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Replication Study – Mark Likeman

Applied Statistical Analysis II – 2023

Unconditional Support for Trump's Resistance Prior to Election Day.

"How a fundamental tradition of American Democracy was almost destroyed."

Alexandra Haver, New York University School of Law, USA.

Brendan Hartnett, Tufts University, USA.

https://doi.org/10.7910/DVN/YNUE8B, Harvard Dataverse, V1

ABSTRACT Using survey data collected less than two weeks before the 2020 presidential election, we investigated why likely Trump voters would support Trump resisting the election results if he lost. We first used an experiment with randomized hypothetical popular-vote margins to test whether support for resistance was contingent on the results of the election. We also directly asked respondents who stated that they would support resistance to explain their reasoning in an open-ended response. In doing so, we gained insight into one of the most turbulent elections in American history and examined how support for resistance existed before the election due to both misinformation about voter fraud and hyperpartisanship that made Trump voters view the electoral process itself as illegitimate.

Background

This research paper proposes[1] an explanation for one of the most turbulent elections in American political history. Leading up to the 2020 presidential election, it was not certain if the then incumbent president, Donald Trump, would accept electoral defeat. In the third debate of the 2016 presidential election, Trump refused to commit to accepting the election results if he lost (Gellman 2020). However, not long after he told his supporters that he would "totally accept the results [of the 2016 presidential election] ..' following with "if I win!". Trump then went on to lose both the popular vote and the Electoral College - but still refused to concede.

The aftermath of which became known as "The Big Lie", asserting that the election was riddled with fraud, in particular, due to the use of mail-in ballots. Although, the reseat makes some assertions about the existence of fraud and hyperpartisanship i.e., political parties in fierce disagreement with each other, before the 2020 election took place.

Amid the uncertainty preceding the election, the authors of this study undertook an experiment in October 2020 to examine the extent to which Trump's supporters would support him if he lost the election but refused to concede. Results from that experiment indicted that the insurrection on January 6, 2021, was a manifestation of an illiberal and contentious culture surrounded the 2020 election fostered by Trump's divisive rhetoric and misinformation campaign, which is one of the two hypotheses put forward by the authors of this research paper.

The following hypothetical question was explored "Would a higher popular-vote margin of victory for Joe Biden increase the acceptance of his Electoral College victory among Trump voters?". If support for resistance was unrelated to the popular vote margins, this could indicate that the legitimacy of the election and its victor were determined before the vote itself.

[1] *doi:10.1017/S1049096522000695 Unconditional Support for Trump's Resistance Prior to Election Day. Haver, Hartnett.*

Details of the Survey

Sample survey: 1,215 American adults provided by Lucid (online market research tool) were interviewed online October 25, 2020. Full survey here.

Weights: Post-stratification weights were implemented to make each week's sample nationally representative of American adults by gender, age, region, education, race, and 2016 presidential vote. Likely voter weights were created using the PGAD approach. Survey Weighting techniques are sometimes employed to generalize results from survey experiments to populations of theoretical and substantive interest.

The authors explored their research questions in an online survey to 1,208 American adults between October 24 and 25, 2020. Respondents were asked if they intended to vote in the 2020 general election. Those who already had voted for Trump, planned to vote for Trump, or leaned toward voting for Trump were categorized as Trump Voters (N=510). There was a hypothetical question about the outcome of the 2020 presidential election where Trump voters were presented with the following statement "Biden wins the popular vote by __ percentage points and wins the Electoral College". Each respondent received a randomized popular vote margin, that ranged between 1 and 15 points.

Variables

Dependent variable is coded 0 for "Trump should concede defeat and commit to a peaceful transfer of power" and 1 for "Trump should resist the results of the election through measures such as discrediting the results as invalid, declaring a state of emergency, and/or taking any means possible to remain in office." The snippet of R code below shows this.

```
'trumploss'
# concede defeat
dat$trumploss[dat$trumplose==2] <- 0
# resist results of the election
dat$trumploss[dat$trumplose==1] <- 1
```

	Dependent variable:
	trumploss
margin	−0.006
	(0.005)
Constant	0.443***
	(0.045)
Observations	510
Log Likelihood	−380.347
Akaike Inf. Crit.	764.694
Note:	*p<0.1; **p<0.05; ***p<0.01

