

# Red Flagging Fake News

Suhas Gupta, Kevin Drever, Imran Manji

```
# load packages
library(data.table)
library(foreign)
library(sandwich)
library(lmtest)
library(stargazer)
library(lfe)
library(car)
library(ggplot2)
library(data.table)
library(knitr)
# options(kableExtra.latex.load_packages = FALSE)
library(kableExtra)
library(rgeolocate)
library(data.table)
library(knitr)
library(lmtest)
library(ri2)
library(dplyr)
library(forcats)
```

## Null & Alternate Hypothesis

- *NULL Hypothesis* : Make people aware of the prevalence of fake news has no effect on its believability
- *Alternate Hypothesis* : General flags about fake news reduce its believability

## Calculating the sample size

In this section, we calculate the minimum required sample size for our experiment.

The statistical power of an experiment is the experiment's ability to reject the NULL hypothesis when a specific alternate hypothesis is true.

$$\alpha = P(\text{reject } H_0 | H_0)$$

where  $\alpha$  is the significance level. We select a significance level of  $\alpha = 0.05$  as a tolerance for Type I errors in our experiment.

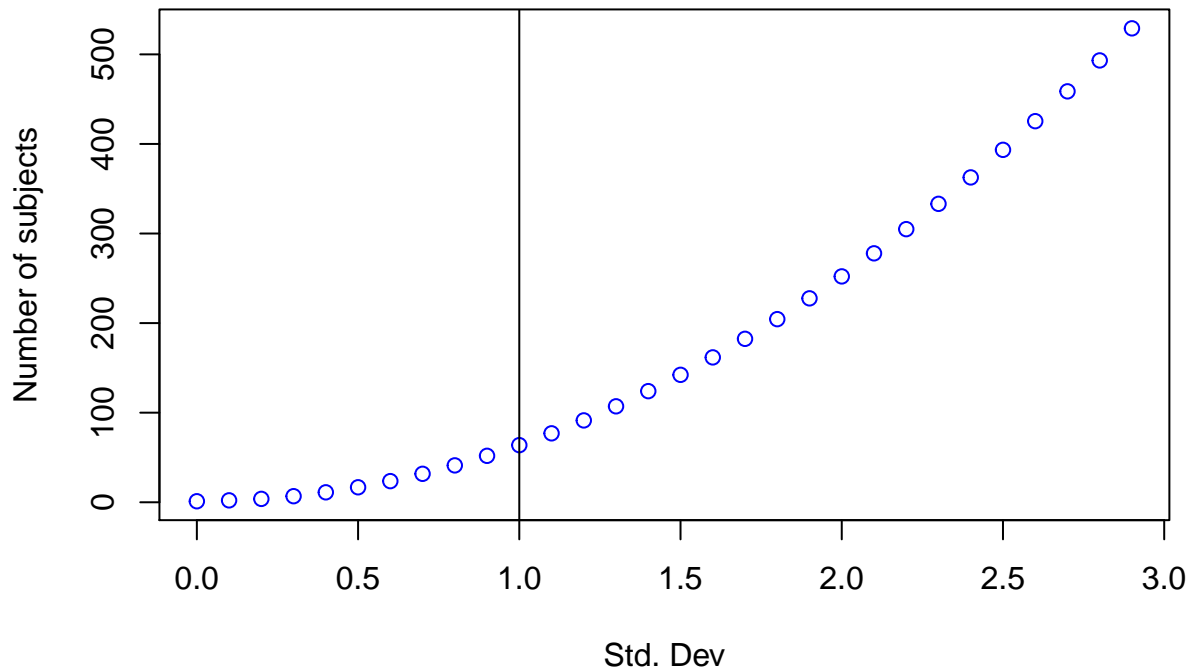
Now that we have chosen our significance level, we would like to minimize the probability of Type II error. i.e. we would like to **maximize** the power of our test against the relevant alternative. Mathematically, power is

$$\text{power} = 1 - P_r(\text{Type II Error}) = P_r(\text{reject } H_0 | H_1 \text{ is true})$$

- We would set the required power of our experiment to be **80%** for this study as a reasonable expectation.
- To calculate the power for the test, we need to conjecture an expected ATE and the standard deviation for the outcome in the experiment.
- The outcome is a rating on a scale of 0-10 on how successful the red flag was in reducing the believability of the fake/misleading social media post. We would like our experiment to be able to detect a difference in means of minimum 2 points on this scale.
- We do expect the measured values for this rating to vary significantly as we poll subjects with different political opinions, life experiences and political affiliations. To be on the conservative side, we would like to have enough power in our experiment to minimize Type II errors when the std. deviation is at least 2.5 times the minimum detectable treatment effect.

```
power_sim <- function(ate,sig_level=0.05,power=0.8,alternate_hyp="two.sided", sd = 1){
  result <- NA
  sims <- seq(1e-5,sd,by=0.1)
  for(i in seq_along(sims)){
    result[i] <- power.t.test(d=ate,
                             sig.level=sig_level,
                             power=power,
                             sd=sims[i],
                             alternative=alternate_hyp)$n
  }
  return(result)
}
sd <- 3
expected_ate <- 0.5
x <- seq(1e-5,sd, by = 0.1)
samples <- power_sim(ate=expected_ate,sd = sd)
plot(x = x, y=samples,col = 'blue',
     xlab="Std. Dev",
     ylab = 'Number of subjects',
     main = "Sample size vs. expected variance in outcome (Power = 0.8)")
abline(v=1.0,col='black',lwd=1)
```

## Sample size vs. expected variance in outcome (Power = 0.8)



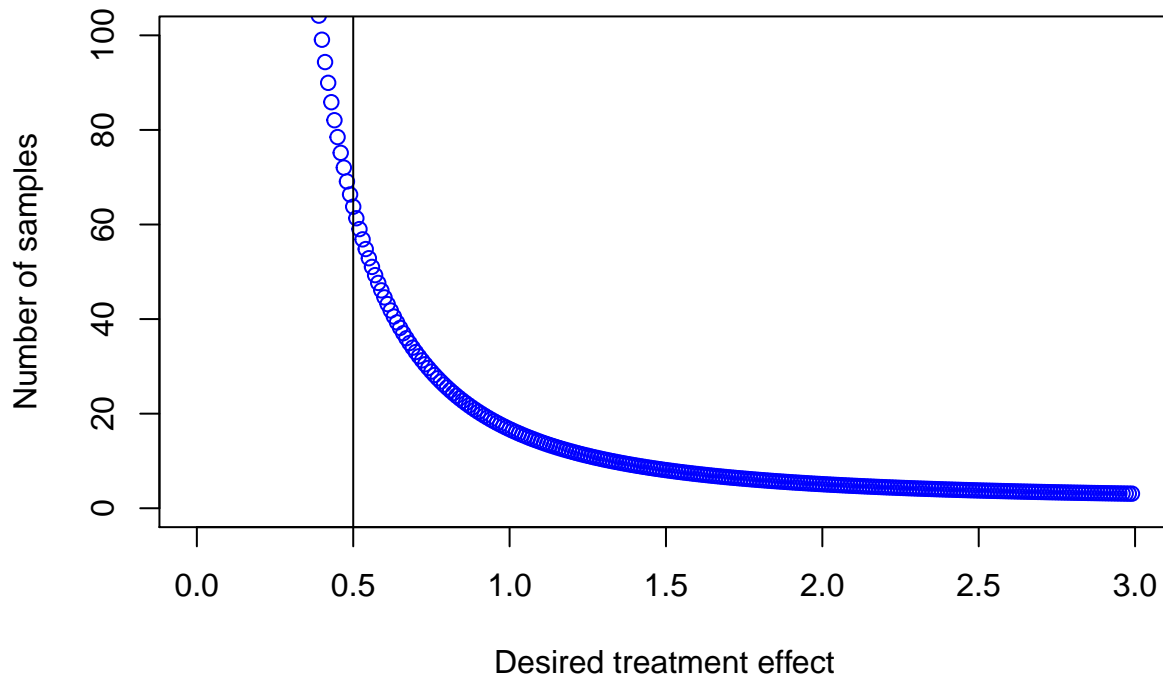
The above plot shows that we need a minimum sample size of 100 to achieve a power of 0.8 when the outcome variable has a standard deviation 1.0 times the treatment effect. The plot below, validates that the absolute value of minimum treatment effect doesn't change the sample size requirement significantly and that this is determined mostly by the expected variance in the measurement data.

```
power_sim_by_ate <- function(ate_vector,sig_level=0.05,power=0.8,alternate_hyp="two.sided",sd = 1){
  result <- NA
  for(i in seq_along(ate_vector)){
    result[i] <- power.t.test(d=ate_vector[i],
                             sig.level=sig_level,
                             power=power,
                             sd=sd,
                             alternative=alternate_hyp)$n
  }
  return(result)
}

sd <- 1
expected_ate <- 3
x <- seq(1e-5,expected_ate,by=0.01)
samples <- power_sim_by_ate(ate=x,sd = sd)

plot(x = x, y=samples,col = 'blue',
     xlab= "Desired treatment effect",
     ylab = 'Number of samples',ylim=c(0,100),
     main = "Sample size vs. minimum detectable treatment effect (Power = 0.8)")
abline(v=0.5,col='black',lwd=1)
```

## Sample size vs. minimum detectable treatment effect (Power = 0.8)



### Covariate questions in the survey

- Age
- Political affiliation
- Registered Voter / non-voter
- race
- are you active on social media?
- education (< high school, high school , undergrad, grad)

### Covariates in regression (not in survey)

- Mturk subject
- location of subject

### Experimental Design

#### 2 x 2

- treatment :
  - banner or no banner
  - tweet is false or true
- block by party affiliation and gender

### Treatment & control assignment

- how to randomly assign while blocking for above

## Regression Models

**Outcome:** Score on how many headlines were correctly identified by subjects (equally balanced True and False posts)

1. Baseline model

outcome ~ general\_flag on survey page

2. Model with co-variables

outcome ~ red\_flag \* gender + red\_flag \* political\_affiliation + factor(age\_group) + factor(education) + red\_flag \* location + registered\_voter + race + social\_media\_active

3. Model with treatment-covariate interactions

- Test if fake news red flagging affects democrats and republicans differently
- Test if fake news red flagging affects different age groups differently
- Test if fake news red flagging affects voters and non voters differently

## Define functions

```
prune_data <- function(dataset){
  data_pruned <- dataset[ 3:nrow(dataset),]
  data_pruned[, c(6,7)] <- lapply(data_pruned[, c(6,7)], as.numeric)
  question_col_names <- c('8B','9B','10B','11B','12B','13B','14B','15B','16B','17B',
                          '8A','9A','10A','11A','12A','13A','14A','15A','16A','17A')
  # Set NA for empty strings in question columns (either in treatment or control but not both)
  for(i in c(31:length(names(data_pruned)))){
    data_pruned[[i]][data_pruned[[i]]==''] <- NA
  }
  # Set assignment group variable (treatment = 1 , control = 0)
  data_pruned[, assignment := ifelse(is.na(data_pruned[, '8B']),0,1)]

  return(data_pruned)
}

compute_score <- function(dataset,answer_guide){
  # compute full score
  for(i in 1:nrow(dataset)){
    dataset[i,"score"] <- sum(dataset[i,31:50] == answer_guide,na.rm=TRUE)
    dataset[i, "score_false"] <- sum(dataset[i,c(33,35,36,39,40,43,45,46,49,50)] == answer_guide[
    dataset[i, "score_true"] <- sum(dataset[i,c(31,32,34,37,38,41,42,44,47,48)] == answer_guide[c
  }
  return(dataset)
}

rename_cols <- function(dataset){
  dt <- rename(dataset,
    Gender = Q1,
    Reg_Voter = Q2,
    Age_bin = Q3,
    Party = Q4,
    Education = Q5,
    Ethnicity = Q6,
    Soc_Med_Active = Q7,
    Voted_2012 = Q38,
```

```

Voted_2016 = Q39,
Marital_status = Q37,
Income = Q36,
Language = Q40

)

dt$Gender[dataset$Gender == ''] <- "Unanswered"
return(dt)
}

create_question_column <- function(dataset){
  dataset[, TestQ1 := ifelse(is.na(dataset$'8B'), dataset$'8A', dataset$'8B')]
  dataset[, TestQ2 := ifelse(is.na(dataset$'9B'), dataset$'9A', dataset$'9B')]
  dataset[, TestQ3 := ifelse(is.na(dataset$'10B'), dataset$'10A', dataset$'10B')]
  dataset[, TestQ4 := ifelse(is.na(dataset$'11B'), dataset$'11A', dataset$'11B')]
  dataset[, TestQ5 := ifelse(is.na(dataset$'12B'), dataset$'12A', dataset$'12B')]
  dataset[, TestQ6 := ifelse(is.na(dataset$'13B'), dataset$'13A', dataset$'13B')]
  dataset[, TestQ7 := ifelse(is.na(dataset$'14B'), dataset$'14A', dataset$'14B')]
  dataset[, TestQ8 := ifelse(is.na(dataset$'15B'), dataset$'15A', dataset$'15B')]
  dataset[, TestQ9 := ifelse(is.na(dataset$'16B'), dataset$'16A', dataset$'16B')]
  dataset[, TestQ10 := ifelse(is.na(dataset$'17B'), dataset$'17A', dataset$'17B')]
  return(dataset)
}

# Color palette for ggplot
cbPalette <- c("#009999", "#AA9900")

compute_robust_ci<- function(mod,type="HC",clustering = FALSE,data=NA) {
  coefs <- names(mod$coefficients)
  if (clustering){
    # calculate robust clustered standard errors
    robust_se <- sqrt(diag(vcovCL(mod,cluster = data,type=type)))
  }
  else{
    # calculate robust standard errors without clustering
    robust_se <- sqrt(diag(vcovHC(mod,type=type)))
  }
  ci_ll <- NA
  ci_ul <- NA
  for(i in 1:length(coefs)){
    ci_ll[i] <- mod$coefficients[[coefs[i]]] - 1.96 * robust_se[i]
    ci_ul[i] <- mod$coefficients[[coefs[i]]] + 1.96 * robust_se[i]
  }
  ci_custom <- matrix(c(ci_ll,ci_ul), nrow = length(coefs), byrow = FALSE)
  return(ci_custom)
}

compute_robust_se<- function(mod,type="HC",clustering = FALSE,data=NA) {
  coefs <- names(mod$coefficients)
  if (clustering){
    # calculate robust clustered standard errors

```

```

    robust_se <- sqrt(diag(vcovCL(mod,cluster = data,type=type)))
  }
  else{
    # calculate robust standard errors without clustering
    robust_se <- sqrt(diag(vcovHC(mod,type=type)))
  }

  return(robust_se)
}

```

## Import data

Study 1: Mturk survey 1 was done with a higher reward and no check for BOTs. The survey subject count was 104 and responses were obtained within 24 hours due to the high reward (5-8 min task paid \$1.5).

