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A Commentary on the Robustness of the Willingness of US Adults to Receive a COVID-19 Vaccine Based on Republican Party Identification

Author

Thoma, Brandon Fu

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by

Brandon Fu Thoma

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ABSTRACT OF THE THESIS

A Commentary on the Robustness of the Willingness of US Adults
to Receive a COVID-19 Vaccine Based on Republican Party Identification

by

Brandon Fu Thoma
Masters of Science in Statistics
University of California, Los Angeles, 2021
Professor Chad J. Hazlett, Chair

Understanding vaccination hesitancy and how political party affiliation influences it has assumed priority in light of former US President Donald Trump's efforts, during his presidency, to undermine the science behind the development of vaccines to fight COVID-19. Using the data from Kreps et al. (2020) and insights from their discrete choice question results, we construct a new parsimonious model by which to investigate the effect of political party identification on one's willingness to receive a hypothetical COVID-19 vaccine, giving specific attention to assessing the robustness of our results. Utilizing a reparameterization in R^2 of the traditional OVB framework that is used to investigate the sensitivity of regression results to unobserved confounding (Cinelli & Hazlett, 2020), and deeming the non-randomized *Republican* party identification of the participants as the "pseudo" treatment effect of interest, we conclude that, under our model, the difference of nearly 3 percentage points in the probability of accepting a hypothetical COVID-19 vaccine for those identifying themselves as Republican is likely not robust to confounding. The approach outlined herein and introduced in Cinelli and Hazlett (2020) to assess the robustness of regression results should be more broadly adopted in the public health literature to better scope study conclusions.

The thesis of Brandon Fu Thoma is approved.

Mark Stephen Handcock

Erin K. Hartman

Chad J. Hazlett, Committee Chair

University of California, Los Angeles

2021

To my family,

whose love and support helped me finish graduate school.

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Chapter 1

Introduction

COVID-19 has become the most severe global pandemic in a generation, with a confirmed death toll of nearly 3.7 million (World Health Organization, 2021) at the time of this writing. As the virus continues to confound the ability of governments and health organizations around the world, including those in the United States, to stop its spread, the focus in many advanced economies, due chiefly to political will and economic considerations, has shifted to ramping up mass public vaccination programs instead of reemphasizing other effective public health measures such as social distancing and the wearing of masks. As the COVID-19 vaccination program in the United States continues, the overarching goal of health officials and policymakers must now shift to instilling confidence in and conveying reassurance to the public at large of the benefits and safety of vaccines (Stolle et al., 2020). However, with broad swaths of the general public still resistant to vaccination despite the pandemic (Ruiz & Bell, 2021), public officials and health experts alike will need to combine time-tested public health educational campaigns with new outreach techniques and arguments to convince a sufficient portion of the population to get vaccinated, with the goal of achieving herd immunity and thereby end the pandemic. Knowing exactly which groups to target is critical to this effort.

Fortunately, strong research has been conducted, both prior to and during the current pandemic, to discern the individualized factors that contribute to one's willingness to receive a vaccination, in general, and the COVID-19 vaccine, in particular. The research results should afford public health officials and government policymakers ample data that can be utilized to develop effective local, state, and national level policies to encourage strong public uptake of COVID-19 vaccines. However, many of the studies have reached their conclusions, as in the case of Kreps et al. (2020) and Malik, McFadden, Elharake, and Omer (2020), by

relying on Ordinary Least Squares (OLS) or Logistic regression to investigate the effect of a set of observed covariates on the likelihood that one will choose to be vaccinated against the virus. Yet the regression approach is vulnerable to the problem of "unobserved confounding": unobserved differences between study subjects that lead to differences in treatment and outcomes which can affect the model's covariate coefficient estimates and lead to erroneous conclusions because only a finite number of covariates can be studied.

