Results Reproduction: Study 2

Jennifer Lin

11/26/2019

Contents

Introduction

The core of the thesis project is to understand the process in which the developers of the Moral Foundations Theory came to their conclusions about the differences between liberals and conservatives on moral grounds, and to apply this knowledge to other mechanisms of measuring morality to see if similar results can be achieved.

The notes in the reproduction of the results from Study 2 in Jesse Graham et al's 2009 paper that positts, from four different angles, that liberals and conservatives conceptualize morality in different domains.

Each of these commands have already been produced using an R script file, which can be located in the Git Repository under the `S2` folder housed under `ProjectImplicit`. The purpose of this document is to add notes for the author's own reference and for the general audience who wishes to reproduce this work.

Data for the Graham paper are posted on the Harvard Dataverse, and is freely available to the public. Here, I will use Study 2 data, which were both collected in the Project Implicit website.

For each dataset, the data was downloaded and cleaned in a R script file that will not be discussed in this file. Using those scripts, I extract pertinent variables and save to the directory as a `.csv` which will be sued in these analyses.

For the reproduction of the results in Study 2, the data cleaning file is `S2Man.R` and the original R script (reproduced in this document) is `Fig3.R`.

Before I begin, I will load all the packages that were used in the analyses in this section.

```
library(car)
library(dplyr)
library(psych)
library(ggplot2)
library(GGally)
library("ggpubr")
library("reshape2")
library(scales)
library(lme4)  #lmer function
library(tidyverse)  #dplyr
library(lsr)  #EtaSquared
library(coefplot)
```

The beauty with the Study 2 data is that it consists of measures related to the entirety of the Moral Foundations Questionnaire, which includes roughly more than 40 items, including some extensions from the dataset used in the first section. In the paper, the authors considered both of the subsections, but only created a graph for the moral judgemnt subsection.

For these notes, I will begin with the reproduction of Figure 3, the moral judgment scale followed by a replication of Figure 1 but using the moral relevance items in this data set.

Before introducing the study, let's load in the data.

```
morals <- read.csv("~/Desktop/Working/Moral-Psychology/ProjectImplicit/PI-study2.csv",
    header = TRUE, na.strings = c("", " ", "NA"))
```

The goal of Study 2 is to expand on the analyses of the findings in Study 1 and add an additional scale as a way to better understand the dimensions of morality. As mentioned earlier and as described later, the moral judgment scale was created to understand how individuals deem acts to be right versus wrong. A series of latent variable models were conducted subsequently to understand how certain individual factors infleunces one's perception of morality.

Reproducing Descriptive Statistics Plot

Figure 3 – Moral Judgment

In Figure 3 of the paper, the authors created a display of average scores on each foundation across each of the levels on the self-identified political ideology variable. The Moral Judgment scale asks participants to rank, from a scale of strongly disagree to strongly agree, the extent they agree that each act, such as kicking dogs in the head, is moral. Each of these items associate with the moral foundations in some way such that there are roughly 4 to 5 items under each foundation.

An attention check, whether someone believed in astrology, was introduced during the course of the sruvey to ensure participants were paying attention to the measures. Those who indicated the higher end of the scale were excluded from the analysis.

To prepare the data for the graph, each foundation needs to be compiled based on the variables that fall under the umbrella of each foundation. In addition, the varaibles in this dataset were coded on a scale of 1-6, but the variables in the paper were averaged out of a scale of 0-5. Therefore, I adjust the coding of each variable and form the foundation variables below.

```
### Harm ###
morals$slap <- morals$Slap - 1
morals$kill <- morals$Kill - 1
morals$compassion <- morals$Compassion - 1
morals$gov <- morals$Govharm - 1
morals$Harm <- rowMeans(morals[, c("slap", "kill", "compassion",
    "gov")], na.rm = TRUE)

### Fairness ###
morals$line <- morals$Line - 1
morals$terror <- morals$TerrorRev - 1
morals$justice <- morals$Justice - 1
morals$fairly <- morals$Fairly - 1
morals$Fairness <- rowMeans(morals[, c("line", "terror", "justice",
    "fairly")], na.rm = TRUE)

### Ingroup ###
morals$brother <- morals$BrotherRev - 1
morals$romantic <- morals$Romantic - 1
morals$grouploy <- morals$Grouploy - 1
morals$wellbeing <- morals$Wellbeing - 1
morals$Ingroup <- rowMeans(morals[, c("brother", "romantic",
    "grouploy", "wellbeing")], na.rm = TRUE)

### Authority ###
morals$sexroles <- morals$Sexroles - 1
morals$soldier <- morals$Soldier - 1
morals$kid <- morals$Kidrespect - 1
morals$heritage <- morals$Heritage - 1
morals$Authority <- rowMeans(morals[, c("sexroles", "soldier",
    "kid", "heritage")], na.rm = TRUE)

### Purity ###
morals$revolt <- morals$Revolting - 1
morals$wrong <- morals$Wrongdisgust - 1
morals$chaste <- morals$Chastity - 1
```

```r
morals$sin <- morals$Sin - 1
morals$Purity <- rowMeans(morals[, c("revolt", "wrong", "chaste",
    "sin")], na.rm = TRUE)
```