Study 2: Mturk survey 2 was done with a higher reward and no check for BOTs. The survey subject count was 132 and responses were obtained over a period of 5 days

Study3: Personal and professional network of the experimenters

```

study1_data <- fread('./data/Mturk_nocaptcha/data.csv')
study2_data <- fread('./data/Mturk_captcha/data.csv')
study3_data <- fread("./data/NonMturk_wCaptcha/data.csv")
# head(study1_data)
# head(study2_data)
# head(study3_data)
# names(study1_data)[31:51]
# names(study2_data)[31:51]
# names(study3_data)[31:51]

```

## Modify data

```
study1_data_pruned <- prune_data(study1_data)
```

```
## Warning in lapply(data_pruned[, c(6, 7)], as.numeric): NAs introduced by
## coercion
```

```
## Warning in `[.data.table`(data_pruned, , `:=`(assignment,
## ifelse(is.na(data_pruned[, : Invalid .internal.selfref detected and fixed by
## taking a (shallow) copy of the data.table so that := can add this new column
## by reference. At an earlier point, this data.table has been copied by R (or
## was created manually using structure() or similar). Avoid names<- and attr<-
## which in R currently (and oddly) may copy the whole data.table. Use set* syntax
## instead to avoid copying: ?set, ?setnames and ?setattr. If this message doesn't
## help, please report your use case to the data.table issue tracker so the root
## cause can be fixed or this message improved.
```

```
study2_data_pruned <- prune_data(study2_data)
```

```
## Warning in lapply(data_pruned[, c(6, 7)], as.numeric): NAs introduced by
## coercion
```

```
## Warning in lapply(data_pruned[, c(6, 7)], as.numeric): Invalid .internal.selfref
## detected and fixed by taking a (shallow) copy of the data.table so that :=
## can add this new column by reference. At an earlier point, this data.table
## has been copied by R (or was created manually using structure() or similar).
## Avoid names<- and attr<- which in R currently (and oddly) may copy the whole
```

```

## data.table. Use set* syntax instead to avoid copying: ?set, ?setnames and ?
## setattr. If this message doesn't help, please report your use case to the
## data.table issue tracker so the root cause can be fixed or this message
## improved.

study3_data_pruned <- prune_data(study3_data)

## Warning in lapply(data_pruned[, c(6, 7)], as.numeric): NAs introduced by
## coercion

## Warning in lapply(data_pruned[, c(6, 7)], as.numeric): Invalid .internal.selfref
## detected and fixed by taking a (shallow) copy of the data.table so that :=
## can add this new column by reference. At an earlier point, this data.table
## has been copied by R (or was created manually using structure() or similar).
## Avoid names<- and attr<- which in R currently (and oddly) may copy the whole
## data.table. Use set* syntax instead to avoid copying: ?set, ?setnames and ?
## setattr. If this message doesn't help, please report your use case to the
## data.table issue tracker so the root cause can be fixed or this message
## improved.

# Rename the covariate columns
study1_data_temp <- rename_cols(study1_data_pruned)
study2_data_temp <- rename_cols(study2_data_pruned)
study3_data_temp <- rename_cols(study3_data_pruned)

# Add score columns
answer_guide <- c('Yes', 'Yes', 'No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'No',
                  'Yes', 'Yes', 'No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'No')

study1_data_mod <- compute_score(study1_data_temp, answer_guide = answer_guide)
study2_data_mod <- compute_score(study2_data_temp, answer_guide = answer_guide)
study3_data_mod <- compute_score(study3_data_temp, answer_guide = answer_guide)

# Add indicator variables
study1_data_mod[, Mturk := 1]
study1_data_mod[, captcha := 0]

study2_data_mod[, Mturk := 1]
study2_data_mod[, captcha := 1]

study3_data_mod[, Mturk := 0]
study3_data_mod[, captcha := 1]

# Check the data
# head(study1_data_mod)
# head(study2_data_mod)
# head(study3_data_mod)

```

## Combine data sets from all studies

```

# combine data set
dt <- rbind(study1_data_mod, study2_data_mod, study3_data_mod)
data_full <- create_question_column(dt)

```



## Hypothesis

The primary hypothesis and effect that we have set out to test is the following:

**H1: Reminding subjects about possibility of misleading tweets using a genral warning will reduce the perceived accuracy of false headlines relative to a no-warning scenario.**

We also want to check the spillover effect of this general warning about fake news on people's trust in true news/headlines.

**H2: Reminding subjects about possibility of misleading tweets using a genral warning will also reduce their trust in true headlines/news relative to a no-warning scenario.**

## Experimental Method

### Participants

The study was conducted online through survey forms created using the Qualtric Survey service provided to us by the University of California, Berkeley. There were two types of participants recruited for this study :

1. Participants recruited using the Amazon Mechanical Turk service
  - Although samples from Mturk are not nationally respresentative, results from the study closely match those obtained from other samples(e.g., Berinsky et al. 2012; Coppock 2016; Horton et al. 2011; Mullinix et al. 2015)
  - Non-US residents, were not allowed to participate.
2. Participants recruited through experimenters' personal and professional network using personal contacts, direct messages, social media network and email.

*< Fill in the text about sample distribution from the data analysis >*

### Procedure

The experiment design used individual random assignment to place subjects in treatment and control. Table 1 shows the distribution of subject randomly assigned to treatment and control for each of the participant group described above. The survey would display warning before presenting the test questions to a subjects if the subject was placed in the treatment group. If the subject was placed in the control group, then no warning would be displayed on the questions. We focused on posts made on the social media platform *Twitter* as the source for all headlines used in the survey. The tweets were mainly from three broad categories 1) US politics 2) Climate change and general belief in science 3) Random facts about US. After each headline, the question asked the participant whether they believe the information in the headline is true or not. The scoring was based on the total number of correct responses (responses that match the group truth about each headline).

```
col1 <- c("Treatment", "Control")
col2 <- c("General Warning", "No Warning")
col3 <- c("X", "Y")
dt<- data.table(col1,col2,col3)

colnames(dt) <- c("Assignment Group", "Flag", "N")
kable(dt, "latex", booktabs=T)
```

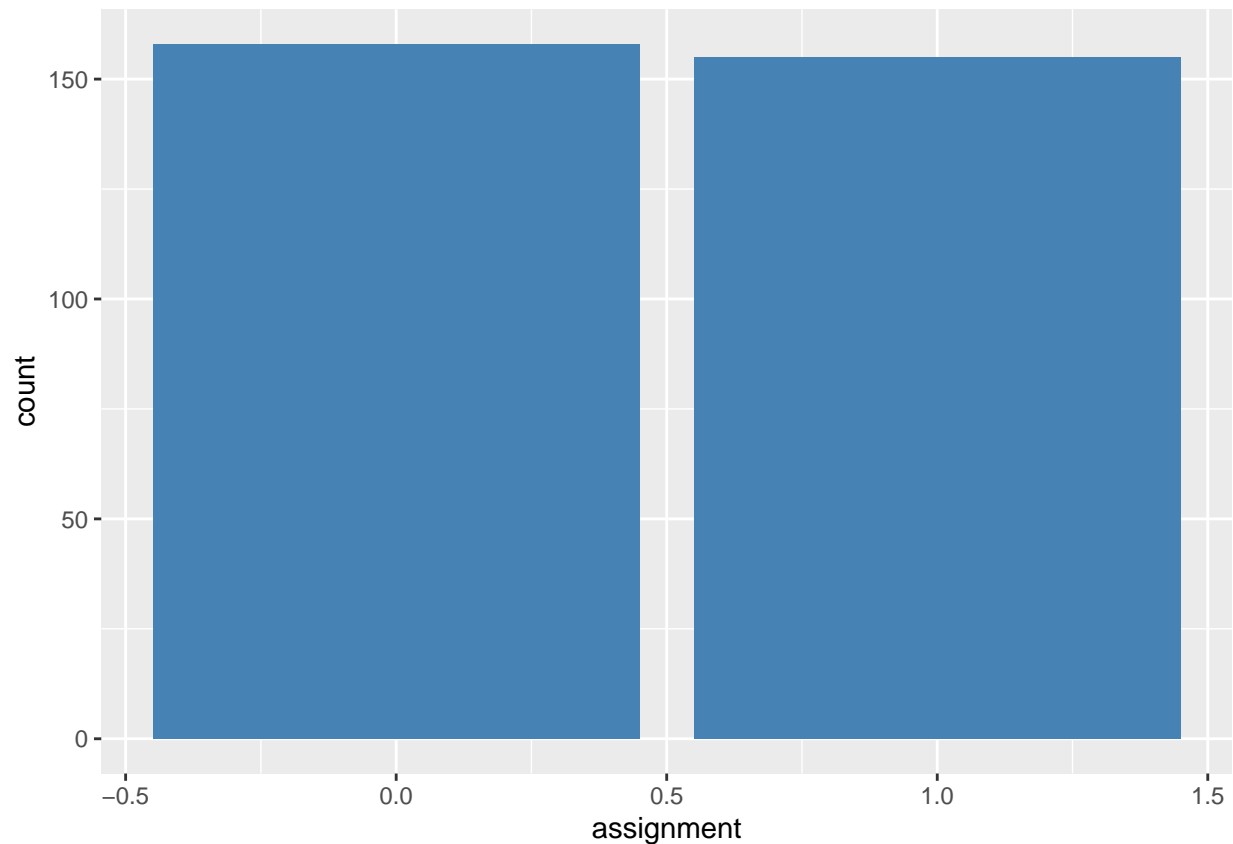
Assignment Group	Flag	N
Treatment	General Warning	X
Control	No Warning	Y

check experimental data

### Randomization

The randomization worked well in the survey software and we had an equal allocation to treatment and control groups in the experiment

```
dt <- data_full[, .(count = .N), by=assignment]
ggplot(dt, aes(x = assignment, y = count)) +
  geom_bar(stat="identity", fill="steelblue")
```



### Power

The data collected has 80% power in detecting any treatment effect that may exist in this experiment

```
## Power calculation
d <- data_full[, .(score_false = mean(score_false)), by = assignment]
ate <- diff(d$score_false)
sd <- data_full[, sd(score_false)]
power.t.test(d=ate, sig.level=0.95, n=nrow(data_full), sd=sd, alternative="one.sided")
```

```
##
##      Two-sample t test power calculation
##
##              n = 313
##            delta = 0.062
##              sd = 1.6
##            sig.level = 0.95
```

