static_treatment		NA	8.629	2.531	3.409	< 0.001	10.6
control		International	1.010	0.654	1.545	0.12241	3.0
conv_treatment		International	16.213	1.506	10.767	< 0.001	87.4
static_treatment		International	7.196	1.127	6.386	< 0.001	32.4
control		Local/State	1.071	0.822	1.303	0.19245	2.4
conv_treatment		Local/State	8.007	2.434	3.289	0.00100	10.0
static_treatment		Local/State	9.739	3.530	2.759	0.00579	7.4
2.5 % 97.5 %							
			-0.00644			2.74	
			11.38207			18.88	
			3.05843			8.59	
			-1.56060			2.23	
			5.33329			17.25	
			3.66755			13.59	
			-0.27143			2.29	
			13.26152			19.16	
			4.98752			9.41	
			-0.53957			2.68	
			3.23639			12.78	
			2.82100			16.66	

Columns: location\_cat3, condition, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high  
Type: response

\$marg\_plot



```
loc_cate_comparisons <- marginaleffects::avg_comparisons(
  loc_het$lm_mod,
  variables = "condition", #list("condition" = "minmax"), # just conv v control
  newdata = "balanced",
  by = c("location_cat3"),
  hypothesis = "pairwise",
  p_adjust = "holm"
)

## NOW for binned variables, cause area (subj) and population served (pop)
subj1_cond <- het_by_bins_cond("subj", d_subj1) #Level 1 of PCS
pop2_cond <- het_by_bins_cond("pop", d_pop2) #Lvl 2 fo PCS
```

## 8 Causal Forest Analysis

```
## Causal forests final

# input -----
```

```

covars_vec <- c(
  "age", "education",
  "Social_Conserv", "Economic_Conserv", #"pol_party",
  "EA_familiarity",
  "ous_instrumental_harm", "ous_impartial_beneficence",
  "crt_prop_cor", "mean_aot",
  "ai_use_1", "trust_ai_pre",
  "income_for_denominator",
  "charity_times_per_year",
  "charity_amount_per_year_log10",
  "charity_proportion_log10",
  "charity_wrong_pre",
  "dogs_v_cats_pre_1",
  "cents_to_amf_pre",
  "AwarenessOfNeed", "Solicitation", "Altruism", "Reputation", "PsychologicalBenefits",
  "Values", "Efficacy", "DoesntGive",
  "encompass_score",
  "revenue_log10"
)

covars_labels <- c(
  "Age", "Education",
  "Social Conservatism", "Economic Conservatism", #"Political Party",
  "EA Familiarity",
  "OUS: Instrumental Harm", "OUS: Impartial Beneficence",
  "CRT % Correct", "Mean AOT-E",
  "AI Use", "Trust in AI",
  "Income",
  "# Donations/yr",
  "$ Donations/yr (log10)",
  "Rel. $/yr (log10)",
  "Not Giving Wrong",
  "Dogs vs Cats",
  "Pre-trt Cents to AMF ",
  "Motivation: Awareness of Need", "Motivation: Solicitation", "Motivation: Altruism",
  "Motivation: Reputation", "Motivation: Psychological Benefits",
  "Motivation: Values", "Motivation: Efficacy", "Motivation: Doesn't Give",
  "Charity Navigator Encompass Score",
  "Revenue (log10)"
)

labels_map <- covars_labels
names(labels_map) <- covars_vec

# Run multi-arm causal forest
ma_cf <- grf::multi_arm_causal_forest(
  X = as.matrix(d[, covars_vec]),
  Y = d$cents_to_amf_change,
  W = d$condition,
  W.hat = rep(1/3, 3)
)

## ATE

```

```
ate <- grf::average_treatment_effect(ma_cf) #ATE
ites <- predict(ma_cf)$predictions
```

```
static_ites <- ites[, 1, ]
conv_ites <- ites[, 2, ]
```

```
sd(conv_ites)
```

```
[1] 1.71286
```

```
sd(static_ites)
```

```
[1] 1.072896
```

```
## plot variable importance
importance_tbl <- tibble(
  variable = covars_labels,
  variable_dirty = covars_vec,
  importance = grf::variable_importance(ma_cf)[, 1]
) |>
  arrange(desc(importance))

importance_plot <- importance_tbl %>%
  ggplot(aes(x = importance, y = reorder(variable, importance))) +
  geom_bar(
    stat = "identity",
    fill = amf_blue
  ) +
  labs(
    x = "Variable importance",
    y = NULL
  ) +
  theme(
    panel.grid = element_blank(),
    #panel.grid.minor = element_blank(),
    #panel.grid.major.y = element_blank(),
    #panel.grid.minor.x = element_blank()
  )
```

## 9 Generalized Additive Models (GAMs)

```
# run gams on these variables
important_covars <- c(
  "revenue_log10", "cents_to_amf_pre", "mean_aot", "ous_impartial_beneficence"
)
```

```
important_covar_names <- c(
  "revenue_log10" = "Charity 2024 Revenue (log10)",
  "cents_to_amf_pre" = "Pre-trt Cents to AMF",
  "mean_aot" = "Open-Minded Thinking (AOT-E)",

```

```

    ous_impartial_beneficence" = "Utilitarianism: Impartial Beneficence (OUS)"
  )

# run gams for each
gams <- lapply(
  important_covars,
  \(cov) run_gam_simple(d, cov, include_data = FALSE, add_hist = TRUE, x_label = important_covar_names[cov], include_legend =
    FALSE)
)

```

## 10 Persuasive Strategies Analysis

```

d_strategy1 <- read_csv("data/strategy_ratings_GPT4Sonnet3Deepseek.csv")
d_strategy3.7 <- read_csv("data/strategy_ratings_GPT4oSonnet3.7.csv") # sonnet 3.7

#combine all
d_strategy <- d_strategy1 |>
  bind_rows(d_strategy3.7)

d_strategy_long <- d_strategy |>
  pivot_longer(
    cols = EffectivenessFraming:GuiltAppeals,
    names_to = "strategy",
    values_to = "rating"
  ) |>
  mutate(
    rating = dplyr::recode(
      rating,
      "None" = 0,
      "Low" = 1,
      "Moderate" = 2,
      "High" = 3
    ),
  )

## MODEL agreement
d_strat_agree_wide <- d_strategy_long |>
  filter(ResponseId %in% ps_final) |> # yes want this just for real sample
  pivot_wider(names_from = model, values_from = rating) |>
  select(strategy, `deepseek/deepseek-chat-v3-0324`,`anthropic/claude-3.7-sonnet`) |>
  rename_with(~ str_remove(.x, "^.*"/))

strat_agreement <- agreement_analysis_by_group(d_strat_agree_wide, group_var = "strategy")

```

Grand ICC:

Call: `psych::ICC(x = select(d, -!!group_sym))`

Intraclass correlation coefficients

	type	ICC	F	df1	df2	p	lower bound	upper bound
Single_raters_absolute	ICC1	0.81	18	16399	49200	0	0.80	0.81
Single_random_raters	ICC2	0.81	19	16399	49197	0	0.79	0.82

```

Single_fixed_raters      ICC3 0.82 19 16399 49197 0      0.81      0.82
Average_raters_absolute ICC1k 0.94 18 16399 49200 0      0.94      0.95
Average_random_raters    ICC2k 0.94 19 16399 49197 0      0.94      0.95
Average_fixed_raters     ICC3k 0.95 19 16399 49197 0      0.95      0.95

```

Number of subjects = 16400      Number of Judges = 4

See the help file for a discussion of the other 4 McGraw and Wong estimates,  
Individual ICCs (ICC2k):

```

# A tibble: 25 x 10
# Groups:   strategy [25]
  strategy      icc_name type   ICC     F   df1   df2      p `lower bound`
  <chr>         <chr>   <chr> <dbl> <dbl> <dbl> <dbl>      <dbl>      <dbl>
1 Effectiveness~ Average~ ICC2k 0.681 3.70 655 1965 6.05e-110 0.585
2 CostEffective~ Average~ ICC2k 0.532 3.07 655 1965 2.93e- 80 0.288
3 GoalMatching~  Average~ ICC2k 0.840 6.34 655 1965 1.91e-222 0.819
4 MoralReasoning Average~ ICC2k 0.380 2.21 655 1965 9.41e- 40 0.149
5 Personalizati~ Average~ ICC2k 0.637 3.67 655 1965 2.11e-108 0.464
6 SplitDonation~ Average~ ICC2k 0.958 30.4 655 1965 0 0.936
7 ExpandingMora~ Average~ ICC2k 0.538 3.13 655 1965 6.41e- 83 0.294
8 AvoidingRegret Average~ ICC2k 0.359 2.20 655 1965 3.33e- 39 0.117
9 SocialNorms    Average~ ICC2k 0.884 8.63 655 1965 2.12e-303 0.869
10 AgencyFraming Average~ ICC2k 0.497 2.53 655 1965 8.40e- 55 0.313
11 MoralConsiste~ Average~ ICC2k 0.706 4.23 655 1965 4.31e-134 0.590
12 EfficiencyAnd~ Average~ ICC2k 0.596 2.98 655 1965 5.40e- 76 0.465
13 Transparency~ Average~ ICC2k 0.949 22.0 655 1965 0 0.936
14 IndependentEn~ Average~ ICC2k 0.878 9.80 655 1965 0 0.836
15 LegitimizingS~ Average~ ICC2k 0.900 11.2 655 1965 0 0.876
16 Observability~ Average~ ICC2k 0.575 2.44 655 1965 1.77e- 50 0.514
17 IdentifiableV~ Average~ ICC2k 0.345 2.26 655 1965 3.84e- 42 0.0880
18 PromotingDeli~ Average~ ICC2k 0.499 3.03 655 1965 3.57e- 78 0.225
19 PiquePricing~  Average~ ICC2k 0.780 4.54 655 1965 3.45e-148 0.751
20 GainFramedMes~ Average~ ICC2k 0.512 3.05 655 1965 4.38e- 79 0.249
21 PerceivedNeed~ Average~ ICC2k 0.596 2.88 655 1965 3.69e- 71 0.487
22 WarmGlow       Average~ ICC2k 0.638 3.51 655 1965 3.03e-101 0.489
23 SocialIdentity Average~ ICC2k 0.670 3.59 655 1965 9.16e-105 0.567
24 VirtueLabeling Average~ ICC2k 0.761 5.26 655 1965 3.83e-179 0.661
25 GuiltAppeals   Average~ ICC2k 0.532 2.51 655 1965 1.14e- 53 0.402
# i 1 more variable: `upper bound` <dbl>

```

mean ICCs (ICC):

```

# A tibble: 1 x 3
  mean_icc2k min_icc2k max_icc2k
    <dbl>      <dbl>      <dbl>
1    0.650    0.345    0.958

```

Cronbach's Alpha:

```

# A tibble: 25 x 10
# Groups:   strategy [25]
  strategy raw_alpha std.alpha `G6(smc)` average_r `S/N`   ase   mean   sd
  <chr>      <dbl>      <dbl>      <dbl>      <dbl> <dbl> <dbl> <dbl> <dbl>
1 Effecti~  0.730    0.751    0.700    0.430 3.01 0.0153 2.74 0.332
2 CostEff~  0.674    0.676    0.612    0.342 2.08 0.0208 2.32 0.313
3 GoalMat~  0.842    0.847    0.808    0.581 5.54 0.00996 2.02 0.581
4 MoralRe~  0.547    0.556    0.487    0.238 1.25 0.0273 1.40 0.277
5 Persona~  0.727    0.736    0.678    0.410 2.78 0.0169 2.33 0.387

```



```

6 SplitDo~ 0.967 0.970 0.961 0.889 31.9 0.00193 1.86 1.01
7 Expandi~ 0.680 0.693 0.636 0.360 2.25 0.0185 1.73 0.343
8 Avoidin~ 0.545 0.568 0.499 0.247 1.32 0.0269 0.646 0.305
9 SocialN~ 0.884 0.889 0.860 0.668 8.04 0.00722 0.0400 0.183
10 AgencyF~ 0.605 0.630 0.567 0.298 1.70 0.0230 1.88 0.312
11 MoralCo~ 0.763 0.774 0.722 0.462 3.43 0.0147 2.02 0.395
12 Efficie~ 0.665 0.691 0.628 0.359 2.24 0.0195 1.71 0.396
13 Transpa~ 0.955 0.957 0.947 0.849 22.5 0.00282 0.362 0.661
14 Indepen~ 0.898 0.902 0.876 0.696 9.17 0.00637 0.516 0.590
15 Legitim~ 0.911 0.913 0.892 0.723 10.5 0.00570 0.624 0.703
16 Observa~ 0.590 0.687 0.666 0.355 2.20 0.0224 0.0366 0.124
17 Identif~ 0.558 0.557 0.488 0.239 1.26 0.0279 0.710 0.312
18 Promoti~ 0.670 0.682 0.623 0.349 2.14 0.0195 1.96 0.339
19 PiquePr~ 0.780 0.775 0.765 0.462 3.44 0.0124 0.00953 0.0841
20 GainFra~ 0.672 0.675 0.616 0.341 2.07 0.0193 2.44 0.309
21 Perceiv~ 0.653 0.676 0.614 0.343 2.09 0.0215 1.98 0.293
22 WarmGlow 0.715 0.727 0.670 0.400 2.67 0.0174 1.11 0.362
23 SocialI~ 0.721 0.724 0.675 0.396 2.63 0.0170 0.454 0.365
24 VirtueL~ 0.810 0.821 0.783 0.534 4.58 0.0112 1.74 0.458
25 GuiltAp~ 0.602 0.615 0.549 0.285 1.59 0.0245 0.295 0.300
# i 1 more variable: median_r <dbl>

```

```
d_strat_agree_wide
```

```

# A tibble: 16,400 x 5
  strategy                `deepseek-chat-v3-0324` `claude-3-sonnet` `gpt-4o`
  <chr>                                <dbl>          <dbl>      <dbl>
1 EffectivenessFraming              3              3          2
2 CostEffectivenessGap              2              3          2
3 GoalMatching                     2              1          2
4 MoralReasoning                   2              2          2
5 Personalization                   2              3          2
6 SplitDonation                     0              0          0
7 ExpandingMoralConcern            2              3          2
8 AvoidingRegret                    1              1          1
9 SocialNorms                       0              0          0
10 AgencyFraming                    2              2          2
# i 16,390 more rows
# i 1 more variable: `claude-3.7-sonnet` <dbl>

```

```

d_strategy_agg_long <- d_strategy_long |>
  group_by(ResponseId, strategy) |>
  summarise(
    rating = mean(rating, na.rm = TRUE)
  )

d_strategy_agg_wide <- d_strategy_agg_long |>
  pivot_wider(
    names_from = strategy,
    values_from = rating
  ) |>
  ungroup()

# Link wide data with whole dataset

```

```

d_strat_all_wide <- d |>
  filter(treatment == "conv_treatment") |>
  select(ResponseId,
    cents_to_amf_change, cents_to_amf_pre, cents_to_amf_post, cents_to_amf_pre_cat, ## donation change
    charity_wrong_pre, charity_wrong_post, charity_wrong_change, link_clicked, ## other dvs

    # control for these other factors that might differ
    AwarenessOfNeed, Solicitation, CostsAndBenefits,
    Altruism, Reputation, PsychologicalBenefits, Values, Efficacy,
    DoesntGive) |>

## add new data
left_join(d_where[, c("ResponseId", "is_international", "location_cat3")], by = "ResponseId") |>
left_join(
  reduce_pcs_matrix(d_subj1 |> filter(condition == "conv_treatment"), "subj", min_n = 30) |>
    select(ResponseId, starts_with("subj")),
  by = "ResponseId"
) |>
left_join(
  reduce_pcs_matrix(d_pop2 |> filter(condition == "conv_treatment"), "pop", min_n = 30) |>
    select(ResponseId, starts_with("pop")),
  by = "ResponseId"
) |>
left_join(d_strategy_agg_wide, by = "ResponseId")

# Models -----

## for Donation change
# with the categorical control for pre score -- the exact same vars are significant.
mod_lm_donation <- d_strat_all_wide |>
  select(
    -ResponseId,
    -location_cat3,
    -cents_to_amf_post, -cents_to_amf_pre,
    -charity_wrong_pre, -charity_wrong_post, -charity_wrong_change, -link_clicked
  ) |>
  estimatr::lm_robust(
    cents_to_amf_change ~ .,
    data = _
  )

# hacky update p values with q values
mod_lm_donation$p.value <- get_qvals(mod_lm_donation, strat_names)
summary(mod_lm_donation)

```

Call:

```

estimatr::lm_robust(formula = cents_to_amf_change ~ ., data = select(d_strat_all_wide,
  -ResponseId, -location_cat3, -cents_to_amf_post, -cents_to_amf_pre,
  -charity_wrong_pre, -charity_wrong_post, -charity_wrong_change,
  -link_clicked))

