# Replication of 'Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment' (2008)

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## 0. Setting Up R and Importing Data

```
library(magrittr)
library(dplyr)
library(rio)
library(tidyverse)
library(pixiedust)
library(kableExtra)
```

```
ggl.dat <- read.csv("GerberGreenLarimer_APSR_2008_social_pressure.csv")
```

## 1. Theory, Data, and Hypotheses

In "Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment" (2008), authors Alan S. Gerber, Donald P. Green, and Christopher W. Larimer expand on the literature of voter turnout theories analyzing new data they collected from 344,084 registered voters in Michigan. In doing so, the authors of this paper intend to support the theory that social pressure plays a significant role in an individual's decision to vote or not. Their theory goes against the prevalent theory that voter turnout can be fully explained as a function of rational self-interested behavior, and that the effect of social pressure in someone's decision to vote is nothing more than irrelevant.

The theories investigated in this paper are about individuals' decision to vote, so the unit of analysis researchers were concerned in this study are the individuals. The independent variables chosen by the researchers are the different treatments they assigned to participants of the experiment. That is, each independent variable was a binary variable that represented whether an individual received a particular treatment or not. This method made for a total of four independent variables, one for each treatment group. The dependent variable is the voter turnout in the 2006 primary elections, a binary variable that represents whether the individual voted or not in the primary elections of 2006. The data on the independent variable was collected through the field experiment, while the data on voter turnout in the 2006 elections came from public records.

As already mentioned, a relevant share of the data used in this study was collected from a field experiment in the state of Michigan with 344,084 subjects from 180,002 different households. This sample is a subset from the total number of registered voters in Michigan. Households that the researchers suspected would ignore mailings systematically or that had an elevated chance of voting absentee were excluded from the experiment. The researchers assigned each household to 1 out of 4 different treatment groups. Each treatment group received a particular message in their mail with different social pressure primers. The treatments are explained in more detail in the next page.

- Civic Duty: individuals from households that received mailing with only the message "DO YOUR CIVIC DUTY—VOTE!"
- Hawthorne: individuals from households that received mailing with the civic duty primer and the message "YOU ARE BEING STUDIED!", adding a mild form of social pressure through the observation by researchers.
- Self: individuals from households that received mailing with the civic duty primer and a list with the names of the household members informing whether they voted in the last elections or not, a stronger form of social pressure.
- Neighbors: individuals from households that received mailing with the civic duty primer and a list with information on whether they and their neighbors had voted or not in the last election, the strongest form of social pressure.

Each group comprised of around 11.5% of the entire sample. The remaining 54% of participants were not sent any letters. They were used as the control group for the experiment.

The strategy to identify a causal relationship between social pressure and voter turnout is the field experiment itself. The experimental design allows us to observe a systematic variation in social pressure and estimate an implied effect of the independent variables in turnout through a differences in differences technique. The main idea in this experiment is that the level of social pressure on subjects increases gradually and predictably with each treatment. Joined with the assumption that there is no other systematic difference between the treatment groups, this experiment makes possible for researchers to argue that the change in voter turnout in the 2006 primaries is due only to the change in social pressure. The potential for reverse causation is very low since the social pressure was assigned randomly by the researchers and therefore could not be caused by anything else, including voter turnout. And as for omitted variables, the researchers control for confounders using data on participants' age, sex, year of birth, and turnout in the past 5 elections. All of this information was collected from the census and public records.

Still, there are reasons to doubt this causal identification strategy. One issue that this method does not take into account is the spillover effect of the treatment. Neighbors communicate with each other. They could very well talk about, for example, the mysterious mail they received showing which of their neighbors voted or not in the past elections. Then, subjects who were assigned to the "Self", "Hawthorne" or the "Civic Duty" treatment would know that their neighbors are receiving information about their decision to vote, so they would receive a social pressure equivalent to that of the "Neighbors" treatment group. If that is true, one could argue that all treatments have an irrelevant effect on voter turnout except for the "Neighbors" treatment. And that the change in turnout observed in "Civic Duty", "Self", or 'Hawthorne" was caused only by the spillover from the "Neighbors" group through communication between neighbors. It is also true that communication could have an opposite effect. Perhaps by talking to their neighbors subjects assigned to the "Neighbors" treatment realize that not all people received the mailing containing their information. This would lower the social pressure researchers intended to assign to this group in the first place. These issues would not necessarily prove the authors' theory wrong, but it does make their evidence less convincing as they would not be sure about the differences in social pressure assigned to each group as they claim in the paper.