Popular-Vote Margin	−0.0056 (0.0049)
Acknowledgment of Racism	
Constant	0.4427*** (0.0447)
Observations	510
Log Likelihood	−380.3468
Akaike Information Criterion	764.6937

Figure 2 - Acknowledgement of Racism (Dependent variable- Support Resistance – Model 1

Figure 1 – stargazer library output for Model 1

This model as shown in *Figure 1,* tested whether the randomly assigned popular-vote margin treatment affected likely Trump voter's support for this resistance. The 'margin' -0.006 is the regression coefficient. Negative coefficient showing there is a negative relationship between 'margin' and 'trumploss' the variable that is being predicted. It provides the expected change in the dependent variable 'trumploss' for a one-unit decrease in the independent variable 'margin'.

'trumploss' is the main one being looked at, and the others were potential confounders. 'Acknowledgement of racism' is a possible confounder, as it could influence both the dependent and independent variables.

Dependent Variables

'Support resistance' as shown in *Table 1* is the main dependent variable.

This was recoded in the R file as:

```
dat$trumploss[dat$trumplose==2] <- 0 # concede defeat
dat$trumploss[dat$trumplose==1] <- 1 # resists result of the election
table(dat$trumploss)
```

(1) Conceding defeat was related to 'Biden's popular vote margin' variable.

(2) Resisting the results of the election were related to the continuous variables; age, education, household income, party ID, and included news interest and racism.

Table 1. Trump Voter's Support for Resistance of Election Defeat (Binary Logit Model)

	Dependent variable:	
	Support resistance	
	(1)	(2)
Popular vote margin	-0.0056 (0.0049)	-0.0072 (0.0051)
Age		
(baseline: under 35)		
35-49		0.0240 (0.0645)
50-64		-0.0614 (0.0628)
Over 65		-0.1697^{**} (0.0685)
Education		
(baseline: no college)		
Some college		-0.0537 (0.0525)
College degree		0.0307 (0.0770)
Household income		
(baseline: less than $25,000)		
$25,000-$74,999		0.0041 (0.0525)
$75,000-$124,999		0.0165 (0.0708)
Over $125,000		0.0113 (0.0914)
Party ID		
(baseline: not Republican)		
Lean Republican		-0.0029 (0.0814)
Republican		0.0802 (0.0751)
Strong Republican		0.0707 (0.0642)
Male		-0.0552 (0.0458)
News interest		0.0403 (0.0289)
Acknowledgement of racism		-0.0245^{*} (0.0134)
Constant	0.4427^{***} (0.0447)	0.4304^{***} (0.1332)
Observations	510	501
Log Likelihood	-380.3468	-363.8858
Akaike Inf. Crit.	764.6937	759.7716

Model 1

The code model1 <- glm(trumploss ~ margin, data=dat, weights=nationalweight) in R is fitting a generalized linear model with a binary outcome variable trumploss and a continuous predictor variable margin. The weight variable nationalweight is included to account for the sampling design and to adjust for any potential biases in the estimates.

The estimated slope is -0.0426, which represents the change in the expected value of ‘trumploss’ for each unit increase in margin.

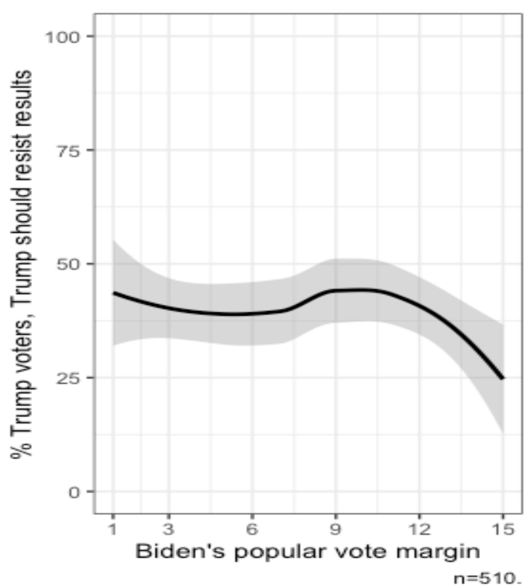
The output suggests that there is a significant negative linear relationship between ‘margin’ and ‘trumploss’. This means that as the margin between Biden and Trump increases, the probability that a Trump voter believes that he should resist the election results decreases. The p-value for the slope coefficient is less than 0.001, indicating strong evidence against the null hypothesis of no relationship between margin and trumploss

```
# Model 1: Test for Trump margin significance using logit model
model1 <- glm(trumploss~margin, data=dat, weights=nationalweight)
Coefficients:
                   Estimate       Std. Error     t value  Pr(>|t|)
(Intercept)  0.442669    0.044679   9.908    <2e-16 ***
margin      -0.005614     0.004942  -1.136     0.256
‘weight’ could have been coded another way
weights <- dat$nationalweight
model <- glm(trumploss ~ margin, data = dat, weights = weights)

MY INERACTION
mylogit <- glm(trumploss ~ margin, data = dat, family = "binomial")
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.26801    0.18285  -1.466    0.143
margin      -0.01761    0.02045  -0.861    0.389
```