```

Standard error type: HC2

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	-41.8199	19.8380	-2.10807
cents_to_amf_pre_cat10-Jan	12.5093	5.8365	2.14328
cents_to_amf_pre_cat20-Nov	3.4793	3.9854	0.87300
cents_to_amf_pre_cat21-30	-8.3573	3.3690	-2.48066
cents_to_amf_pre_cat31-40	-6.3085	5.3272	-1.18421
cents_to_amf_pre_cat41-50	-10.0836	2.5893	-3.89437
cents_to_amf_pre_cat51-100	-23.0533	3.8215	-6.03253
AwarenessOfNeed	1.3723	1.2331	1.11289
Solicitation	2.7581	1.9732	1.39772
CostsAndBenefits	-0.1027	0.9461	-0.10855
Altruism	0.3859	1.9086	0.20221
Reputation	-1.0834	2.7216	-0.39808
PsychologicalBenefits	0.7249	1.0383	0.69814
Values	-0.8121	1.2262	-0.66230
Efficacy	-0.2607	0.8934	-0.29183
DoesntGiveTRUE	2.1374	3.6922	0.57888
is_international	4.1754	3.0973	1.34805
subj_environment	2.4848	3.2749	0.75874
subj_health	-3.1466	3.0136	-1.04415
subj_human_services	2.4486	2.7568	0.88821
subj_public_safety_and_disaster_management	9.4284	5.1591	1.82752
subj_community_and_economic_development	-3.8915	3.9738	-0.97928
subj_international_relations	-14.6658	5.7708	-2.54136
subj_philanthropy	0.9475	4.1293	0.22946
subj_international_human_rights	12.1351	5.7115	2.12469
subj_unknown_or_not_classified	2.2061	4.7744	0.46208
subj_other_categorization	1.5554	2.2307	0.69726
pop_adults	-1.3997	2.7720	-0.50497
pop_children_and_youth	-1.0577	2.7317	-0.38720
pop_economically_disadvantaged_people	0.5148	3.0136	0.17083
pop_veterans	-8.9266	4.4874	-1.98924
pop_people_with_disabilities	2.6667	3.3526	0.79541
pop_people_with_diseases_and_illnesses	1.6493	4.2135	0.39145
pop_families	-1.9820	3.4711	-0.57100
pop_victims_of_violence_or_disasters	3.5648	6.9488	0.51301
pop_unknown_or_not_classified	-4.6744	4.7460	-0.98491
pop_pregnant_people	5.7446	6.4875	0.88549
pop_immigrants_and_migrants	-17.1423	7.3785	-2.32326
pop_military_personnel	-0.3745	6.4860	-0.05774
pop_women_and_girls	0.3721	4.6327	0.08032
pop_asian_people	11.4172	5.1286	2.22620
pop_other_categorization	-4.6763	3.1971	-1.46267
AgencyFraming	5.7709	3.7682	1.53146
AvoidingRegret	12.4395	4.5701	2.72190
CostEffectivenessGap	-3.6324	3.6011	-1.00869
EffectivenessFraming	10.9522	5.2844	2.07257
EfficiencyAndScale	-1.5120	2.1500	-0.70326
ExpandingMoralConcern	-4.6716	2.3223	-2.01166
GainFramedMessaging	11.3439	5.5072	2.05984
GoalMatching	2.0514	1.9974	1.02707
GuiltAppeals	-12.8915	4.9100	-2.62558

IdentifiableVictim	-2.3709	3.9059	-0.60701	
IndependentEndorsements	0.1127	1.9521	0.05771	
LegitimizingSmallContributions	-2.4822	1.2523	-1.98213	
MoralConsistency	0.3688	2.9901	0.12334	
MoralReasoning	2.8931	3.0844	0.93799	
Observability	4.5495	8.4300	0.53968	
PerceivedNeed	1.9767	3.4805	0.56793	
Personalization	-6.9724	4.1535	-1.67868	
PiquePricing	-9.3981	10.3018	-0.91227	
PromotingDeliberation	-3.7470	3.2617	-1.14880	
SocialIdentity	-1.3637	3.3763	-0.40390	
SocialNorms	-4.5485	5.1528	-0.88272	
SplitDonation	-1.0634	1.2785	-0.83172	
Transparency	4.1972	1.9843	2.11521	
VirtueLabeling	5.4618	1.9672	2.77635	
WarmGlow	3.2762	2.8971	1.13085	
	Pr(> t )	CI Lower	CI Upper	DF
(Intercept)	3.545e-02	-80.7818	-2.85798	589
cents_to_amf_pre_cat10-Jan	3.250e-02	1.0464	23.97231	589
cents_to_amf_pre_cat20-Nov	3.830e-01	-4.3480	11.30656	589
cents_to_amf_pre_cat21-30	1.339e-02	-14.9739	-1.74061	589
cents_to_amf_pre_cat31-40	2.368e-01	-16.7711	4.15411	589
cents_to_amf_pre_cat41-50	1.097e-04	-15.1690	-4.99828	589
cents_to_amf_pre_cat51-100	2.853e-09	-30.5587	-15.54788	589
AwarenessOfNeed	2.662e-01	-1.0495	3.79410	589
Solicitation	1.627e-01	-1.1174	6.63351	589
CostsAndBenefits	9.136e-01	-1.9608	1.75536	589
Altruism	8.398e-01	-3.3626	4.13453	589
Reputation	6.907e-01	-6.4286	4.26180	589
PsychologicalBenefits	4.854e-01	-1.3144	2.76413	589
Values	5.080e-01	-3.2203	1.59609	589
Efficacy	7.705e-01	-2.0153	1.49391	589
DoesntGiveTRUE	5.629e-01	-5.1141	9.38884	589
is_international	1.782e-01	-1.9078	10.25857	589
subj_environment	4.483e-01	-3.9471	8.91661	589
subj_health	2.968e-01	-9.0653	2.77203	589
subj_human_services	3.748e-01	-2.9657	7.86288	589
subj_public_safety_and_disaster_management	6.813e-02	-0.7041	19.56081	589
subj_community_and_economic_development	3.278e-01	-11.6961	3.91311	589
subj_international_relations	1.130e-02	-25.9997	-3.33184	589
subj_philanthropy	8.186e-01	-7.1624	9.05741	589
subj_international_human_rights	3.403e-02	0.9178	23.35248	589
subj_unknown_or_not_classified	6.442e-01	-7.1707	11.58297	589
subj_other_categorization	4.859e-01	-2.8257	5.93640	589
pop_adults	6.138e-01	-6.8439	4.04437	589
pop_children_and_youth	6.987e-01	-6.4227	4.30729	589
pop_economically_disadvantaged_people	8.644e-01	-5.4039	6.43354	589
pop_veterans	4.714e-02	-17.7399	-0.11329	589
pop_people_with_disabilities	4.267e-01	-3.9178	9.25108	589
pop_people_with_diseases_and_illnesses	6.956e-01	-6.6259	9.92458	589
pop_families	5.682e-01	-8.7993	4.83525	589
pop_victims_of_violence_or_disasters	6.081e-01	-10.0826	17.21223	589
pop_unknown_or_not_classified	3.251e-01	-13.9954	4.64672	589
pop_pregnant_people	3.763e-01	-6.9968	18.48609	589
pop_immigrants_and_migrants	2.050e-02	-31.6337	-2.65080	589

pop_military_personnel	9.540e-01	-13.1130	12.36405	589
pop_women_and_girls	9.360e-01	-8.7266	9.47083	589
pop_asian_people	2.638e-02	1.3447	21.48976	589
pop_other_categorization	1.441e-01	-10.9554	1.60278	589
AgencyFraming	1.952e-01	-1.6299	13.17161	589
AvoidingRegret	4.575e-02	3.4637	21.41521	589
CostEffectivenessGap	3.436e-01	-10.7049	3.44015	589
EffectivenessFraming	9.265e-02	0.5737	21.33074	589
EfficiencyAndScale	3.925e-01	-5.7346	2.71056	589
ExpandingMoralConcern	9.265e-02	-9.2325	-0.11067	589
GainFramedMessaging	9.265e-02	0.5278	22.15993	589
GoalMatching	3.436e-01	-1.8714	5.97430	589
GuiltAppeals	4.575e-02	-22.5346	-3.24834	589
IdentifiableVictim	4.145e-01	-10.0421	5.30027	589
IndependentEndorsements	5.902e-01	-3.7214	3.94669	589
LegitimizingSmallContributions	9.265e-02	-4.9417	-0.02271	589
MoralConsistency	5.812e-01	-5.5038	6.24139	589
MoralReasoning	3.436e-01	-3.1646	8.95087	589
Observability	4.145e-01	-12.0070	21.10609	589
PerceivedNeed	4.145e-01	-4.8590	8.81235	589
Personalization	1.611e-01	-15.1300	1.18508	589
PiquePricing	3.436e-01	-29.6308	10.83471	589
PromotingDeliberation	3.333e-01	-10.1530	2.65893	589
SocialIdentity	4.616e-01	-7.9947	5.26732	589
SocialNorms	3.436e-01	-14.6687	5.57163	589
SplitDonation	3.487e-01	-3.5745	1.44767	589
Transparency	9.265e-02	0.3000	8.09444	589
VirtueLabeling	4.575e-02	1.5981	9.32544	589
WarmGlow	3.333e-01	-2.4137	8.96610	589

Multiple R-squared: 0.3281 , Adjusted R-squared: 0.2528

F-statistic: 3.706 on 66 and 589 DF, p-value: < 2.2e-16

```
## For moral belief change
mod_lm_char_wrong <- d_strat_all_wide |>
  select(
    -ResponseId,
    -location_cat3,
    -cents_to_amf_post, -cents_to_amf_pre, -cents_to_amf_change, -cents_to_amf_pre_cat,
    -charity_wrong_post, -link_clicked
  ) |>
  estimatr::lm_robust(
    charity_wrong_change ~ . ,
    data = _
  )

# hacky update p values with q values
mod_lm_char_wrong$p.value <- get_qvals(mod_lm_char_wrong, strat_names)
mod_lm_char_wrong |> summary()
```

Call:

```
estimatr::lm_robust(formula = charity_wrong_change ~ ., data = select(d_strat_all_wide,
  -ResponseId, -location_cat3, -cents_to_amf_post, -cents_to_amf_pre,
  -cents_to_amf_change, -cents_to_amf_pre_cat, -charity_wrong_post,
```

-link\_clicked))

Standard error type: HC2

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	-3.66435	6.47768	-0.56569
charity_wrong_pre	-0.07560	0.02007	-3.76577
AwarenessOfNeed	0.80694	0.72238	1.11705
Solicitation	0.34334	0.80364	0.42723
CostsAndBenefits	-0.05869	0.60934	-0.09632
Altruism	0.20071	1.48724	0.13495
Reputation	0.06663	1.29965	0.05127
PsychologicalBenefits	-0.30133	0.68192	-0.44189
Values	-0.48426	1.08785	-0.44515
Efficacy	-0.71598	0.58286	-1.22839
DoesntGiveTRUE	-0.16729	2.21998	-0.07536
is_international	1.06391	2.06275	0.51577
subj_environment	-0.92735	1.51094	-0.61376
subj_health	-1.91810	1.80174	-1.06458
subj_human_services	-1.30676	1.48677	-0.87893
subj_public_safety_and_disaster_management	-1.14885	1.80099	-0.63790
subj_community_and_economic_development	-3.45496	2.50383	-1.37987
subj_international_relations	4.52282	2.70749	1.67049
subj_philanthropy	1.34674	2.40754	0.55938
subj_international_human_rights	0.17647	2.16884	0.08137
subj_unknown_or_not_classified	-1.01834	2.44225	-0.41697
subj_other_categorization	-0.77281	0.99660	-0.77545
pop_adults	-2.81427	1.53921	-1.82839
pop_children_and_youth	0.82014	1.51855	0.54008
pop_economically_disadvantaged_people	1.73918	1.36186	1.27707
pop_veterans	-0.76794	4.16639	-0.18432
pop_people_with_disabilities	1.79572	2.23995	0.80167
pop_people_with_diseases_and_illnesses	2.94944	3.07272	0.95988
pop_families	-0.77284	1.57950	-0.48930
pop_victims_of_violence_or_disasters	0.42452	4.60668	0.09215
pop_unknown_or_not_classified	-0.79765	2.03353	-0.39225
pop_pregnant_people	-0.71803	3.02811	-0.23712
pop_immigrants_and_migrants	-0.34469	4.88493	-0.07056
pop_military_personnel	-4.40006	4.75688	-0.92499
pop_women_and_girls	-1.37810	3.27923	-0.42025
pop_asian_people	-0.48023	2.45351	-0.19573
pop_other_categorization	1.53363	1.53698	0.99782
AgencyFraming	0.54247	2.04785	0.26490
AvoidingRegret	-4.78231	2.40554	-1.98804
CostEffectivenessGap	-0.62032	2.09387	-0.29626
EffectivenessFraming	0.09851	2.88026	0.03420
EfficiencyAndScale	-1.69794	1.40719	-1.20662
ExpandingMoralConcern	-1.73499	1.66691	-1.04084
GainFramedMessaging	3.81116	3.05640	1.24695
GoalMatching	-1.87913	1.53147	-1.22701
GuiltAppeals	2.46177	2.60222	0.94603
IdentifiableVictim	0.79013	1.89111	0.41782
IndependentEndorsements	1.72982	1.42267	1.21590
LegitimizingSmallContributions	-0.84986	0.69739	-1.21864

MoralConsistency	4.21431	1.91617	2.19934	
MoralReasoning	1.86120	2.02788	0.91781	
Observability	-0.27165	5.62575	-0.04829	
PerceivedNeed	1.54413	2.25339	0.68525	
Personalization	-4.13966	1.71154	-2.41867	
PiquePricing	21.79101	25.05740	0.86964	
PromotingDeliberation	1.67392	1.89746	0.88219	
SocialIdentity	0.51082	1.68794	0.30263	
SocialNorms	-2.56965	2.80265	-0.91686	
SplitDonation	-0.37112	0.60921	-0.60919	
Transparency	-0.52414	1.10263	-0.47536	
VirtueLabeling	0.79080	1.27571	0.61989	
WarmGlow	2.64018	2.13744	1.23521	
	Pr(> t )	CI Lower	CI Upper	DF
(Intercept)	0.5718189	-16.3863	9.05759	594
charity_wrong_pre	0.0001826	-0.1150	-0.03617	594
AwarenessOfNeed	0.2644235	-0.6118	2.22568	594
Solicitation	0.6693635	-1.2350	1.92165	594
CostsAndBenefits	0.9233013	-1.2554	1.13803	594
Altruism	0.8926936	-2.7202	3.12159	594
Reputation	0.9591300	-2.4858	2.61909	594
PsychologicalBenefits	0.6587282	-1.6406	1.03793	594
Values	0.6563744	-2.6208	1.65225	594
Efficacy	0.2197875	-1.8607	0.42874	594
DoesntGiveTRUE	0.9399566	-4.5272	4.19267	594
is_international	0.6062037	-2.9873	5.11508	594
subj_environment	0.5396088	-3.8948	2.04007	594
subj_health	0.2874972	-5.4566	1.62045	594
subj_human_services	0.3797957	-4.2267	1.61320	594
subj_public_safety_and_disaster_management	0.5237856	-4.6859	2.38824	594
subj_community_and_economic_development	0.1681448	-8.3724	1.46247	594
subj_international_relations	0.0953502	-0.7946	9.84024	594
subj_philanthropy	0.5761116	-3.3816	6.07506	594
subj_international_human_rights	0.9351778	-4.0830	4.43599	594
subj_unknown_or_not_classified	0.6768524	-5.8148	3.77815	594
subj_other_categorization	0.4383810	-2.7301	1.18447	594
pop_adults	0.0679925	-5.8372	0.20868	594
pop_children_and_youth	0.5893427	-2.1622	3.80252	594
pop_economically_disadvantaged_people	0.2020771	-0.9355	4.41382	594
pop_veterans	0.8538266	-8.9506	7.41471	594
pop_people_with_disabilities	0.4230616	-2.6035	6.19491	594
pop_people_with_diseases_and_illnesses	0.3375056	-3.0853	8.98416	594
pop_families	0.6248118	-3.8749	2.32924	594
pop_victims_of_violence_or_disasters	0.9266077	-8.6228	9.47188	594
pop_unknown_or_not_classified	0.6950163	-4.7914	3.19614	594
pop_pregnant_people	0.8126447	-6.6651	5.22907	594
pop_immigrants_and_migrants	0.9437698	-9.9385	9.24915	594
pop_military_personnel	0.3553479	-13.7424	4.94229	594
pop_women_and_girls	0.6744549	-7.8184	5.06220	594
pop_asian_people	0.8448867	-5.2988	4.33838	594
pop_other_categorization	0.3187708	-1.4849	4.55221	594
AgencyFraming	0.8127897	-3.4794	4.56437	594
AvoidingRegret	0.3722710	-9.5067	-0.05791	594
CostEffectivenessGap	0.8127897	-4.7326	3.49196	594
EffectivenessFraming	0.9193525	-5.5582	5.75524	594

EfficiencyAndScale	0.5987394	-4.4616	1.06574	594
ExpandingMoralConcern	0.6062148	-5.0087	1.53876	594
GainFramedMessaging	0.5987394	-2.1915	9.81383	594
GoalMatching	0.5987394	-4.8869	1.12862	594
GuiltAppeals	0.6062148	-2.6489	7.57244	594
IdentifiableVictim	0.7989081	-2.9239	4.50420	594
IndependentEndorsements	0.5987394	-1.0643	4.52388	594
LegitimizingSmallContributions	0.5987394	-2.2195	0.51978	594
MoralConsistency	0.3336130	0.4510	7.97761	594
MoralReasoning	0.6062148	-2.1215	5.84388	594
Observability	0.9193525	-11.3204	10.77713	594
PerceivedNeed	0.7123024	-2.8814	5.96971	594
Personalization	0.3336130	-7.5011	-0.77825	594
PiquePricing	0.6062148	-27.4209	71.00288	594
PromotingDeliberation	0.6062148	-2.0526	5.40046	594
SocialIdentity	0.8127897	-2.8042	3.82587	594
SocialNorms	0.6062148	-8.0740	2.93466	594
SplitDonation	0.7123024	-1.5676	0.82534	594
Transparency	0.7893144	-2.6897	1.64138	594
VirtueLabeling	0.7123024	-1.7147	3.29625	594
WarmGlow	0.5987394	-1.5577	6.83805	594