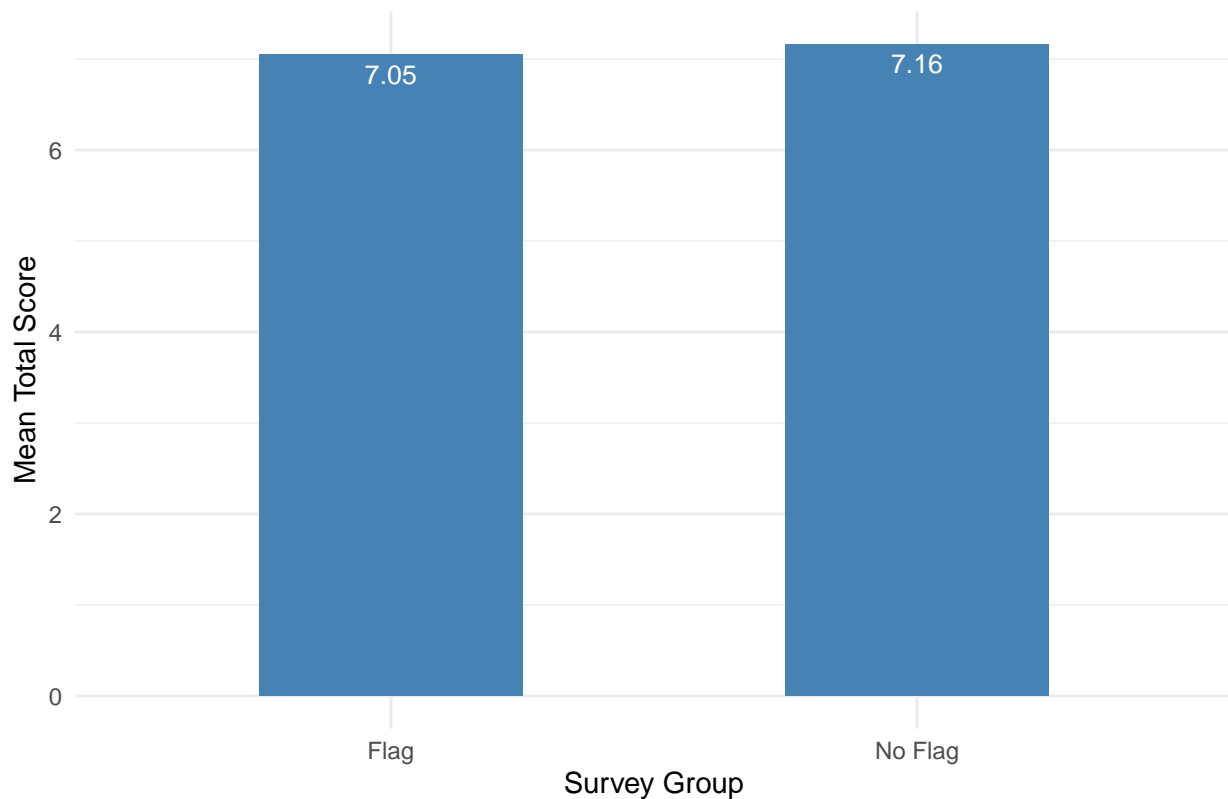
```
##           power = 0.98
##   alternative = one.sided
##
## NOTE: n is number in *each* group
```

## EDA

**Figure 1** summarizes the score of subjects in each assignment group (treatment/control) and for true and false tweets. The table and figures indicate that a general flag slightly decreased the overall score for the subjects ability to detect whether a tweet was true or false. Looking at the third and fourth column of Table1, we see that the detection ability (score) for true tweets decreased slightly in the presence of the general warning flag while the score for detecting false tweets improved slightly. This suggests that though the general warning flag about fake news might improve people's ability to accurately detect false information, it also reduces the belief in true information as well. We will test our hypothesis and research questions more formally in the upcoming sections.

```
dt <- data_full[, .(mean_total_score = mean(score), mean_true_score = mean(score_true), mean_false_score = mean(score_false))]
dt$Warning_Flag[dt$assignment == 0] <- "No Flag"
dt$Warning_Flag[dt$assignment == 1] <- "Flag"
dfm <- melt(dt[, c('Warning_Flag', 'mean_total_score')], id.vars = 1)
dfm <- rename(dfm,
              Assignment = Warning_Flag,
              Score_Type = variable,
              Score = value)
ggplot(dfm, aes(x = Assignment, y = Score, label=sprintf("%.2f", round(Score, digits = 2)))) +
  geom_bar(stat="identity", fill="steelblue", width = 0.5) +
  geom_text(size=3.5, color="white", vjust=1.5) +
  ggtitle("Figure 1. Average score for all tweets by survey assignment group") +
  ylab("Mean Total Score") +
  xlab("Survey Group") +
  theme(plot.title = element_text(hjust = 0.5)) +
  theme_minimal()
```

Figure 1. Average score for all tweets by survey assignment group

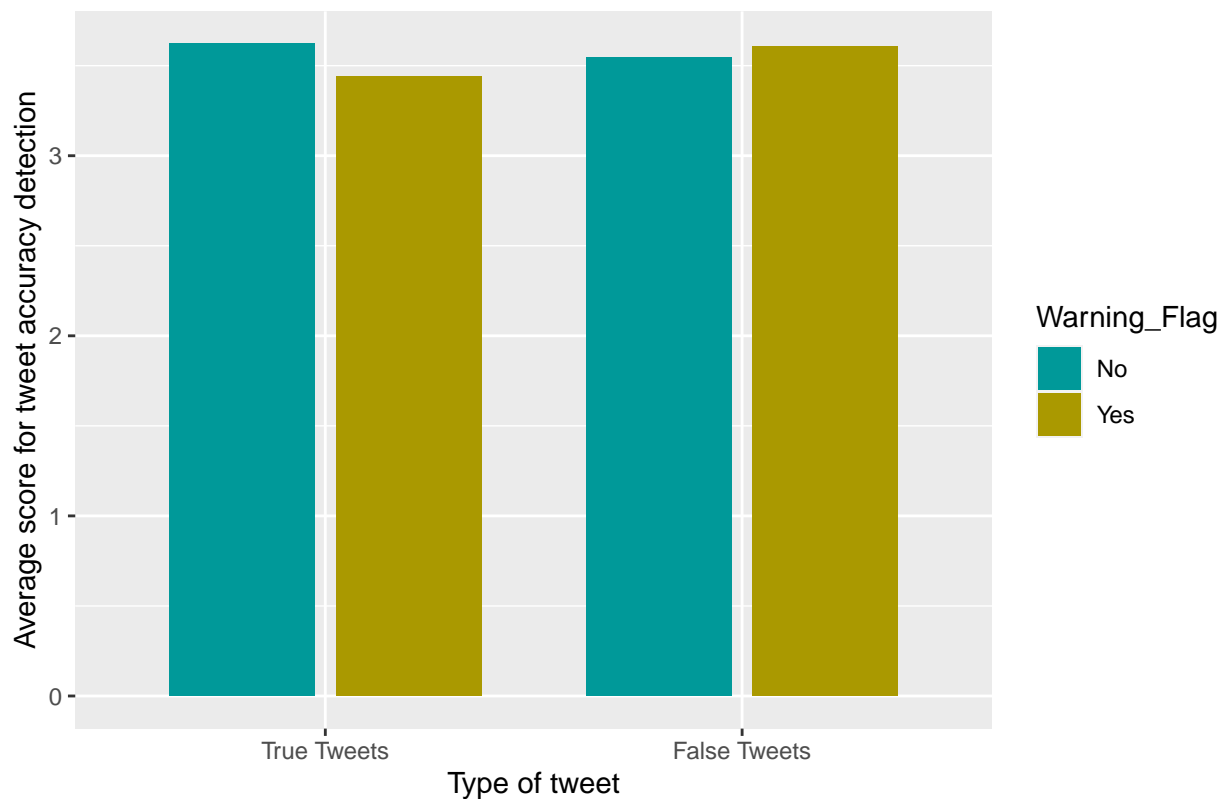


```
dt$Warning_Flag[dt$assignment == 0] <- "No"
dt$Warning_Flag[dt$assignment == 1] <- "Yes"

dfm <- melt(dt[,c('Warning_Flag', 'mean_true_score', 'mean_false_score')], id.vars = 1)
dfm <- rename(dfm,
  Score_Type = variable,
  Score = value)
levels(dfm$Score_Type) = c("True Tweets", "False Tweets")

p <- ggplot(dfm, aes(x = Score_Type, y = Score)) +
  geom_bar(aes(fill = Warning_Flag), stat = "identity", width=0.7, position=position_dodge(width=0.8)) +
  ggtitle("Figure2. General warning effect on true and false tweets") +
  ylab("Average score for tweet accuracy detection") +
  xlab("Type of tweet") +
  theme(plot.title = element_text(hjust = 0.5)) +
  scale_fill_manual(values = cbPalette)
p
```

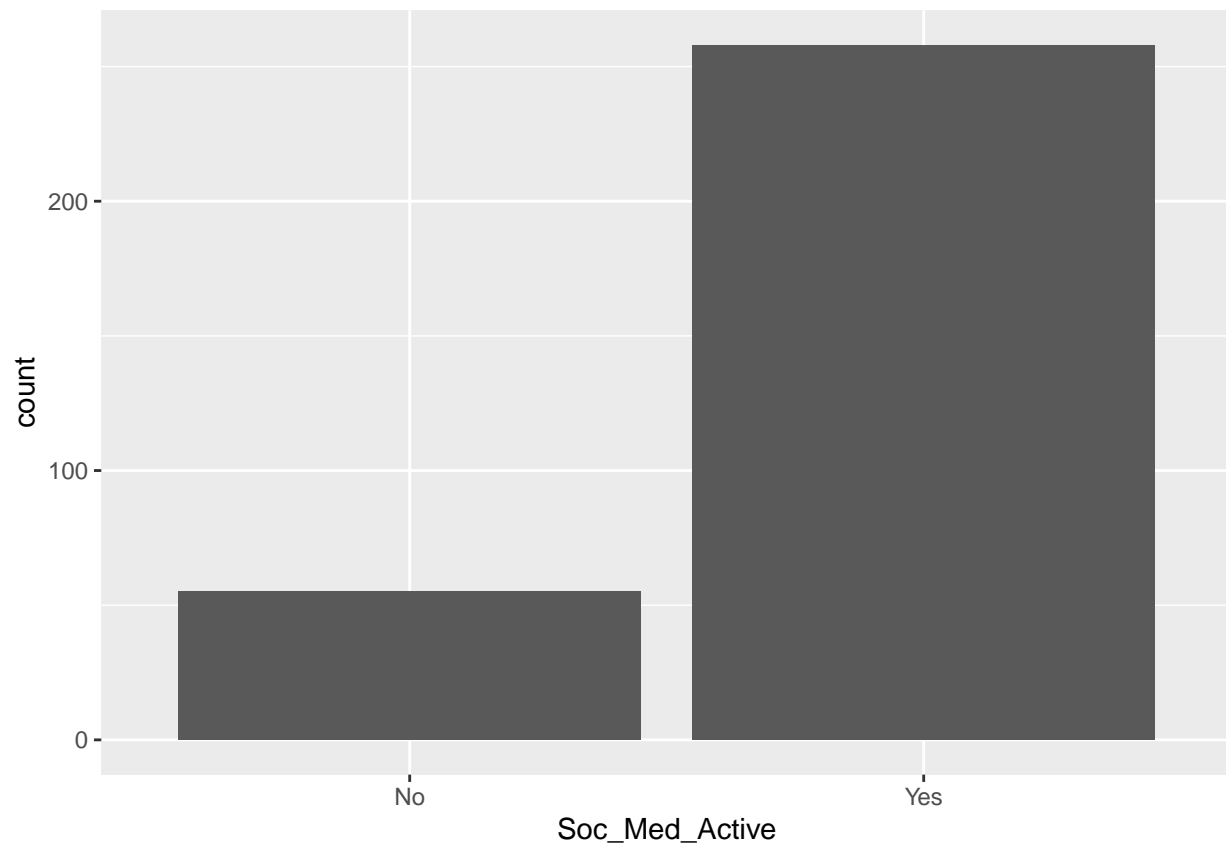
Figure2. General warning effect on true and false tweets



We find from figures 3 and 4 that a large majority of users identified themselves as being active on social media and most of the survey participants were registered voters in the united states.

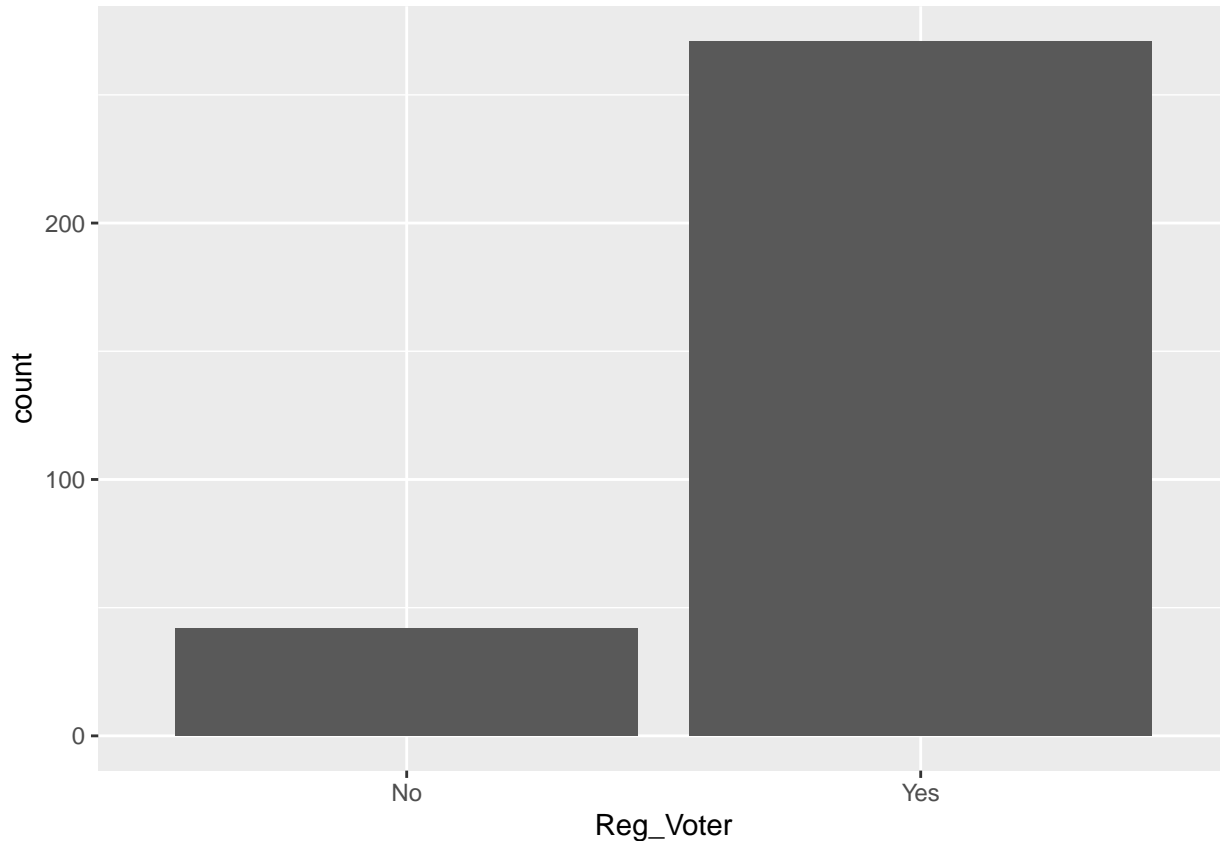
**A large portion of survey subjects said that they considered themselves to be active on social media**

```
data_full$Soc_Med_Active[data_full$Soc_Med_Active == ''] <- "Unanswered"  
ggplot(data_full) + geom_bar(aes(x = Soc_Med_Active))
```