Independent Variable:

This plot has a smoothed line that shows the relationship between two variables: margin, which represents Biden's popular vote margin, and trumploss, which is a binary variable indicating whether Trump should resist the election results. The plot also includes a weight variable nationalweight which adjusts for sampling bias. The black line in the plot is a smoothed line that represents the estimated relationship between margin and trumploss. The plot shows that as the margin between Biden and Trump increases, the percentage of Trump voters who believe that Trump should resist the election results decreases. At a margin of 1, almost all Trump voters believe that he should resist the results, while at a margin of 15, the percentage drops to almost 0%. The plot below suggests that there is a strong negative relationship between margin and trumploss, indicating that the wider Biden's margin of victory, the less likely Trump supporters are to believe that he should resist the election results.



Plot shows Trump resist vs Pop Vote Margin. Loess graph using x ~ y formula.

Independent/Explanatory variable (x) and Dependent/Response variable (y).

Model 2

This is Generalized Linear Model (GLM) in R, with the dependent variable 'trumploss' and several predictor variables. The 'weights=nationalweight' argument specifies that the model that the sample weights provided in the 'nationalweight' variable when fitting the model. These weights adjust for the fact that the sample may not be representative of the population. The model attempts to predict whether Trump lost or won in a given location based on the values of the predictor variables. The coefficients of the model indicate how strongly each variable predicts a Trump loss, holding the other variables constant. The 'factor()' function indicates that categorical variables have been treated as factors, and the GLM uses dummy variable coding to represent these categories in the model. In summary, the code fits a binomial GLM in R to predict the outcome of the 2020 presidential election for different locations, based on various demographic and political factors.

```
model2 <- glm(trumploss ~ margin + factor(agecat) + factor(education3) +
factor(hhinc)
              + factor(partyid) + factor(gen) + newsinterest + ackracism,
              data=dat, weights=nationalweight)


Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                       0.430395   0.133155   3.232  0.00131 **
margin                           -0.007243   0.005087  -1.424  0.15510
factor(agecat)35-49               0.023986   0.064523   0.372  0.71025
factor(agecat)50-64              -0.061435   0.062815  -0.978  0.32854
factor(agecat)65 and over        -0.169745   0.068533  -2.477  0.01360 *
factor(education3)Some college   -0.053741   0.052515  -1.023  0.30665
factor(education3)College degree  0.030719   0.076981   0.399  0.69003
factor(hhinc)$25,000-$74,999      0.004097   0.052543   0.078  0.93789
factor(hhinc)$75,000-$124,999     0.016490   0.070797   0.233  0.81593
factor(hhinc)Over $125,000        0.011344   0.091440   0.124  0.90132
factor(partyid)Lean Republican   -0.002943   0.081371  -0.036  0.97116
factor(partyid)Republican         0.080158   0.075104   1.067  0.28637
factor(partyid)Strong Republican  0.070735   0.064211   1.102  0.27118
factor(gen)Male                  -0.055235   0.045804  -1.206  0.22845
newsinterest                      0.040299   0.028936   1.393  0.16435
ackracism                        -0.024516   0.013396  -1.830  0.06784
```

Hypothesis:

H1 – Misinformation about voter fraud

H2 – Illiberal political motivations to overturn the elections results.

My focus is on H2. Related to Model 2.

Models used in the study:

Model 1 – this tested whether the randomly assigned popular-vote margin treatment affected likely Trump voters' support for his resistance.