But assuming this causal relationship is true, what is the mechanism through which this effect takes place? As suggested by the researchers, the mechanism through which social pressure causes greater voter turnout is as an additional factor that is introduced to the individual's calculus of voting. This additional factor can be interpreted as a cost in shame or social ostracism that is exacerbated as social isolation is reduced. If they are correct, this would mean that social pressure should have a similar effect in all participants independent of their predisposition to vote, which can be inferred from their individual's turnout in the last elections.

Additional, if Gerber et al. were right about their main theory, then the voter turnout for individuals in the control group should be lower than the turnout of individuals assigned to the other treatment groups. We should expect the difference between the control group and the treatment groups to increase as the treatment groups applied a stronger level of social pressure. So, again, if their theory is correct we should see

'Neighbors' Effect on Turnout > 'Self' Effect on Turnout > 'Hawthorne' Effect on Turnout > 'Civic Duty' Effect on Turnout > Control Turnout.

## 2. Descriptive statistics

As we can see in the code below and as was previously stated, the database for this study originated from a field experiment that studied 344,084 subjects. Each of these subjects had 16 different variables associated with them. Some of these variables are

- Age
- Sex
- Year of Birth
- Voted in 2000 general elections
- Voted in 2002 general elections
- Voted in 2004 general elections
- Voted in 2000 primary elections
- Voted in 2002 primary elections
- Voted in 2004 primary elections
- Treatment Group
- Voted in 2006 primary elections

Each treatment group had around 38,000 subjects and the control group had approximately 192,000 subjects. With respect to sex, the sample was split evenly with around 50% males and females participating in the study, and the mean participant year of birth was 1956. The majority of participants did not vote in the 2006 primary elections, with around 70% subjects who did not vote and 30% who did vote.

Dimensions of the dataset:

```
dim(ggl.dat)
```

```
## [1] 344084     16
```

Proportion of turnout in 2006 primaries:

```
turnout.prop <- round(prop.table( table( ggl.dat$voted ) ),3)
turnout.prop
```

```
##
##    No   Yes
## 0.684 0.316
```

Proportion of treatment groups:

```
treatment.prop <- round(prop.table( table( ggl.dat$treatment ) ),3)

tab <- matrix(treatment.prop,nrow=5, ncol=1, byrow=TRUE)

rownames(tab) <- c('Civic Duty', 'Control', 'Hawthorne', 'Neighbors', 'Self')
colnames(tab) <- c('Percentage of Individuals in Each Treatment')

tab <- as.table(tab)

tab
```

```
##            Percentage of Individuals in Each Treatment
## Civic Duty                                       0.111
## Control                                          0.556
## Hawthorne                                        0.111
## Neighbors                                        0.111
## Self                                             0.111
```