Also, majority of survey subjects said that they were registered as a voter

```
data_full$Reg_Voter[data_full$Reg_Voter == ''] <- "Unanswered"  
ggplot(data_full) + geom_bar(aes(x = Reg_Voter))
```



There appears to be an increase of 6% in score of participants for correctly identifying the false tweets with a confidence interval of  $(-0.3, 0.420)$  before including control for mechanical turk participants and BOT checks. We added indicator variables for participants recruited on mechanical turk as participants on amazon's mechanical turk may not be accurate representatives of general US population. Furthermore, we also added an indicator variable for a BOT check being present in the survey to control for any malignant activity on mechanical turk (using BOTs to answer survey and earn monetray rewards). Since the CAPTCHA verification was added in the latter half of the experiment, we added an indicator variable in regression to control for errors due to BOT activity. We see that the 95% confidence intervals shrink slightly when we control for these covariates. The model in the third column will be our baseline model. The coefficient for assignment variable in the table is not statistically significant in this model.

```
mod1 <- lm(score_false ~ assignment, data_full)
mod2 <- lm(score_false ~ assignment+Mturk, data_full)
mod3 <- lm(score_false ~ assignment+Mturk+captcha, data_full)
ci_custom1 <- compute_robust_ci(mod1)
ci_custom2 <- compute_robust_ci(mod2)
ci_custom3 <- compute_robust_ci(mod3)
se_custom1 <- compute_robust_se(mod1)
se_custom2 <- compute_robust_se(mod2)
se_custom3 <- compute_robust_se(mod3)
# stargazer(mod1,mod2,mod3, type="text",ci.custom = list(ci_custom1,ci_custom2,ci_custom3))
stargazer(mod1,mod2,mod3, type="latex",se = list(se_custom1,se_custom2,se_custom3))
```

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu  
 % Date and time: Sat, Aug 08, 2020 - 20:48:54

**Figure 5** examines the distribution of the survey participants by Gender and shows that we have a well balanced data set in terms of gender distribution.

Table 1:

	<i>Dependent variable:</i>		
	score_false		
	(1)	(2)	(3)
assignment	0.062 (0.180)	0.056 (0.170)	0.061 (0.140)
Mturk		-1.200*** (0.150)	-0.180 (0.120)
captcha			2.300*** (0.190)
Constant	3.500*** (0.130)	4.400*** (0.130)	2.100*** (0.220)
Observations	313	313	313
R <sup>2</sup>	0.0004	0.096	0.450
Adjusted R <sup>2</sup>	-0.003	0.090	0.440
Residual Std. Error	1.600 (df = 311)	1.600 (df = 310)	1.200 (df = 309)
F Statistic	0.110 (df = 1; 311)	16.000*** (df = 2; 310)	83.000*** (df = 3; 309)

Note:

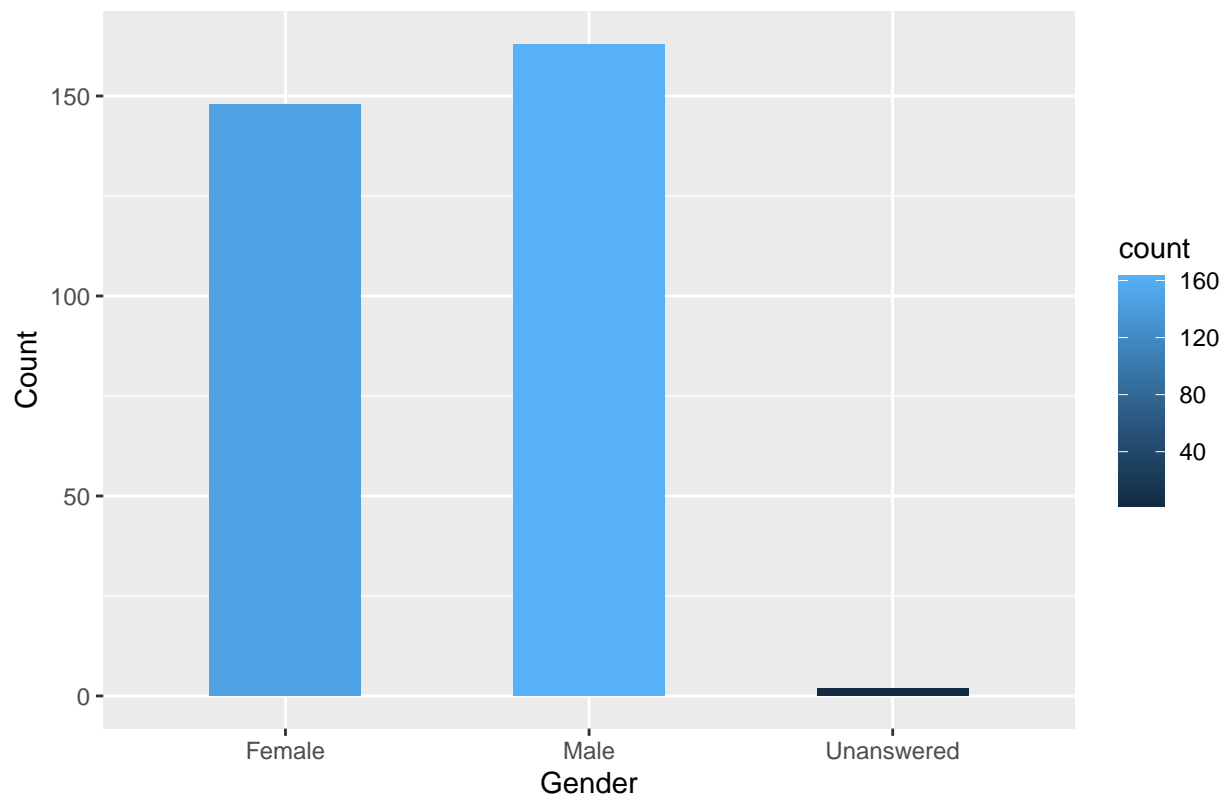
\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

```
dt <- data_full[, .(count = .N), by=Gender]
dt$Gender[dt$Gender == ''] <- "Unanswered"

ggplot(dt, aes(x = Gender, y = count)) +
  geom_bar(aes(fill=count), stat="identity", width = 0.5) +
  ggtitle("Figure 5. Gender distribution of survey takers") +
  ylab("Count") + xlab("Gender") +
  theme(plot.title = element_text(hjust = 0.5))
```



Figure 5. Gender distribution of survey takers



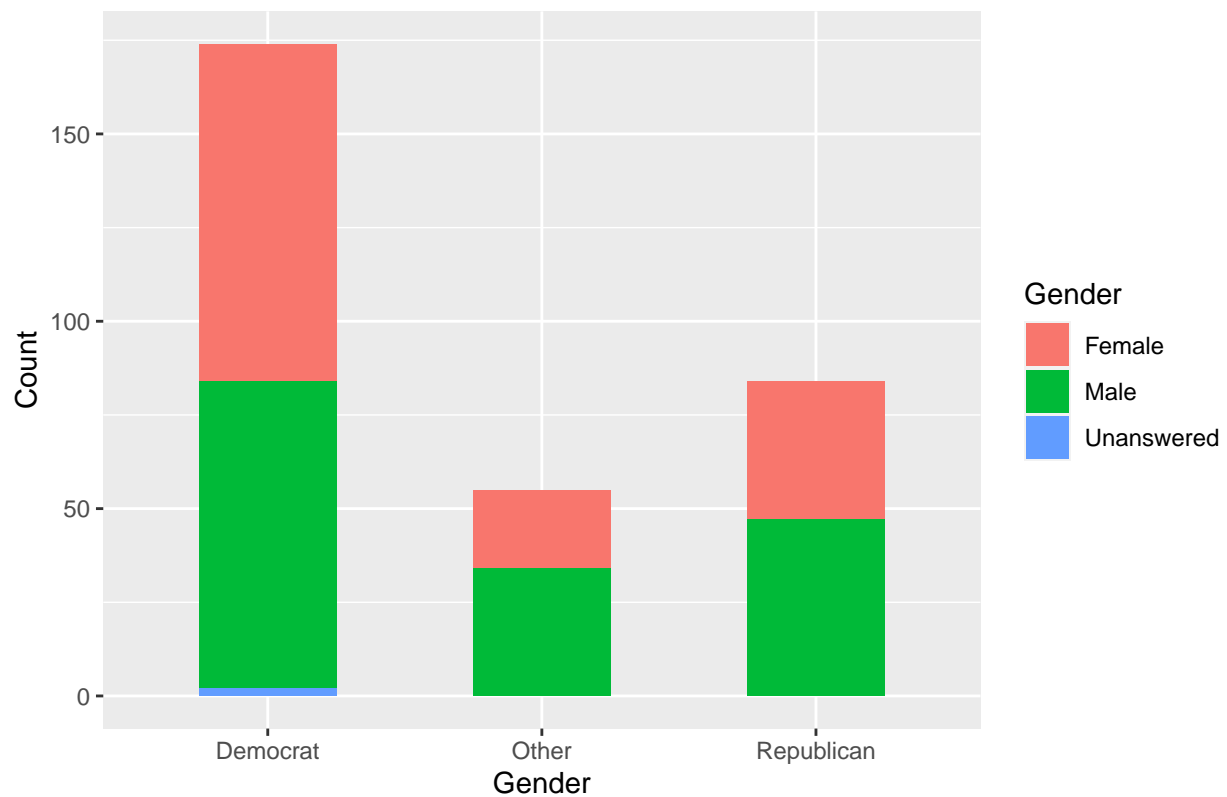
**Figure 6** examines the data distribution based on party affiliation. We see that the Male and Female genders are well balanced for Democrats and Republicans parties while there is a slight skew towards males in *Other* party affiliations. The unanswered or non-conforming genders are only 2 counts in the data set and hence not represented well in this experimental data.

```
data_full$Party[data_full$Party == ''] <- "Unanswered"

dt <- data_full[, .(count = .N), by=(Gender,Party)]
dt$Gender[dt$Gender == ''] <- "Unanswered"

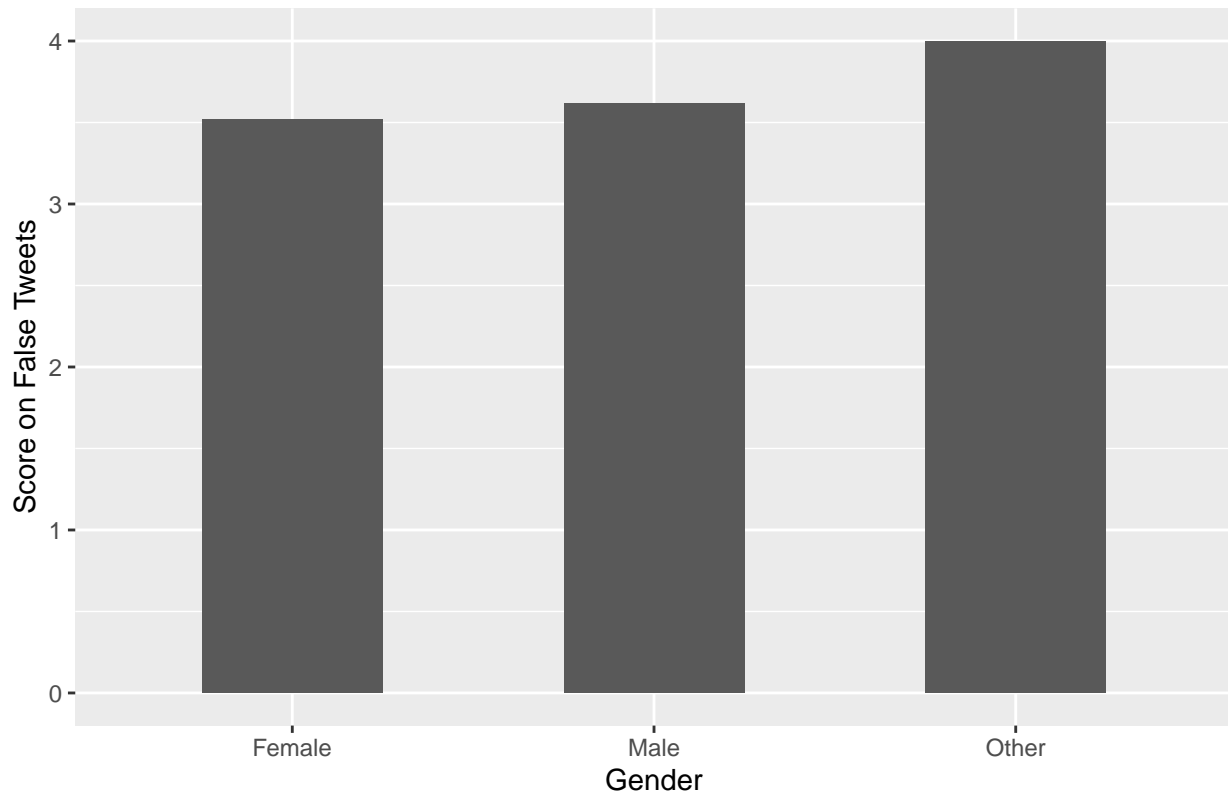
ggplot(dt, aes(x = Party, y = count)) +
  geom_bar(aes(fill=Gender), stat="identity", width = 0.5) +
  ggtitle("Figure 6. Gender distribution by party affiliation") +
  ylab("Count") + xlab("Gender") +
  theme(plot.title = element_text(hjust = 0.5))
```