Understanding Resistance

The authors of the study hypothesized that there would be two motivations for Trump voters to support him if he attempted to undermine the legitimacy of the 2020 presidential election:

- Misinformation about voter fraud.
- Illiberal political motivations to overturn the election results.

The authors conducted two logit regression analysis using generalized linear models.

Their model also used partisanship (adherence to a political party) as a measure of alignment with Trump's policy.

H2 – Illiberal political motivations to overturn the elections results.

Model 2 – Analysed how the demographics of respondents were associated with their support for Trump's resistance. The model also tested the extent to which news interest and acknowledgement of racism impacted their support for resistance.

The 'Over 65' is a negative coefficient -0.1697 and not significant. 'News Interest' is positive coefficient 0.0403 which is favorable because it indicates a positive relationship between the variables involved.

My Model binomial GLM with a logit link as follows.

```
dat$newsinterest <- factor(dat$newsinterest)
mylogit <- glm(trumploss ~ newsinterest, data =
dat, family = binomial(link="logit"))
```

Then I used a Confidence Interval with confint() function. The confidence for both the intercept and 'newsinterest2' contain zero, which means we cannot reject the null hypothesis that these parameters are equal to zero. Therefore, cannot say with confidence that either of them is statistically significant at the 95% level of confidence.

factor(agecat)65 and over	-0.170^{**} (0.069)
factor(education3)Some college	-0.054 (0.053)
factor(education3)College degree	0.031 (0.077)
74,999	0.004 (0.053)
124,999	0.016 (0.071)
125,000	0.011 (0.091)
factor(partyid)Lean Republican	-0.003 (0.081)
factor(partyid)Republican	0.080 (0.075)
factor(partyid)Strong Republican	0.071 (0.064)
factor(gen)Male	-0.055 (0.046)
newsinterest	0.040 (0.029)
ackracism	-0.025^{*} (0.013)

3

```
### Model 2: Test for Trump margin significance
using logit model and demographics ####
model2 <- glm(trumploss ~ margin +
factor(agecat) + factor(education3) +
factor(hhinc)
              + factor(partyid) + factor(gen) +
newsinterest + ackracism,
              data=dat, weights=nationalweight)
```

```
> summary(mylogit)
Call:
glm(formula = trumploss ~ newsinterest, family =
binomial(link = "logit"),
    data = dat)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0652  -1.0652  -0.9673   1.2939   1.4671
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.62861    0.43780  -1.436    0.151
newsinterest2 -0.03064    0.54112  -0.057    0.955
newsinterest3  0.11192    0.46384   0.241    0.809
newsinterest4  0.35878    0.45527   0.788    0.431
```

```
> confint(mylogit)
Waiting for profiling to be done...
                   2.5 %    97.5 %
(Intercept)   -1.5383792 0.2050683
newsinterest2 -1.0828917 1.0579522
newsinterest3 -0.7753891 1.0666294
newsinterest4 -0.5107110 1.2987556
```

H2 – Illiberal political motivations to overturn the elections results (cont.)

The findings from the survey stated that:
No significant relationship was discovered between respondents' interest in news and current events, nor their acknowledgement of racism, on supporting Trump's resistance.
The output of the code I have provided is from the summary of a logistic regression model 'mylogit' that relates the binary response variable 'trumploss' to the predictor variable 'newsinterest' at different levels. The Coefficients section shows the estimated regression coefficients for the intercept and each level of newsinterest. The Estimate column shows the estimated coefficient for each variable. For example, the estimated coefficient for 'newsinterest2' is -0.03064, which means that increasing the level of newsinterest from 1 to 2 is associated with a decrease in the log-odds of trumploss by 0.03064.

My Model binomial GLM with a logit link:

```
dat$newsinterest <- factor(dat$newsinterest)
mylogit <- glm(trumploss ~ newsinterest, data = dat, family =
binomial(link="logit"))
```

```
glm(formula = trumploss ~ newsinterest, family = binomial(link =
"logit"), data = dat)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0652  -1.0652  -0.9673   1.2939   1.4671
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.62861    0.43780  -1.436    0.151
newsinterest2 -0.03064    0.54112  -0.057    0.955
newsinterest3  0.11192    0.46384   0.241    0.809
newsinterest4  0.35878    0.45527   0.788    0.431
```

In this example, the coefficients for all levels of newsinterest are not statistically significant at the 5% level since their p-values are greater than 0.05, which means we cannot reject the null hypothesis that these coefficients are equal to zero. Therefore, we cannot say with confidence that any level of newsinterest is associated with a significant change in the odds of trumploss.