Multiple R-squared: 0.125 , Adjusted R-squared: 0.03511  
F-statistic: 0.782 on 61 and 594 DF, p-value: 0.8845

```
## For link clicked
mod_lm_clicked <- d_strat_all_wide |>
  select(
    -ResponseId,
    -location_cat3,
    -cents_to_amf_post, -cents_to_amf_pre, -cents_to_amf_change,
    -charity_wrong_pre, -charity_wrong_post, -charity_wrong_change,
  ) |>
  estimatr::lm_robust(
    link_clicked ~ . ,
    data = _
  )

mod_lm_clicked$p.value <- get_qvals(mod_lm_clicked, strat_names)
mod_lm_clicked |>
  summary()
```

Call:

```
estimatr::lm_robust(formula = link_clicked ~ ., data = select(d_strat_all_wide,
  -ResponseId, -location_cat3, -cents_to_amf_post, -cents_to_amf_pre,
  -cents_to_amf_change, -charity_wrong_pre, -charity_wrong_post,
  -charity_wrong_change, ))
```

Standard error type: HC2

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	-0.1442196	0.15804	-0.912541
cents_to_amf_pre_cat10-Jan	0.0989843	0.08255	1.199137



cents_to_amf_pre_cat20-Nov	-0.0468291	0.03379	-1.386066
cents_to_amf_pre_cat21-30	0.0660051	0.05381	1.226657
cents_to_amf_pre_cat31-40	0.1465738	0.08832	1.659525
cents_to_amf_pre_cat41-50	0.0854559	0.03923	2.178364
cents_to_amf_pre_cat51-100	0.0829792	0.06291	1.318939
AwarenessOfNeed	-0.0197934	0.01542	-1.283924
Solicitation	-0.0195889	0.01462	-1.339519
CostsAndBenefits	0.0214017	0.01578	1.356200
Altruism	-0.0024820	0.02870	-0.086477
Reputation	-0.0631622	0.02635	-2.396812
PsychologicalBenefits	0.0229992	0.01436	1.601283
Values	0.0265298	0.02200	1.205761
Efficacy	-0.0007643	0.01403	-0.054484
DoesntGiveTRUE	0.0125623	0.05684	0.221008
is_international	-0.0125199	0.03954	-0.316607
subj_environment	0.0037307	0.04614	0.080856
subj_health	-0.0550338	0.03756	-1.465160
subj_human_services	-0.0114188	0.03523	-0.324109
subj_public_safety_and_disaster_management	0.0282918	0.06043	0.468146
subj_community_and_economic_development	-0.0291522	0.04745	-0.614348
subj_international_relations	0.0036580	0.05629	0.064980
subj_philanthropy	-0.0928244	0.05120	-1.812821
subj_international_human_rights	-0.0111595	0.06004	-0.185872
subj_unknown_or_not_classified	0.0499592	0.07656	0.652543
subj_other_categorization	0.0071462	0.02765	0.258483
pop_adults	-0.0209989	0.03583	-0.586144
pop_children_and_youth	-0.0037499	0.04301	-0.087178
pop_economically_disadvantaged_people	0.0424832	0.03620	1.173524
pop_veterans	-0.0906360	0.07776	-1.165590
pop_people_with_disabilities	0.0369945	0.05885	0.628619
pop_people_with_diseases_and_illnesses	0.1388637	0.06300	2.204065
pop_families	-0.0314943	0.04729	-0.666042
pop_victims_of_violence_or_disasters	-0.0066427	0.09732	-0.068256
pop_unknown_or_not_classified	-0.0243907	0.06527	-0.373682
pop_pregnant_people	0.0813802	0.07899	1.030253
pop_immigrants_and_migrants	-0.0079113	0.09733	-0.081285
pop_military_personnel	-0.0005386	0.09340	-0.005767
pop_women_and_girls	-0.0945334	0.05474	-1.727052
pop_asian_people	-0.0983600	0.05211	-1.887538
pop_other_categorization	-0.0013590	0.03250	-0.041812
AgencyFraming	-0.0004600	0.04348	-0.010579
AvoidingRegret	0.0414186	0.07080	0.585019
CostEffectivenessGap	0.0185552	0.05514	0.336483
EffectivenessFraming	-0.0484890	0.06625	-0.731951
EfficiencyAndScale	-0.0229015	0.02922	-0.783842
ExpandingMoralConcern	0.0654269	0.03668	1.783897
GainFramedMessaging	0.0879522	0.07520	1.169610
GoalMatching	0.0446633	0.03254	1.372624
GuiltAppeals	-0.0943094	0.05703	-1.653810
IdentifiableVictim	-0.0299515	0.05253	-0.570136
IndependentEndorsements	0.0295093	0.03105	0.950445
LegitimizingSmallContributions	-0.0004766	0.01815	-0.026264
MoralConsistency	-0.0910066	0.04363	-2.085892
MoralReasoning	-0.0185010	0.04810	-0.384671
Observability	0.1205360	0.18767	0.642292

PerceivedNeed	-0.0364387	0.05117	-0.712135	
Personalization	-0.0001967	0.04720	-0.004166	
PiquePricing	-0.1899344	0.09918	-1.915006	
PromotingDeliberation	0.1182559	0.04672	2.531318	
SocialIdentity	0.0005043	0.05311	0.009496	
SocialNorms	0.1635297	0.11519	1.419620	
SplitDonation	0.0020485	0.01651	0.124077	
Transparency	-0.0168537	0.02833	-0.594987	
VirtueLabeling	0.0035839	0.02803	0.127849	
WarmGlow	-0.0609796	0.04205	-1.450084	
	Pr(> t )	CI Lower	CI Upper	DF
(Intercept)	0.36186	-0.454613	0.166174	589
cents_to_amf_pre_cat10-Jan	0.23096	-0.063137	0.261105	589
cents_to_amf_pre_cat20-Nov	0.16625	-0.113184	0.019526	589
cents_to_amf_pre_cat21-30	0.22044	-0.039676	0.171686	589
cents_to_amf_pre_cat31-40	0.09754	-0.026892	0.320040	589
cents_to_amf_pre_cat41-50	0.02977	0.008409	0.162502	589
cents_to_amf_pre_cat51-100	0.18770	-0.040583	0.206542	589
AwarenessOfNeed	0.19967	-0.050071	0.010484	589
Solicitation	0.18092	-0.048310	0.009132	589
CostsAndBenefits	0.17556	-0.009591	0.052395	589
Altruism	0.93112	-0.058852	0.053888	589
Reputation	0.01685	-0.114919	-0.011406	589
PsychologicalBenefits	0.10985	-0.005210	0.051208	589
Values	0.22839	-0.016683	0.069743	589
Efficacy	0.95657	-0.028316	0.026787	589
DoesntGiveTRUE	0.82516	-0.099073	0.124198	589
is_international	0.75165	-0.090184	0.065144	589
subj_environment	0.93558	-0.086888	0.094350	589
subj_health	0.14341	-0.128805	0.018737	589
subj_human_services	0.74597	-0.080613	0.057776	589
subj_public_safety_and_disaster_management	0.63985	-0.090400	0.146983	589
subj_community_and_economic_development	0.53922	-0.122348	0.064044	589
subj_international_relations	0.94821	-0.106902	0.114218	589
subj_philanthropy	0.07037	-0.193390	0.007741	589
subj_international_human_rights	0.85261	-0.129075	0.106756	589
subj_unknown_or_not_classified	0.51431	-0.100406	0.200324	589
subj_other_categorization	0.79612	-0.047152	0.061444	589
pop_adults	0.55800	-0.091360	0.049362	589
pop_children_and_youth	0.93056	-0.088229	0.080730	589
pop_economically_disadvantaged_people	0.24106	-0.028616	0.113583	589
pop_veterans	0.24425	-0.243356	0.062084	589
pop_people_with_disabilities	0.52984	-0.078588	0.152577	589
pop_people_with_diseases_and_illnesses	0.02791	0.015125	0.262603	589
pop_families	0.50564	-0.124363	0.061375	589
pop_victims_of_violence_or_disasters	0.94561	-0.197780	0.184494	589
pop_unknown_or_not_classified	0.70878	-0.152583	0.103802	589
pop_pregnant_people	0.30331	-0.073757	0.236518	589
pop_immigrants_and_migrants	0.93524	-0.199063	0.183241	589
pop_military_personnel	0.99540	-0.183978	0.182901	589
pop_women_and_girls	0.08468	-0.202037	0.012970	589
pop_asian_people	0.05958	-0.200704	0.003984	589
pop_other_categorization	0.96666	-0.065194	0.062476	589
AgencyFraming	0.99668	-0.085854	0.084935	589
AvoidingRegret	0.83647	-0.097630	0.180467	589

CostEffectivenessGap	0.96925	-0.089749	0.126859	589
EffectivenessFraming	0.83647	-0.178596	0.081618	589
EfficiencyAndScale	0.83647	-0.080284	0.034481	589
ExpandingMoralConcern	0.46847	-0.006606	0.137459	589
GainFramedMessaging	0.67397	-0.059736	0.235641	589
GoalMatching	0.53247	-0.019243	0.108569	589
GuiltAppeals	0.49349	-0.206308	0.017689	589
IdentifiableVictim	0.83647	-0.133128	0.073225	589
IndependentEndorsements	0.83647	-0.031469	0.090487	589
LegitimizingSmallContributions	0.99668	-0.036114	0.035161	589
MoralConsistency	0.46647	-0.176695	-0.005318	589
MoralReasoning	0.96925	-0.112961	0.075959	589
Observability	0.83647	-0.248039	0.489111	589
PerceivedNeed	0.83647	-0.136933	0.064056	589
Personalization	0.99668	-0.092895	0.092502	589
PiquePricing	0.46647	-0.384728	0.004859	589
PromotingDeliberation	0.29056	0.026503	0.210008	589
SocialIdentity	0.99668	-0.103798	0.104806	589
SocialNorms	0.53247	-0.062709	0.389768	589
SplitDonation	0.99668	-0.030377	0.034474	589
Transparency	0.83647	-0.072486	0.038779	589
VirtueLabeling	0.99668	-0.051472	0.058639	589
WarmGlow	0.53247	-0.143571	0.021611	589

Multiple R-squared: 0.12 , Adjusted R-squared: 0.02136  
F-statistic: 0.9291 on 66 and 589 DF, p-value: 0.6359

## 11 AI Accuracy Assessment

```
## correlation between accuracy and donation change

d_fact <- read_csv("data/fact_check_results.csv") |>
  mutate(
    round = ordered(
      round,
      levels = c("round1", "round2", "round3", "round4"),
      labels = c("Round 1", "Round 2", "Round 3", "Round 4")
    ),
    round_num = as.numeric(gsub("Round", "", round)),
  )

## agreement analysis
d_fact_wide <- d_fact %>%
  filter(ResponseId %in% ps_final) |> # yes want this just for real sample
  select(-explanation) |>
  pivot_wider(names_from = model, values_from = rating) |>
  select(-round, -round_num, -text, -ResponseId) |>
  rename_with(~ str_remove(.x, "^.*(/"))

d_fact_wide_by_round <- d_fact %>%
  filter(ResponseId %in% ps_final) |> # yes want this just for real sample
  select(-explanation) |>
```

```

pivot_wider(names_from = model, values_from = rating) |>
select(-round_num, -text, -ResponseId) |>
rename_with(~ str_remove(.x, "^.*"/))

agreement_analysis(d_fact_wide)

```

=== Intraclass Correlation (ICC) ===

Call: psych::ICC(x = d)

Intraclass correlation coefficients

	type	ICC	F	df1	df2	p	lower bound
Single_raters_absolute	ICC1	0.23	1.9	1811	3624	1.2e-60	0.20
Single_random_raters	ICC2	0.24	2.0	1811	3622	5.6e-68	0.21
Single_fixed_raters	ICC3	0.25	2.0	1811	3622	5.6e-68	0.22
Average_raters_absolute	ICC1k	0.48	1.9	1811	3624	1.2e-60	0.43
Average_random_raters	ICC2k	0.49	2.0	1811	3622	5.6e-68	0.44
Average_fixed_raters	ICC3k	0.50	2.0	1811	3622	5.6e-68	0.46
	upper bound						
Single_raters_absolute		0.26					
Single_random_raters		0.27					
Single_fixed_raters		0.28					
Average_raters_absolute		0.52					
Average_random_raters		0.53					
Average_fixed_raters		0.54					

Number of subjects = 1812      Number of Judges = 3

See the help file for a discussion of the other 4 McGraw and Wong estimates,

=== Cronbach's Alpha ===

raw_alpha	std.alpha	G6(smc)	average_r	S/N	ase	mean	sd
0.4968543	0.5089252	0.4170259	0.2567542	1.03635	0.02046639	93.19224	5.366181
median_r							
0.238058							

```

agreement_analysis_by_group(d_fact_wide_by_round, group_var = "round")

```

Grand ICC:

Call: psych::ICC(x = select(d, -!!group\_sym))

Intraclass correlation coefficients

	type	ICC	F	df1	df2	p	lower bound
Single_raters_absolute	ICC1	0.23	1.9	1811	3624	1.2e-60	0.20
Single_random_raters	ICC2	0.24	2.0	1811	3622	5.6e-68	0.21
Single_fixed_raters	ICC3	0.25	2.0	1811	3622	5.6e-68	0.22
Average_raters_absolute	ICC1k	0.48	1.9	1811	3624	1.2e-60	0.43
Average_random_raters	ICC2k	0.49	2.0	1811	3622	5.6e-68	0.44
Average_fixed_raters	ICC3k	0.50	2.0	1811	3622	5.6e-68	0.46
	upper bound						
Single_raters_absolute		0.26					
Single_random_raters		0.27					
Single_fixed_raters		0.28					
Average_raters_absolute		0.52					
Average_random_raters		0.53					
Average_fixed_raters		0.54					

```

Number of subjects = 1812      Number of Judges = 3
See the help file for a discussion of the other 4 McGraw and Wong estimates,
Individual ICCs (ICC2k):
# A tibble: 4 x 10
# Groups:   round [4]
  round  icc_name      type  ICC    F  df1  df2      p `lower bound`
  <ord>   <chr>          <chr> <dbl> <dbl> <dbl> <dbl>   <dbl>      <dbl>
1 Round 1 Average_random_r~ ICC2k 0.359 1.66 652 1304 7.63e-15    0.246
2 Round 2 Average_random_r~ ICC2k 0.401 1.69 578 1156 4.73e-14    0.311
3 Round 3 Average_random_r~ ICC2k 0.542 2.20 364 728 1.47e-19    0.455
4 Round 4 Average_random_r~ ICC2k 0.421 1.74 214 428 6.82e-7     0.275
# i 1 more variable: `upper bound` <dbl>

```

```

mean ICCs (ICC):
# A tibble: 1 x 3
  mean_icc2k min_icc2k max_icc2k
    <dbl>      <dbl>      <dbl>
1    0.431    0.359    0.542

```

```

Cronbach's Alpha:
# A tibble: 4 x 10
# Groups:   round [4]
  round  raw_alpha std.alpha `G6(smc)` average_r `S/N`   ase mean  sd
  <ord>   <dbl>      <dbl>      <dbl>      <dbl> <dbl>   <dbl> <dbl> <dbl>
1 Round 1    0.399    0.447    0.360    0.213 0.810 0.0383 90.9 3.89
2 Round 2    0.408    0.429    0.334    0.200 0.750 0.0414 93.6 5.86
3 Round 3    0.545    0.548    0.459    0.288 1.21 0.0380 95.2 5.34
4 Round 4    0.427    0.456    0.361    0.218 0.838 0.0657 95.8 5.12
# i 1 more variable: median_r <dbl>

```

```

# average across models
d_fact_ave <- d_fact %>%
  group_by(ResponseId, round, round_num, text) %>%
  summarise(accuracy = mean(rating)) %>%
  ungroup()

# likelihood of being factual claim reduces throughout rounds
trt_n <- d |> filter(condition == "conv_treatment") |> nrow()
d_fact_ave |>
  count(round) |>
  mutate(pct = n / trt_n * 100)

```

```

# A tibble: 4 x 3
  round    n  pct
  <ord> <int> <dbl>
1 Round 1  653 99.1
2 Round 2  579 87.9
3 Round 3  365 55.4
4 Round 4  215 32.6

```

```

## get factual accuracy over rounds
d_fact_ave |>
  group_by(round) %>%
  summarise(mean = mean(accuracy),

```

```

sd = sd(accuracy),
n = n(),
se = sd/sqrt(n),
min = min(accuracy),
max = max(accuracy),
) |>
ungroup()

```

```

# A tibble: 4 x 7
  round mean sd n se min max
<ord> <dbl> <dbl> <int> <dbl> <dbl> <dbl>
1 Round 1 90.9 3.89 653 0.152 68.3 98.3
2 Round 2 93.6 5.86 579 0.244 60 100
3 Round 3 95.2 5.34 365 0.279 60 100
4 Round 4 95.8 5.12 215 0.350 66.7 100

```

```

# model this increase over time
# linearly, reported in paper (but same general result regardless of specification)
d_fact_ave |> lm(accuracy ~ round_num, data = _) |> summary()

```

Call:

```
lm(formula = accuracy ~ round_num, data = d_fact_ave)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-34.838	-1.624	0.400	3.495	7.067

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	89.4801	0.2704	330.87	<2e-16 ***
round_num	1.7861	0.1169	15.28	<2e-16 ***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.052 on 1810 degrees of freedom  
Multiple R-squared: 0.1142, Adjusted R-squared: 0.1137  
F-statistic: 233.3 on 1 and 1810 DF, p-value: < 2.2e-16

```

## as successive differences (adjacent category comparison)
d_fact_ave |>
  within(contrasts(round) <- MASS::contr.sdif(nlevels(round))) |>
  lm(accuracy ~ round, data = _) |>
  summary()

```

Call:

```
lm(formula = accuracy ~ round, data = within(d_fact_ave, contrasts(round) <- MASS::contr.sdif(nlevels(round))))
```

Residuals:

	Min	1Q	Median	3Q	Max
	-35.181	-1.917	0.778	3.153	7.445