Figure 6. Gender distribution by party affiliation



```
dt <- data_full[, .(mean_score_by_gender = mean(score_false)), by=Gender]
dt$Gender[dt$Gender == ''] <- "Other"
ggplot(dt, aes(x = Gender, y = mean_score_by_gender)) +
  geom_bar(aes(Gender), stat="identity", width = 0.5) +
  ggtitle("Figure X. Mean scores by Gender") +
  ylab("Score on False Tweets") + xlab("Gender") +
  theme(plot.title = element_text(hjust = 0.5))
```

Figure X. Mean scores by Gender



The tweets selected for our experiment deal with US politics, climate change and general US current affair topics. Believability in social media news/headlines/tweets (and thus ability to score correctly on the survey) can have large variation between Republicans vs Democrats or Male vs Female, depending on the type of the tweets selected. Therefore, we next test the affect of displaying a general warning flag on participant score by including interaction terms on top of the baseline regression model. The mean score of different gender identities is different from each other and we will control for this in the regression model to get a better estimate of the treatment effect.

```
mod4 <- lm(score_false ~ assignment*factor(Gender)+Mturk+captcha, data_full)
mod5 <- lm(score_false ~ assignment*factor(Party)+Mturk+captcha, data_full)
mod6 <- lm(score_false ~ assignment*factor(Gender)+assignment*factor(Party)+Mturk+captcha, data_full)
ci_custom4 <- compute_robust_ci(mod4)
ci_custom5 <- compute_robust_ci(mod5)
ci_custom6 <- compute_robust_ci(mod6)

se_custom4 <- compute_robust_se(mod4)
se_custom5 <- compute_robust_se(mod5)
se_custom6 <- compute_robust_se(mod6)

stargazer(mod4,mod5,mod6,type="text",se=list(se_custom4,se_custom5,se_custom6))
```

```
##
## =====
##                                     Dependent variable:
##                                     -----
##                                     score_false
##                                     (1)                (2)                (3)
## -----
```

```

## assignment                -0.038                -0.037                -0.160
##                          (0.190)                (0.170)                (0.240)
##
## factor(Gender)Female      -1.100***            -1.000***
##                          (0.290)                (0.280)
##
## factor(Gender)Male        -0.670***            -0.660***
##                          (0.220)                (0.200)
##
## factor(Party)Other                0.280                0.260
##                          (0.230)                (0.230)
##
## factor(Party)Republican      -0.540**            -0.540**
##                          (0.260)                (0.250)
##
## Mturk                      -0.180                -0.120                -0.130
##                          (0.120)                (0.120)                (0.120)
##
## captcha                    2.300***            2.100***            2.100***
##                          (0.190)                (0.190)                (0.190)
##
## assignment:factor(Gender)Female      0.180                0.230
##                          (0.280)                (0.280)
##
## assignment:factor(Gender)Male
##
## assignment:factor(Party)Other                0.250                0.250
##                          (0.300)                (0.310)
##
## assignment:factor(Party)Republican      0.120                0.130
##                          (0.350)                (0.350)
##
## Constant                    3.000***            2.300***            3.200***
##                          (0.290)                (0.240)                (0.300)
## -----
## Observations                313                313                313
## R2                          0.460                0.470                0.480
## Adjusted R2                 0.450                0.460                0.470
## Residual Std. Error        1.200 (df = 306)        1.200 (df = 305)        1.200 (df = 304)
## F Statistic                43.000*** (df = 6; 306) 39.000*** (df = 7; 305) 28.000*** (df = 8; 304)
## =====
## Note:                                *p<0.1; **p<0.05; ***p<0.01

mod11a <- lm(score_false ~ assignment+TestQ3+Mturk+captcha, data_full)
mod11b <- lm(score_false ~ assignment+TestQ5+Mturk+captcha, data_full)
mod11c <- lm(score_false ~ assignment+TestQ6+Mturk+captcha, data_full)
mod11d <- lm(score_false ~ assignment+TestQ9+Mturk+captcha, data_full)
mod11e <- lm(score_false ~ assignment+TestQ3+TestQ5+TestQ6+TestQ9+TestQ10+Mturk+captcha, data_full)

stargazer(mod11a,mod11b,mod11c,mod11d,mod11e,type="text")

##
## =====

```

```

##
##
## ----- Dependent variable:
##
## (1) (2) (3) score_true
## -----
## assignment 0.087 0.085 0.200*
## (0.100) (0.110) (0.100)
##
## TestQ3Yes -2.400***
## (0.150)
##
## TestQ5Yes -1.500***
## (0.120)
##
## TestQ6Yes -2.300***
## (0.150)
##
## TestQ9Yes
##
## TestQ10Yes
##
## Mturk -0.200 -0.130 -0.120
## (0.130) (0.140) (0.130)
##
## captcha 0.980*** 1.600*** 1.200***
## (0.140) (0.140) (0.140)
##
## Constant 3.600*** 3.300*** 3.300***
## (0.190) (0.200) (0.180)
##
## -----
## Observations 313 313 313
## R2 0.690 0.630 0.680
## Adjusted R2 0.690 0.620 0.680
## Residual Std. Error 0.910 (df = 308) 1.000 (df = 308) 0.930 (df = 308)
## F Statistic 174.000*** (df = 4; 308) 129.000*** (df = 4; 308) 166.000*** (df = 4; 308)
## =====
## Note:
mod11a <- lm(score_true ~ assignment+TestQ3+Mturk+captcha, data_full)
mod11b <- lm(score_true ~ assignment+TestQ5+Mturk+captcha, data_full)
mod11c <- lm(score_true ~ assignment+TestQ3+TestQ5+TestQ6+Mturk+captcha, data_full)
mod11d <- lm(score_true ~ assignment+TestQ9+Mturk+captcha, data_full)
mod11e <- lm(score_true ~ assignment+TestQ3+TestQ5+TestQ6+TestQ9+TestQ10+Mturk+captcha, data_full)

stargazer(mod11a,mod11b,mod11c,mod11d,mod11e,type="text",
add.lines=list(c("Question Fixed Effects", rep("Yes",5))))

##
## =====
##
## ----- Dependent variable:
##
## ----- score_true

```

```

##                                (1)                                (2)                                (3)
## -----
## assignment                    -0.190*                        -0.180                        -0.200*
##                                (0.110)                        (0.110)                        (0.110)
##
## TestQ3Yes                     0.560***                       0.450**
##                                (0.160)                       (0.180)
##
## TestQ5Yes                     0.130
##                                (0.120)                       (0.120)
##
## TestQ6Yes                     0.220
##                                (0.180)
##
## TestQ9Yes
##
## TestQ10Yes
##
## Mturk                        0.047                          0.037                          0.038
##                                (0.140)                        (0.140)                        (0.140)
##
## captcha                      -0.400**                       -0.640***                       -0.320*
##                                (0.160)                        (0.140)                        (0.170)
##
## Constant                     3.700***                       4.000***                       3.600***
##                                (0.200)                        (0.200)                        (0.220)
## -----
## Question Fixed Effects       Yes                          Yes                          Yes
## Observations                 313                          313                          313
## R2                          0.140                          0.110                          0.140
## Adjusted R2                 0.130                          0.098                          0.130
## Residual Std. Error         0.980 (df = 308)              1.000 (df = 308)              0.980 (df = 306)
## F Statistic                 12.000*** (df = 4; 308)          9.500*** (df = 4; 308)          8.600*** (df = 6; 306)
## =====
## Note:

```

```

data_full[, score_TestQ1 := ifelse(TestQ1 == "Yes", 1, 0)]
data_full[, score_TestQ2 := ifelse(TestQ2 == "Yes", 1, 0)]
data_full[, score_TestQ3 := ifelse(TestQ3 == "No", 1, 0)]
data_full[, score_TestQ4 := ifelse(TestQ4 == "Yes", 1, 0)]
data_full[, score_TestQ5 := ifelse(TestQ5 == "No", 1, 0)]
data_full[, score_TestQ6 := ifelse(TestQ6 == "No", 1, 0)]
data_full[, score_TestQ7 := ifelse(TestQ7 == "Yes", 1, 0)]
data_full[, score_TestQ8 := ifelse(TestQ8 == "Yes", 1, 0)]
data_full[, score_TestQ9 := ifelse(TestQ9 == "No", 1, 0)]
data_full[, score_TestQ10 := ifelse(TestQ10 == "No", 1, 0)]

dt <- data_full[, .(countQ1 = sum(score_TestQ1),
                          countQ2 = sum(score_TestQ2),
                          countQ3 = sum(score_TestQ3),
                          countQ4 = sum(score_TestQ4),

```

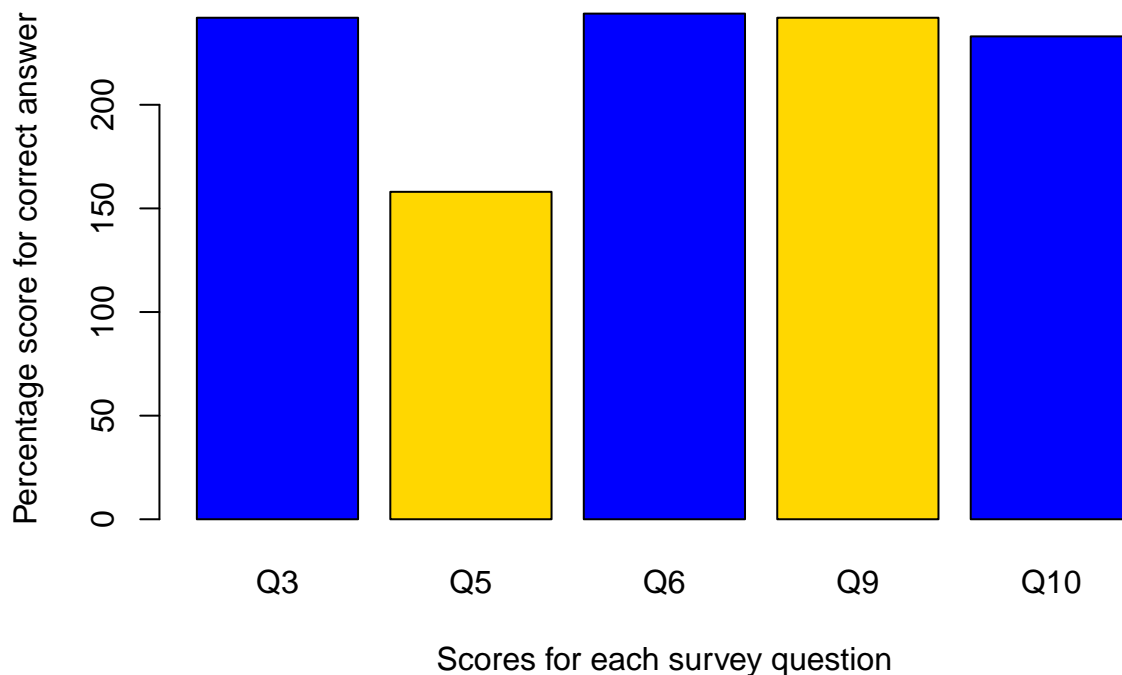
```

countQ5 = sum(score_TestQ5),
countQ6 = sum(score_TestQ6),
countQ7 = sum(score_TestQ7),
countQ8 = sum(score_TestQ8),
countQ9 = sum(score_TestQ9),
countQ10 = sum(score_TestQ10)
)]

d2 <- data_full[, .(countQ1 = sum(score_TestQ1),
countQ2 = sum(score_TestQ2),
countQ3 = sum(score_TestQ3),
countQ4 = sum(score_TestQ4),
countQ5 = sum(score_TestQ5),
countQ6 = sum(score_TestQ6),
countQ7 = sum(score_TestQ7),
countQ8 = sum(score_TestQ8),
countQ9 = sum(score_TestQ9),
countQ10 = sum(score_TestQ10)
), by =assignment]

barplot(dt[,c(countQ3,countQ5,countQ6,countQ9,countQ10)],
col = c('blue','gold'),
ylab = "Percentage score for correct answer",
xlab = "Scores for each survey question",
names.arg= c("Q3","Q5","Q6","Q9","Q10")
)