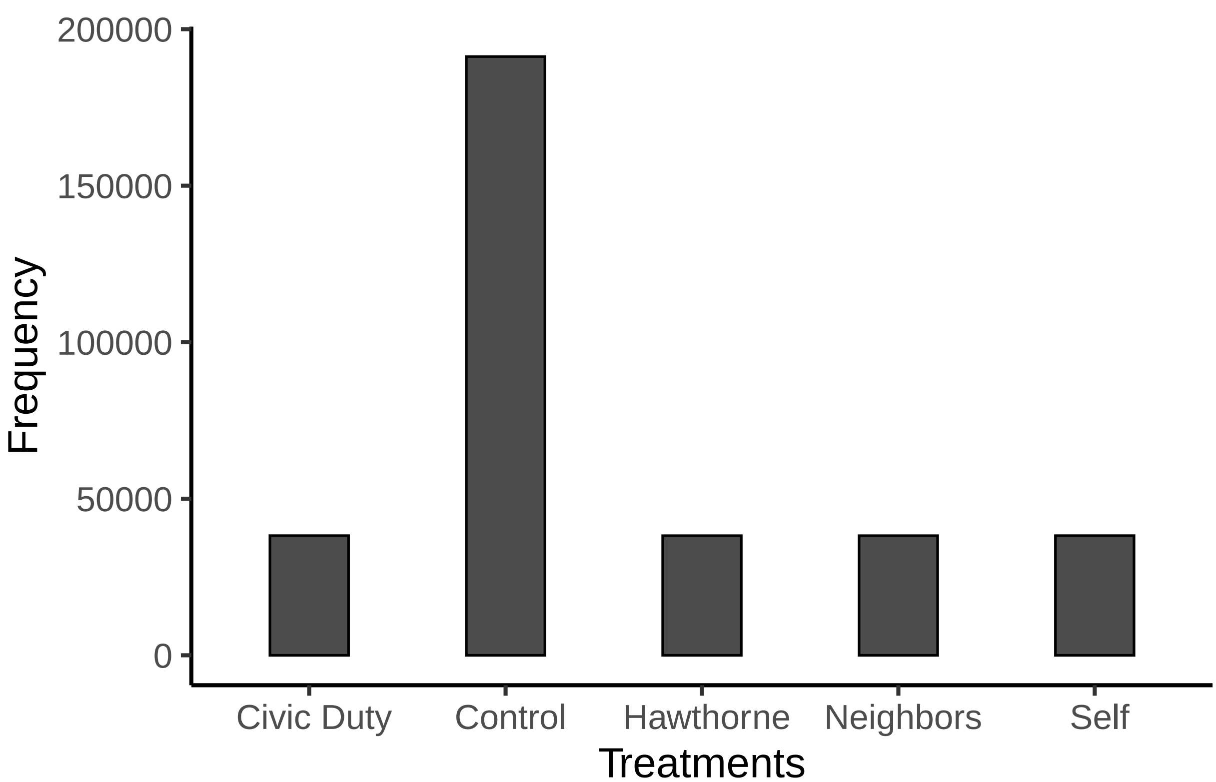
The relevant descriptive statistics on treatment groups are plotted below:

```
ggplot(ggl.dat) +

  geom_bar( aes(x = treatment),color="black", fill=rgb(0,0,0,0.7), width=0.4) +

    labs(x="Treatments", y="Frequency") +

      theme_classic(base_size = 17)
```



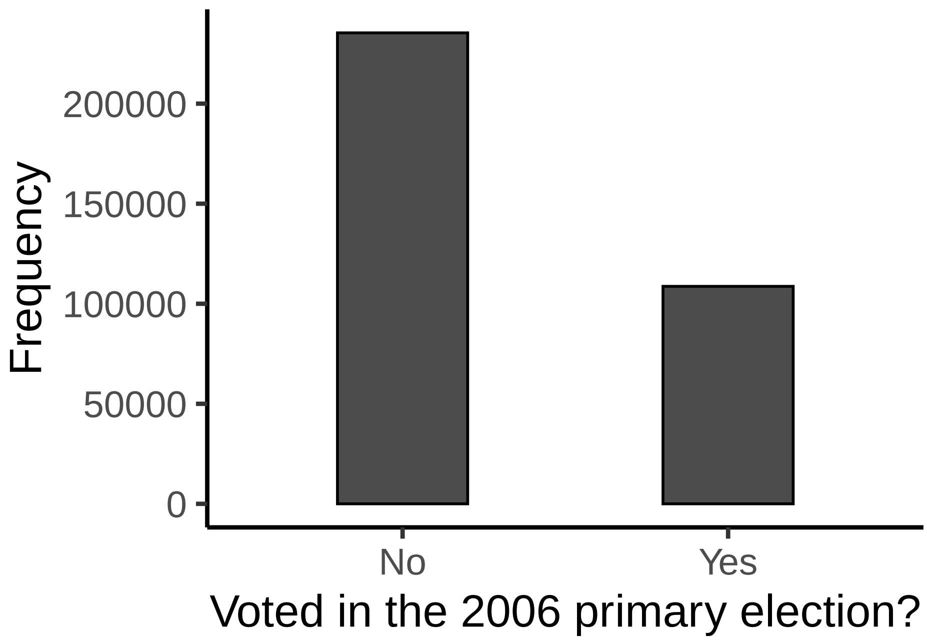
The relevant descriptive statistics on voter turnout are plotted below:

```
ggplot(ggl.dat) +

  geom_bar( aes(x = voted), color="black", fill=rgb(0,0,0,0.7), width=0.4) +

    labs(x="Voted in the 2006 primary election?", y="Frequency") +

      theme_classic(base_size = 17)
```