```

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  93.8531      0.1298 723.316 < 2e-16 ***
round2-1      2.6956      0.2871   9.389 < 2e-16 ***
round3-2      1.5971      0.3361   4.751 2.18e-06 ***
round4-3      0.5789      0.4324   1.339   0.181
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.029 on 1808 degrees of freedom
Multiple R-squared:  0.123, Adjusted R-squared:  0.1216
F-statistic: 84.55 on 3 and 1808 DF,  p-value: < 2.2e-16

```

```

# now with quadratic term
d_fact_ave |> lm(accuracy ~ round_num + I(round_num^2), data = _) |> summary()

```

```

Call:
lm(formula = accuracy ~ round_num + I(round_num^2), data = d_fact_ave)

```

```

Residuals:
    Min       1Q   Median       3Q      Max
-35.195  -1.908   0.776   3.138   7.442

```

```

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  87.1433      0.6102 142.803 < 2e-16 ***
round_num     4.2794      0.5958   7.182 9.96e-13 ***
I(round_num^2) -0.5318      0.1246  -4.267 2.08e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

Residual standard error: 5.028 on 1809 degrees of freedom
Multiple R-squared:  0.123, Adjusted R-squared:  0.1221
F-statistic: 126.9 on 2 and 1809 DF,  p-value: < 2.2e-16

```

```

## get overall totals
d_fact_ave |>
  summarise(
    mean = mean(accuracy),
    sd = sd(accuracy),
    n = n(),
    min = min(accuracy),
    max = max(accuracy)
  )

```

```

# A tibble: 1 x 5
  mean    sd    n  min  max
<dbl> <dbl> <int> <dbl> <dbl>
1  93.2  5.37 1812    60  100

```

```
## NOW lets get one accuracy per conversation, to get overall correlation with donation change
d_fact_subj_ave <- d_fact_ave %>%
  group_by(ResponseId) %>%
  summarise(accuracy = mean(accuracy)) %>%
  ungroup()

d_acc <- d |>
  select(ResponseId, cents_to_amf_change, cents_to_amf_pre, cents_to_amf_pre_cat, cents_to_amf_post) |>
  inner_join(d_fact_subj_ave, by = "ResponseId")

## regressions
estimatr::lm_robust(cents_to_amf_change ~ accuracy, data = d_acc) ## sig just by itself -- reported in paper
```

	Estimate	Std. Error	t value	Pr(> t )	CI Lower	CI Upper
(Intercept)	-37.7967950	21.242732	-1.779281	0.07566014	-79.50933534	3.9157453
accuracy	0.5404142	0.230214	2.347443	0.01920132	0.08836265	0.9924658
	DF					
(Intercept)	651					
accuracy	651					

```
estimatr::lm_robust(cents_to_amf_change ~ accuracy + cents_to_amf_pre_cat, data = d_acc) ## also sig when controlling for pre
↳ score.
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-33.2061118	21.1321526	-1.5713549	1.165906e-01
accuracy	0.5023934	0.2274136	2.2091612	2.751412e-02
cents_to_amf_pre_cat10-Jan	16.8706903	6.9340636	2.4330164	1.524434e-02
cents_to_amf_pre_cat20-Nov	9.3932582	4.5401019	2.0689532	3.894829e-02
cents_to_amf_pre_cat21-30	-1.6307244	2.7974219	-0.5829383	5.601386e-01
cents_to_amf_pre_cat31-40	2.1500650	4.4728549	0.4806919	6.308985e-01
cents_to_amf_pre_cat41-50	-3.1449275	1.8917566	-1.6624377	9.691090e-02
cents_to_amf_pre_cat51-100	-14.5469792	2.4516401	-5.9335703	4.838010e-09
	CI Lower	CI Upper	DF	
(Intercept)	-74.70223610	8.2900126	645	
accuracy	0.05583288	0.9489538	645	
cents_to_amf_pre_cat10-Jan	3.25462513	30.4867554	645	
cents_to_amf_pre_cat20-Nov	0.47809287	18.3084235	645	
cents_to_amf_pre_cat21-30	-7.12387844	3.8624296	645	
cents_to_amf_pre_cat31-40	-6.63305082	10.9331808	645	
cents_to_amf_pre_cat41-50	-6.85967291	0.5698180	645	
cents_to_amf_pre_cat51-100	-19.36113921	-9.7328192	645	

## 12 Figures

### 12.1 Charity Descriptive Plot

```
# charity descriptives plot

## charites plot?
top10 <- d |>
```



```

drop_na(charity_name_final) |>
count(charity_name_final) |>
arrange(desc(n)) |>
head(n = 10) |>
pull(charity_name_final)

# 1) Compute overall counts and total mentions
overall_counts <- d %>%
  drop_na(charity_name_final) %>%
  count(charity_name_final, sort = TRUE)

total_mentions <- sum(overall_counts$n)

# 2) Keep top 10
top_df <- overall_counts %>%
  slice_head(n = 10) %>% # top 10 by n
  mutate(
    prop = n / total_mentions, # proportion of all mentions
    short = dplyr::recode(charity_name_final, !!!short_names)
  )

charity_tab <-
  top_df %>%
  mutate(
    charity = short,
    prop = scales::percent(prop, accuracy = 0.1),
  ) |>
  select(charity, prop)

charity_tab_gt <-
  charity_tab |>
  gt() |>
  tab_header(
    title = "Top 10 Favorite Charities"
  ) |>
  cols_label(
    charity = "Charity",
    prop = "Proportion of Sample"
  ) |>
  fmt_percent(
    columns = vars(prop),
    decimals = 1
  ) |>
  tab_options(
    table.font.size = px(10),
    data_row.padding = px(2.5)
  )

# 3) Plot percentages
charity_plot <- ggplot(top_df, aes(x = fct_reorder(short, prop), y = prop)) +
  geom_col(fill = "steelblue") +
  scale_y_continuous(
    labels = scales::percent_format(accuracy = 0.1),
    expand = expansion(mult = c(0, 0.05))
  )

```

```

) +
labs(
  x = "Charity",
  y = "Proportion"
) +
theme_bw()

## population plot
pop_plot <- pop2_counts |>
  filter(count >= 20) |>
  filter(population_area != "adults") |>
  ggplot(
    aes(x = reorder(population_area, count), y = count, fill = amf_blue)
  ) +
  geom_col() +
  coord_flip() +
  labs(
    x = "Population served",
    y = "Count",
    title = "Population served by chosen favorite charities"
  ) +
  scale_x_discrete(labels = clean_names) +
  theme_bw() +
  theme(
    panel.grid.major.y = element_blank(),
    panel.grid.minor.y = element_blank(),
    axis.title.y = element_blank()
  ) +
  scale_fill_identity()

## subject plot
subject_plot <- subj1_counts |>
  ggplot(
    aes(x = reorder(subject_area, count), y = count,
        fill = amf_blue
        # fill = ifelse(
        #   subject_area == "health",
        #   amf_red,
        #   amf_blue
        # )
    )
  ) +
  geom_col() +
  scale_x_discrete(labels = clean_names) +
  coord_flip() +
  labs(
    x = "Subject area",
    y = "Count",
    title = "Cause area of chosen favorite charities"
  ) +
  theme_bw() +
  theme(
    panel.grid.major.y = element_blank(),
    panel.grid.minor.y = element_blank(),

```

```

    axis.title.y = element_blank()
  ) +
  scale_fill_identity()

## where plot (could probably inset this on3
where_plot <- d_where |>
  ggplot(
    aes(x = location_cat3,
        fill = amf_blue
        # fill = ifelse(
        #   location_cat3 == "International" & !is.na(location_cat3),
        #   amf_red,
        #   amf_blue
        # )
    )
  ) +
  geom_bar(aes(y = after_stat(count/sum(count)))) +
  #geom_bar() + #for count
  scale_y_continuous(
    labels = scales::percent_format(accuracy = 1),
    expand = expansion(mult = c(0, 0.05))
  ) +
  labs(title = "Where do the charities operate?",
       x = NULL,
       y = NULL) +
  theme_bw() +
  theme(
    title = element_text(size = 10),
    panel.grid = element_blank(),
    axis.title.x = element_blank()
  ) +
  scale_fill_identity()

## size plot?
d_size <- d |>
  select(ResponseId, condition, starts_with("cents_to_amf"), ein, revenue)

size_plot <- ggplot(d_size, aes(x = revenue)) +
  stat_bin(
    bins = 15,
    aes(
      #fill = ifelse(after_stat(x) > 5e7 & after_stat(x) < 6.5e7, amf_red, amf_blue)
      fill = amf_blue
    ),
    geom = "bar",
    show.legend = FALSE
  ) +
  scale_fill_identity() +
  scale_x_log10(
    breaks = scales::breaks_log(n = 7),
    labels = scales::label_number(

```

```

    scale_cut = scales::cut_short_scale(),
    prefix = "$",
    accuracy = 1
  )
) +
labs(
  title = "Charity size",
  x = "Charity 2024 Revenue (log10)",
  y = "Count"
)

### NOW LETS PUT IT ALL TOGETHER

p1 <- subject_plot +
  #inset_element(charity_plot, .1, .1, 1, .9)
  inset_element(charity_tab_gt, .35, .20, .975, .75)

p2 <- pop_plot +
  inset_element(when_plot, .23, 0.025, .975, .55)

# — 1) Shared theme —————
shared_theme <- theme(
  plot.title = element_text(size = 10),
  axis.title = element_text(size = 8.5),
  axis.text = element_text(size = 7),
  plot.tag.position = c(0.0, 0.95), # top-left corner
  plot.tag = element_text(size = 10, hjust = 0, vjust = 0, face = "bold"),
  panel.grid = element_blank()
)

# — 2) Read & style the JPEG logo —————
img <- jpeg::readJPEG("logo_amf.jpg")
img_grob <- rasterGrob(
  img,
  x = unit(0.20, "npc"), # 2% in from left
  y = unit(0.90, "npc"),
  just = c("left", "top") # align top-left
  #width = unit(1, "npc"), # fill its cell
  #height = unit(1, "npc"),
  #just = c("left", "top") # align top-left
)

# colours from logo
amf_blue <- "#0193CF"
amf_red <- "#CB1031"

# — 3) Build your rich HTML text —————
info_html <- paste0(
  "<b>Against Malaria Foundation (AMF)</b><br>",
  "<i>“We fund and provide long-lasting insecticidal<br>”,
  “nets to protect those at risk from malaria.”</i><br>",

```

```

" <b>Cause area</b>: Health<br/>",
" <b>Population</b>: People with diseases and illnesses<br/>",
" <b>Operation</b>: Internationally<br/>",
" <b>Size (2024 Revenue)</b>: $62.3M"
)

info_txt <- paste0(
  "**Against Malaria Foundation (AMF)**\n\n",
  "_We fund and provide long-lasting insecticidal nets \n",
  "to protect those at risk from malaria."_\n\n",
  "**Cause area**: Health \n",
  "**Population**: People with diseases and illnesses \n",
  "**Operation**: Internationally \n",
  "**Size (2024 Revenue)**: $62.3M"
)

text_grob <- richtext_grob(
  info_html,
  x      = unit(0.05, "npc"),
  y      = unit(0.5, "npc"),
  hjust  = 0,
  vjust  = 0.5,
  halign = 0, # left-align text
  align_widths = TRUE, # align text width
  gp     = gpar(fontsize = 8, lineheight = 1.1) # smaller text
)

# — 4) Arrange image + text in 1:4 ratio with null units —————
info_inner <- arrangeGrob(
  img_grob,
  nullGrob(), # spacer column
  text_grob,
  ncol      = 3,
  widths    = unit(c(1, 0.05, 4), "null"), # 0.05 = small space
  heights   = unit(1, "null")
)

# — 5) Draw a white background + border around that two-column block —————
#info_bordered <- grobTree(
#  rectGrob(gp = gpar(fill = "white", col = "black", lwd = 0.8)),
#  info_inner
#)

# — 6) Turn into one patchwork element —————
info_elem <- wrap_elements(full = info_inner)

# plot altogether
plots <- list(
  A = p1,
  B = p2,
  C = free(size_plot),
  D = free(info_elem)
)

```

```

final_plot <- wrap_plots(
  plots,
  design = "
    AA
    BB
    CD
  ",
  heights = c(2.5, 2.5, 1),
  widths = c(1, 4) # this only works on the aligned part of the plots, not the whole space!
) +
  plot_annotation(tag_levels = "A") &
  shared_theme

final_plot

```

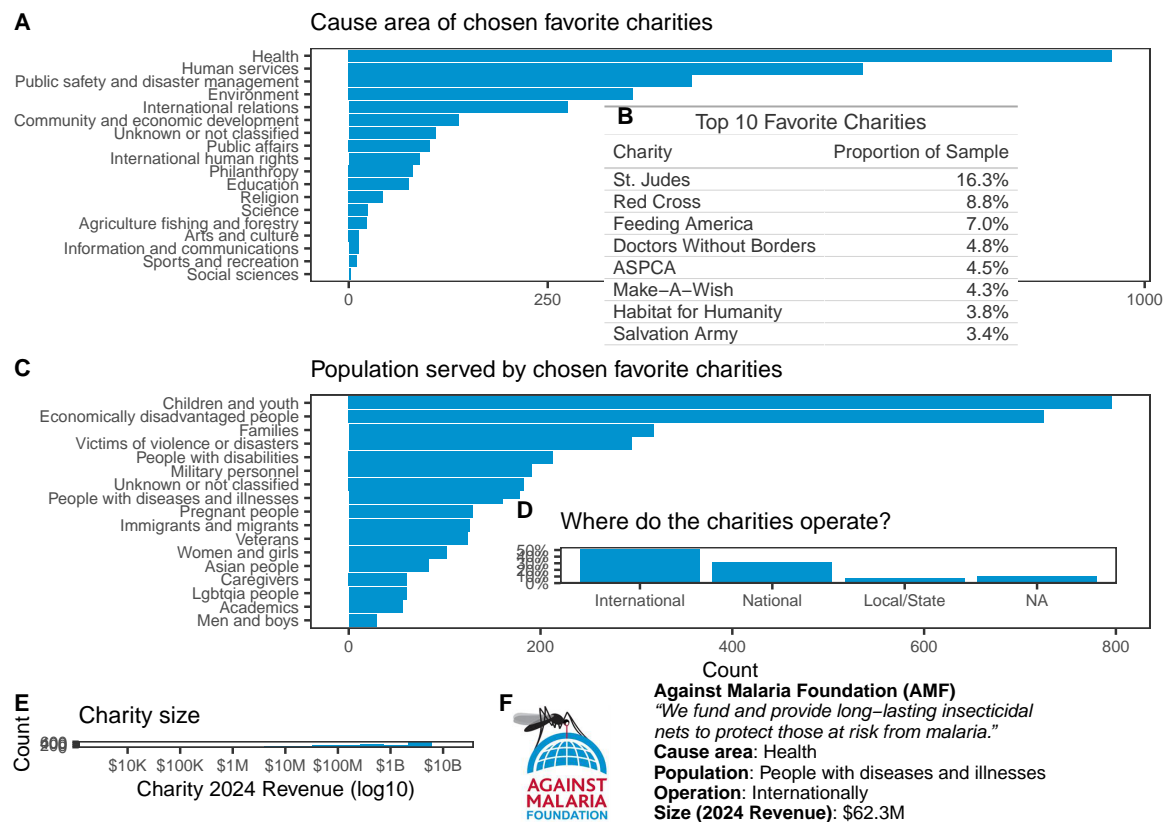


Figure 1: Figure 2: Charity descriptive statistics

```
# — 9) Save —————
ggsave("output/figures/charity_descriptive_plot_no_adults.png",
      final_plot,
      width = 6.25, # max width according to NHB is 7.1
      height = 7.1,
      dpi = FIGURE_DPI,
      create.dir = TRUE
)
```

## 12.2 Motivation Plots

```
# Add long label to your dataframe
m_dat_long <- m_dat %>%
  pivot_longer(AwarenessOfNeed:Efficacy, names_to = "variable", values_to = "value") |>
  filter(variable != "DoesntGive") %>%
  mutate(
    label = fct_rev(factor(variable)),
    label_formatted = fct_rev(factor(glue(
      "**{variable}**\n<span style='font-weight:normal; font-size:9pt'>{MOTIVATION_DESCRIPTIONS[variable]}</span>"
    ), levels = unique(variable)))
  )

# 1. Build HTML labels with <b> and <br>
label_map <- imap_chr(MOTIVATION_DESCRIPTIONS, ~ {
  clean_name <- str_to_sentence(str_replace_all(.y, "{?<=[a-z]}(?=[A-Z])", " " " "))
  paste0(
    "<b>", clean_name, "</b><br>",
    "<span style='font-size:8pt;'>", .x, "</span>"
  )
})
# Ensure names(label_map) match your factor levels

# 3. Plot
m_dat_long %>%
  filter(variable != "DoesntGive") %>%
  mutate(variable = factor(variable, levels = names(label_map))) %>%
  ggplot(aes(x = value, y = variable)) +
  stat_histinterval(
    point_interval = "mean_q1",
    breaks = seq(0.75, 5.25, by = 0.5),
    slab_color = NA,
    fill = amf_blue,
    alpha = 0.9,
    linewidth = 2,
    size = 3,
    .width = 0.5,
    interval_color = NA # REMOVE interval
  ) +
  scale_y_discrete(
    labels = label_map,
    expand = expansion(add = c(0.5, 0))
  )
```

```

) +
scale_x_continuous(
  breaks = seq(1, 5, 1),
  expand = expansion(add = c(0.25, 0.25))
) +
labs(
  x = "Rating",
  y = NULL#,
  #title = "Distribution of Motivation Ratings (Histogram Slabs)"
) +
theme_bw(base_size = 11) +
theme(
  axis.text.y = element_markdown(lineheight = 0.9),
  plot.title = element_text(face = "bold", size = 13, margin = margin(b = 4)),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank()
)