This paper will first provide an overview of the literature on vaccination hesitancy and willingness, both prior to and in response to COVID-19, and the literature on the political factors, namely party identification, that influence one's response. Next, utilizing the data used by Kreps et al. (2020), as well as insights gleaned from their discrete choice model results, and focusing on the non-randomized *Republican* party identification of the survey participants as the "treatment" of interest, we construct a new parsimonious model to investigate the effect of Republican party identification on COVID-19 vaccination willingness and, to properly scope the results of our conclusion, analyze the robustness of this effect utilizing the novel, principled approach to sensitivity analysis introduced in Cinelli and Hazlett (2020). Brief concluding remarks will then follow.

Chapter 2

Background

The topic of vaccination willingness and the factors that can influence it has been well studied recently in the public health literature. Set forth below is a brief overview of some of the relevant literature on such factors, of specific literature related to vaccination willingness and hesitancy as they pertain to COVID-19 itself, and of studies that explore the relationship between political affiliation and ideology, on the one hand, and vaccination willingness, on the other.

2.1 Factors Influencing Vaccination Willingness

There are likely many factors that influence one's willingness to have himself/herself or his/her children vaccinated. Fortunately, many recent studies in the medical literature have explored in detail the factors that may influence such willingness in a variety of contexts. For example, in some countries, the willingness to get vaccinated against seasonal flu is strongly influenced by one's educational level, gender, and age (Jang & Kim, 2019); similar conclusions concerning the influence of race on vaccination willingness have been proposed, through the lens of racial consciousness, fairness, and discrimination (Quinn et al., 2017). Additionally, select groups, such as Orthodox Protestants in some countries, might reject vaccination for themselves and their children for religious reasons (Ruijs et al., 2012). In other cases, factors such as the level of trust one has in the information provided by government sources or the government itself can influence one's willingness to be vaccinated (Jamison, Quinn, & Freimuth, 2019). Lastly, social responsibility, perception of risks, recommendations of health professionals, personal vaccination history, and level of knowledge about vaccines can all be

potentially informative of vaccination acceptance among individuals of varied backgrounds (Dubé et al., 2013). While it is impossible to test robustly for every factor that can affect vaccination willingness, it is important to keep in mind the economic, social, political, and religious contexts in which the decision is being made.

2.2 Vaccination Willingness and COVID-19

Numerous surveys and studies have been conducted within the past year concerning the willingness among US adults to receive a COVID-19 vaccine. Broad surveys and polls suggest that many factors can play a role in the decision, such as one's trust in politicians and the government, race, flu vaccination history, institutional trust and trust in scientists (Baum et al., 2020), whether an individual lives outside a metropolitan area (Nguyen et al., 2021), or whether the individual is older or has pre-existing medical conditions (Ruiz & Bell, 2021). Studies have also revealed potential associations between COVID-19 vaccination acceptance and gender, perceived vaccine efficacy, organizational endorsements, insurance status, vaccine origins, vaccine protection duration, and one's belief about the current state of the pandemic (Kreps et al., 2020). Other studies have explored the influence of the COVID-19 vaccine's potential side effects and the severity thereof (Kaplan & Milstein, 2021), as well as the perceived risk of COVID-19 infection and injury (Lin, Tu, & Beitsch, 2021), on one's decision about whether to accept or reject vaccination. Many of the foregoing factors are accounted for in Kreps et al. (2020); however, the purpose of this paper is to build upon some of the incidental results in Kreps et al. (2020), exploring specifically the effect of political party identification on one's willingness to receive a hypothetical COVID-19 vaccine and the robustness of same.