### 3. Analysis

The primary analysis in "Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment" (2008) is the difference in differences method to estimate the implied effect of each treatment on voter turnout and the OLS regression performed with respect to each treatment variable. This is the main analysis of the paper because it establishes the positive causal link between the independent and the dependent variables. It also demonstrates the strength and statistical significance of this causal relationship. The other analysis in the paper were executed to investigate the causal mechanism hypotheses, but they all rely on the evidence of this primary analysis.

Below we can see a replication of Gerber et al. differences in differences analysis followed by the ordinary least squares regression that shows the statistical significance of the correlation between the independent and the dependent variables.

```
ggl.dat$turnout <- ggl.dat$voted

ggl.dat <- ggl.dat %>%
      mutate(turnout = ifelse(turnout == "No",0,1))

control.meanturnout <- round(
  mean(
```

```r
    ggl.dat$turnout[ggl.dat$treatment == " Control"],na.rm=T),3
  )

civicduty.meanturnout <- round(
  mean(
    ggl.dat$turnout[ggl.dat$treatment == " Civic Duty"], na.rm = T),3
  )

hawthorne.meanturnout <- round(
  mean(
    ggl.dat$turnout[ggl.dat$treatment == " Hawthorne"], na.rm = T),3
  )

civicduty.impliedeffect = round((civicduty.meanturnout - control.meanturnout) ,3)

hawthorne.impliedeffect = round((hawthorne.meanturnout - control.meanturnout) ,3)

control.meanturnout
```

```
## [1] 0.297
```

```r
civicduty.meanturnout
```

```
## [1] 0.315
```

```r
civicduty.impliedeffect
```

```
## [1] 0.018
```

```r
hawthorne.meanturnout
```

```
## [1] 0.322
```

```r
hawthorne.impliedeffect
```

```
## [1] 0.025
```

```r
self.meanturnout <- round(
  mean(
    ggl.dat$turnout[ggl.dat$treatment == " Self"], na.rm=T),3
  )

self.impliedeffect = round((self.meanturnout - control.meanturnout) ,3)

neighbors.meanturnout <- round(
  mean(
    ggl.dat$turnout[ggl.dat$treatment == " Neighbors"],na.rm = T),3
  )

neighbors.impliedeffect = round((neighbors.meanturnout - control.meanturnout) ,3)

self.meanturnout
```

```
## [1] 0.345
```

```
self.impliedeffect
```

```
## [1] 0.048
```

```
neighbors.meanturnout
```

```
## [1] 0.378
```

```
neighbors.impliedeffect
```

```
## [1] 0.081
```

```
ggl.dat$control <- ggl.dat$treatment
ggl.dat <- ggl.dat %>%
      mutate(control = ifelse(control == " Control",1,0))

ggl.dat$civicduty <- ggl.dat$treatment
ggl.dat <- ggl.dat %>%
      mutate(civicduty = ifelse(civicduty == " Civic Duty",1,0))

ggl.dat$hawthorne <- ggl.dat$treatment
ggl.dat <- ggl.dat %>%
      mutate(hawthorne = ifelse(hawthorne == " Hawthorne",1,0))

ggl.dat$self <- ggl.dat$treatment
ggl.dat <- ggl.dat %>%
      mutate(self = ifelse(self == " Self",1,0))

ggl.dat$neighbors <- ggl.dat$treatment
ggl.dat <- ggl.dat %>%
      mutate(neighbors = ifelse(neighbors == " Neighbors",1,0))
```

```
civicduty.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$civicduty == 1],
      ggl.dat$turnout[ggl.dat$control == 1],
          alternative = "two.sided"
  )

civicduty.conf <- round((civicduty.ttest$conf.int), 3)

hawthorne.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$hawthorne == 1],
      ggl.dat$turnout[ggl.dat$control == 1],
          alternative = "two.sided"
  )

hawthorne.conf <- round((hawthorne.ttest$conf.int), 3)

self.ttest<- t.test(
```

```
  ggl.dat$turnout[ggl.dat$self == 1],
      ggl.dat$turnout[ggl.dat$control== 1],
          alternative = "two.sided"
  )

self.conf <- round((self.ttest$conf.int), 3)

neighbors.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$neighbors == 1],
      ggl.dat$turnout[ggl.dat$control == 1],
          alternative = "two.sided"
  )

neighbors.conf <- round((neighbors.ttest$conf.int), 3)

civicduty.conf
```

```
## [1] 0.013 0.023
## attr(,"conf.level")
## [1] 0.95
```

```
hawthorne.conf
```

```
## [1] 0.021 0.031
## attr(,"conf.level")
## [1] 0.95
```

```
self.conf
```

```
## [1] 0.043 0.054
## attr(,"conf.level")
## [1] 0.95
```

```
neighbors.conf
```

```
## [1] 0.076 0.087
## attr(,"conf.level")
## [1] 0.95
```