H2 – Illiberal political motivations to overturn the elections results.

The results in this study indicated that the insurrection on January 6, 2021, was not a surprise, but a manifestation of an illiberal and contentious culture surrounding the 2020 Presidential Election fostered by Trump's divisive rhetoric and misinformation campaign.

My Interaction:

Interpretation of the model: That 'newsinterest2' and 'newsinterest3' are statistically significant and significant predictors to 'trumploss' or that "Trump should resist the results of the election through measures such as discrediting the results as invalid.." (p=0.937,p=0.828)

```
dat$newsinterest <- factor(dat$newsinterest)
mylogit <- glm(trumploss ~ margin + newsinterest, data = dat, family = "binomial")

> summary(mylogit)
Call:
glm(formula = trumploss ~ margin + newsinterest, family = "binomial",
    data = dat)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1066  -1.0294  -0.9342   1.3108   1.5090
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.49254    0.47344  -1.040    0.298
margin        -0.01550    0.02057  -0.753    0.451
newsinterest2 -0.04280    0.54167  -0.079    0.937
newsinterest3  0.10067    0.46433   0.217    0.828
newsinterest4  0.33929    0.45623   0.744    0.457
```

```
#Recode News interest
#so that higher values indicate more interest in the news
dat$newsinterest <- NA
dat$newsinterest[dat$newsint==1] <- 4
dat$newsinterest[dat$newsint==2] <- 3
dat$newsinterest[dat$newsint==3] <- 2
dat$newsinterest[dat$newsint==4] <- 1
#Descriptive table of news interest
table(dat$newsinterest)
```

Interpretation of ANOVA

This shows the results of an analysis of variance (ANOVA) table for the model with 'trumploss' as the dependent variable and 'margin' as the only predictor. The table provides information on the sum of squares, mean squares, F-value, and p-value for each variable in the model.
The 'F value' column shows the F-statistic, which is a ratio of the variance explained by the model (the mean square for the predictor variable) to the residual variance (the mean square for the residuals). In this case, the F-value is 0.74, indicating that the predictor variable ('margin') is not a significant predictor of 'trumploss', as the F-value is less than 1.
The 'Pr(>F)' column shows the p-value associated with the F-value. In this case, the p-value is 0.39, which is greater than the conventional threshold of 0.05. This suggests that there is no significant relationship between 'margin' and 'trumploss', as the p-value is not less than the threshold. This ANOVA table suggests that 'margin' does not have a significant impact on 'trumploss'.

Added an ANOVA test for an interaction

```
# Interpetation of Anova
# the margin variable has a low sum of squares and a high P-Val which means there is
not much variation that can
# be explained by the interaction between trumploss and margin.
interaction <- aov(trumploss ~ margin, data = dat)
```

```
      Df     Sum Sq       Mean Sq F value Pr(>F)
margin        1     0.18   0.1781    0.74      0.39
Residuals   508     122.22       0.2406
```

Final Thoughts:

40% of Trump voters in this study stated that Trump should resist the election results even in a scenario in which Biden won by a large popular-vote margin, the precedent of a peaceful transfer of power in American elections was shaken even before the election.

It appears that not even misinformation pertaining to voter fraud and the use of mail-in ballots cannot explain away all support for Trump’s resistance, and that partisanship and negative partisanship also prompted voters to disregard the democratic electoral process entirely to support their preferred candidate in his quest for office by any means possible.

The authors of the study undertook an experiment with randomized hypothetical popular vote margins to test if support for resistance is contingent upon the results of the election itself. It seemed that Trump voters simply did not care for the election itself but wanted Trump in power no matter what. Misinformation in the 2020 election campaign was in full force, with Trump telling his followers that the only way he could lose would be through voter fraud. However, it was Biden who won the popular vote and the Electoral College. Biden accepted the result, without any illiberal political motivations or partisan motivations.

Illiberal political motivations to overturn the elections results.