2.3 Party Identification and Vaccination Willingness

The effect of party identification on vaccination willingness had been explored prior to the current pandemic. During the 2009-2010 H1N1 Swine Flu Pandemic, vaccination decisions were highly polarized across party lines, with Republicans and Independents significantly more wary to receive a vaccine than Democrats (Mesch & Schwirian, 2015a), potentially due in part to differing degrees of perceived trust in government as well as party positions concerning the proper role of government (Mesch & Schwirian, 2015b). A similar polarization has been very pronounced during the current COVID-19 pandemic. Survey research by Baum et al. (2020) suggests that during the period from July 2020 through August 2020, Republicans and Independents were, in general, less willing to receive a COVID-19 vaccine than Democrats, potentially related to their lack of trust in specific institutional spokespersons involved in discussions about the vaccine, such as Dr. Anthony Fauci, (former President) Donald Trump, and (former Presidential Candidate and current President) Joe Biden. Additional evidence that political party affiliation affects COVID-19 vaccination willingness has been found in Lin et al. (2021), Ruiz and Bell (2021), and Raja, Niforatos, Anaya, Graterol, and Rodriguez (2021). Multiple regression analyses, including those in Khubchandani et al. (2021), have concluded that, even controlling for an individual's gender, education, income, and other factors, those who identify as Republican generally have higher rates of COVID-19 vaccination hesitancy as compared to individuals who identify with a different political party; further evidence supporting this assertion is found in Kreps et al. (2020). The remaining focus of this paper is to provide additional insight into the incidental result concerning the relationship between Republican party identification and COVID-19 vaccination willingness in Kreps et al. (2020) to expand upon their findings, and to present a principled way by which confounding can be systematically analyzed and discussed.

Chapter 3

Research Design

Before focusing on the research design for this paper, a brief overview of the data and methodology in Kreps et al. (2020) is presented.

3.1 Overview of Kreps et al. (2020)

A brief summary of the original paper is below set forth. For additional detail, please consult Kreps et al. (2020) directly.

Data was collected through the online platform Lucid on July 9, 2020. Of the 3708 US adults that were contacted on that date, a non-probability convenience sample of 2000 were recruited to participate in a survey. Participants were asked to answer a choice-based conjoint experiment in order to assess the factors that influenced their self-reported likelihood of accepting a vaccination for COVID-19. The following demographic characteristics were collected for each participant: race / ethnicity, sex, age, education, income level, and political ideology and partisanship. Participants were given a set of hypothetical COVID-19 vaccines then under development, where 7 categories of vaccine attributes were varied in each hypothetical vaccine. Multiple factors were considered in selecting the attributes and determining the levels of each to be included in each vaccine, including potential characteristics of vaccines that were in development at the time.

Two specific scenarios were assessed: the "discrete choice question" scenario and the "individual vaccination evaluation" scenario. However, for brevity, this paper is focused on understanding the robustness of the results for the "discrete choice question" scenario, where each participant was presented with 5 choice tasks and was asked whether he/she

would choose Vaccine A, Vaccine B or neither in light of the characteristics given: this response was denoted by the *vaxbin* binary variable, which was generated using the Likert Scale number assigned by each respondent to his/her potential willingness to take a proposed COVID-19 vaccine in the "individual vaccine evaluation" scenario that was stored in the variable *vaxord*.

Based on the fully randomized conjoint design, 576 unique vaccine profiles were tested. Using the outcome variable *vaxbin*, an OLS regression was used to estimate the average marginal component effect size for each attribute, with standard errors clustered on the respondent. This "benchmark" OLS regression was constructed solely on the characteristics of the hypothetical vaccine, with the average marginal contribution of each attribute to the outcome computed. Finally, another OLS regression that contained additional self-reported demographic characteristics was constructed.

3.2 A Rigorous Approach to Sensitivity Analysis

Below is a brief discussion of the omitted variable bias framework, as well as an extension of it in Cinelli and Hazlett (2020) to allow for a principled sensitivity analysis approach that can avoid a merely qualitative debate on whether a confounder of significant strength exists to invalidate the results of interest. Only the key results of Cinelli and Hazlett (2020) are presented: for a more in-depth discussion, please refer to the original paper.