This code outputs important results for our research question. First of all we should note that the average turnout for subjects where no social pressure was added was around 29.7%. For subjects in the "Civic Duty" group, average turnout was 1.8% higher than the control group, making for an average turnout of 31.5%. The 95% confidence interval of this effect is between 1.3% and 2.3%. For subjects in the "Hawthorne" group, average turnout was approximately 2.6% higher than the control group, that is a 32.2% average turnout. The 95% CI for the "Hawthorne" effect is between 2.1% and 3.1%. For the "Self" group, average turnout was 4.9% higher than the control group, or 34.5%. The 95% CI for the "Self" effect is between 4.3% and 5.4%. Finally, for the "Neighbors" group we observed a 8.1% difference in average turnout when compared to the control group, making for an average turnout of 37.8%. The 95% CI for the "Neighbors" effect is between 7.6% and 8.7%. Even after controlling for fixed effects and for fixed effects+covariates, these effect estimates remain very similar, varying at most by 0.1%. All of these estimates had a reported p-value lower than 0.001, which puts these findings within the threshold for statistical significance ($< 0.05$).

## 4. Discussion and conclusion

The statistical findings from the last section are summarized in the tables below.

```
treatment.lm <- lm(turnout ~ (civicduty+hawthorne+self+neighbors), ggl.dat)


table1<- dust(treatment.lm) %>%
  sprinkle(col = 2:4, round = 3) %>%
  sprinkle(col = 5, fn = quote(pvalString(value))) %>%
  sprinkle_colnames(term = "Term",
                    estimate = "Estimate",
                    std.error = "SE",
                    statistic = "T-statistic",
                    p.value = "P-value") %>%
  kable()%>%
  kable_styling(latex_options = "HOLD_position")

ggl.dat$civicduty.fixedeffect<-ggl.dat$civicduty-ave(
  ggl.dat$civicduty,ggl.dat$cluster)+mean(
    ggl.dat$civicduty
)

ggl.dat$hawthorne.fixedeffect<-ggl.dat$hawthorne-ave(
  ggl.dat$hawthorne,ggl.dat$cluster)+mean(
    ggl.dat$hawthorne
)

ggl.dat$self.fixedeffect<-ggl.dat$self-ave(
  ggl.dat$self,ggl.dat$cluster)+mean(
    ggl.dat$self
)

ggl.dat$neighbors.fixedeffect<-ggl.dat$neighbors-ave(
  ggl.dat$neighbors,ggl.dat$cluster)+mean(
    ggl.dat$neighbors
)

ggl.dat$turnout.fixedeffect<-ggl.dat$turnout-ave(
  ggl.dat$turnout,ggl.dat$cluster)+mean(
    ggl.dat$turnout
)

fixedeffect.lm<-lm(turnout.fixedeffect~(
  hawthorne.fixedeffect+civicduty.fixedeffect+neighbors.fixedeffect+self.fixedeffect
  ),
  ggl.dat
)

table2 <- dust(fixedeffect.lm) %>%
  sprinkle(col = 2:4, round = 3) %>%
  sprinkle(col = 5, fn = quote(pvalString(value))) %>%