Now, we move to looking at the political ideology variable that forms the x-axis. Again, the variables are coded based on numerical data such that those with a higher number (in absolute value terms) is more extreme, and liberals are represented with a negative value and conservatives are represented with a positive number.

```r
table(morals$politics)
```

```
##
##  -3  -2  -1   0   1   2   3
## 358 568 217 517 182 220  73
```

```r
morals$ideology <- as.character(as.integer(morals$politics))
```

```r
morals$ideology <- recode(morals$ideology, `-3` = "Strongly Liberal")
morals$ideology <- recode(morals$ideology, `-2` = "Moderately Liberal")
morals$ideology <- recode(morals$ideology, `-1` = "Slightly Liberal")
morals$ideology <- recode(morals$ideology, `0` = "Neutral")
morals$ideology <- recode(morals$ideology, `1` = "Slightly Conservative")
morals$ideology <- recode(morals$ideology, `2` = "Moderately Conservative")
morals$ideology <- recode(morals$ideology, `3` = "Strongly Conservative")
```

Now, let's check to see if we did the recoding correctly.

```r
table(morals$ideology)
```

```
##
## Moderately Conservative      Moderately Liberal                 Neutral
##                     220                     568                     517
##   Slightly Conservative        Slightly Liberal   Strongly Conservative
##                     182                     217                      73
##        Strongly Liberal
##                     358
```

Nonresponse on sruveys is common yet it creates what R "knows" as implicit NA's. These values should be brought out and addressed before graphing.

```r
library(forcats)
morals$ideology <- fct_explicit_na(morals$ideology, na_level = "NA")
table(morals$ideology)
```

```
##
## Moderately Conservative      Moderately Liberal                 Neutral
##                     220                     568                     517
##   Slightly Conservative        Slightly Liberal   Strongly Conservative
```

```
##                    182                         217                         73
##         Strongly Liberal
##                    358
```

In the ggplot2 package, variables that are graphed and labeled as characters should be declared as factors. Therefore, the political ideology variable needs to be changed from the character string in the recoding step to factors for plotting.

```
morals$ideology <- as.factor(as.character(morals$ideology))
morals$ideology <- factor(morals$ideology, levels = c("Strongly Liberal",
    "Moderately Liberal", "Slightly Liberal", "Neutral", "Slightly Conservative",
    "Moderately Conservative", "Strongly Conservative"))
```

In the paper, the authors plot average scores on each foundation as a function of each level of political ideology. To do this, I aggregate the scores on each foundation across political ideology, and store the items as its own data frame.

```
Harm <- aggregate(Harm ~ ideology, morals, mean, na.rm = TRUE)
Fairness <- aggregate(Fairness ~ ideology, morals, mean, na.rm = TRUE)
Ingroup <- aggregate(Ingroup ~ ideology, morals, mean, na.rm = TRUE)
Authority <- aggregate(Authority ~ ideology, morals, mean, na.rm = TRUE)
Purity <- aggregate(Purity ~ ideology, morals, mean, na.rm = TRUE)
```

Yet, to plot, we would need one succinct data frame. Therefore, I merge each of these data frames to one.

```
moral <- merge(Harm, Fairness, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
moral <- merge(moral, Ingroup, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
moral <- merge(moral, Authority, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
moral <- merge(moral, Purity, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
```