```

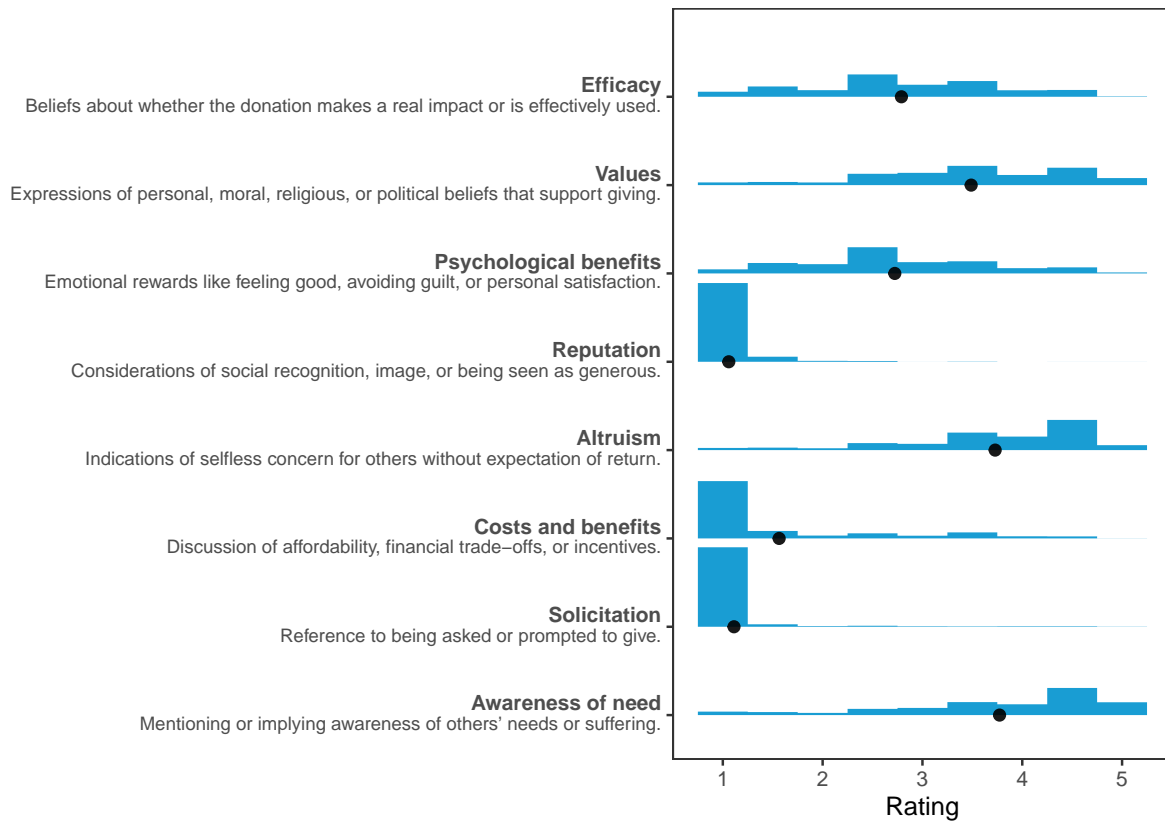


Figure 2: Figure S1: Motivation analysis plots



```

ggsave(
  filename = "output/figures/motivation-descriptives.png",
  width    = 7,
  height   = 3.5,
  dpi      = FIGURE_DPI
)

```

## 12.3 Main Treatment Effects Plot

```

# main plot

# Define condition labels
cond_names <- c(
  control = "Control conversation",
  static_treatment = "Static message",
  conv_treatment = "Persuasive LLM conversation"
)

cond_names_short <- c(
  control = "Control",
  static_treatment = "Static Msg",
  conv_treatment = "LLM Conv."
)

# --- Create Individual Plots ---
# --- Plot A, change by condition ---
a <- plot_predictions(
  lm_robust(cents_to_amf_change ~ condition * cents_to_amf_pre, data = d),
  by = c("condition"),
  newdata = "balanced",
) +
  aes(color = condition, fill = condition) +
  labs(
    x = NULL,
    color = "Condition",
    fill = "Condition",
    y = "Donation change"
  ) +
  scale_x_discrete(labels = cond_names_short) +
  scale_y_continuous(
    labels = scales::label_number(suffix = "c")
  ) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  coord_flip() +
  guides(color = guide_legend(reverse = TRUE), fill = guide_legend(reverse = TRUE)) +
  theme(
    #panel.grid.major.y = element_blank(),
    legend.position = "bottom"
  )

## Plot B, change by pre (binned)

```

```

nl_preds <- plot_predictions(
  lm_robust(cents_to_amf_change ~ condition * cents_to_amf_pre_cat, data = d),
  by = c("cents_to_amf_pre_cat", "condition"),
  newdata = "balanced",
  draw = FALSE
) |>
  ggplot(
    aes(x = cents_to_amf_pre_cat,
        y = estimate, ymin = conf.low, ymax = conf.high,
        colour = condition, fill = condition)
  ) +
  geom_pointrange(size = 0.25, position = position_dodge(width = 0.25), show.legend = FALSE) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  labs(
    x = "Pre-treatment donation to AMF",
    y = "Donation change"
  ) +
  scale_y_continuous(
    labels = scales::label_number(suffix = "c")
  ) +
  scale_x_discrete(labels = function(x) paste0(x, "c")) +
  ggsci::scale_color_locuszoom(labels = cond_names) +
  ggsci::scale_fill_locuszoom(labels = cond_names) +
  theme(
    panel.grid.major.x = element_blank(),
    plot.margin = margin(0, 0, 0, 0)
  )

# get n counts and have histogram
n_counts <- d %>%
  count(cents_to_amf_pre_cat) %>%
  mutate(label = paste0("n = ", n))

histogram_plot <- ggplot(n_counts, aes(x = as.factor(cents_to_amf_pre_cat), y = n)) +
  geom_bar(stat = "identity", fill = "darkgray", alpha = 0.4) +
  theme_void() +
  theme(axis.text.x = element_blank(), axis.ticks.x = element_blank()) +
  geom_text(
    data = n_counts,
    aes(label = label),
    y = 100,
    size = 2.5
  ) +
  theme(plot.margin = margin(0, 0, 0, 0))

b <- (histogram_plot /
      (nl_preds + plot_layout(tag_level = "new")))
) +
  plot_layout(heights = c(0.3, 1))

# --- Apply Consistent Scales After Creating Plots ---

```

```

color_scale <- ggsci::scale_color_locuszoom(labels = cond_names)
fill_scale <- ggsci::scale_fill_locuszoom(labels = cond_names)

a <- a + color_scale + fill_scale
b <- b + color_scale + fill_scale
l <- guide_area() # specify legend space

# --- Arrange Plots in Patchwork ---

# Define layout
design <- "
ABB
LLL
"

# Combine plots with shared legend
final_plot <- wrap_plots(a, b, l, design = design) +
  plot_annotation(tag_levels = "A") +
  plot_layout(guides = "collect", heights = c(1, 0.1)) &
  theme(
    panel.grid = element_blank(),
    plot.tag.position = c(0.0, 0.95), # top-left corner
    plot.tag = element_text(size = 10, hjust = 0, vjust = 0, face = "bold")
  )

final_plot

```

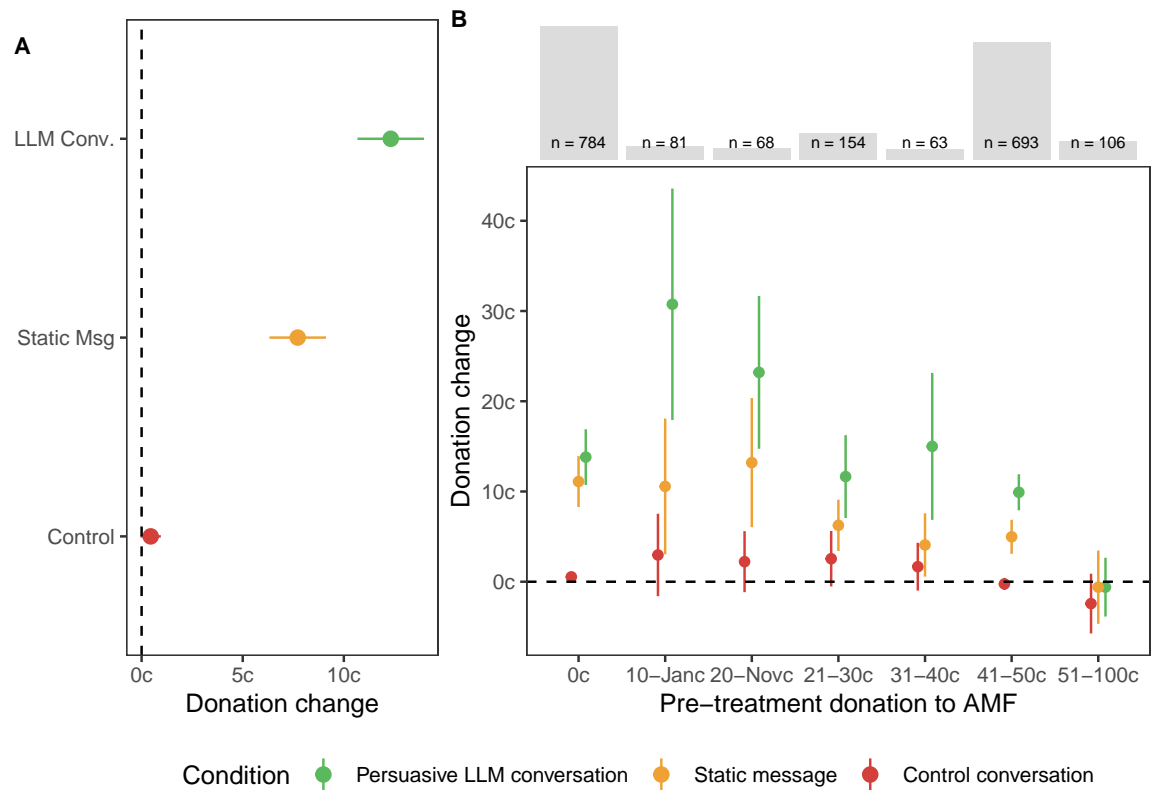


Figure 3: Figure 3: Main treatment effects

```
shared_theme <- theme(
  plot.title = element_text(size = 10),
  axis.title = element_text(size = 8.5),
  axis.text = element_text(size = 7),
  plot.tag.position = c(0.0, 0.95), # top-left corner
  plot.tag = element_text(size = 10, hjust = 0, vjust = 0, face = "bold"),
  panel.grid = element_blank()
)

# Save and Display
ggsave(
  "output/figures/main_plot.png",
  final_plot, width = FIGURE_WIDTH, height = 3, units = "in", dpi = FIGURE_DPI
)
```

## 12.4 Categorical Heterogeneity Plot

```
#categorical heterogeneity plot

# -----
# POSITION PARAMETERS FOR SIG DIFFERENCES (fractions of panel CI-range)
initial_offset_frac <- 0.05 # how far beyond the max CI the first bracket stem sits
bracket_spacing_frac <- 0.04 # spacing between successive bracket stems
leg_length_frac <- 0.02 # horizontal "leg" tick length
symbol_offset_frac <- 0.5 # distance from the bracket stem to the star
symbol_size <- 1.5
# -----

## FOR CHARITY HETEROGENEITY
df_plot <- char_het$comparisons |>
  filter(contrast == "mean(conv_treatment) - mean(control)") |>
  mutate(
    charity_fct = fct_reorder(charity_fct, estimate, \(x) median(abs(x))),
    #charity_fct = fct_rev(charity_fct),
    contrast = factor(contrast, levels = unique(contrast))
  )

manual_p <- char_cate_comparisons %>%
  tidyr::extract(
    term,
    into = c("group1", "group2"),
    regex = "^\\((.+)\\)\\s*~\\s*\\((.+)\\)$"
  ) %>%
  mutate(
    contrast = "mean(conv_treatment) - mean(control)",
    code1 = as.integer(factor(group1, levels = levels(df_plot$charity_fct))),
    code2 = as.integer(factor(group2, levels = levels(df_plot$charity_fct))),
    group1 = factor(levels(df_plot$charity_fct)[pmax(code1, code2)],
      levels = levels(df_plot$charity_fct)),
    group2 = factor(levels(df_plot$charity_fct)[pmin(code1, code2)],
      levels = levels(df_plot$charity_fct))
  ) |>
  select(-code1, -code2) |>
  mutate(
    p_str = as.character(p.value),
    p_num = readr::parse_number(p_str),
    signif = case_when(
      str_detect(p_str, "^<") & p_num <= 0.001 ~ "***",
      p_num < 0.001 ~ "***",
      p_num < 0.01 ~ "**",
      p_num < 0.05 ~ "*",
      p_num < 0.1 ~ "+",
      TRUE ~ NA_character_
    ),
    shape = case_when(
      p_num < 0.001 ~ "triangle",

```

```

    p_num < 0.01      ~ "square",
    p_num < 0.05      ~ "circle",
    p_num < 0.10      ~ "diamond",
    TRUE             ~ NA_character_
  )
) %>%
filter(!is.na(signif)) %>%
mutate(
  contrast = factor(contrast, levels = levels(df_plot$contrast)),
  y1       = as.numeric(factor(group1, levels = levels(df_plot$charity_fct))),
  y2       = as.numeric(factor(group2, levels = levels(df_plot$charity_fct))),
  y        = (y1 + y2) / 2
) %>%
group_by(contrast) |>
arrange(desc(group1), desc(group2)) %>%
mutate(idx = row_number()) %>%
ungroup()

# 4. Compute per-panel CI stats & scaled offsets
panel_info <- df_plot %>%
  group_by(contrast) %>%
  summarise(
    max_hi = max(conf.high),
    min_lo = min(conf.low)
  ) %>%
  mutate(
    range      = max_hi - min_lo,
    offset     = initial_offset_frac * range,
    spacing    = bracket_spacing_frac * range,
    leg_length = leg_length_frac * range,
    symbol_offset = symbol_offset_frac * range
  )

# 5. Join & turn those fractions into absolute positions
manual_p <- manual_p %>%
  left_join(panel_info, by = "contrast") %>%
  mutate(
    x_start = max_hi + offset,
    x       = x_start + (idx - 1) * spacing,
    x_leg_end = x - leg_length,
    labelx   = x + symbol_offset
  )

# 6. Plot everything
p1 <- ggplot(df_plot, aes(x = estimate, y = charity_fct, color = contrast)) +
  # forest plot
  geom_point(position = position_dodge(0.4)) +
  geom_linerange(aes(xmin = conf.low, xmax = conf.high),
    position = position_dodge(0.4)) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  facet_wrap(~contrast, ncol = 1,
    labeller = labeller(contrast = comparison_names_cate)) +
  scale_color_manual(
    values = contrast_colors,

```

```

    labels = comparison_names_short
  ) +
  scale_y_discrete(labels = short_names) +
  labs(x = "Conditional Average Treatment Effect (95% CI)", y = NULL) +
  theme(legend.position = "bottom") +
  # bracket stems
  geom_segment(data = manual_p,
    aes(x = x, xend = x, y = y1, yend = y2),
    inherit.aes = FALSE) +
  # inward legs
  geom_segment(data = manual_p,
    aes(x = x, xend = x_leg_end, y = y1, yend = y1),
    inherit.aes = FALSE) +
  geom_segment(data = manual_p,
    aes(x = x, xend = x_leg_end, y = y2, yend = y2),
    inherit.aes = FALSE) +
  # stars
  geom_text(data = manual_p,
    aes(x = x, y = y, label = signif),
    inherit.aes = FALSE,
    hjust = 0.5, vjust = 0.25, size = 4)

# shapes
# geom_point(
#   data = manual_p,
#   aes(x = x, y = y, shape = shape),
#   inherit.aes = FALSE,
#   size = symbol_size
# ) +
# scale_shape_manual(
#   values = c(
#     circle = 16, # filled circle
#     square = 15, # filled square
#     triangle = 17, # filled triangle-up
#     diamond = 18 # filled diamond
#   ),
#   na.translate = FALSE
# )

## LOCATION HETEROGENEITY

# 2. Prepare forest-plot data
df_plot <- loc_het$comparisons %>%
  filter(contrast == "mean(conv_treatment) - mean(control)") %>%
  mutate(
    location = fct_rev(location_cat3),
    contrast = factor(contrast, levels = unique(contrast))
  )

# 3. Parse & filter only within-contrast significant tests
manual_p <- loc_cate_comparisons %>%
  tidyr::extract(
    term,
    into = c("contrast1", "group1", "contrast2", "group2"),

```

```

    regex = "^\\(([^,]+), ([^)]+)\\) - \\(([^,]+), ([^)]+)\\)$"
  ) %>%
  filter(contrast1 == contrast2) %>%
  rename(contrast = contrast1) %>%
  mutate(
    p_str = as.character(p.value),
    p_num = readr::parse_number(p_str),
    signif = case_when(
      str_detect(p_str, "^<") & p_num <= 0.001 ~ "***",
      p_num < 0.001 ~ "***",
      p_num < 0.01 ~ "**",
      p_num < 0.05 ~ "*",
      p_num < 0.1 ~ "+",
      TRUE ~ NA_character_
    ),
    shape = case_when(
      p_num < 0.001 ~ "triangle",
      p_num < 0.01 ~ "square",
      p_num < 0.05 ~ "circle",
      p_num < 0.10 ~ "diamond",
      TRUE ~ NA_character_
    )
  ) %>%
  filter(!is.na(signif)) %>%
  mutate(
    contrast = factor(contrast, levels = levels(df_plot$contrast)),
    y1 = as.numeric(factor(group1, levels = levels(df_plot$location))),
    y2 = as.numeric(factor(group2, levels = levels(df_plot$location))),
    y = (y1 + y2) / 2
  ) %>%
  group_by(contrast) %>%
  mutate(idx = row_number()) %>%
  ungroup()

# 4. Compute per-panel CI stats & scaled offsets
panel_info <- df_plot %>%
  group_by(contrast) %>%
  summarise(
    max_hi = max(conf.high),
    min_lo = min(conf.low)
  ) %>%
  mutate(
    range = max_hi - min_lo,
    offset = initial_offset_frac * range,
    spacing = bracket_spacing_frac * range,
    leg_length = leg_length_frac * range,
    symbol_offset = symbol_offset_frac * range
  )

# 5. Join & turn those fractions into absolute positions
manual_p <- manual_p %>%
  left_join(panel_info, by = "contrast") %>%
  mutate(
    x_start = max_hi + offset,