  sprinkle_colnames(term = "Term",
                    estimate = "Estimate",
```

```
                     std.error = "SE",
                     statistic = "T-statistic",
                     p.value = "P-value") %>%
  kable()%>%
  kable_styling(latex_options = "HOLD_position")

covariate.fixedeffect.lm <- lm(turnout.fixedeffect~(
  hawthorne.fixedeffect+civicduty.fixedeffect+neighbors.fixedeffect+self.fixedeffect
  +g2000+g2002+p2000+p2002+p2004),
  ggl.dat

  )

table3 <- dust(covariate.fixedeffect.lm) %>%
  sprinkle(col = 2:4, round = 3) %>%
  sprinkle(col = 5, fn = quote(pvalString(value))) %>%
  sprinkle_colnames(term = "Term",
                     estimate = "Estimate",
                     std.error = "SE",
                     statistic = "T-statistic",
                     p.value = "P-value") %>%
  kable()%>%
  kable_styling(latex_options = "HOLD_position")


ConfidenceIntervals <- c("Civic Duty: 0.013 - 0.023","Hawthorne: 0.021 - 0.031","Self: 0.043 - 0.054","

table4 <- data.frame(ConfidenceIntervals)


table1
```

| Term | Estimate | SE | T-statistic | P-value |
|---|---|---|---|---|
| (Intercept) | 0.297 | 0.001 | 279.525 | $< 0.001$ |
| civicduty | 0.018 | 0.003 | 6.884 | $< 0.001$ |
| hawthorne | 0.026 | 0.003 | 9.896 | $< 0.001$ |
| self | 0.049 | 0.003 | 18.657 | $< 0.001$ |
| neighbors | 0.081 | 0.003 | 31.263 | $< 0.001$ |

Table 1 shows the implied effects of each independent variable in voter turnout. The intercept represents voter turnout of the control group.

```
table2
```

| Term | Estimate | SE | T-statistic | P-value |
|---|---|---|---|---|
| (Intercept) | 0.296 | 0.001 | 294.374 | $< 0.001$ |
| hawthorne.fixedeffect | 0.026 | 0.002 | 10.576 | $< 0.001$ |
| civicduty.fixedeffect | 0.018 | 0.002 | 7.295 | $< 0.001$ |
| neighbors.fixedeffect | 0.082 | 0.002 | 33.084 | $< 0.001$ |
| self.fixedeffect | 0.049 | 0.002 | 19.768 | $< 0.001$ |

Table 2 shows the implied effects of each independent variable on the dependent variable controlling for fixed effects. Again, the intercept represents voter turnout of the control group.

```
table3
```

| Term | Estimate | SE | T-statistic | P-value |
|---|---|---|---|---|
| (Intercept) | 0.09 | 0.002 | 40.845 | $< 0.001$ |
| hawthorne.fixedeffect | 0.025 | 0.002 | 10.512 | $< 0.001$ |
| civicduty.fixedeffect | 0.018 | 0.002 | 7.6 | $< 0.001$ |
| neighbors.fixedeffect | 0.081 | 0.002 | 34.073 | $< 0.001$ |
| self.fixedeffect | 0.048 | 0.002 | 20.209 | $< 0.001$ |
| g2000yes | 0.004 | 0.002 | 2.019 | 0.044 |
| g2002yes | 0.095 | 0.002 | 45.987 | $< 0.001$ |
| p2000yes | 0.086 | 0.002 | 50.31 | $< 0.001$ |
| p2002yes | 0.117 | 0.002 | 75.737 | $< 0.001$ |
| p2004Yes | 0.147 | 0.001 | 98.723 | $< 0.001$ |

