Moderating Factors Moral Relevance: CCES 2012

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Contents

Introduction

In this section, I conduct analyses that include other demographic variables such as religion, gender, income and education on moral foundations using the CCES Duke 2012 team module. This section focuses on the Moral Relevance questions.

Before I begin, let's load in the data (available for download here) and relevant packages.

```
# Load Data
cces <- read.csv("~/Desktop/Working/Moral-Psychology/DukeCCES12/CCES-MFQ.csv")
```

```
library(tidyverse)
```

Clean Data

I clean the data similar to the way that it was cleaned for the Moral Foundations analyses.

First, I filter out the people who did not pass the attention checks.

```
cces <- cces[!(cces$math == "4"), ]
cces <- cces[!(cces$math == "5"), ]
cces <- cces[!(cces$math == "6"), ]

cces <- cces[!(cces$dogood == "1"), ]
cces <- cces[!(cces$dogood == "3"), ]
```

Then, I create a score for each foundation that represents the average of the responses for each of the foundations in this subscale.

I also generate an aggregate individualizing and binding foundation subscale, as well as a difference score that represents the difference between the two scores.

```
### Harm ###
cces$emote <- cces$emote - 1
cces$weak <- cces$weak - 1
cces$cruel <- cces$cruel - 1
cces$Harm <- rowMeans(cces[, c("emote", "weak", "cruel")], na.rm = TRUE)

### Fairness ###
cces$treatd <- cces$treatd - 1
cces$unfair <- cces$unfair - 1
cces$rights <- cces$rights - 1
cces$Fairness <- rowMeans(cces[, c("treatd", "unfair", "rights")],
    na.rm = TRUE)

### Ingroup ###
cces$lovec <- cces$lovec - 1
cces$betray <- cces$betray - 1
cces$loyal <- cces$loyal - 1
cces$Ingroup <- rowMeans(cces[, c("lovec", "betray", "loyal")],
    na.rm = TRUE)

### Authority ###
cces$auth <- cces$auth - 1
cces$conform <- cces$conform - 1
cces$chaos <- cces$chaos - 1
cces$Authority <- rowMeans(cces[, c("auth", "conform", "chaos")],
    na.rm = TRUE)

### Purity ###
cces$pure <- cces$purity - 1
cces$disgust <- cces$disgust - 1
cces$goddis <- cces$goddis - 1
cces$Purity <- rowMeans(cces[, c("pure", "disgust", "goddis")],
    na.rm = TRUE)

# Create Individualizing (indiv) and Binding (bind)
# foundation scores
cces$indiv <- rowMeans(cces[, c("emote", "weak", "cruel", "treatd",
    "unfair", "rights")], na.rm = TRUE)
cces$bind <- rowMeans(cces[, c("lovec", "betray", "loyal", "auth",
    "conform", "chaos", "pure", "disgust", "goddis")], na.rm = TRUE)
```

```r
# Create a difference score
cces$diffscore <- cces$indiv - cces$bind

# Declare Gender as factor
cces$gender <- as.factor(cces$gender)
```

Fit Models

I fit five models to include politics, gender, religion, income and education, one at a time.

First, I fit the model with politics, which recreates the model that I reported in the Moral Foundations Questionnaire analysis. Each subsequent model adds the demographic variables in the order listed above.

```r
# With Politics
fit1 <- lm(diffscore ~ ideo5, data = cces)
summary(fit1)
```

```
##
## Call:
## lm(formula = diffscore ~ ideo5, data = cces)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4553 -0.6434 -0.0434  0.6670  3.3329
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.87899    0.20308   9.252  < 2e-16 ***
## ideo5       -0.41187    0.06019  -6.843 8.97e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.04 on 203 degrees of freedom
##   (534 observations deleted due to missingness)
## Multiple R-squared:  0.1874, Adjusted R-squared:  0.1834
## F-statistic: 46.83 on 1 and 203 DF,  p-value: 8.97e-11
```

```r
# Plus Gender
fit2 <- lm(diffscore ~ ideo5 + gender, data = cces)
summary(fit2)
```

```
##
## Call:
```

```
## lm(formula = diffscore ~ ideo5 + gender, data = cces)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4882 -0.6728 -0.0334  0.6605  3.3512
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.91903    0.23033   8.332 1.21e-14 ***
## ideo5       -0.41541    0.06107  -6.802 1.14e-10 ***
## gender2     -0.05477    0.14755  -0.371    0.711
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.042 on 202 degrees of freedom
##   (534 observations deleted due to missingness)
## Multiple R-squared:  0.188,  Adjusted R-squared:   0.18
## F-statistic: 23.38 on 2 and 202 DF,  p-value: 7.336e-10
```

```r
# Plus Religion
fit3 <- lm(diffscore ~ ideo5 + gender + religattend, data = cces)
summary(fit3)
```

```
##
## Call:
## lm(formula = diffscore ~ ideo5 + gender + religattend, data = cces)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5112 -0.6488 -0.0313  0.7019  3.3720
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.06239    0.36090   5.715 3.95e-08 ***
## ideo5       -0.42749    0.06559  -6.518 5.69e-10 ***
## gender2     -0.06260    0.15100  -0.415    0.679
## religattend -0.02406    0.04644  -0.518    0.605
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.045 on 200 degrees of freedom
##   (535 observations deleted due to missingness)
## Multiple R-squared:  0.1896, Adjusted R-squared:  0.1775
## F-statistic:  15.6 on 3 and 200 DF,  p-value: 3.722e-09
```

```r
# Plus Income
fit4 <- lm(diffscore ~ ideo5 + gender + religattend + income,
    data = cces)
summary(fit4)
```

```
##
## Call:
## lm(formula = diffscore ~ ideo5 + gender + religattend + income,
##     data = cces)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4448 -0.6576 -0.0135  0.5960  3.3714
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.019204   0.412139   4.899 2.23e-06 ***
## ideo5       -0.422069   0.069861  -6.042 9.36e-09 ***
## gender2      0.002431   0.162975   0.015    0.988
## religattend -0.024781   0.049501  -0.501    0.617
## income      -0.004454   0.024207  -0.184    0.854
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.016 on 170 degrees of freedom
##   (564 observations deleted due to missingness)
## Multiple R-squared:  0.1953, Adjusted R-squared:  0.1764
## F-statistic: 10.32 on 4 and 170 DF,  p-value: 1.672e-07
```

```r
# Plus Education
fit5 <- lm(diffscore ~ ideo5 + gender + religattend + income +
    educ, data = cces)
summary(fit5)
```

```
##
## Call:
## lm(formula = diffscore ~ ideo5 + gender + religattend + income +
##     educ, data = cces)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5538 -0.5947  0.0276  0.6078  3.4843
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  1.437537   0.467278   3.076  0.00244 **
## ideo5       -0.389857   0.069981  -5.571 9.82e-08 ***
## gender2      0.007903   0.160503   0.049  0.96079
## religattend -0.005016   0.049377  -0.102  0.91921
## income      -0.024314   0.025115  -0.968  0.33436
## educ         0.137251   0.054646   2.512  0.01296 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1 on 169 degrees of freedom
##   (564 observations deleted due to missingness)
## Multiple R-squared:  0.2243, Adjusted R-squared:  0.2013
## F-statistic: 9.773 on 5 and 169 DF,  p-value: 3.224e-08
```