```



```

    x      = x_start + (idx - 1) * spacing,
    x_leg_end = x - leg_length,
    labelx   = x + symbol_offset
  )

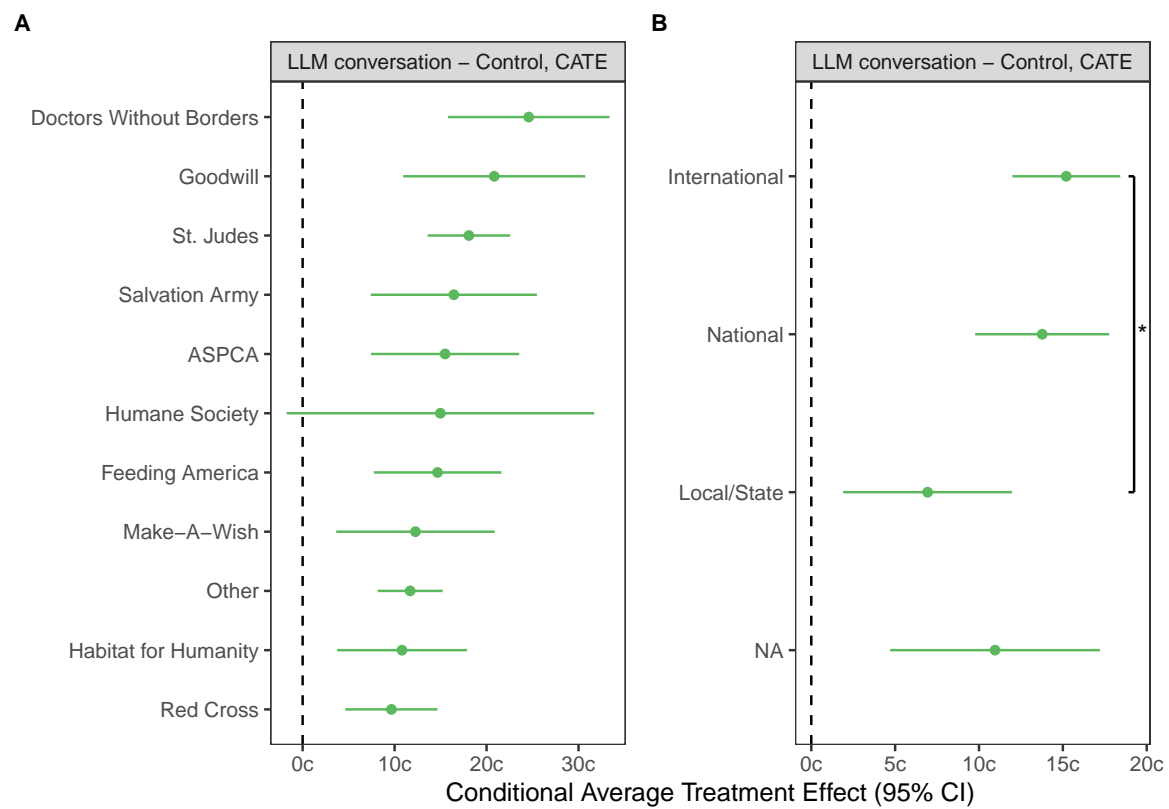
# 6. Plot everything
p2 <- ggplot(df_plot, aes(x = estimate, y = location, color = contrast)) +
  # forest plot
  geom_point(position = position_dodge(0.4)) +
  geom_linerange(aes(xmin = conf.low, xmax = conf.high),
    position = position_dodge(0.4)) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  facet_wrap(~contrast, ncol = 1,
    labeller = labeller(contrast = comparison_names_cate)) +
  scale_color_manual(
    values = contrast_colors,
    labels = comparison_names_short
  ) +
  labs(x = "Conditional Average Treatment Effect (95% CI)", y = NULL) +
  theme(legend.position = "bottom") +
  # bracket stems
  geom_segment(data = manual_p,
    aes(x = x, xend = x, y = y1, yend = y2),
    inherit.aes = FALSE) +
  # inward legs
  geom_segment(data = manual_p,
    aes(x = x, xend = x_leg_end, y = y1, yend = y1),
    inherit.aes = FALSE) +
  geom_segment(data = manual_p,
    aes(x = x, xend = x_leg_end, y = y2, yend = y2),
    inherit.aes = FALSE) +
  # stars
  geom_text(data = manual_p,
    aes(x = x, y = y, label = signif),
    inherit.aes = FALSE,
    hjust = -.35, vjust = 0.5, size = 4)

# shapes
# geom_point(
#   data      = manual_p,
#   aes(x = x, y = y, shape = shape),
#   inherit.aes = FALSE,
#   size      = symbol_size
# ) +
# scale_shape_manual(
#   values = c(
#     circle = 16, # filled circle
#     square = 15, # filled square
#     triangle = 17 # filled triangle-up
#   ),
#   na.translate = FALSE
# )

# PUT TOGETHER

```

```
(p1 + p2) +
  plot_annotation(tag_levels = "A") +
  plot_layout(guides = "collect", axes = "collect", widths = c(3/3, 1)) &
  geom_hline(yintercept = 0, linetype = "dashed", color = "black") &
  scale_x_continuous(label = scales::label_number(suffix = "c")) &
  theme(
    legend.position = "none",
    #axis.title.x = element_blank(),
    panel.grid = element_blank(),
    #plot.tag.position = c(0.0, 1), # top-left corner
    plot.tag = element_text(size = 10, vjust = 2, face = "bold")
  )
)
```



```
ggsave(
  "output/figures/cat_het_cates.png",
  width = FIGURE_WIDTH,
```

```
height = 3.5  
)
```

## 12.5 Binned Heterogeneity Plot

```
## binned categorical variable plots  
  
subj1_cond$mod |>  
  broom::tidy() |>  
  dplyr::filter(grepl("^conditionconv_treatment:subj_", term)) |>  
  mutate(  
    cause_area = gsub("conditionconv_treatment:subj_", "", term),  
    cause_area = clean_names(cause_area)  
  ) |>  
  ggplot(aes(x = estimate, y = cause_area)) +  
  geom_point() +  
  geom_errorbar(aes(xmin = conf.low, xmax = conf.high)) +  
  labs(x = "Estimated CATE", y = "Cause Area") +  
  theme_minimal()
```

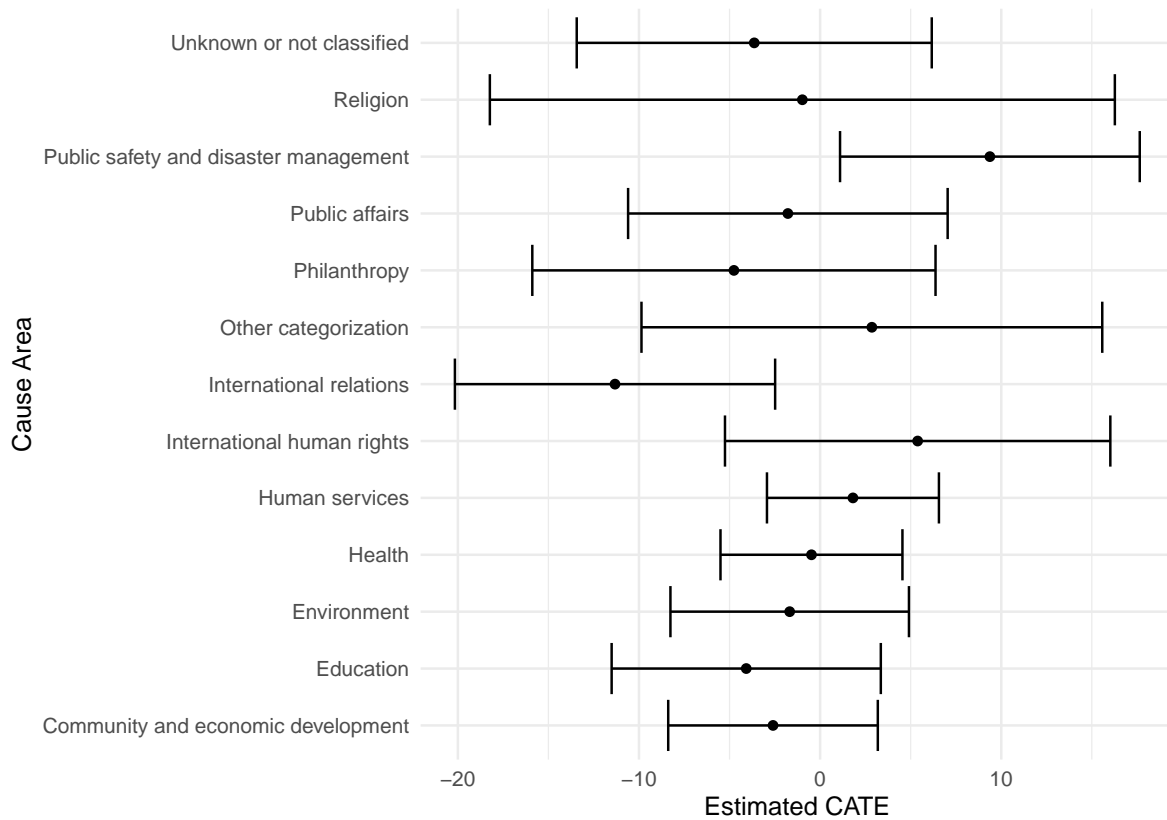


Figure 5: Figure S2: Binned heterogeneity analysis

```
## Profile TEs
# no sig differences between any groups
#subj1_cond$profile_tes_diff
#pop2_cond$profile_tes_diff

p1 <- subj1_cond$profile_tes |>
  filter(contrast == "mean(conv_treatment) - mean(control)") |>
  mutate(
    cause_area = clean_names(gsub("subj_", "", profile_var)),
    cause_area = fct_reorder(cause_area, estimate)
  ) |>
  ggplot(aes(x = estimate, y = cause_area, color = contrast)) +
  # forest plot
  geom_point() +
  geom_linerange(aes(xmin = conf.low, xmax = conf.high)) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  facet_wrap(~contrast, ncol = 1,
    labeller = labeller(contrast = comparison_names_cate)) +
  scale_color_manual(
    values = contrast_colors,
```

```

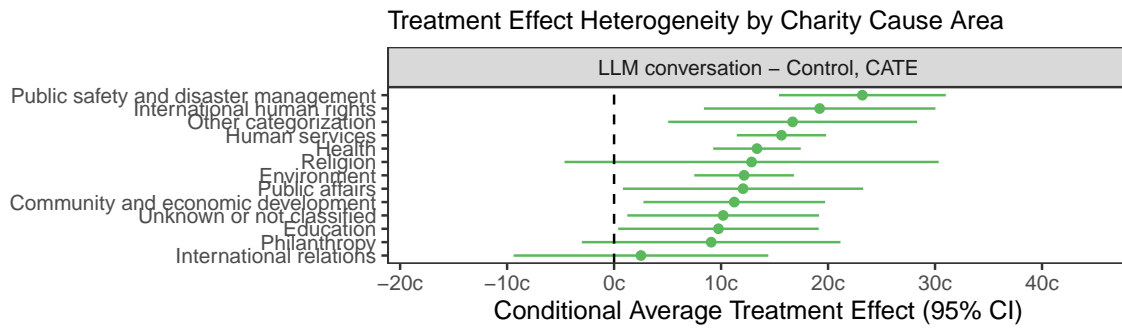
      labels = comparison_names_short
    ) +
    labs(
      title = "Treatment Effect Heterogeneity by Charity Cause Area",
      x = "Conditional Average Treatment Effect (95% CI)",
      y = NULL) +
    theme(legend.position = "bottom")

p2 <- pop2_cond$profile_tes |>
  filter(contrast == "mean(conv_treatment) - mean(control)") |>
  mutate(
    population_served = clean_names(gsub("pop_", "", profile_var)),
    population_served = fct_reorder(population_served, estimate)
  ) |>
  ggplot(aes(x = estimate, y = population_served, color = contrast)) +
  # forest plot
  geom_point() +
  geom_linerange(aes(xmin = conf.low, xmax = conf.high)) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  facet_wrap(~contrast, ncol = 1,
    labeller = labeller(contrast = comparison_names_cate)) +
  scale_color_manual(
    values = contrast_colors,
    labels = comparison_names_short
  ) +
  labs(
    title = "Treatment Effect Heterogeneity by Charity Population Served",
    x = "Conditional Average Treatment Effect (95% CI)",
    y = NULL) +
  theme(legend.position = "bottom")

(p1 / p2) +
  plot_annotation(tag_levels = "A") +
  plot_layout(guides = "collect", heights = c(1, 1.5)) & #axis_titles = "collect",
  scale_x_continuous(
    label = scales::label_number(suffix = "c"),
    limits = c(-18, 45),
    breaks = seq(-20, 40, by = 10)
  ) &
  theme(
    legend.position = "none",
    plot.title = element_text(size = 11),
    #axis.title.x = element_blank(),
    panel.grid = element_blank(),
    #plot.tag.position = c(0.0, 1), # top-left corner
    plot.tag = element_text(size = 10, vjust = 2, face = "bold")
  )

```

**A**



**B**

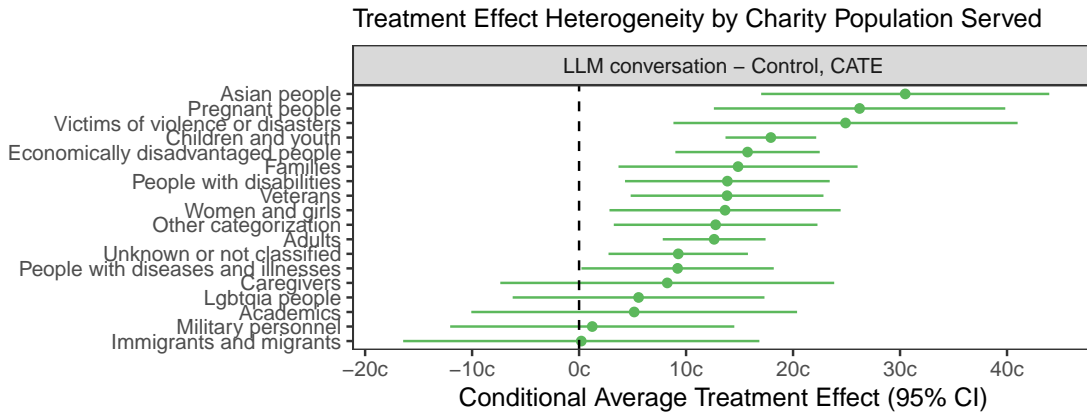


Figure 6: Figure S2: Binned heterogeneity analysis

```
ggsave(
  "output/figures/binnet_het_cates.png",
  width = FIGURE_WIDTH,
  height = 6
)
```

## 12.6 VIP and GAM Plot

```
## causal forest and GAM plot.
##

# do one gam plot to extract legend
plot_w_legend <- run_gam_simple(d, "age", add_hist = FALSE, include_legend = TRUE)$pred_plot +
  theme(legend.position = "bottom")

legend <- cowplot::get_plot_component(plot_w_legend, "guide-box", return_all = TRUE)[[3]]
```

```

gam_plots <- lapply(gams, function(g) g$pred_plot)
all_plots <- c(list(importance_plot), gam_plots[c(1, 3, 4)], list(legend))

layout <- "
ABB
ACC
ADD
EEE
"

wrap_plots(all_plots, design = layout, heights = c(1, 1, 1, 0.1)) +
  plot_annotation(tag_levels = list(c("A", "B", "C", "D", " "))) &
  theme(
    plot.tag.position = c(0.0, 0.975), # top-left corner
    plot.tag = element_text(size = 10, hjust = .5, vjust = 0, face = "bold")
  )