3.2.1 Omitted Variable Bias Framework

In traditional regression analysis, a researcher investigates whether an outcome Y is dependent on a treatment D, given a set of observed covariates denoted by $\mathbf{X}$ and Z, whose relationship can be described as:

$$Y = \hat{\tau}D + \hat{\beta}\mathbf{X} + \hat{\gamma}Z + \hat{\epsilon}_{full}$$

where Y: $(n \times 1)$ vector of outcomes for n observations; D: $(n \times 1)$ treatments, one for each n observation; $\mathbf{X}$: $(n \times p)$ matrix of pre-treatment (observed) covariates; and Z: a $(n \times 1)$ unobserved covariate. Since Z is unobserved, the researcher needs to estimate the restricted model:

$$Y = \hat{\tau}_{res} D + \hat{\beta}_{res} \mathbf{X} + \hat{\epsilon}_{res}$$

where $\hat{\tau}_{res}$, $\hat{\beta}_{res}$ represent the restricted OLS coefficient estimates where only D and $\mathbf{X}$ are included in the model, and $\hat{\epsilon}_{res}$ the resulting residual.

Considering how $\hat{\tau}_{res}$ overestimates $\hat{\tau}$, we can define the $\hat{bias} := \hat{\tau}_{res} - \hat{\tau}$ as the difference between the two. Using the Frisch-Waugh-Lovell (FWL) theorem, the classic omitted variable bias solution then becomes

$$\hat{\tau}_{res} = \hat{\tau} + \hat{\gamma}\hat{\delta}$$

where $\hat{\delta} := \frac{cov(D^{\perp \mathbf{X}}, Y^{\perp \mathbf{X}})}{var(D^{\perp \mathbf{X}})}$. Thus,

$$\hat{bias} = \hat{\gamma}\hat{\delta}$$

which is known as the Omitted Variable Bias formula.

This framework can customarily be used to understand the robustness of the treatment effect under study. However, there are a few notable issues with the methodology that can make it difficult to utilize sensitivity analyses to study treatment effect robustness: it can be challenging to measure the effects of multiple confounders on the treatment effect coefficient; we cannot easily determine the statistical significance of a treatment effect without determining the sensitivity of the standard errors of the treatment coefficient estimate; subjectivity is introduced in calculating the bias which can hinder the interpretation of sensitivity plots (Cinelli & Hazlett, 2020). However, by extending the original sensitivity analysis framework through a reparameterization of the OVB formula proposed in Cinelli and Hazlett (2020), we gain the ability to more rigorously discuss the robustness of the treatment effect of interest while addressing some of the concerns above mentioned.

3.2.2 Reparameterization of Bias Using Partial R^2

A key consequence of Cinelli and Hazlett (2020) is that we can reparameterize the OVB formula to use partial R^2 values, which allows us to replace $\hat{\gamma}$ and $\hat{\delta}$, the sensitivity parameters, with those that use R^2 instead to measure the strength of the relationships between the confounder and the treatment as well as the confounder and the outcome, assuming the pre-treatment observed covariates $\mathbf{X}$ have been controlled for. In this way, the partial R^2 parameterization enables us to better assess the sensitivity of an estimate to multiple confounders acting together in a linear or non-linear fashion; to evaluate the sensitivity of point estimates, t-values, and confidence intervals; to use expert knowledge to surmise the strength of confounders; and to generate easily accessible sensitivity results (Cinelli & Hazlett, 2020). We can thus easily construct routine sensitivity results that capture important statistics concerning the sensitivity of our treatment effect estimates.

Key information that can be determined includes Robustness Values (RV), which capture the types of confounders that can affect our regression results and indicate how problematic unobserved confounding is to a point estimate; $R^2_{Y\sim D|\mathbf{X}}$, the worst-case scenario where the unobserved confounder explains 100% of the residual variation in the outcome; and $R^2_{D\sim Z|\mathbf{X}}$ and $R^2_{Y\sim Z|D,\mathbf{X}}$, which can help to quantify the strength of the confounder with respect to the treatment and outcome. Detailed derivation and discussion of each of these quantities can be found in Cinelli and Hazlett (2020).

3.2.3 Expanding on Incidental Results in Kreps et al. (2020)

The remainder of this paper describes how we utilized the results from Kreps et al. (2020) to conduct additional analysis.

