ATTACHEMENT 1
Pre-Analysis Plan

C1 Background and explanation of rationale

The main focus is to develop tools to account for non-response on unobservables. The vast majority of survey analyses account for differential response rates by weighting results. These methods only work if, conditional on covariates used in weighting, the respondents are representative of the entire population. (Other methods such as imputation and targeted sampling require the same assumption.)

Many statistical tools exist to deal with samples that are unrepresentative in unmeasured ways. These tools are very demanding of the data, however, and in many common cases, fail to produce useful analyses.

This research assesses a survey design approach in which potential respondents are randomized into groups that make response more (or less) likely. Since this factor affecting response propensity is, by design, uncorrelated with any other factors affecting the dependent variable of interest (both observed and unobserved) it can be used in a first stage response equation in a manner that vastly improves the ability of these models to make meaningful predictions.

Previous work has implemented this research design for Mechanical Turk surveys. This research now extends the approach to a more rigorous polling environment, one in which respondents were identified for an internet panel via random selection. Previous results suggest that non-response biases exist within the whole population for some questions (such as turnout). Previous research showed even stronger non-response biases among partisan subsamples, especially on policy questions. In addition, many suspect there are demographic differences in the way non-response bias affects results with, white working class respondents more liberal than the underlying population and Hispanic respondents less liberal than the underlying populations.

One of the themes of this research is that there is heterogeneity in non-response. While I make specific predictions for the groupings discussed above (entire population, partisan subsample and race-based groups), I will also use two-stage selection modeling tools to look for additional heterogeneity. Any patterns found based on other groupings will be labelled exploratory.

Survey non-response can affect two things: the distribution of responses for any given question and also the estimated treatment affects. Hence I will assess survey question answers and also estimated treatment affects, comparing weighting approaches to the two-stage selection modeling approach.

There are two additional substantive questions that this research will address. I expect these questions to be addressed in separate papers.

The first is whether generational identity can be activated. Recent political science research has made it clear that racial, partisan and gender identities (Mason 2018) are very important in how people process information and behave in the political sphere. I would like to explore whether age (a) is a politically salient identity and (b) whether it can be politicized (see Rouse and Ross 2018).

The second additional substantive question relates to the extent to which policy preferences affect evaluation of political leader versus the extent to which evaluation of political leaders affects policy preferences (Bailey and Wilcox 2016; Lenz 2012). To assess the extent to which citizens take cues from leaders, I will assess treatments that associate Trump with specific policies to see if policy preferences are affected by association with Trump. To assess the extent to which policies affect citizens views of leaders, I will also assess whether treatments associating policies with specific leaders changes voting intentions.

C2 What are the hypotheses to be tested/quantities of interest to be estimated?

Hypothesis 1: Controlling for non-response on unobservables will yield different results for political questions.

1a: Applied to the entire population

This is a foundational hypothesis. In previous work, it was strongly supported for turnout and weakly supported for questions on views of specific politicians and policy.

1b: Applied to Democrats, Republicans and Independents (respectively)

This hypothesis was strongly supported for turnout and for questions on views of specific politicians. It was less strongly supported for policy questions.

1c: Applied to White working class and Hispanic populations (respectively)

My previous work has not directly addressed this, but analyses of the 2016 presidential election by others indicates potential non-response among white working class (especially in the midwest) and Hispanics (especially in the west).

Hypothesis 2: Activating generational identity will lead to a change in self-reported vote propensity and preferences in the 2018 congressional election.

2a: Young people will be more motivated to vote if the identity is activated (Treatment 1) and more likely to vote and prefer Democrats in the congressional election if the identity is activated and associated with anti-Trump sentiment (Treatment 2), relative to the control treatment.

2b: Older people will be more motivated to vote if the identity is activated (Treatment 1) and more likely to vote and prefer Republicans in the congressional election if the identity is activated and associated with pro-Trump sentiment (Treatment 2), relative to the control treatment

Hypothesis 3: Associating Trump with policies will affect support/opposition to policies.

3a: Associating Trump with specific policies will lead those who like Trump and Republicans to be more favorable to Trump's positions than control group who were asked questions with no reference to Trump.

3b: Associating Trump with specific policies will lead those who dislike Trump and Democrats to be less favorable to Trump's positions than control group who were asked questions with no reference to Trump.

C3 How will these hypotheses be tested?

I will use survey data from the attached survey, as administered by the Gfk polling firm based on their internet survey panel.

<u>Hypothesis 1</u> will be tested in two ways. These analytical plans follow methods used in Bailey (2018).

First, I will use two-stage selection models. My main focus will be on using Heckman-type selection models along with copula methods in order to allow for more flexible relationships between the errors in the first and second stage models. I will also use control function models. I will report-based results as main results and the other results as robustness checks. (I will specifically run standard Heckman models with and without the randomized response treatments as one of the arguments is that Heckman models perform poorly without randomization that affects only the first stage.)

Half of all respondents are given choice of answering a question on politics, sports or health. I will refer to those who were given this choice (Z == 1) and who chose sports or health as OptOut == 1.