```



```

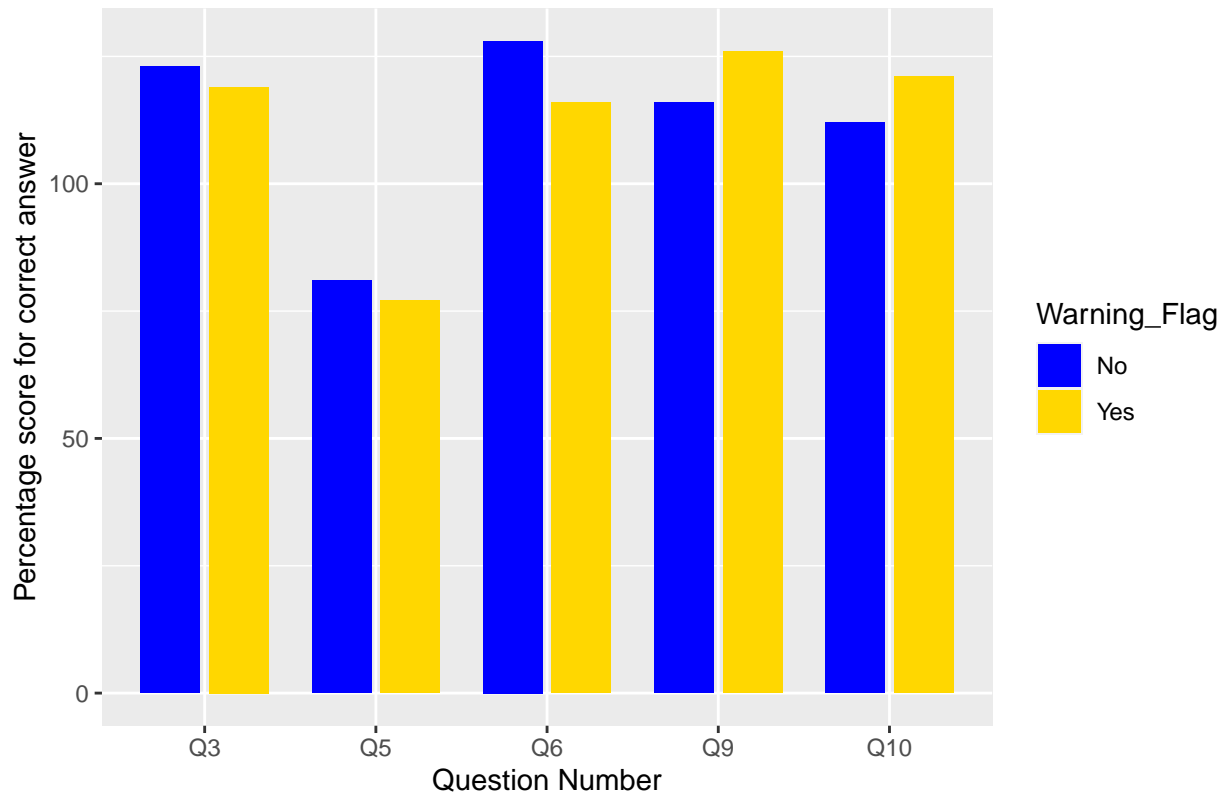
d2$Warning_Flag[d2$assignment == 0] <- "No"
d2$Warning_Flag[d2$assignment == 1] <- "Yes"

dfm <- melt(d2[,c('Warning_Flag','countQ3','countQ5','countQ6','countQ9','countQ10')],id.vars = 1)
levels(dfm$variable) = c("Q3","Q5","Q6","Q9","Q10")

```

```
p <- ggplot(dfm,aes(x = variable,y = value)) +
  geom_bar(aes(fill = Warning_Flag),stat = "identity", width=0.7, position=position_dodge(width=0.8)) +
  ggtitle("Figure2. General warning effect on scores for each tweet ") +
  ylab("Percentage score for correct answer") +
  xlab("Question Number") +
  theme(plot.title = element_text(hjust = 0.5)) +
  scale_fill_manual(values = c("blue","gold"))
p
```

Figure2. General warning effect on scores for each tweet



- \*\*Score on question 10 is collinear with the scores on other questions. Running regression with the fixed effects of question 10 leads to singularities.

```
mod1 <- lm(score_false ~ assignment+score_TestQ3+score_TestQ5+score_TestQ6, data = data_full)
se_custom1 <- compute_robust_se(mod1)
```

```
stargazer(mod1,type="text",se=list(se_custom1))
```

```
##
## =====
##               Dependent variable:
##               -----
##               score_false
## -----
## assignment                0.190***
##                          (0.057)
##
## score_TestQ3              1.700***
```



```
## (0.120)
##
## score_TestQ5 1.300***
## (0.065)
##
## score_TestQ6 1.500***
## (0.120)
##
## Constant 0.340***
## (0.080)
##
## -----
## Observations 313
## R2 0.900
## Adjusted R2 0.900
## Residual Std. Error 0.520 (df = 308)
## F Statistic 703.000*** (df = 4; 308)
## =====
## Note: *p<0.1; **p<0.05; ***p<0.01
```

```
# mod1 <- lm(score_TestQ1 ~ assignment, data = data_full)
# mod2 <- lm(score_TestQ2 ~ assignment, data = data_full)
# mod3 <- lm(score_TestQ3 ~ assignment, data = data_full)
# mod4 <- lm(score_TestQ4 ~ assignment, data = data_full)
# mod5 <- lm(score_TestQ5 ~ assignment, data = data_full)
# mod6 <- lm(score_TestQ6 ~ assignment, data = data_full)
# mod7 <- lm(score_TestQ7 ~ assignment, data = data_full)
# mod8 <- lm(score_TestQ8 ~ assignment, data = data_full)
# mod9 <- lm(score_TestQ9 ~ assignment, data = data_full)
# mod10 <- lm(score_TestQ10 ~ assignment, data = data_full)
mod11 <- lm(score_false ~ assignment*Ethnicity+TestQ3+TestQ5+TestQ6, data_full)
mod12 <- lm(score_false ~ assignment*Gender+TestQ3+TestQ5+TestQ6, data_full)
mod13 <- lm(score_false ~ assignment*Education+TestQ3+TestQ5+TestQ6, data_full)
mod14 <- lm(score_false ~ assignment*factor(Income)+TestQ3+TestQ5+TestQ6, data_full)

#stargazer(mod1,mod2,mod3,mod4,mod5,mod6,mod7,mod8,mod9,mod10,mod11,type="text")
stargazer(mod11,mod12,mod13,mod14,type="text")
```

```
##
## =====
## Dependent variable
## -----
## (1) (2) score_false
## -----
## assignment 0.010 0.240***
## (0.140) (0.082)
##
## EthnicityBlack / African -0.610***
## (0.180)
##
## EthnicityCaucasian -0.190
## (0.120)
##
## EthnicityHispanic / Latinx -0.250
```

##	(0.170)	
##		
## EthnicityNative American	-0.390	
##	(0.240)	
##		
## EthnicityOther	0.120	
##	(0.380)	
##		
## GenderFemale		0.470
##		(0.380)
##		
## GenderMale		0.400
##		(0.370)
##		
## EducationGraduate degree		
##		
##		
## EducationHigh school graduate		
##		
##		
## EducationLess than high school		
##		
##		
## EducationSome college		
##		
##		
## 250000		
##		
##		
## 250000		
##		
##		
## 150000		
##		
##		
## TestQ3Yes	-1.700***	-1.700***
##	(0.092)	(0.090)
##		
## TestQ5Yes	-1.300***	-1.300***
##	(0.062)	(0.063)
##		
## TestQ6Yes	-1.500***	-1.500***
##	(0.093)	(0.092)
##		
## assignment:EthnicityBlack / African	0.820***	
##	(0.260)	
##		
## assignment:EthnicityCaucasian	0.130	
##	(0.150)	
##		
## assignment:EthnicityHispanic / Latinx	0.510*	
##	(0.280)	
##		
## assignment:EthnicityNative American	0.280	

```

##                                     (0.310)
##
## assignment:EthnicityOther          -0.170
##                                     (0.450)
##
## assignment:GenderFemale            -0.085
##                                     (0.120)
##
## assignment:GenderMale
##
##
## assignment:EducationGraduate degree
##
##
## assignment:EducationHigh school graduate
##
##
## assignment:EducationLess than high school
##
##
## assignment:EducationSome college
##
##
## 250000
##
## 250000
##
## 150000
##
##
## Constant                5.000***          4.400***
##                          (0.110)          (0.380)
## -----
## Observations              313              313
## R2                        0.910              0.900
## Adjusted R2               0.900              0.900
## Residual Std. Error       0.510 (df = 298)      0.520 (df = 305)      0.530 (df = 305)
## F Statistic               207.000*** (df = 14; 298) 401.000*** (df = 7; 305) 232.000*** (df = 7; 305)
## =====
## Note:

```

- The SEs don't appear to be changing with different question fixed effects but the magnitude of the coefficient is changing. We will explore cumulating the fixed effects from false questions.

```

mod11a <- lm(score_true ~ assignment+TestQ3+Mturk+captcha, data_full)
mod11b <- lm(score_true ~ assignment+TestQ3+TestQ5+Mturk+captcha, data_full)
mod11c <- lm(score_true ~ assignment+TestQ3+TestQ5+TestQ6+Mturk+captcha, data_full)
mod11d <- lm(score_true ~ assignment+TestQ3+TestQ5+TestQ6+TestQ9+Mturk+captcha, data_full)
mod11e <- lm(score_true ~ assignment+TestQ3+TestQ5+TestQ6+TestQ9+TestQ10+Mturk+captcha, data_full)

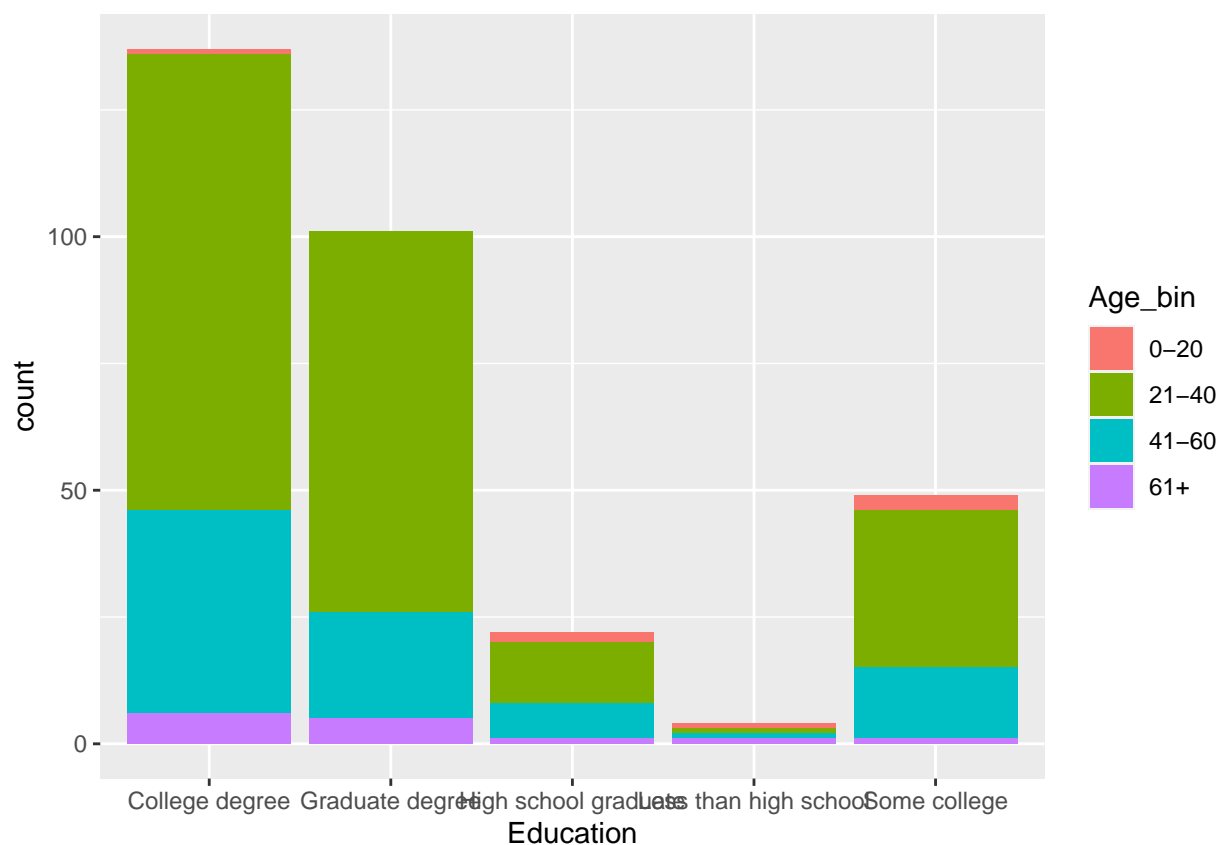
stargazer(mod11a,mod11b,mod11c,mod11d,mod11e,type="text")

```

```
##
## =====
##                                     Dependent variable:
## -----
##                                     score_true
##                                     (3)
## (1) (2)
## -----
## assignment          -0.190*          -0.190*          -0.200*          -0.
##                      (0.110)          (0.110)          (0.110)          (0
##
## TestQ3Yes           0.560***          0.550***          0.450**          0.
##                      (0.160)          (0.170)          (0.180)          (0
##
## TestQ5Yes           0.090              0.074              0.074              0
##                      (0.120)          (0.120)          (0.120)          (0
##
## TestQ6Yes           0.220              0.220              0.220              0
##                      (0.180)          (0.180)          (0.180)          (0
##
## TestQ9Yes           0.000              0.000              0.000              -0
##                      (0.180)          (0.180)          (0.180)          (0
##
## TestQ10Yes          0.000              0.000              0.000              0
##                      (0.180)          (0.180)          (0.180)          (0
##
## Mturk               0.047              0.044              0.038              0
##                      (0.140)          (0.140)          (0.140)          (0
##
## captcha             -0.400**          -0.360**          -0.320*          -0
##                      (0.160)          (0.160)          (0.170)          (0
##
## Constant            3.700***          3.700***          3.600***          3.
##                      (0.200)          (0.220)          (0.220)          (0
##
## -----
## Observations        313              313              313              3
## R2                   0.140            0.140            0.140            0
## Adjusted R2         0.130            0.130            0.130            0
## Residual Std. Error 0.980 (df = 308) 0.980 (df = 307) 0.980 (df = 306) 0.980
## F Statistic         12.000*** (df = 4; 308) 10.000*** (df = 5; 307) 8.600*** (df = 6; 306) 7.600***
## =====
## Note:
```

Our dataset does appear to consist mostly of people with atleast a college degree or higher and the participants mostly belong to the 21-40 age bucket.