Using the results of Table 3 in Kreps et al. (2020), as well as the original data, a parsimonious model of Model 2 was constructed using only variables that were statistically significant under the Bejamini-Hochberg correction, to control for false discovery in multiple

comparisons. These variables included a combination of randomized hypothetical vaccine characteristics and non-randomized self-reported participant demographic characteristics, as delineated in Kreps et al. (2020). After fitting the parsimonious model, and deeming the non-randomized Republican party identification of the participants as a "pseudo" treatment rather than as a "true" treatment since we cannot randomly assign such identification to survey participants, we conducted a sensitivity analysis under the extended omitted variable bias framework proposed in Cinelli and Hazlett (2020) to investigate the robustness of the effect estimate for identifying as Republican on *vaxbin* under this model.

A presentation of the results of the minimal report table used in Cinelli and Hazlett (2020) is then given, along with a description of the resulting sensitivity contour plots and extreme scenario plot, followed by a brief discussion and some concluding remarks.

Chapter 4

Results

4.1 Model Results

Table 4.1 shows the parsimonious regression model for Model 2 in Table 3 of Kreps et al. (2020) whereby all non-statistically-significant covariates are removed under the Benjamini-Hochberg correction. Note that the first nine indicated covariates are randomized features of the hypothetical vaccine presented to the participants, with remaining covariates being the self-reported demographic characteristics provided by each participant. As expected, the statistical significance of the predictors did not change; in particular, the effect size of the "pseudo" treatment *Republican* did not change: for purposes of this paper hereafter, we will refer to Republican party identification as the treatment of interest even though it is a "pseudo" treatment as it cannot be randomly assigned to each study participant. This model indicates that, controlling for other factors, identifying as a Republican (or as Republican-leaning) has a nearly 3 percentage point greater mean willingness to get vaccinated against COVID-19.

Even at a more conservative $\alpha = 0.01$, the *Republican* treatment effect is statistically significant in the parsimonious model. As the conjoint survey design approximates actual decision-making and shows a moderately strong prediction of future health decisions (Quaife, Terris-Prestholt, Tanna, & Vickerman, 2018), we can be confident that analyzing the parsimonious model with respect to the willingness to take a hypothetical COVID-19 vaccine is reasonable in predicting eventual individualized vaccination decisions. Thus, it is reasonable to still analyze the sensitivity of this party identification treatment effect under this model.

Table 4.1: Parsiminious Model Results

	Dependent variable:
	vaxbin
Efficacy: 70%	0.078
	$t = 9.633^{***}$
Efficacy: 90%	0.168
	$t = 20.934^{***}$
Duration: 5 years	0.054
	$t = 8.187^{***}$
Major adverse effects: 1 in 1,000,000	0.068
	$t = 10.215^{***}$
FDA: Emergency Use Authorization	−0.028
	$t = -4.225^{***}$
Origin: United Kingdom	−0.036
	$t = -4.460^{***}$
Origin: China	−0.131
	$t = -16.252^{***}$
Endorsed: CDC	0.083
	$t = 10.233^{***}$
Endorsed: WHO	0.049
	$t = 6.013^{***}$
Democrat	0.058
	$t = 6.360^{***}$
Republican	0.031
	$t = 3.328^{***}$
Female	−0.021
	$t = -3.218^{***}$
Education	0.015
	$t = 7.783^{***}$
Flu vaccination frequency	0.028
	$t = 9.451^{***}$
Uninsured	−0.031
	$t = -5.318^{***}$
Pharma Favorability	0.031
	$t = 11.549^{***}$
Know a COVID-19 case	0.019
	$t = 2.689^{***}$
Worst of pandemic to come	0.039
	$t = 5.565^{***}$
Black	−0.023
	$t = -2.318^{**}$
Observations	19,710
R^2	0.437
Adjusted R^2	0.437
Residual Std. Error	0.472 (df = 19691)
F Statistic	805.137^{***} (df = 19; 19691)
Note: Created with stargazer, 2021 R package	*p<0.1; **p<0.05; ***p<0.01

4.2 Sensitivity Analysis Results

Table 4.2 reports basic robustness statistics for the sensitivity analysis respecting the treatment effect of *Republican* party identification under the parsimonious model. Also included are some common statistics from multiple software packages' regression outputs to allow for quick understanding of the results of the sensitivity analyses. The information provided in this table is generated from *sensemakr*, an R package developed in Cinelli and Hazlett (2019).