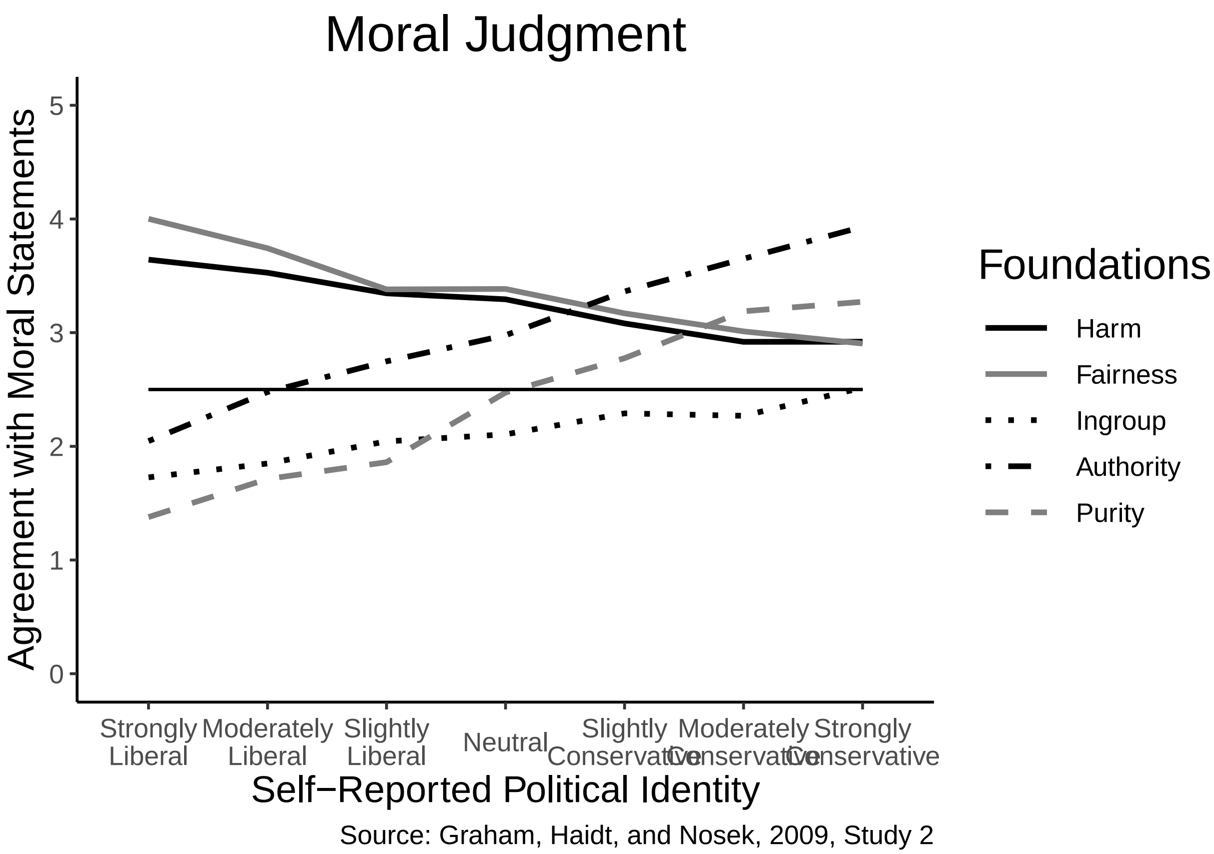
This merge creates some problems since the foundations are column names and ideology are row names. These need to be "reshaped" such that ideology forms one variable, foundations are merged as one variable and the averages are its own variable.

```
mfq <- reshape2::melt(moral, id.var = "ideology")
```