Table 3 shows the implied effects of each independent variable on the dependent variable controlling for fixed effects and covariates. It also shows the factor of each covariate, but this is less relevant for the study. Once more, the intercept represents voter turnout of the control group.

```
table4
```

```
##         ConfidenceIntervals
## 1 Civic Duty: 0.013 - 0.023
## 2  Hawthorne: 0.021 - 0.031
## 3       Self: 0.043 - 0.054
## 4  Neighbors: 0.076 - 0.087
```

Table 4 shows the 95% Confidence Intervals for each of the treatment variables turnout in relation to the control turnout.

From these results we learn that the strongest effect comes from "Neighbors" intervention, followed by the "Self", the "Hawthorne", and the "Civic Duty" treatments, in that order. All of these effects are positive, increasing the amount of subjects that voted when compared to the control group. This is exactly what we expected to see if the authors' theory was correct. This is evidence that the effect of social pressure on voter turnout is in the positive direction and becomes stronger as social pressure increases. Another element of the analysis that provides strong evidence to the authors' main theory are the confidence intervals. None of the 95% confidence intervals calculated for each of the implied effects contained 0%. This means that there is a very low probability that the difference in mean turnout between the control group and any of the treatment groups is 0. In other words, it is very unlikely that we would observe no positive effect on voter turnout given any of the treatments. The fact that these findings have a p-value lower than 0.001, on the other hand, is less impressive. Because the experiment is dealing with an incredibly big amount of observations, it was expected that the standard error would be very low and, consequently, the p-value would be below the threshold for statistical significance.

What I am more interested in discussing is the substantive significance of these findings. For that we need to think more deeply about the external validity of these findings. As stated in the paper, this experiment limited itself to subjects who were already registered voters in Michigan. As of 2020, the number of registered voters in the US is around 168 millions according to the United States Census Bureau. This represents a bit more than 50% of the US population. Assuming their experiment was a good representation of the effect of social pressure in the behavior of registered voters across the entire US, their results might still not be representative for almost 50% of the US population. This, however, does not mean that these findings are not substantially significant as even an increase of 5% turnout in a population of 168 millions can make a huge difference in an election. The fact that the experiment restricted itself to Michigan is also something that has to be taken into account. Michigan is a state that has more than 80% of its population living in urban areas, data from the US Census Bureau. This is higher than the US average, and many states have a higher level of social isolation between its citizens than Michigan has. Seeing that social pressure is an extremely important variable in this study, there must be important differences across states when it comes to the effect of social pressure in voter behavior. Again, this does not mean the results of this study have their validity compromised. But I would say these findings are much more relevant for states that have a demographic composition similar to that of Michigan in terms of residents proximity than for states with an increased level of social isolation.

"The Spreading of Disorder" (2008) by Keizer et al. is another contemporary study that used a field experiment to analyze the effect of social pressure on the likelihood of an individual to follow a social norm. This study, however, was concerned with the effect of signs of disorder on the decision of a person to commit petty crimes. According to the authors, their findings support the theory that a lack of social pressure (i.e. a demonstrated lower expectation from your neighbors of you following the social norms) makes you more likely to not follow social norms. This evidence and the conclusion drawn from it are relevant for our discussion because it gives support to a very similar claim as the one Gerber et al. are trying to make. From "The Spreading of Disorder" we have that lower social expectation/pressure drives lower commitment to social norms such as littering and not committing crime. And from "Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment" we have that a higher social pressure drives higher commitment to voting, which is an example of social norm. So these papers complement each other in a very clear way as they both argue that social pressure has a positive causal effect on respect to the social norms.