These models are based on two equations, a response equation and an outcome equation.
Response = $\phi(\gamma_0 + \gamma_Z + \gamma_X)$
$Y = \beta_0 + \beta_1X + \rho$ x f(fitted response)

The dependent variables will be the political outcomes: political feeling thermometers, race battery, policy preferences, turnout and generic congressional ballot. I will also assess a question about volunteerism because this will allow my work to connect to the large literature that shows non-response bias in volunteerism surveys. As an exploration, I will also assess one health question. This is a proof-of-concept that would be used as a basis to develop these tools in health and related fields.

Given the research design, there are three ways to conceptualize non-response. I plan on reporting Versions A and C in the paper and will report Version B in an appendix.

Version A: Use the 2000 responses from GfK to estimate a first stage equation and only those with OptOut==0 in the outcome equation. In this case, we treat those individuals who chose not to discuss politics as non-responders (even though we do later on ask them the political questions).

Version B: Use the 2000 responses from GfK plus the information provided by Gfk on people who were given the survey, but did not respond ("true non-respondents"). The number of true non-respondents is unknown ahead of time, but since this is a survey panel, Gfk has demographic information plus, in some cases, party id available for everyone given an opportunity to respond. We have political answers even from the OptOut==1 respondents and they will be treated as full-on respondents in this version, meaning there will be roughly 2000 respondents and a to-be-determined number of non-respondents.

Version C: Hybrid treat OptOut==1 and true non-respondents as non-respondents. Hence there will be less than 2000 respondents in the outcome equation and more than 2000 in the selection equation.

Control variables

For each dependent variable, I will use four different sets of control variables. Every analysis reported in the paper will have at least two models, one sparse and one with more controls. There will not be space in the paper to report all results, but any anomalies or results that differ from the results reported in the paper will be noted and included in an appendix.

- Sparse: Models with only Z as a control in the first stage and no controls in the outcome equation.
- Minimal: Add randomized variables (the generational and leader treatment categories)
- Standard: Add standard "pre-treatment" controls for age, gender, race, education, metropolitan area status (urban versus rural) and potentially employment status.
- Full: Add racial battery, partisan identification and political ideology. The polling firm has indicated that they will provide partisan identification responses from the last 3 years. I'm not sure how comprehensive this variable will be; if it has a lot of missing data, I may use the party id reported in my survey.

Second, I will conduct direct tests (see Bailey 2018 for examples). In these, I compare responses conditional on covariates by those who chose politics to those who chose something else as a question topic. The sample size for this analysis will be smaller (expected to be 1000 given the randomization) but is a direct test of the assumption that conditional on covariates the response function is independent of the outcome function.

Hypothesis 2: The expectation is that the treatments will have different effect depending on the age category (Young, middle-aged, old) of the respondent.

I will estimate models broken out by age:

$Y = \beta_0 + \beta_1 \text{Treatment1} + \beta_2 \text{Treatment2}$

The dependent variables are political questions that follow the treatment: turnout intention, generic congressional ballot and party id.

I will conduct balance tests to assess whether the treatments were in fact random with regard to demographic and pre-treatment partisan variables.

I will estimate models with and without the addition of additional control variables. If there are imbalances, control variables will help offset these effects. The expectation is that the addition of controls will have little effect on the coefficients of interest, but that they may increase the precision of estimates.

Placebo: since the treatment occurs mid-way through the survey, I will also run models with dependent variables from the earlier questions. The treatments should exert no effect on those variables.

As robustness, I will estimate the following equation for reporting in the appendix
Y = \beta_0 + \beta_1 Treatment1 + \beta_2 Treatment2 + \beta_3 Treatment1 x Age category + \beta_4 Treatment2 x Age category + \beta_5 Age category dummies

In order to assess the efficacy of the generational identity I will assess treatment effects on the last two identity questions related to age.

<u>Hypothesis 3:</u>

There are two directions of influence to assess. The first, which is more likely given results such as Lenz (2012) is that associating a policy with Trump will cause pro-Trump respondents to like the policy more and anti-Trump respondents to like the policy less.

Y = \beta_0 + \beta_1 Trump Treatment + \beta_2 Trump Treatment x Pro-Trump
where Pro-Trump is measured with the Trump feeling thermometer or partisan identification from previous surveys.

The dependent variable will be the four policy questions.

The second is that policy preferences will affect evaluation of political leaders. The model will be
Y = \beta_0 + \beta_1 Trump Treatment + \beta_2 Trump Treatment x Pro-Trump
where Pro-Trump is measured with the Trump feeling thermometer or partisan identification from previous surveys.

The dependent variable will be the generic congressional vote and the partisan identification variable. While I would ideally have pre-existing policy preferences for the respondents (as in Bailey 2013), I will use indicators of being pro/anti-Trump and Republican/Democrat as predispositions. The expectation is that anti-Trump

Democrats, for example, will become even less favorable toward the Republicans and more likely to vote when Trump and the Republicans are associated with specific policies they have pursued.

For both of these analyses, I will conduct balance tests to assess whether the treatments were in fact random with regard to demographic and pre-treatment partisan variables.

I will estimate models with and without the addition of additional control variables. If there are imbalances, control variables will help offset these effects. The expectation is that the addition of controls will have little effect on the coefficients of interest, but that they may increase the precision of estimates.

Placebo: since the treatment occurs mid-way through the survey, I will also run models with dependent variables from the earlier questions. The treatments should exert no effect on those variables.