Finally, it is time to plot. I use the ggplot2 package to do this. In addition, the paper inserts a horizontal line at the 2.5 point to show "average". In the spirit of reporducing this, I also insert this line using the geom_line() subfunction of the ggplot() command.

```
ggplot(mfq, aes(x = ideology, y = value, group = variable)) +
    geom_line(aes(linetype = variable, color = variable), size = 1) +
    theme_classic() + geom_line(aes(y = 2.5)) + scale_linetype_manual("Foundations",
```

```
    breaks = c("Harm", "Fairness", "Ingroup", "Authority", "Purity"),
    values = c(Harm = "solid", Fairness = "solid", Ingroup = "dotted",
        Authority = "dotdash", Purity = "dashed")) + scale_color_manual("Foundations",
    breaks = c("Harm", "Fairness", "Ingroup", "Authority", "Purity"),
    values = c(Harm = "black", Fairness = "grey50", Ingroup = "black",
        Authority = "black", Purity = "grey50")) + ggtitle("Moral Judgment") +
    xlab("Self-Reported Political Identity") + ylab("Agreement with Moral Statements") +
    ylim(0, 5) + labs(caption = "Source: Graham, Haidt, and Nosek, 2009, Study 2") +
    theme(text = element_text(size = 12, colour = "black"), axis.title = element_text(s
        colour = "black"), title = element_text(size = 16, colour = "black"),
        plot.caption = element_text(size = 10, color = "black"),
        axis.text.x = element_text(angle = 0, hjust = 0.5, vjust = 0.5),
        plot.title = element_text(hjust = 0.5), legend.key.width = unit(2,
            "line")) + scale_x_discrete(labels = wrap_format(10))
```



Moral Relevance Figure Replication

In Study 2, the authors also considered the moral relevance questions that were used in Study 1 and added some additional items. Using the same dataset loaded earlier, we can jump to compiling the variables.

```r
### Harm ###
morals$emotion <- morals$Emotionally - 1
morals$violence <- morals$Violence - 1
morals$harmed <- morals$Harmed - 1
morals$weak <- morals$Weak - 1
morals$Harm <- rowMeans(morals[, c("emotion", "violence", "harmed",
    "weak")], na.rm = TRUE)

### Fairness ###
morals$treated <- morals$Treated - 1
morals$rights <- morals$Rights - 1
morals$unfairly <- morals$Unfair - 1
morals$profit <- morals$Profiting - 1
morals$Fairness <- rowMeans(morals[, c("treated", "rights", "unfairly",
    "profit")], na.rm = TRUE)

### Ingroup ###
morals$betray <- morals$Betray - 1
morals$friend <- morals$Friend - 1
morals$loyalty <- morals$Loyalty - 1
morals$group <- morals$Group - 1
morals$interest <- morals$Interests - 1
morals$Ingroup <- rowMeans(morals[, c("betray", "friend", "loyalty",
    "group", "interest")], na.rm = TRUE)

### Authority ###
morals$rank <- morals$Rank - 1
morals$duties <- morals$Duties - 1
morals$respect <- morals$Respect - 1
morals$auth <- morals$Author - 1
morals$traditions <- morals$Traditions - 1
morals$Authority <- rowMeans(morals[, c("rank", "duties", "respect",
    "auth", "traditions")], na.rm = TRUE)

### Purity ###
morals$decent <- morals$Decency - 1
morals$uplift <- morals$Uplifting - 1
morals$unnatural <- morals$Unnat - 1
morals$desires <- morals$Desires - 1
morals$Purity <- rowMeans(morals[, c("decent", "uplift", "unnatural",
    "desires")], na.rm = TRUE)
```