```

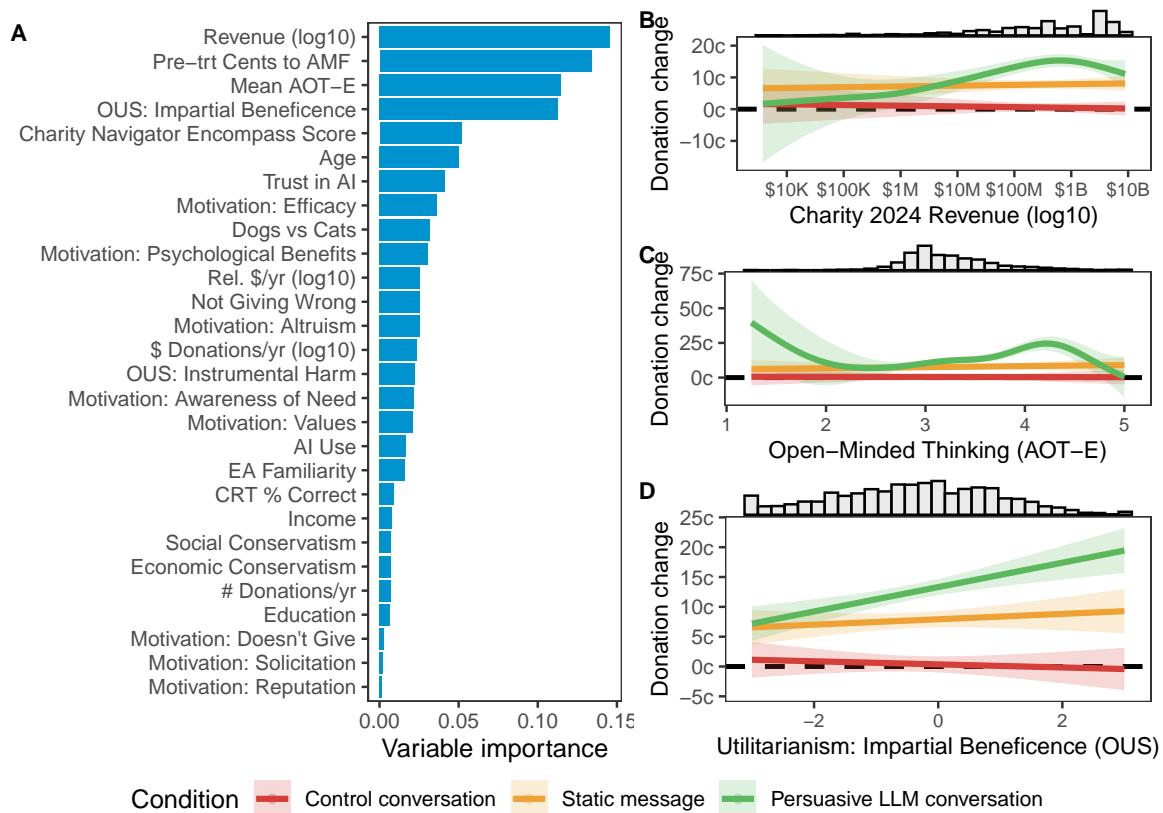


Figure 7: Figure 5: Variable importance and GAM analysis

```
ggsave("output/figures/htes_cf.png",
       width = FIGURE_WIDTH, height = 6, dpi = FIGURE_DPI
)
```

## 12.7 Causal Forest Plots

```
## Now do unadjusted heterogeneity plots and partial dependence plots for all variables
uhps <- plot_all_uhps(
  conv_ites, static_ites, d,
  importance_tbl$variable_dirty, importance_tbl$variable
)
ggsave(
  "output/figures/uhps.png",
  uhps,
  width = 8.25, height = 9.3, dpi = FIGURE_DPI
)

## now get PDps
pdps <- plot_all_pdps(
  ma_cf, as.matrix(d[, covars_vec]),
  importance_tbl$variable_dirty, labels_map
)
ggsave(
  "output/figures/pdps.png",
  pdps,
  width = 8.25, height = 9.3, dpi = FIGURE_DPI
)
```

## 12.8 Strategy Plot

```
# strategy plot

# Plot distributions -----

# 1. Pull out and rank your strategy coefficients
coef_df <- broom::tidy(mod_lm_donation) |>
  filter(term %in% names(STRATEGY_DESCRIPTIONS)) |>
  mutate(
    strategy = str_remove(term, "^strategy"),
    strategy = factor(strategy, levels = strategy[order(-estimate)]),
    sig = case_when(
      p.value < .10 & estimate > 0 ~ "pos",
      p.value < .10 & estimate < 0 ~ "neg",
      TRUE ~ "ns"
    )
  )

ranked_strats <- levels(coef_df$strategy)
```



```

# 2. Build HTML labels using centralized strategy descriptions
label_map <- imap_chr(SHORT_STRAT_DESCRIPTIONS, ~ {
  clean_name <- str_to_sentence(str_replace_all(.y, "(?<=[a-z])(?=[A-Z])", " "))
  paste0(
    "<b>", clean_name, "</b><br>",
    "<span style='font-size:8pt;'>", .x, "</span>"
  )
})

# I could just do it as a boxplot with dots if these are causing too much trouble
# probably just need to separate out the point interval and the slab and it should all work:
↪ https://github.com/mjskay/ggdist/issues/93

# 4. Plot, ordering by your OLS rank
p1 <- d_strategy_agg_long %>%
  mutate(
    strategy = factor(strategy, levels = ranked_strats)
  ) %>%
  ggplot(aes(x = rating, y = strategy)) +
  stat_slab(
    density = "histogram",
    breaks = seq(-0.25, 3.25, by = 0.5),
    fill = amf_blue,
    height = 0.5,
    justification = 0.5
  ) +
  stat_pointinterval(
    point_interval = "mean_qi",
    .width = 0.5, #IQR
    interval_size_domain = c(0, 20),
    position = position_nudge(y = -.2),
    interval_color = NA
  ) +
  scale_y_discrete(
    labels = label_map,
    #expand = expansion(add = c(0.5, 0))
  ) +
  scale_x_continuous(
    breaks = seq(0, 3, 1),
    #expand = expansion(add = c(0.25, 0.25)),
    labels = c("Not\nused", "Used\nminimally", "Used\nmoderately", "Used\nextensively"),
  ) +
  labs(
    x = "Strategy Rating",
    y = NULL
  ) +
  theme_bw(base_size = 11) +
  theme(
    axis.text.y = element_markdown(lineheight = 0.9),
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank()
  )

# try p1 as a boxplot?

```

```

# -----
# 3. Panel B: horizontal bar plot of coefficients ± SE
p2 <- ggplot(coef_df, aes(x = estimate, y = strategy, fill = sig)) +
  geom_col() +
  geom_errorbarh(aes(xmin = estimate - std.error, xmax = estimate + std.error),
    height = 0) +
  scale_y_discrete(labels = NULL,
    expand = expansion(add = c(.6, .6))
  ) +
  geom_vline(xintercept = 0, linetype = "dashed", color = "black") +
  scale_fill_manual(
    values = c(
      pos = amf_blue,    # significant & positive
      neg = amf_red,     # significant & negative
      ns = "grey80"     # non-significant
    ),
    guide = FALSE
  ) +
  labs(x = "OLS Coefficient", y = NULL) +
  theme_bw(base_size = 11) +
  theme(
    axis.text.y      = element_blank(),
    #axis.ticks.y     = element_blank(),
    panel.grid.major.y = element_blank(),
    panel.grid.minor  = element_blank()
  )

# Combine -----

shared_theme <- theme(
  plot.title = element_text(size = 10),
  axis.title = element_text(size = 8.5),
  axis.text  = element_text(size = 7),
  plot.tag.position = c(0.0, 1), # top-left corner
  plot.tag = element_text(size = 10, hjust = 1, vjust = 0, face = "bold"),
  panel.grid = element_blank()
)

combined <- p1 + p2 +
  plot_layout(ncol = 2, widths = c(1.6, 1)) +
  plot_annotation(tag_levels = "A") &
  shared_theme

# Print it
combined

```

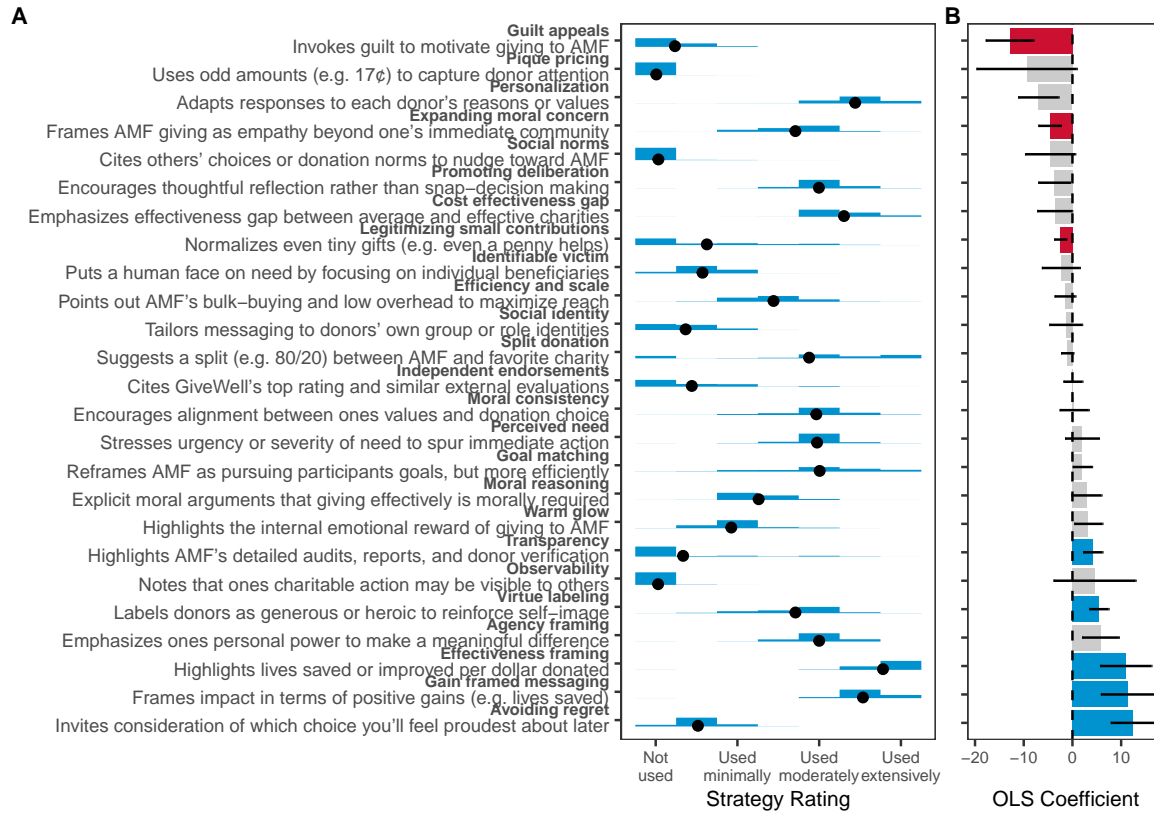


Figure 8: Figure 6: Persuasive strategies analysis

```
ggsave(
  "output/figures/strategy_plot.png",
  combined,
  width = FIGURE_WIDTH,
  height = 7,
  dpi = FIGURE_DPI
)
```

## 12.9 Accuracy Figure

```
# accuracy of factual claim increases over rounds
plot_a <- d_fact_ave |>
ggplot(aes(x = round, y = accuracy)) +
  geom_violin() +
  geom_jitter(alpha = 0.1) +
  stat_summary(fun = mean, geom = "point", col = "red", size = 1) +
  stat_summary(fun.data = ~ mean_se(.x), geom = "errorbar", width = 0.2, col = "red") +
```

```

#geom_smooth(method = "lm", se = TRUE, col = "black", aes(x = round_num)) +
#geom_smooth(method = "lm", formula = y ~ x + I(x^2), se = TRUE, col = "blue", aes(x = round_num)) +
labs(x = "Round", y = "Factual Accuracy Rating")

# correlation between accuracy and donation change
plot_b <- d_acc %>%
  ggplot(aes(x = accuracy, y = cents_to_amf_change)) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_jitter(alpha = 0.25) +
  geom_smooth(method = "lm", se = FALSE) +
  geom_smooth(col = "red", se = FALSE) +
  scale_y_continuous(labels = scales::label_number(suffix = "c")) +
  labs(x = "Factual Accuracy Rating", y = "Donation Change")

## plot
(plot_a + plot_b) +
  plot_annotation(
    tag_levels = "A",
  )

```

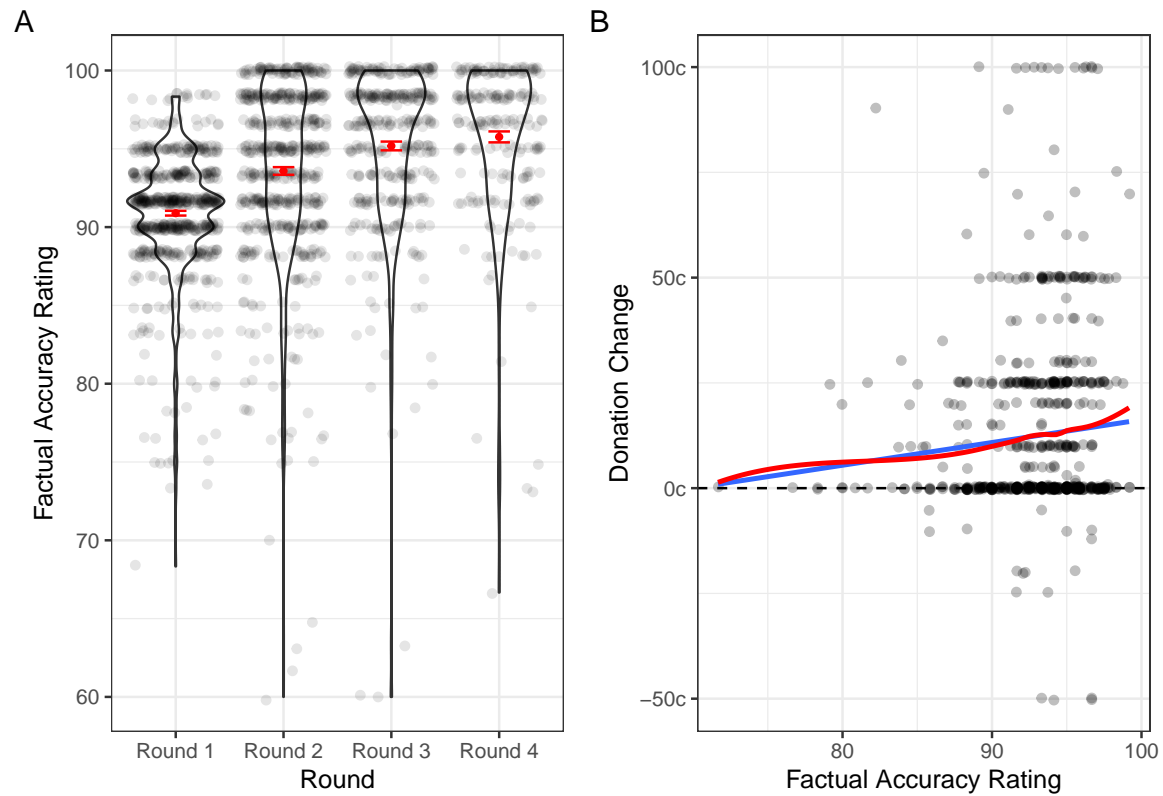


Figure 9: Figure S5: AI accuracy assessment

```
ggsave("output/figures/accuracy_plot.png",
       width = FIGURE_WIDTH, height = 4, dpi = FIGURE_DPI
)
```

## 13 Tables

### 13.1 GAM Tables

```
m1 <- gams[[1]]$mod
m2 <- gams[[3]]$mod
m3 <- gams[[4]]$mod

mods <- list(
  "Charity Revenue" = m1,
  "AOT-E" = m2,
  "Impartial Beneficence" = m3
)
```

Table 1: Fixed Parameters from General Additive Models

	Charity Revenue	AOT-E	Impartial Beneficence
Intercept	0.550 (0.692)	0.438 (0.668)	0.459 (0.673)
Static treatment	7.190*** (0.975)	7.281*** (0.941)	7.276*** (0.948)
LLM Conv. Treatment	12.228*** (0.972)	12.085*** (0.939)	12.037*** (0.945)
R2	0.088	0.093	0.082
Num.Obs.	1811	1949	1949

Each column shows separate GAM predicting donation change with a different covariate.