## 5 Additional Analysis

When running the 95% confidence intervals for each treatment with relation to the control variable I noticed that there was an overlap between the confidence intervals for the "Civic Duty" and the "Hawthorne" effects. So one question remained to be addressed. We have found strong evidence that there was real effect of each treatment on voter turnout when these treatments are compared with the control group. But what about when these treatments are compared to each other? Essentialy, I want to learn whether there is a significant difference in voter turnout if I assign someone to the "Civic Duty", "Hawthorne", "Self", or "Neighbors" group. To answer data I intend to calculate the 95% confidence interval of the treatment groups with each other. I expect the difference between each treatment group to be smaller than when they were compared to the control group, and perhaps find some treatments that have the possibility of being redundant when it comes to effect on voter turnout, such as the "Civic Duty" and "Hawthorne" effects. According to the Gerber et al. theory this could mean that the treatments have the possibility of applying equivalent social pressure on participants of the study.

```
civicduty.hawthorne.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$hawthorne == 1],
      ggl.dat$turnout[ggl.dat$civicduty == 1],
          alternative = "two.sided" )

civicduty.hawthorne.conf <- round((civicduty.hawthorne.ttest$conf.int), 3)

civicduty.self.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$self == 1],
      ggl.dat$turnout[ggl.dat$civicduty == 1],
          alternative = "two.sided" )

civicduty.self.conf <- round((civicduty.self.ttest$conf.int), 3)

civicduty.neighbors.ttest<- t.test(
```

```r
  ggl.dat$turnout[ggl.dat$neighbors == 1],
      ggl.dat$turnout[ggl.dat$civicduty == 1],
          alternative = "two.sided" )

civicduty.neighbors.conf <- round((civicduty.neighbors.ttest$conf.int), 3)

hawthorne.self.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$self == 1],
      ggl.dat$turnout[ggl.dat$hawthorne == 1],
          alternative = "two.sided" )

hawthorne.self.conf <- round((hawthorne.self.ttest$conf.int), 3)

hawthorne.neighbors.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$neighbors == 1],
      ggl.dat$turnout[ggl.dat$hawthorne == 1],
          alternative = "two.sided" )

hawthorne.neighbors.conf <- round((hawthorne.neighbors.ttest$conf.int), 3)

self.neighbors.ttest<- t.test(
  ggl.dat$turnout[ggl.dat$neighbors == 1],
      ggl.dat$turnout[ggl.dat$self== 1],
          alternative = "two.sided" )

self.neighbors.conf <- round((self.neighbors.ttest$conf.int), 3)


civicduty.hawthorne.conf
```

```
## [1] 0.001 0.014
## attr(,"conf.level")
## [1] 0.95
```

```r
civicduty.self.conf
```

```
## [1] 0.024 0.037
## attr(,"conf.level")
## [1] 0.95
```

```r
civicduty.neighbors.conf
```

```
## [1] 0.057 0.070
## attr(,"conf.level")
## [1] 0.95
```

```r
hawthorne.self.conf
```

```
## [1] 0.016 0.029
## attr(,"conf.level")
## [1] 0.95
```

```
hawthorne.neighbors.conf
```

```
## [1] 0.049 0.062
## attr(,"conf.level")
## [1] 0.95
```

```
self.neighbors.conf
```

```
## [1] 0.026 0.040
## attr(,"conf.level")
## [1] 0.95
```

From the confidence intervals I found it seems like we can be fairly confident that there was no redundancy or equivalency between the quantity of social pressure that each treatment applied to participants. However, we can still observe how some treatments had very similar impacts on voter turnout. The best example is "Civic Duty" and "Hawthorne". The difference between mean turnout of participants who were assigned to these groups can be expected to be as low as 0.001, and anything higher than a difference of 0.014 would be exceedingly unusual. So even though we can rule out the possibility of these treatments having exactly the same effect on voter turnout, we cannot rule out the possibility that they are so similar that there is no substantive difference on choosing one treatment over the other if your goal is to increase voter turnout.