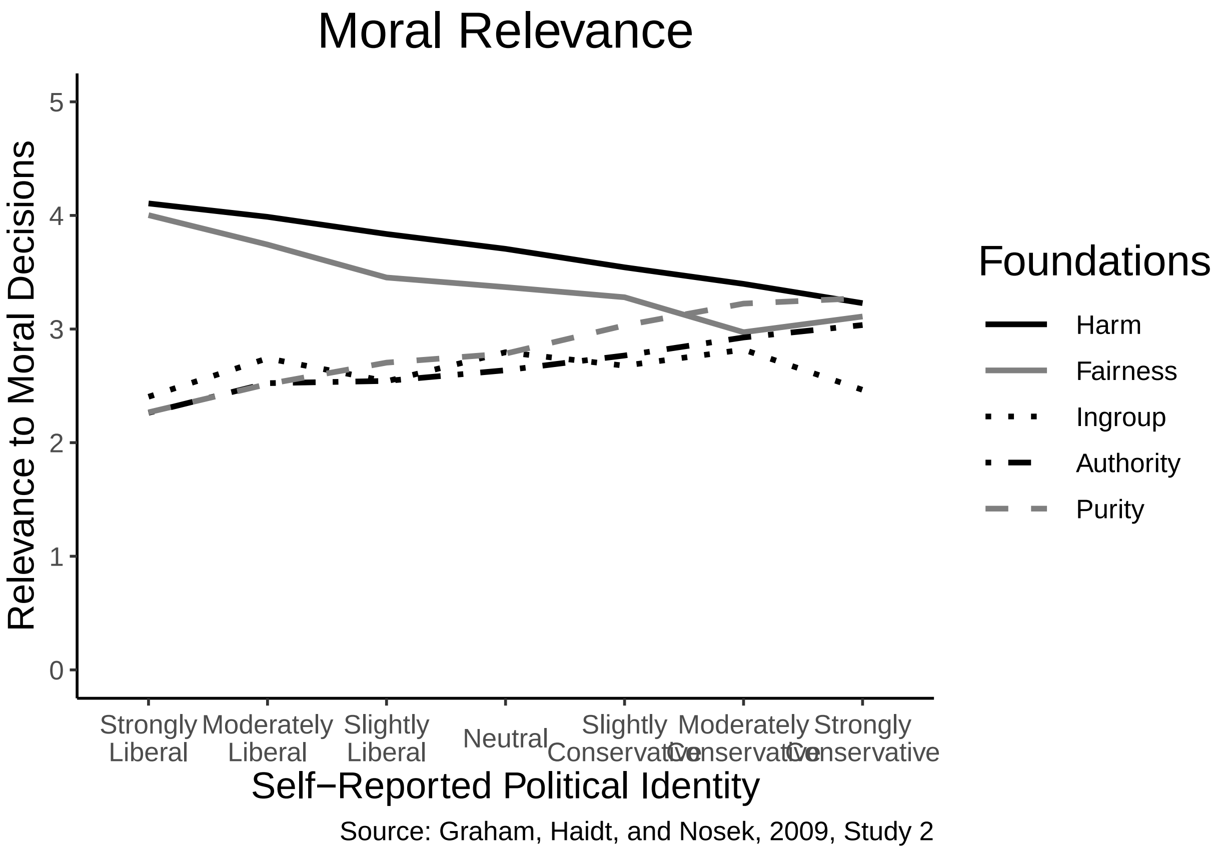
Here, we can skip the ideology recode since it was done earlier in this notebook. We can move to the aggregation of the variables, reshape and graph.

```r
Harm <- aggregate(Harm ~ ideology, morals, mean, na.rm = TRUE)
Fairness <- aggregate(Fairness ~ ideology, morals, mean, na.rm = TRUE)
Ingroup <- aggregate(Ingroup ~ ideology, morals, mean, na.rm = TRUE)
Authority <- aggregate(Authority ~ ideology, morals, mean, na.rm = TRUE)
Purity <- aggregate(Purity ~ ideology, morals, mean, na.rm = TRUE)

moral <- merge(Harm, Fairness, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
moral <- merge(moral, Ingroup, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
moral <- merge(moral, Authority, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)
moral <- merge(moral, Purity, by.x = "ideology", by.y = "ideology",
    all.x = TRUE, all.y = TRUE)

mfq <- reshape2::melt(moral, id.var = "ideology")
```

```r
ggplot(mfq, aes(x = ideology, y = value, group = variable)) +
    geom_line(aes(linetype = variable, color = variable), size = 1) +
    theme_classic() + scale_linetype_manual("Foundations", breaks = c("Harm",
    "Fairness", "Ingroup", "Authority", "Purity"), values = c(Harm = "solid",
    Fairness = "solid", Ingroup = "dotted", Authority = "dotdash",
    Purity = "dashed")) + scale_color_manual("Foundations", breaks = c("Harm",
    "Fairness", "Ingroup", "Authority", "Purity"), values = c(Harm = "black",
    Fairness = "grey50", Ingroup = "black", Authority = "black",
    Purity = "grey50")) + ggtitle("Moral Relevance") + xlab("Self-Reported Political Ide
    ylab("Relevance to Moral Decisions") + ylim(0, 5) + labs(caption = "Source: Graham,
    theme(text = element_text(size = 12, colour = "black"), axis.title = element_text(s
        colour = "black"), title = element_text(size = 16, colour = "black"),
        plot.caption = element_text(size = 10, color = "black"),
        axis.text.x = element_text(angle = 0, hjust = 0.5, vjust = 0.5),
        plot.title = element_text(hjust = 0.5), legend.key.width = unit(2,
            "line")) + scale_x_discrete(labels = wrap_format(10))
```