\*\*\* p<0.001, standard errors in parentheses.

```
)

coef_map = c(
  `(Intercept)` = "Control",
  conditionstatic_treatment = "Static Treatment",
  conditionconv_treatment = "LLM Conv. Treatment"
)

## ----- 1) Parametric-only model table -----
param_tbl <- msummary(
  mods,
  output = "kableExtra",
  format = "latex",
  float = TRUE,
  booktabs = TRUE,
  escape = FALSE,
  estimate = "{estimate}{stars} ({std.error})",
  title = "\\label{tab:gam-params}Fixed Parameters from General Additive Models",
  statistic = NULL,
  gof_map = c("r.squared", "nobs"),
  coef_omit = "^s\\(",
  coef_rename = c(
    "(Intercept)" = "Intercept",
    "conditionstatic_treatment" = "Static treatment",
    "conditionconv_treatment" = "LLM Conv. Treatment"
  ),
  notes = c(
    "Each column shows separate GAM predicting donation change with a different covariate.",
    "*** p<0.001, standard errors in parentheses."
  )
)

param_tbl
```

```
## ----- 2) Smooth terms table -----

# optional: clean smooth labels (turn "s(revenue_log10):conditionconv_treatment"
# into "s(revenue_log10) × LLM Conv.Treatment")
pretty_condition <- function(x) {
```

```

x |>
  str_replace_all("conditioncontrol", "Control") |>
  str_replace_all("conditionstatic_treatment", "Static Treatment") |>
  str_replace_all("conditionconv_treatment", "LLM Conv. Treatment") |>
  str_replace_all("s\\(revenue_log10\\)", "Revenue (Log10)") |>
  str_replace_all("s\\(ous_impartial_beneficence\\)", "Impartial Beneficence") |>
  str_replace_all("s\\(mean_aot\\)", "AOT-E")
}

smooth_tbl <- purrr::imap_dfr(mods, ~{
  st <- summary(.x)$s.table
  # coerce to dataframe with named columns
  st_df <- as.data.frame(st)
  st_df$Term <- rownames(st)
  st_df |>
    transmute(
      Model = .y,
      Smooth = Term |>
        pretty_condition() |>
        # replace ":" with " x " for readability
        str_replace(":", " x "),
      edf = sprintf("%.2f", `edf`),
      Ref.df = sprintf("%.2f", `Ref.df`),
      F = sprintf("%.2f", `F`),
      p = ifelse(`p-value` < .001, "<0.001***", sprintf("%.3f", `p-value`))
    ) |>
    select(Smooth, edf, Ref.df, F, p) %>%
    remove_rownames()
})

smooth_tbl_kbl <- smooth_tbl %>%
  kbl(
    format = "latex",
    booktabs = TRUE,
    escape = TRUE, # we already escaped text; keep stars and symbols
    align = c("l", "l", "r", "r", "r", "r"),
    caption = "\\label{tab:gam-smooths}Approximate significance of smooth terms",
    col.names = c("Smooth", "Edf", "Ref.df", "F", "p-value")
  ) |>
  kable_styling(latex_options = "hold_position")

smooth_tbl_kbl

```

## 13.2 Strategy Regression Table

```

options("modelsummary_format_numeric_latex" = "plain")

# need to get clean names.
strat_names <- names(SHORT_STRAT_DESCRIPTIONS)
strat_names_clean <- paste0(

```

Table 2: Approximate significance of smooth terms

Smooth	Edf	Ref.df	F	p-value
Revenue (Log10) $\times$ Control	1.00	1.01	0.12	0.733
Revenue (Log10) $\times$ Static Treatment	1.00	1.00	0.14	0.707
Revenue (Log10) $\times$ LLM Conv. Treatment	3.22	4.01	4.74	<0.001***
AOT-E $\times$ Control	1.00	1.01	0.00	0.976
AOT-E $\times$ Static Treatment	1.00	1.00	0.25	0.618
AOT-E $\times$ LLM Conv. Treatment	5.62	6.59	5.97	<0.001***
Impartial Beneficence $\times$ Control	1.01	1.01	0.26	0.615
Impartial Beneficence $\times$ Static Treatment	1.01	1.01	0.76	0.383
Impartial Beneficence $\times$ LLM Conv. Treatment	1.00	1.00	15.43	<0.001***

```

"Strategy: ",
  str_to_sentence(str_replace_all(strat_names, "(?<=[a-z])(?=[A-Z])", " "))
)

motivations <- names(MOTIVATION_DESCRIPTIONS)
motivations_clean <- paste0(
  "Motivation: ",
  str_to_sentence(str_replace_all(motivations, "(?<=[a-z])(?=[A-Z])", " "))
)

pop_served <- mod_lm_donation |> coef() |> names() |> grep("^pop_", x = _, value = TRUE)
pop_served_clean <- pop_served |>
  str_remove("^pop_")          |> # drop the pop_ prefix
  str_replace_all("_", " ")    |> # turn underscores into spaces
  str_to_sentence()            |> # capitalize first letter
  (\(x) paste0("Population: ", x))()

subjects <- mod_lm_donation |> coef() |> names() |> grep("^subj_", x = _, value = TRUE)
subjects_clean <- subjects |>
  str_remove("^subj_")          |> # drop the subj_ prefix
  str_replace_all("_", " ")    |> # turn underscores into spaces
  str_to_sentence()            |> # capitalize first letter
  (\(x) paste0("Subject Area: ", x))() # prepend label

# rename some vars
coef_map = c(
  `(Intercept)` = "Intercept",
  `cents_to_amf_pre_cat1-10` = "Pre-treatment Donation, 1-10c",
  `cents_to_amf_pre_cat11-20` = "Pre-treatment Donation, 11-20c",
  `cents_to_amf_pre_cat21-30` = "Pre-treatment Donation, 21-30c",
  `cents_to_amf_pre_cat31-40` = "Pre-treatment Donation, 31-40c",
  `cents_to_amf_pre_cat41-50` = "Pre-treatment Donation, 41-50c",
  `cents_to_amf_pre_cat51-100` = "Pre-treatment Donation, 51-100c",
  charity_wrong_pre = "Pre-treatment Moral Belief",
  setNames(strat_names_clean, strat_names),
  setNames(motivations_clean, motivations),
  `DoesntGiveTRUE` = "Motivation: Doesn't Give",
  is_international = "Scope: International",

```



```

setNames(pop_served_clean, pop_served),
setNames(subjects_clean, subjects)
)

# 2) Move controls to top
coef_order = c(
  "Strategy",
  "Intercept",
  "cents_to_amf_pre_cat1-10",
  "cents_to_amf_pre_cat11-20",
  "cents_to_amf_pre_cat21-30",
  "cents_to_amf_pre_cat31-40",
  "cents_to_amf_pre_cat41-50",
  "cents_to_amf_pre_cat51-100",
  "charity_wrong_pre",
  ".*"
)

table_latex <- modelsummary(
  list(
    "Donation Change" = mod_lm_donation,
    "Moral Belief Change" = mod_lm_char_wrong,
    "Click-through" = mod_lm_clicked
  ),
  output = "kableExtra", #you need to go via kable to get longtable
  format = "latex",
  float = TRUE,
  booktabs = TRUE,
  longtable = TRUE,
  title = "\\label{tab:strategy-regressions}Persuasive Strategy Regression Results",
  escape = FALSE,
  gof_omit = ".*", # drop goodness-of-fit rows if you like
  estimate = "{estimate} ({std.error}){stars}",
  statistic = NULL,
  notes = c(
    "*** p<0.001, ** p<0.01; * p<0.05; + p<0.10. Standard errors (HC2) in parentheses.",
    "Strategy coef. p values replaced with q values to maintain pFDR < .05 (Storey)"
  ),
  coef_map = coef_map,
  coef_order = coef_order
)

table_latex <- kableExtra::column_spec(table_latex, 1, width = "6cm")
table_latex

```

Table 3: Persuasive Strategy Regression Results

	Donation Change	Moral Belief Change	Click-through
Intercept	-41.820 (19.838)*	-3.664 (6.478)	-0.144 (0.158)
Pre-treatment Donation, 21-30c	-8.357 (3.369)*		0.066 (0.054)
Pre-treatment Donation, 31-40c	-6.308 (5.327)		0.147 (0.088)+

Pre-treatment Donation, 41-50c	-10.084 (2.589)***		0.085 (0.039)*
Pre-treatment Donation, 51-100c	-23.053 (3.822)***		0.083 (0.063)
Pre-treatment Moral Belief		-0.076 (0.020)***	
Strategy: Effectiveness framing	10.952 (5.284)*	0.099 (2.880)	-0.048 (0.066)
Strategy: Cost effectiveness gap	-3.632 (3.601)	-0.620 (2.094)	0.019 (0.055)
Strategy: Goal matching	2.051 (1.997)	-1.879 (1.531)	0.045 (0.033)
Strategy: Moral reasoning	2.893 (3.084)	1.861 (2.028)	-0.019 (0.048)
Strategy: Personalization	-6.972 (4.154)+	-4.140 (1.712)*	0.000 (0.047)
Strategy: Split donation	-1.063 (1.279)	-0.371 (0.609)	0.002 (0.017)
Strategy: Expanding moral concern	-4.672 (2.322)*	-1.735 (1.667)	0.065 (0.037)+
Strategy: Avoiding regret	12.439 (4.570)**	-4.782 (2.406)*	0.041 (0.071)
Strategy: Social norms	-4.549 (5.153)	-2.570 (2.803)	0.164 (0.115)
Strategy: Agency framing	5.771 (3.768)	0.542 (2.048)	0.000 (0.043)
Strategy: Moral consistency	0.369 (2.990)	4.214 (1.916)*	-0.091 (0.044)*
Strategy: Efficiency and scale	-1.512 (2.150)	-1.698 (1.407)	-0.023 (0.029)
Strategy: Transparency	4.197 (1.984)*	-0.524 (1.103)	-0.017 (0.028)
Strategy: Independent endorsements	0.113 (1.952)	1.730 (1.423)	0.030 (0.031)
Strategy: Legitimizing small contributions	-2.482 (1.252)*	-0.850 (0.697)	0.000 (0.018)
Strategy: Observability	4.550 (8.430)	-0.272 (5.626)	0.121 (0.188)
Strategy: Identifiable victim	-2.371 (3.906)	0.790 (1.891)	-0.030 (0.053)
Strategy: Promoting deliberation	-3.747 (3.262)	1.674 (1.897)	0.118 (0.047)*
Strategy: Pique pricing	-9.398 (10.302)	21.791 (25.057)	-0.190 (0.099)+
Strategy: Gain framed messaging	11.344 (5.507)*	3.811 (3.056)	0.088 (0.075)
Strategy: Perceived need	1.977 (3.480)	1.544 (2.253)	-0.036 (0.051)
Strategy: Warm glow	3.276 (2.897)	2.640 (2.137)	-0.061 (0.042)
Strategy: Social identity	-1.364 (3.376)	0.511 (1.688)	0.001 (0.053)
Strategy: Virtue labeling	5.462 (1.967)**	0.791 (1.276)	0.004 (0.028)
Strategy: Guilt appeals	-12.891 (4.910)**	2.462 (2.602)	-0.094 (0.057)+
Motivation: Awareness of need	1.372 (1.233)	0.807 (0.722)	-0.020 (0.015)
Motivation: Solicitation	2.758 (1.973)	0.343 (0.804)	-0.020 (0.015)
Motivation: Costs and benefits	-0.103 (0.946)	-0.059 (0.609)	0.021 (0.016)
Motivation: Altruism	0.386 (1.909)	0.201 (1.487)	-0.002 (0.029)
Motivation: Reputation	-1.083 (2.722)	0.067 (1.300)	-0.063 (0.026)*
Motivation: Psychological benefits	0.725 (1.038)	-0.301 (0.682)	0.023 (0.014)
Motivation: Values	-0.812 (1.226)	-0.484 (1.088)	0.027 (0.022)
Motivation: Efficacy	-0.261 (0.893)	-0.716 (0.583)	-0.001 (0.014)
Motivation: Doesn't Give	2.137 (3.692)	-0.167 (2.220)	0.013 (0.057)
Scope: International	4.175 (3.097)	1.064 (2.063)	-0.013 (0.040)
Population: Adults	-1.400 (2.772)	-2.814 (1.539)+	-0.021 (0.036)
Population: Children and youth	-1.058 (2.732)	0.820 (1.519)	-0.004 (0.043)
Population: Economically disadvantaged people	0.515 (3.014)	1.739 (1.362)	0.042 (0.036)
Population: Veterans	-8.927 (4.487)*	-0.768 (4.166)	-0.091 (0.078)
Population: People with disabilities	2.667 (3.353)	1.796 (2.240)	0.037 (0.059)
Population: People with diseases and illnesses	1.649 (4.213)	2.949 (3.073)	0.139 (0.063)*
Population: Families	-1.982 (3.471)	-0.773 (1.579)	-0.031 (0.047)
Population: Victims of violence or disasters	3.565 (6.949)	0.425 (4.607)	-0.007 (0.097)
Population: Unknown or not classified	-4.674 (4.746)	-0.798 (2.034)	-0.024 (0.065)
Population: Pregnant people	5.745 (6.488)	-0.718 (3.028)	0.081 (0.079)
Population: Immigrants and migrants	-17.142 (7.379)*	-0.345 (4.885)	-0.008 (0.097)
Population: Military personnel	-0.374 (6.486)	-4.400 (4.757)	-0.001 (0.093)
Population: Women and girls	0.372 (4.633)	-1.378 (3.279)	-0.095 (0.055)+

Population: Asian people	11.417 (5.129)*	-0.480 (2.454)	-0.098 (0.052)+
Population: Other categorization	-4.676 (3.197)	1.534 (1.537)	-0.001 (0.033)
Subject Area: Environment	2.485 (3.275)	-0.927 (1.511)	0.004 (0.046)
Subject Area: Health	-3.147 (3.014)	-1.918 (1.802)	-0.055 (0.038)
Subject Area: Human services	2.449 (2.757)	-1.307 (1.487)	-0.011 (0.035)
Subject Area: Public safety and disaster management	9.428 (5.159)+	-1.149 (1.801)	0.028 (0.060)
Subject Area: Community and economic development	-3.891 (3.974)	-3.455 (2.504)	-0.029 (0.047)
Subject Area: International relations	-14.666 (5.771)*	4.523 (2.707)+	0.004 (0.056)
Subject Area: Philanthropy	0.948 (4.129)	1.347 (2.408)	-0.093 (0.051)+
Subject Area: International human rights	12.135 (5.711)*	0.176 (2.169)	-0.011 (0.060)
Subject Area: Unknown or not classified	2.206 (4.774)	-1.018 (2.442)	0.050 (0.077)
Subject Area: Other categorization	1.555 (2.231)	-0.773 (0.997)	0.007 (0.028)

\*\*\* p<0.001, \*\* p<0.01; \* p<0.05; + p<0.10. Standard errors (HC2) in parentheses.

Strategy coef. p values replaced with q values to maintain pFDR < .05 (Storey)

## 14 Session Information

```
sessionInfo()
```

```
R version 4.5.1 (2025-06-13 ucrt)
Platform: x86_64-w64-mingw32/x64
Running under: Windows 11 x64 (build 22631)
```

```
Matrix products: default
LAPACK version 3.12.1
```

```
locale:
[1] LC_COLLATE=English_United States.utf8
[2] LC_CTYPE=English_United States.utf8
[3] LC_MONETARY=English_United States.utf8
[4] LC_NUMERIC=C
[5] LC_TIME=English_United States.utf8
```

```
time zone: America/New_York
tzcode source: internal
```

```
attached base packages:
[1] grid      stats    graphics  grDevices  utils      datasets  methods
[8] base
```

```
other attached packages:
[1] qvalue_2.15.0      BiocManager_1.30.24  tibble_3.2.1
[4] forcats_1.0.0      car_3.1-2            carData_3.0-5
[7] tidyr_1.3.1        readr_2.1.5          modelsummary_2.1.1
[10] kableExtra_1.4.0   gt_0.11.0            osfr_0.2.9
[13] fs_1.6.4           here_1.0.1           xml2_1.3.6
[16] rvest_1.0.4        gridExtra_2.3        gridtext_0.1.5
[19] jpeg_0.1-10        ggsci_3.2.0          ggExtra_0.10.1
[22] ggtext_0.1.2       ggdist_3.3.2         patchwork_1.3.0
```

[25] ggplot2_3.5.2	broom_1.0.6	marginalEffects_0.21.0
[28] estimatr_1.0.4	grf_2.3.2	mgcv_1.9-3
[31] nlme_3.1-168	glue_1.7.0	stringr_1.5.1
[34] purrr_1.0.2	data.table_1.15.4	dplyr_1.1.4

loaded via a namespace (and not attached):

[1] RColorBrewer_1.1-3	rstudioapi_0.16.0	jsonlite_1.8.8
[4] datawizard_0.12.2	magrittr_2.0.3	farver_2.1.2
[7] nloptr_2.1.1	rmarkdown_2.28	ragg_1.3.2
[10] vctrs_0.6.5	memoise_2.0.1	minqa_1.2.8
[13] effectsize_0.8.9	janitor_2.2.0	htmltools_0.5.8.1
[16] distributional_0.4.0	curl_5.2.1	Formula_1.2-5
[19] parallelly_1.38.0	sass_0.4.9	plyr_1.8.9
[22] zoo_1.8-12	lubridate_1.9.3	cachem_1.1.0
[25] commonmark_1.9.1	mime_0.12	lifecycle_1.0.4
[28] pkgconfig_2.0.3	Matrix_1.7-0	R6_2.5.1
[31] fastmap_1.2.0	future_1.34.0	shiny_1.9.1
[34] snakecase_0.11.1	digest_0.6.37	selectr_0.4-2
[37] colorspace_2.1-1	rprojroot_2.0.4	textshaping_0.4.0
[40] labeling_0.4.3	fansi_1.0.6	timechange_0.3.0
[43] http_1.4.7	abind_1.4-8	compiler_4.5.1
[46] bit64_4.0.5	withr_3.0.1	backports_1.5.0
[49] psych_2.5.3	performance_0.12.2	MASS_7.3-65
[52] gratia_0.10.0	tools_4.5.1	lmtest_0.9-40
[55] httpuv_1.6.15	future.apply_1.11.2	promises_1.3.0
[58] checkmate_2.3.2	reshape2_1.4.4	generics_0.1.3
[61] gtable_0.3.5	tzdb_0.4.0	hms_1.1.3
[64] utf8_1.2.4	tables_0.9.28	pillar_1.9.0
[67] markdown_1.13	vroom_1.6.5	later_1.3.2
[70] splines_4.5.1	lattice_0.22-7	bit_4.0.5
[73] tidyselect_1.2.1	miniUI_0.1.1.1	knitr_1.48
[76] svglite_2.1.3	cru_1.6.0	xfun_0.47
[79] stringi_1.8.4	yaml_2.3.10	boot_1.3-31
[82] codetools_0.2-20	ggokabeito_0.1.0	evaluate_0.24.0
[85] httpcode_0.3.0	cli_3.6.3	parameters_0.22.1
[88] xtable_1.8-4	systemfonts_1.1.0	munsell_0.5.1
[91] Rcpp_1.0.13	globals_0.16.3	parallel_4.5.1
[94] bayestestR_0.16.1	mvnfast_0.2.8	listenv_0.9.1
[97] lme4_1.1-35.5	viridisLite_0.4.2	scales_1.3.0
[100] insight_1.4.0	crayon_1.5.3	rlang_1.1.4
[103] cowplot_1.1.3	mnormt_2.1.1	

## 15 Appendix

### 15.1 Additional Notes

- All figures are saved in the `output/figures/` directory
- Raw data and processed datasets are available in the `data/` directory
- Python scripts for NLP processing are located in `scripts/nlp/`
- This report can be generated with or without code chunks using the `include_code` parameter

## 15.2 Reproducibility

To reproduce this analysis:

1. Ensure all required R packages are installed (see `libraries.R`)
2. Install Quarto if not already installed: `install.packages("quarto")` then `quarto::quarto_install()`
3. Download the data using the provided OSF repository
4. Run this Quarto file with `quarto render main_report.qmd`

The analysis can be customized by modifying the YAML parameters at the top of this document.

## 15.3 Alternative: R Markdown Version

For users who prefer R Markdown or don't have Quarto installed, a compatible version of this report is available as `main_report.Rmd` which uses child chunks for script execution.