The term "illiberal" is often used to describe political movements or leaders that are perceived as anti-democratic, intolerant, and/or authoritarian in their approach to governance and policy. This is arguably the main reason that not only explains Trump’s refusal to accept defeat or his resistance to election results but his continuance to espouse “the Big Lie”. According to the authors of this study, Trump voters bought into this, and was ultimately credited with inspiring the January 6th Capitol insurrection.

References

Gellman, Barton. 2020. "The Election That Could Break America." The Atlantic, September 23. www.theatlantic.com/magazine/archive/2020/11/what-if-trumprefuses-concede/616424. Graham, Matthew, and Milan.

Appendix A. Unconditional Support for Trump Resist.R

```
#Replication code for "Unconditional Support for Trump's Resistance Prior to
Election Day"

#Brendan Hartnett and Alexandra Haver

#PS: Political Science and Politics


#Read data into R

library(readr)

dat <- read_csv("Documents/R&R for PS/Unconditional Support for Trump Resist.
csv")


#Subset only likely Trump voters, those those who had already voted, and lean
ers

dat <- subset(dat, presvote2020==2 | presvote2020_voted==2 | presvote_2020lea
n==2)


## Recode support for Trump's resistance ####

# Basic Trump lose

table(dat$trumplose)

prop.table(table(dat$trumplose))

# Recode support for Trump's resistance as dummy variable

dat$trumploss <- NA

dat$trumploss[dat$trumplose==2] <- 0

dat$trumploss[dat$trumplose==1] <- 1

table(dat$trumploss)
```

```
prop.table(table(dat$trumploss))
#Weighted mean for percent supporting Trump's resistance
weighted.mean(dat$trumploss, dat$nationalweight)

#### Figure 1 Trump resist vs Pop Vote Margin Loess graph using x ~ y formula
####
#weight data using national weights
library(ggplot2)
plotT <- ggplot(dat, aes(x=margin, y=trumploss*100, weight=nationalweight)) +
  geom_smooth(colour = "black", se=T, span=1, level=.95) + theme_bw() +
  xlab("Biden's popular vote margin") +
  ylab("% Trump voters, Trump should resist results") +
  scale_color_manual(values="#000000", "#000000") +
  theme(plot.title = element_text(hjust = 0.5)) + ylim(0,100) +
  labs(caption="n=510.") + scale_x_continuous(breaks=c(1, 3, 6, 9, 12, 15))
PlotT

#### Model 1: Test for Trump margin significance using logit model####
model1 <- glm(trumploss~margin, data=dat, weights=nationalweight)
summary(model1)
model1

#Recode demographics ####

#Recode Party Identification
table(dat$pid3)
dat$partyid <- NA
#Code all who identified as Democrats or Independents as 'Non-Republican'
dat$partyid[dat$pid7<5] <- "Non-Republican"
#Code those who identified as other/not sure as 'Non-Republican
dat$partyid[dat$pid7==8] <- "Non-Republican"
#Code Lean Republican
dat$partyid[dat$pid7==5] <- "Lean Republican"
#Code Republican
```

```
dat$partyid[dat$pid7==6] <- "Republican"
#Code Strong Republicans
dat$partyid[dat$pid7==7] <- "Strong Republican"
#Descriptive table of party ID
table(dat$partyid)
#Order Party Identification
dat$partyid <- factor(dat$partyid, levels = c("Non-Republican", "Lean Republi
can",
                                              "Republican", "Strong Republica
n"))
table(dat$partyid)


#Recode Level of Education
dat$education3 <- NA
table(dat$education)
#Code those who did not graduate high school, only graduated high school, or
  #went to vocational school as 'no -college'
dat$education3[dat$education<4] <- "No college"
#Code those who have some college experience but no degree, or an associates
degree
  #as 'Some college'
dat$education3[dat$education==4 | dat$education==5] <- "Some college"