Repeated Measures GLM

In the paper, the authors conducted a series of repeated measures general linear models for the Moral Relevance and Moral Judgment subscales. Here, I will reproduce the results.

Moral Relevance

For the Moral Relevance subscale, the authors conducted a general linear model to test the differences between the average individual foundation score and the binding foundation score.

For this subscale they find the following:

1. Average difference between individualizing and binding foundations – $F(1, 1205) = 1215.62$, $\eta^2 = .50$
2. Model moderated by politics – $F(1, 1205) = 450.42$, $\eta^2 = .27$

In the reproduction, I build the foundation scores along with aggregate scores for the individualizing and binding foundations.

```
### Harm ###
morals$emotion <- morals$Emotionally - 1
```

```r
morals$violence <- morals$Violence - 1
morals$harmed <- morals$Harmed - 1
morals$weak <- morals$Weak - 1
morals$Harm <- rowMeans(morals[, c("emotion", "violence", "harmed",
    "weak")], na.rm = TRUE)

### Fairness ###
morals$treated <- morals$Treated - 1
morals$rights <- morals$Rights - 1
morals$unfairly <- morals$Unfair - 1
morals$profit <- morals$Profiting - 1
morals$Fairness <- rowMeans(morals[, c("treated", "rights", "unfairly",
    "profit")], na.rm = TRUE)

### Ingroup ###
morals$betray <- morals$Betray - 1
morals$friend <- morals$Friend - 1
morals$loyalty <- morals$Loyalty - 1
morals$group <- morals$Group - 1
morals$interest <- morals$Interests - 1
morals$Ingroup <- rowMeans(morals[, c("betray", "friend", "loyalty",
    "group", "interest")], na.rm = TRUE)

### Authority ###
morals$rank <- morals$Rank - 1
morals$duties <- morals$Duties - 1
morals$respect <- morals$Respect - 1
morals$auth <- morals$Author - 1
morals$traditions <- morals$Traditions - 1
morals$Authority <- rowMeans(morals[, c("rank", "duties", "respect",
    "auth", "traditions")], na.rm = TRUE)

### Purity ###
morals$decent <- morals$Decency - 1
morals$uplift <- morals$Uplifting - 1
morals$unnatural <- morals$Unnat - 1
morals$desires <- morals$Desires - 1
morals$Purity <- rowMeans(morals[, c("decent", "uplift", "unnatural",
    "desires")], na.rm = TRUE)

# Individualizing and Binding score
morals$indiv <- rowMeans(morals[, c("emotion", "violence", "harmed",
    "weak", "treated", "rights", "unfairly", "profit")], na.rm = TRUE)
morals$bind <- rowMeans(morals[, c("betray", "friend", "loyalty",
```

```r
    "group", "interest", "rank", "duties", "respect", "auth",
    "traditions", "decent", "uplift", "unnatural", "desires")],
    na.rm = TRUE)
```

I create a difference score to reflect the difference between the individualizing and binding foundations. This will serve as the dependent measure for the GLM model

```r
# Difference Scores
morals$reldiff <- morals$indiv - morals$bind
```

Finally, I build the repeated measures GLM. The results here are a bit off from the expected results in the paper using the same dataset that the authors posted. The F value for the average difference between the scales without politics is the squared t-value in the (Intercept) portion of the output.

```r
# Moderator linear model for Judgment
rel.diff <- lm(reldiff ~ politics, data = morals)
summary(rel.diff)
```

```
##
## Call:
## lm(formula = reldiff ~ politics, data = morals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.3366 -0.5140 -0.0292  0.5217  2.5765
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.80863    0.02414   33.49   <2e-16 ***
## politics    -0.27171    0.01296  -20.96   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7715 on 1205 degrees of freedom
##   (928 observations deleted due to missingness)
## Multiple R-squared:  0.2673, Adjusted R-squared:  0.2666
## F-statistic: 439.5 on 1 and 1205 DF,  p-value: < 2.2e-16
```

```r
etaSquared(rel.diff)
```

```
##             eta.sq eta.sq.part
## politics 0.2672533   0.2672533
```