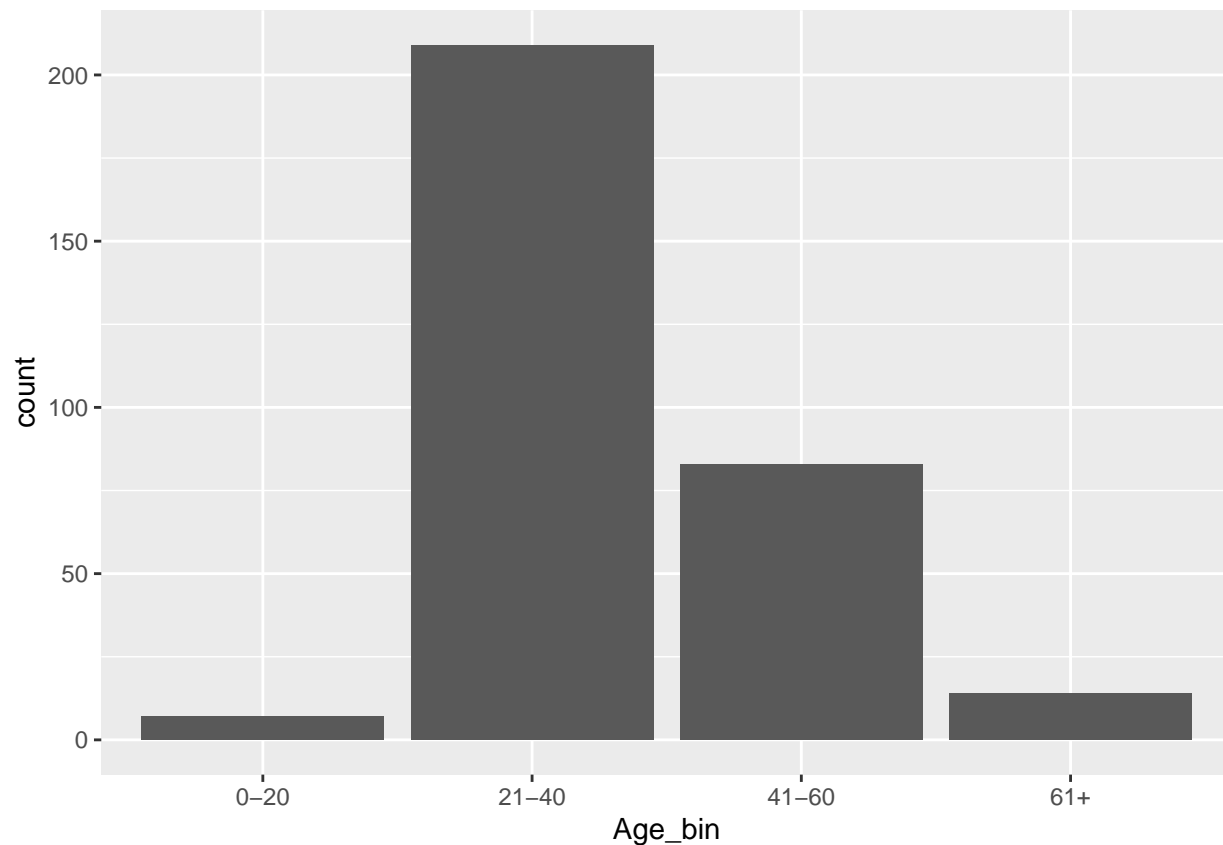
```
ggplot(data_full) + geom_bar(aes(x = Education,fill=Age_bin))
```



```
mod7 <- lm(score_false ~ assignment*factor(Party)+factor(Gender)+assignment*factor(Age_bin)+Mturk+captcha, data_full)
mod8 <- lm(score_false ~ assignment*factor(Age_bin)+assignment*factor(Party)+Mturk+captcha, data_full)
se_custom7 <- compute_robust_se(mod7)
se_custom8 <- compute_robust_se(mod8)
stargazer(mod7,mod8,type="text",se=list(se_custom7,se_custom8))
```

```
##
## =====
##                               Dependent variable:
##                               -----
##                               score_false
##                               (1)           (2)
## -----
## assignment                    -0.780**      -0.950***
##                               (0.350)        (0.320)
##
## factor(Party)Other            0.280         0.290
##                               (0.230)        (0.230)
##
## factor(Party)Republican       -0.510**      -0.510**
##                               (0.260)        (0.260)
##
## factor(Gender)Female          -0.810***
##                               (0.190)
##
## factor(Gender)Male           -0.560***
##                               (0.200)
```

```
##
## factor(Age_bin)21-40          -0.240          -0.350
##                               (0.270)          (0.280)
##
## factor(Age_bin)41-60          -0.360          -0.480
##                               (0.320)          (0.320)
##
## factor(Age_bin)61+            -0.600          -0.800
##                               (0.590)          (0.590)
##
## Mturk                         -0.085          -0.086
##                               (0.130)          (0.130)
##
## captcha                       2.200***          2.100***
##                               (0.190)          (0.200)
##
## assignment:factor(Party)Other  0.160          0.200
##                               (0.300)          (0.300)
##
## assignment:factor(Party)Republican 0.068          0.074
##                               (0.350)          (0.350)
##
## assignment:factor(Age_bin)21-40 0.780**          0.950***
##                               (0.360)          (0.330)
##
## assignment:factor(Age_bin)41-60 0.880**          1.100***
##                               (0.400)          (0.370)
##
## assignment:factor(Age_bin)61+   0.480          0.720
##                               (0.710)          (0.700)
##
## Constant                      3.200***          2.700***
##                               (0.340)          (0.330)
##
## -----
## Observations                   313             313
## R2                             0.490             0.480
## Adjusted R2                   0.460             0.460
## Residual Std. Error           1.200 (df = 297)      1.200 (df = 299)
## F Statistic                   19.000*** (df = 15; 297) 22.000*** (df = 13; 299)
## =====
## Note:                          *p<0.1; **p<0.05; ***p<0.01
ggplot(mutate(data_full, Age = fct_infreq(Age_bin))) + geom_bar(aes(x = Age_bin))
```



```
data_full[, .N, by=(Party, Age_bin)]
```

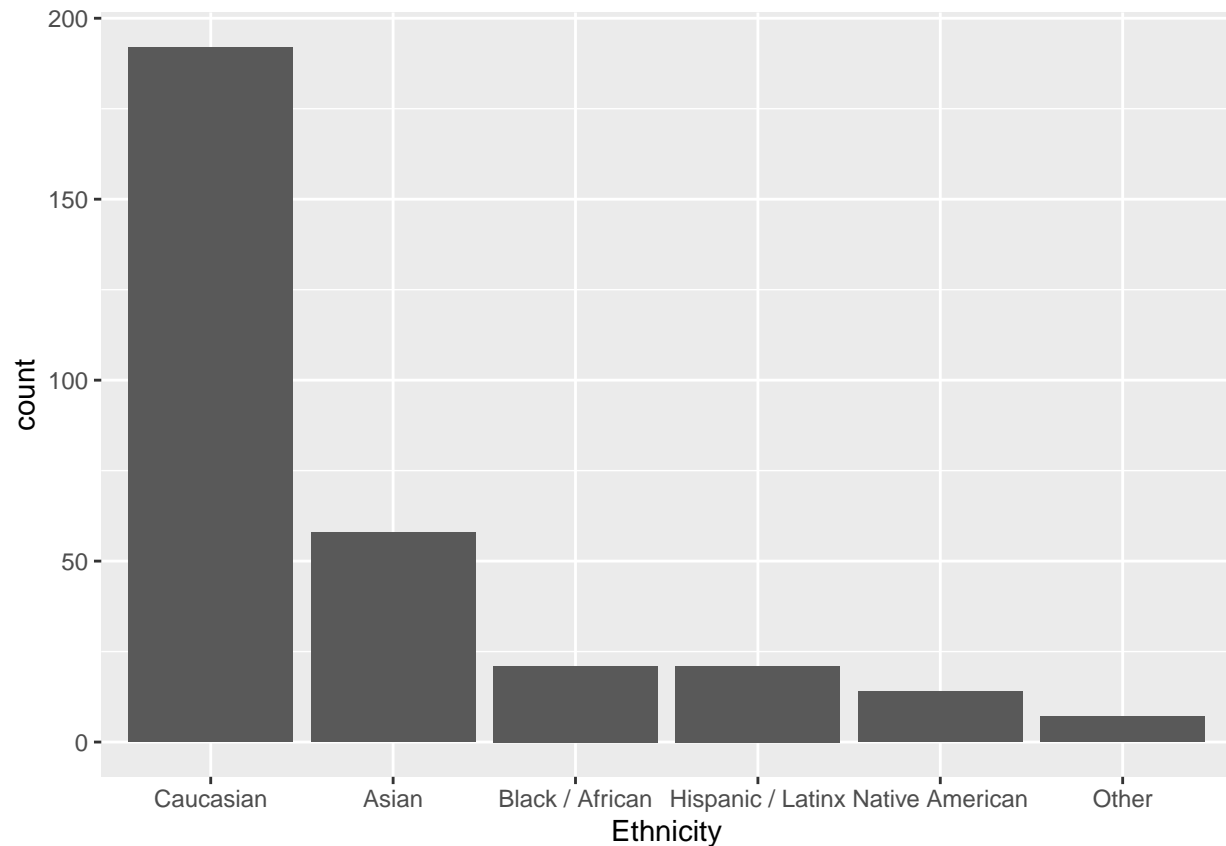
```
##      Party Age_bin  N
## 1: Democrat  21-40 126
## 2: Republican 21-40  52
## 3:   Other    21-40  31
## 4: Republican 41-60  26
## 5:   Other    41-60  20
## 6: Democrat  41-60  37
## 7: Democrat   61+   8
## 8: Republican 61+   5
## 9: Democrat   0-20   3
##10:   Other    61+   1
##11:   Other    0-20   3
##12: Republican 0-20   1
```

In terms of ethnicity of the randomly sampled subjects, the majority were Caucasian followed by approximately equal counts of Hispanic and Native americans, followed by african americans and asians.

```
data_full[, .N, by=Ethnicity]
```

```
##      Ethnicity  N
## 1:    Caucasian 192
## 2: Hispanic / Latinx 21
## 3:  Native American 14
## 4:  Black / African 21
## 5:      Asian    58
## 6:      Other     7
```