Table 4.2: Sensitivity Statistics for *Republican* treatment effect

Outcome: *vaxbin*

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Republican	0.031	0.009	3.328	0.1%	2.3%	1%
df = 19691				*Bound (1x Efficacy: 90%)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 2.2\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0.4\%$		
				Bound (1x Pharma Favorability): $R^2_{Y\sim Z\|\mathbf{X},D} = 0.8\%$, $R^2_{D\sim Z\|\mathbf{X}} = 9.4\%$		
				Bound (1x Hybrid Dummy): $R^2_{Y\sim Z\|\mathbf{X},D} = 2.2\%$, $R^2_{D\sim Z\|\mathbf{X}} = 9.4\%$		

Assessing the estimate itself, the standard error, and t-value likely shows that potential affiliation as a Republican indeed affects the willingness to be vaccinated. From Table 4.2, the robustness value $RV_{q=1}$ indicates that unobserved confounders that explain 2.3% of the residual variances in *both* treatment and outcome would be sufficient to turn the effect of identifying as a Republican on the probability of receiving a hypothetical COVID-19 vaccine to 0. However, in the "extreme scenario" where the unobserved confounders explain 100% of the residual variance in the outcome, given by $R^2_{Y\sim D|\mathbf{X}}$, the unobserved confounders would only need to explain at least 0.1% of the residual variance in *Republican* to nullify the observed treatment effect.

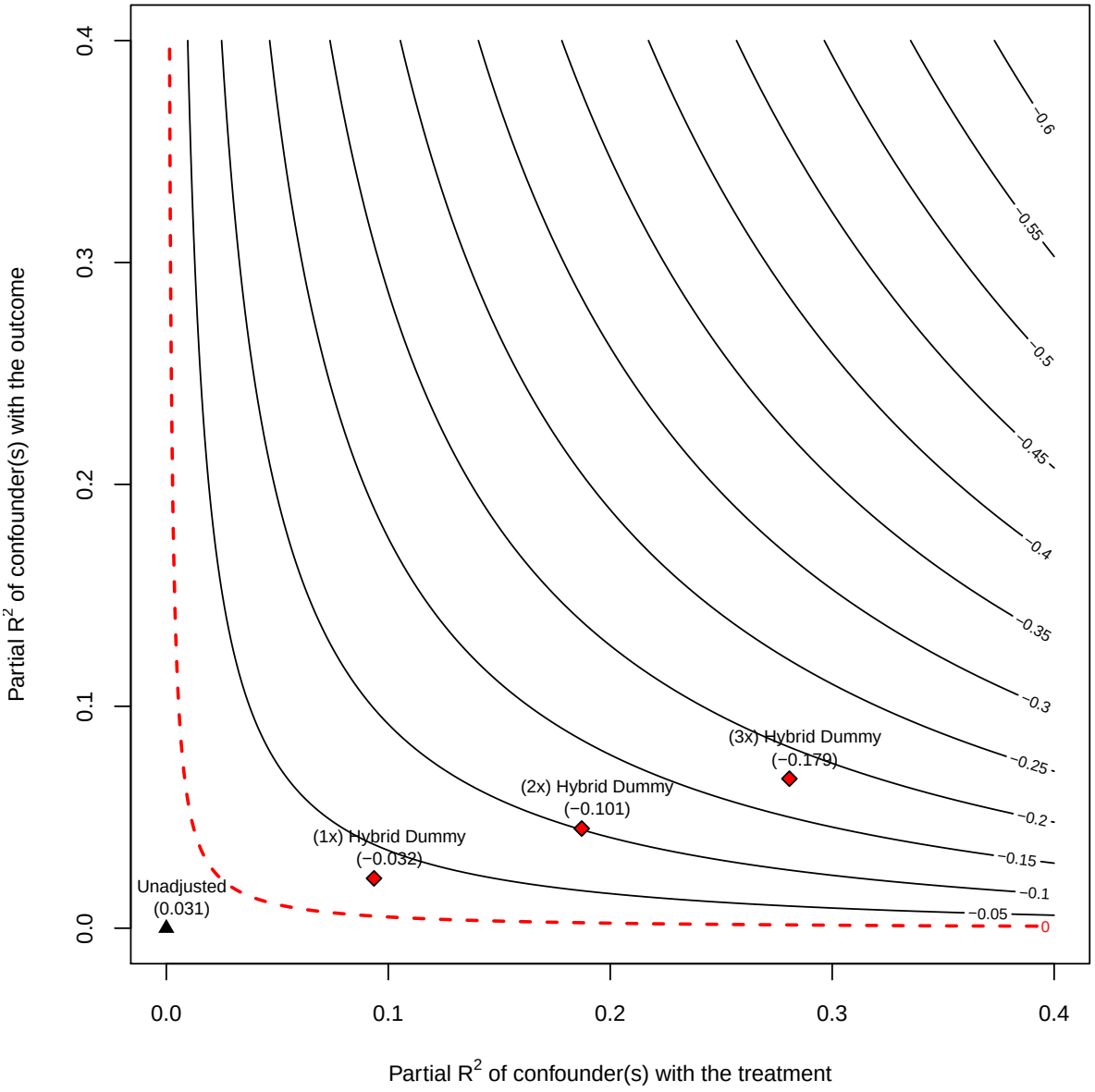
To better assess the potential for unobserved confounding to nullify this treatment effect, we can analyze the relationship between benchmark variables, or other observed covariates in the regression model that are not the treatment, and the treatment and outcome; these benchmark variables help us to "bound" the strength of unobserved confounding and enable