#Code those who have a bachelors degree as 'college degree'
dat$education3[dat$education>5] <- "College degree"
#Descriptive degree of education
table(dat$education3)
#Order Level of Education
dat$education3 <- factor(dat$education3, levels = c("No college", "Some colle
ge",
                                                    "College degree"))
table(dat$education3)


#Recode Household Income
table(dat$hhi)
dat$hhinc <- NA
```

```
#Less than $25k
dat$hhinc[dat$hhi<4] <- "Less than $25,000"
#Between $25k-75k
dat$hhinc[dat$hhi>3 & dat$hhi < 14] <- "$25,000-$74,999"
#Between $75k-125k
dat$hhinc[dat$hhi>13 & dat$hhi < 20] <- "$75,000-$124,999"
#Over $125k
dat$hhinc[dat$hhi>19] <- "Over $125,000"
#Descriptive table of household income
table(dat$hhinc)
#Order Household Income
dat$hhinc <- factor(dat$hhinc, levels = c("Less than $25,000", "$25,000-$74,9
99",
                                          "$75,000-$124,999", "Over $125,000"
))
table(dat$hhinc)


#Recode Age into Categorical Variable
dat$agecat <- NA
#Under age 35
dat$agecat[dat$age<35] <- "Under 35"
#Between 35 years old and 50
dat$agecat[dat$age>34 & dat$age<50] <- "35-49"
#Between 50 and 65
dat$agecat[dat$age>49 & dat$age<65] <- "50-64"
#Over 65
dat$agecat[dat$age>65] <- "65 and over"
#Descriptive table of age categories
table(dat$agecat)
#Order age category
dat$agecat <- factor(dat$agecat, levels = c("Under 35", "35-49", "50-64", "65
and over"))
table(dat$agecat)


#Recode gender
```

```
table(dat$gender)
dat$gen <- NA
#Male
dat$gen[dat$gender==1] <- "Male"
#Female
dat$gen[dat$gender==2] <- "Female"
#Descriptive table of gender identity
table(dat$gen)

#Recode News interest
  #so that higher values indicate more interest in the news
dat$newsinterest <- NA
dat$newsinterest[dat$newsint==1] <- 4
dat$newsinterest[dat$newsint==2] <- 3
dat$newsinterest[dat$newsint==3] <- 2
dat$newsinterest[dat$newsint==4] <- 1
#Descriptive table of news interest
table(dat$newsinterest)

#Acknowledgment of racism
  #so that higher values indicate more acknowledgment of racism
table(dat$acknowledgment)
dat$ackracism <- NA
dat$ackracism[dat$acknowledgment==1] <- 6
dat$ackracism[dat$acknowledgment==2] <- 5
dat$ackracism[dat$acknowledgment==3] <- 4
dat$ackracism[dat$acknowledgment==4] <- 3
dat$ackracism[dat$acknowledgment==5] <- 2
dat$ackracism[dat$acknowledgment==6] <- 1
#Descriptive table of acknowledgment of racism
table(dat$ackracism)
```

```
### Model 2: Test for Trump margin significance using logit model and demogra
phics ####
model2 <- glm(trumploss ~ margin + factor(agecat) + factor(education3) + fact
or(hhinc)
              + factor(partyid) + factor(gen) + newsinterest + ackracism,
              data=dat, weights=nationalweight)
model2
summary(model2)

#Table 1: Models 1 and 2 ####
#Export for paper
library(stargazer)
stargazer(model1, model2, type="html", out="Table_1_regression_models.doc",
          intercept.bottom = T, intercept.top = F, digits=4, single.row=T)

#Recode Trump Qualitative Code####
# Subset data for anyone who provided at least one reason for Trump to resist
# Recode reasons to dummy  variables in data set to get proportion
#of total respondents (147)
# Need to subset only for when tres11 is not NA,
#because any respondent in this proportion
# would have given a valid answer (not NA) to this question
table(dat$tres11)
trumprea <- subset(dat, dat$tres11!="NA")

#Recode responses into categories as to why they support resistance
# Support Trump
trumprea$supporttrump <- 0
trumprea$supporttrump[trumprea$tres11=="Support Trump"] <- "Support Trump"
trumprea$supporttrump[trumprea$tres22=="Support Trump"] <- "Support Trump"