Moral Judgment

A similar set of analyses were created for the Moral Judgment subscale. Here the authors achieved the following results, which I am reproducing below.

1. Average difference between individualizing and binding foundations – F(1, 1200) = 635.58, $\eta^2 = .33$
2. Model moderated by politics – F(1, 1200) = 649.40, $\eta^2 = .35$

In this reproduction, I generate average scores for each of the foundations then combine them to form average individualizing and binding foundation scores.

```
### Harm ###
morals$slap <- morals$Slap - 1
morals$kill <- morals$Kill - 1
morals$compassion <- morals$Compassion - 1
morals$gov <- morals$Govharm - 1
morals$Harm <- rowMeans(morals[, c("slap", "kill", "compassion",
    "gov")], na.rm = TRUE)

### Fairness ###
morals$line <- morals$Line - 1
morals$terror <- morals$TerrorRev - 1
morals$justice <- morals$Justice - 1
morals$fairly <- morals$Fairly - 1
morals$Fairness <- rowMeans(morals[, c("line", "terror", "justice",
    "fairly")], na.rm = TRUE)

### Ingroup ###
morals$brother <- morals$BrotherRev - 1
morals$romantic <- morals$Romantic - 1
morals$grouploy <- morals$Grouploy - 1
morals$wellbeing <- morals$Wellbeing - 1
morals$Ingroup <- rowMeans(morals[, c("brother", "romantic",
    "grouploy", "wellbeing")], na.rm = TRUE)

### Authority ###
morals$sexroles <- morals$Sexroles - 1
morals$soldier <- morals$Soldier - 1
morals$kid <- morals$Kidrespect - 1
morals$heritage <- morals$Heritage - 1
morals$Authority <- rowMeans(morals[, c("sexroles", "soldier",
    "kid", "heritage")], na.rm = TRUE)

### Purity ###
morals$revolt <- morals$Revolting - 1
```

```r
morals$wrong <- morals$Wrongdisgust - 1
morals$chaste <- morals$Chastity - 1
morals$sin <- morals$Sin - 1
morals$Purity <- rowMeans(morals[, c("revolt", "wrong", "chaste",
    "sin")], na.rm = TRUE)

# Individualizing (indiv) and Binding (bind) Scores
morals$indiv <- rowMeans(morals[, c("slap", "kill", "compassion",
    "gov", "line", "terror", "justice", "fairly")], na.rm = TRUE)
morals$bind <- rowMeans(morals[, c("brother", "romantic", "grouploy",
    "wellbeing", "sexroles", "soldier", "kid", "heritage", "revolt",
    "wrong", "chaste", "sin")], na.rm = TRUE)
```

Like the Moral Relevance reproduction, I generage a difference score between the foundations, which will be the dependent variable for the model.

```r
# Difference Scores
morals$judgediff <- morals$indiv - morals$bind
```

Finally, I build the model. The results here are more closely aligned to the results from the original paper using their data

```r
# Moderator linear model for Judgment
judge.diff <- lm(judgediff ~ politics, data = morals)
summary(judge.diff)
```

```
##
## Call:
## lm(formula = judgediff ~ politics, data = morals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.6836 -0.6139  0.0415  0.6750  3.0832
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.79178    0.03144   25.18   <2e-16 ***
## politics    -0.42227    0.01658  -25.47   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.001 on 1200 degrees of freedom
##   (933 observations deleted due to missingness)
## Multiple R-squared:  0.351,  Adjusted R-squared:  0.3504
## F-statistic: 648.9 on 1 and 1200 DF,  p-value: < 2.2e-16
```

```r
etaSquared(judge.diff)
```

```
##            eta.sq eta.sq.part
## politics 0.350963    0.350963
```