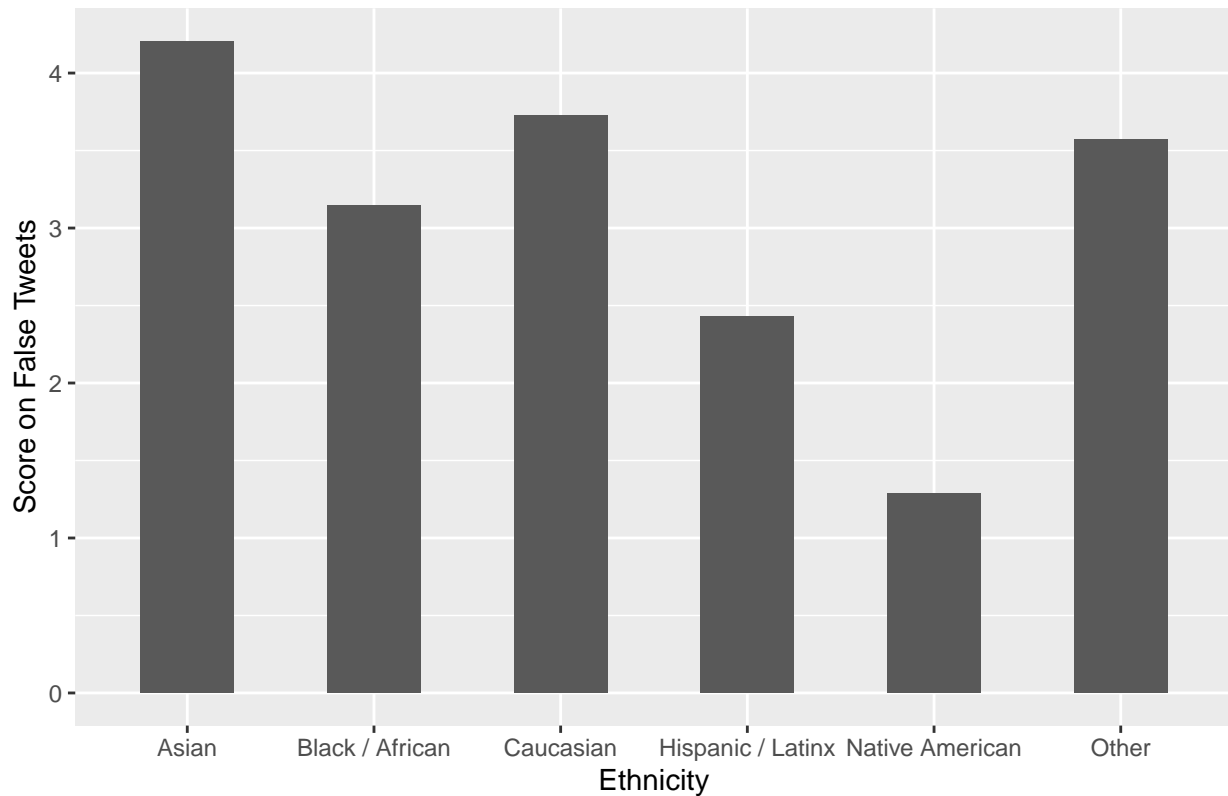
```
ggplot(mutate(data_full, Ethnicity = fct_infreq(Ethnicity))) + geom_bar(aes(x = Ethnicity))
```



```
dt <- data_full[, .(mean_score_by_Ethnicity = mean(score_false)), by=Ethnicity]
dt$Gender[dt$Gender == ''] <- "Other"
ggplot(dt, aes(x = Ethnicity, y = mean_score_by_Ethnicity)) +
  geom_bar(aes(Ethnicity), stat="identity", width = 0.5) +
  ggtitle("Figure X. Mean scores by Ethnicity") +
  ylab("Score on False Tweets") + xlab("Ethnicity") +
  theme(plot.title = element_text(hjust = 0.5))
```



Figure X. Mean scores by Ethnicity



```
mod9 <- lm(score_false ~ assignment*Age_bin+Gender+Party+Ethnicity + Mturk+captcha, data_full)
mod10 <- lm(score_false ~ assignment*Ethnicity*Age_bin + Party+Gender+Mturk+captcha, data_full)
se_custom9 <- compute_robust_se(mod9)
se_custom10 <- compute_robust_se(mod10)
stargazer(mod9,mod10,type="text",se=list(se_custom9,se_custom10)
)
```

```
##
## =====
##                                     Dependent variable:
##                                     -----
##                                     score_false
##                                     (1)                (2)
## -----
## assignment                        -0.660*           -0.770**
##                                   (0.350)           (0.320)
##
## Age_bin21-40                      -0.180           -0.490
##                                   (0.280)           (0.360)
##
## Age_bin41-60                      -0.390           -1.500**
##                                   (0.320)           (0.660)
##
## Age_bin61+                        -0.420           0.360
##                                   (0.530)           (0.710)
##
## GenderFemale                     -0.720***          -0.620***
```

##	(0.160)	(0.160)
##		
## GenderMale	-0.420**	-0.400**
##	(0.170)	(0.170)
##		
## PartyOther	0.340**	0.390**
##	(0.160)	(0.150)
##		
## PartyRepublican	-0.450**	-0.390**
##	(0.190)	(0.190)
##		
## EthnicityBlack / African	-0.090	-0.850**
##	(0.330)	(0.400)
##		
## EthnicityCaucasian	0.200	-0.390
##	(0.160)	(0.290)
##		
## EthnicityHispanic / Latinx	-0.360	-2.600***
##	(0.330)	(0.820)
##		
## EthnicityNative American	-0.710*	-2.600***
##	(0.390)	(0.820)
##		
## EthnicityOther	-0.320	-0.092
##	(0.410)	(0.360)
##		
## Mturk	-0.150	-0.230
##	(0.140)	(0.140)
##		
## captcha	2.000***	1.900***
##	(0.200)	(0.210)
##		
## assignment:EthnicityBlack / African		0.850**
##		(0.400)
##		
## assignment:EthnicityCaucasian		-0.230
##		(0.320)
##		
## assignment:EthnicityHispanic / Latinx		-0.500
##		(0.690)
##		
## assignment:EthnicityNative American		2.200*
##		(1.200)
##		
## assignment:EthnicityOther		-0.440
##		(0.650)
##		
## assignment:Age_bin21-40	0.700*	0.880**
##	(0.390)	(0.420)
##		
## assignment:Age_bin41-60	0.840**	1.800**
##	(0.420)	(0.730)
##		
## assignment:Age_bin61+	0.380	-0.360

##	(0.700)	(0.700)
##		
## EthnicityBlack / African:Age_bin21-40		0.750
##		(0.620)
##		
## EthnicityCaucasian:Age_bin21-40		0.510
##		(0.410)
##		
## EthnicityHispanic / Latinx:Age_bin21-40		2.400***
##		(0.910)
##		
## EthnicityNative American:Age_bin21-40		1.600
##		(0.980)
##		
## EthnicityOther:Age_bin21-40		
##		
##		
## EthnicityBlack / African:Age_bin41-60		-0.071
##		(0.710)
##		
## EthnicityCaucasian:Age_bin41-60		1.600**
##		(0.680)
##		
## EthnicityHispanic / Latinx:Age_bin41-60		2.100*
##		(1.100)
##		
## EthnicityNative American:Age_bin41-60		2.500***
##		(0.970)
##		
## EthnicityOther:Age_bin41-60		
##		
##		
## EthnicityBlack / African:Age_bin61+		1.000***
##		(0.00000)
##		
## EthnicityCaucasian:Age_bin61+		0.074
##		(0.560)
##		
## EthnicityHispanic / Latinx:Age_bin61+		
##		
##		
## EthnicityNative American:Age_bin61+		
##		
##		
## EthnicityOther:Age_bin61+		
##		
##		
## assignment:EthnicityBlack / African:Age_bin21-40		-2.600***
##		(0.690)
##		
## assignment:EthnicityCaucasian:Age_bin21-40		0.230
##		(0.480)
##		
## assignment:EthnicityHispanic / Latinx:Age_bin21-40		

```
##
##
## assignment:EthnicityNative American:Age_bin21-40 -1.900
## (1.500)
##
## assignment:EthnicityOther:Age_bin21-40
##
##
## assignment:EthnicityBlack / African:Age_bin41-60 0.300
## (0.830)
##
## assignment:EthnicityCaucasian:Age_bin41-60 -0.900
## (0.770)
##
## assignment:EthnicityHispanic / Latinx:Age_bin41-60
##
##
## assignment:EthnicityNative American:Age_bin41-60
##
##
## assignment:EthnicityOther:Age_bin41-60
##
##
## assignment:EthnicityBlack / African:Age_bin61+
##
##
## assignment:EthnicityCaucasian:Age_bin61+
##
##
## assignment:EthnicityHispanic / Latinx:Age_bin61+
##
##
## assignment:EthnicityNative American:Age_bin61+
##
##
## assignment:EthnicityOther:Age_bin61+
##
##
## Constant 3.100*** 3.500***
## (0.280) (0.340)
## -----
## Observations 313 313
## R2 0.510 0.530
## Adjusted R2 0.480 0.470
## Residual Std. Error 1.200 (df = 294) 1.200 (df = 274)
## F Statistic 17.000*** (df = 18; 294) 8.200*** (df = 38; 274)
## =====
## Note: *p<0.1; **p<0.05; ***p<0.01
mod1a <- lm(score_true ~ assignment, data_full)
mod2a <- lm(score_true ~ assignment+Mturk, data_full)
mod3a <- lm(score_true ~ assignment+Mturk+captcha+Age_bin+Party+Gender+Ethnicity, data_full)
ci_custom1a <- compute_robust_ci(mod1a)
```

```

ci_custom2a <- compute_robust_ci(mod2a)
ci_custom3a <- compute_robust_ci(mod3a)
stargazer(mod1a,mod2a,mod3a, type="text",ci.custom = list(ci_custom1a,ci_custom2a,ci_custom3a))

```

```

##
## =====
##                               Dependent variable:
##                               -----
##                               score_true
##                               (1)         (2)         (3)
## -----
## assignment                    -0.180         -0.180         -0.150
##                               (-0.410, 0.051)   (-0.410, 0.050)   (-0.380, 0.075)
##
## Mturk                          0.340**
##                               (0.072, 0.610)         (-0.310, 0.410)
##
## captcha                       -0.600***
##                               (-0.890, -0.320)
##
## Age_bin21-40                  -0.190
##                               (-0.670, 0.280)
##
## Age_bin41-60                  -0.300
##                               (-0.800, 0.200)
##
## Age_bin61+                    -0.560
##                               (-1.400, 0.260)
##
## PartyOther                     0.085
##                               (-0.230, 0.400)
##
## PartyRepublican               -0.067
##                               (-0.350, 0.210)
##
## GenderFemale                  1.100
##                               (0.750, 1.400)
##
## GenderMale                    1.000
##                               (0.740, 1.300)
##
## EthnicityBlack / African      -0.084
##                               (-0.640, 0.470)
##
## EthnicityCaucasian            0.098
##                               (-0.240, 0.440)
##
## EthnicityHispanic / Latinx    0.280
##                               (-0.190, 0.750)
##
## EthnicityNative American      0.710**
##                               (0.120, 1.300)
##
## EthnicityOther                -0.160

```

```
##
##
## Constant          3.600***          3.400***          3.100***
##                   (3.500, 3.800)      (3.100, 3.600)      (2.500, 3.700)
##
## -----
## Observations      313                313                313
## R2                0.007              0.028              0.140
## Adjusted R2       0.004              0.021              0.094
## Residual Std. Error 1.100 (df = 311)  1.000 (df = 310)  1.000 (df = 297)
## F Statistic       2.300 (df = 1; 311) 4.400** (df = 2; 310) 3.200*** (df = 15; 297)
## =====
## Note:                                     *p<0.1; **p<0.05; ***p<0.01
```

```
mod4a <- lm(score_true ~ assignment*factor(Gender)+factor(Party)+Mturk+captcha, data_full)
mod5a <- lm(score_true ~ assignment*factor(Party)+factor(Gender)+Mturk+captcha, data_full)
mod6a <- lm(score_true ~ assignment*factor(Gender)*factor(Party)+Mturk+captcha, data_full)
ci_custom4a <- compute_robust_ci(mod4a)
ci_custom5a <- compute_robust_ci(mod5a)
ci_custom6a <- compute_robust_ci(mod6a)

se_custom4a <- compute_robust_se(mod4a)
se_custom5a <- compute_robust_se(mod5a)
se_custom6a <- compute_robust_se(mod6a)

stargazer(mod4a,mod5a,mod6a,type="text",se=list(se_custom4a,se_custom5a,se_custom6a))
```

```
##
## =====
##                                     Dependent variable:
##                                     -----
##                                     (1)                (2)
## -----
## assignment                -0.150                0.022
##                          (0.160)                (0.150)
##
## factor(Gender)Female      1.100***              1.200***
##                          (0.220)                (0.150)
##
## factor(Gender)Male        1.100***              1.200***
##                          (0.150)                (0.140)
##
## factor(Party)Other        0.059                0.170
##                          (0.150)                (0.220)
##
## factor(Party)Republican   -0.051                0.220
##                          (0.150)                (0.180)
##
## Mturk                     0.038                0.046
##                          (0.150)                (0.150)
##
## captcha                   -0.720***             -0.710***
##                          (0.130)                (0.130)
##
```

```

## assignment:factor(Gender)Female                -0.045
##                                                  (0.230)
##
## assignment:factor(Gender)Male
##
##
## assignment:factor(Party)Other                    -0.210
##                                                  (0.310)
##
## assignment:factor(Party)Republican              -0.580**
##                                                  (0.270)
##
## factor(Gender)Female:factor(Party)Other
##
##
## factor(Gender)Male:factor(Party)Other
##
##
## factor(Gender)Female:factor(Party)Republican
##
##
## factor(Gender)Male:factor(Party)Republican
##
##
## assignment:factor(Gender)Female:factor(Party)Other
##
##
## assignment:factor(Gender)Male:factor(Party)Other
##
##
## assignment:factor(Gender)Female:factor(Party)Republican
##
##
## assignment:factor(Gender)Male:factor(Party)Republican
##
##
## Constant                3.000***                2.800***
##                          (0.220)                (0.210)
## -----
## Observations                313                313
## R2                0.120                0.130
## Adjusted R2                0.091                0.100
## Residual Std. Error        1.000 (df = 304)        1.000 (df = 303)
## F Statistic        4.900*** (df = 8; 304) 4.900*** (df = 9; 303)
## =====
## Note:

```

\*p