trumprea$supporttrump[trumprea$tres33=="Support Trump"] <- "Support Trump"
table(trumprea$supporttrump)
prop.table(table(trumprea$supporttrump))

# Democrats are radicals
```

```
trumprea$demrad <- 0

trumprea$demrad[trumprea$tres11=="Democrats are Radical"] <- "Democrats are R
adicals"

trumprea$demrad[trumprea$tres22=="Democrats are Radical"] <- "Democrats are R
adicals"

trumprea$demrad[trumprea$tres33=="Democrats are Radical"] <- "Democrats are R
adicals"

table(trumprea$demrad)


# Election Irregularities

trumprea$elecirreg <- 0

trumprea$elecirreg[trumprea$tres11=="Distrust Election"] <- "Election Irregul
arities"

trumprea$elecirreg[trumprea$tres22=="Distrust Election"] <- "Election Irregul
arities"

trumprea$elecirreg[trumprea$tres33=="Distrust Election"] <- "Election Irregul
arities"

table(trumprea$elecirreg)


# Voter Fraud / Vote by Mail

trumprea$tmail <- 0

trumprea$tmail[trumprea$tres11=="Voter Fraud"] <- "Voter Fraud/Mail in Ballot
s"

trumprea$tmail[trumprea$tres22=="Voter Fraud"] <- "Voter Fraud/Mail in Ballot
s"

trumprea$tmail[trumprea$tres33=="Voter Fraud"] <- "Voter Fraud/Mail in Ballot
s"

table(trumprea$tmail)


# Democrats are Corrupt

trumprea$dcur <- 0

trumprea$dcur[trumprea$tres11=="Democrats are Corrupt"] <- "Democrats are Cor
rupt"

trumprea$dcur[trumprea$tres22=="Democrats are Corrupt"] <- "Democrats are Cor
rupt"

trumprea$dcur[trumprea$tres33=="Democrats are Corrupt"] <- "Democrats are Cor
rupt"

table(trumprea$dcur)
```

```
# Biden is incompetent
trumprea$binc <- 0
trumprea$binc[trumprea$tres11=="Biden is Incompetent"] <- "Biden is Incompetent"
trumprea$binc[trumprea$tres22=="Biden is Incompetent"] <- "Biden is Incompetent"
trumprea$binc[trumprea$tres33=="Biden is Incompetent"] <- "Biden is Incompetent"
table(trumprea$binc)

# Other
trumprea$tother <- 0
trumprea$tother[trumprea$tres11=="Other"] <- "Other"
trumprea$tother[trumprea$tres22=="Other"] <- "Other"
trumprea$tother[trumprea$tres33=="Other"] <- "Other"
table(trumprea$tother)

#### Number of Trump Respondents Giving Reason for Tables ####
table(trumprea$supportrump)
table(trumprea$demrad)
table(trumprea$elecirreg)
table(trumprea$tmail)
table(trumprea$dcur)
table(trumprea$binc)
table(trumprea$tother)

#### Proportions of Trump Respondents Giving Reason for Tables ####
prop.table(table(trumprea$supportrump))
prop.table(table(trumprea$demrad))
prop.table(table(trumprea$elecirreg))
prop.table(table(trumprea$tmail))
prop.table(table(trumprea$dcur))
prop.table(table(trumprea$binc))
prop.table(table(trumprea$tother))
```

```
####Recode Categories for general motivating theme ####
#partisanship and negative partisanship
trumprea$partisan <- NA
trumprea$partisan <- 0
trumprea$partisan[trumprea$supportrump=="Support Trump"] <- 1
trumprea$partisan[trumprea$demrad=="Democrats are Radicals"] <- 1
prop.table(table(trumprea$partisan))
#Concerns about election legitimacy
table(trumprea$partisan)
trumprea$electionconcerns <- NA
trumprea$electionconcerns <- 0
trumprea$electionconcerns[trumprea$elecirreg=="Election Irregularities"] <- 1
trumprea$electionconcerns[trumprea$tmail=="Voter Fraud/Mail in Ballots"] <- 1
prop.table(table(trumprea$electionconcerns))
table(trumprea$electionconcerns)
#other themes
trumprea$others <- NA
trumprea$others <- 0
trumprea$others[trumprea$tother=="Other"] <- 1
trumprea$others[trumprea$binc=="Biden is Incompetent"] <- 1
trumprea$others[trumprea$dcur=="Democrats are Corrupt"] <- 1
table(trumprea$others)
prop.table(table(trumprea$others))


#### t-test for misinformation and election concerns compared to partisan rea
son ####
t.test(trumprea$electionconcerns, trumprea$partisan, alternative = "greater",
       var.equal = FALSE)
```