us to comment on whether or not such confounding is a legitimate threat to the treatment. However, considering all the covariates under this parsimonious model that are not *Republican*, there exists no covariate (randomized or non-randomized) that is significantly related to *both* treatment and outcome and thereby reasonable to use as a benchmark. To address this, two covariates indicated in Table 4.2 are combined into a hybrid benchmark variable to create an adequate benchmark for use in the sensitivity analysis: the randomized *Efficacy: 90%* and non-randomized *Pharma Favorability*, due to the greatest magnitude effect of the former on the outcome from Table 4.1 and the latter being one of the most strongly associated variables with the treatment that is present in the parsimonious model. Thus, the *Hybrid Dummy* variable in Table 4.2 simulates a confounder that explains no more of the treatment than *Pharma Favorability* and no more of the outcome than *Efficacy: 90%*, but is sufficiently related to *both* treatment and outcome (within the confines of the data) to be worthwhile to use as a benchmark.

Considering this dummy variable, $R^2_{Y\sim Z|\mathbf{X},D}$ and $R^2_{D\sim Z|\mathbf{X}}$ provide useful insight: for confounders "as strong" as the (hypothetical) benchmark *Hybrid Dummy*, since $R^2_{Y\sim Z|\mathbf{X},D}$ is close to $RV_{q=1}$ and $R^2_{D\sim Z|\mathbf{X}}$ is greater than $RV_{q=1}$, this confounder would be able to eliminate the *Republican* treatment effect estimate. This conclusion concerning the potential effect of unobserved confounders to nullify the treatment effect estimate vis-à-vis an analysis of benchmark variables can be visualized in Figures 4.1 and 4.2, which show additional scenarios where the treatment effect estimates are adjusted for a confounder k times as strong as *Hybrid Dummy*. From Figure 4.1, for a confounder "at least as strong as *Hybrid Dummy*" (*1x Hybrid Dummy*), the treatment effect estimate is nullified, a result which is supported by Figure 4.2 that indicates a change in the statistical significance of the treatment effect estimate at this level of confounding.

These results are potentially informative as the relationship of *Hybrid Dummy* to *both* treatment and outcome is sufficiently strong and *Hybrid Dummy* is itself a combination of two relevant covariates: *Efficacy: 90%*, which is naturally related to the outcome as the strength

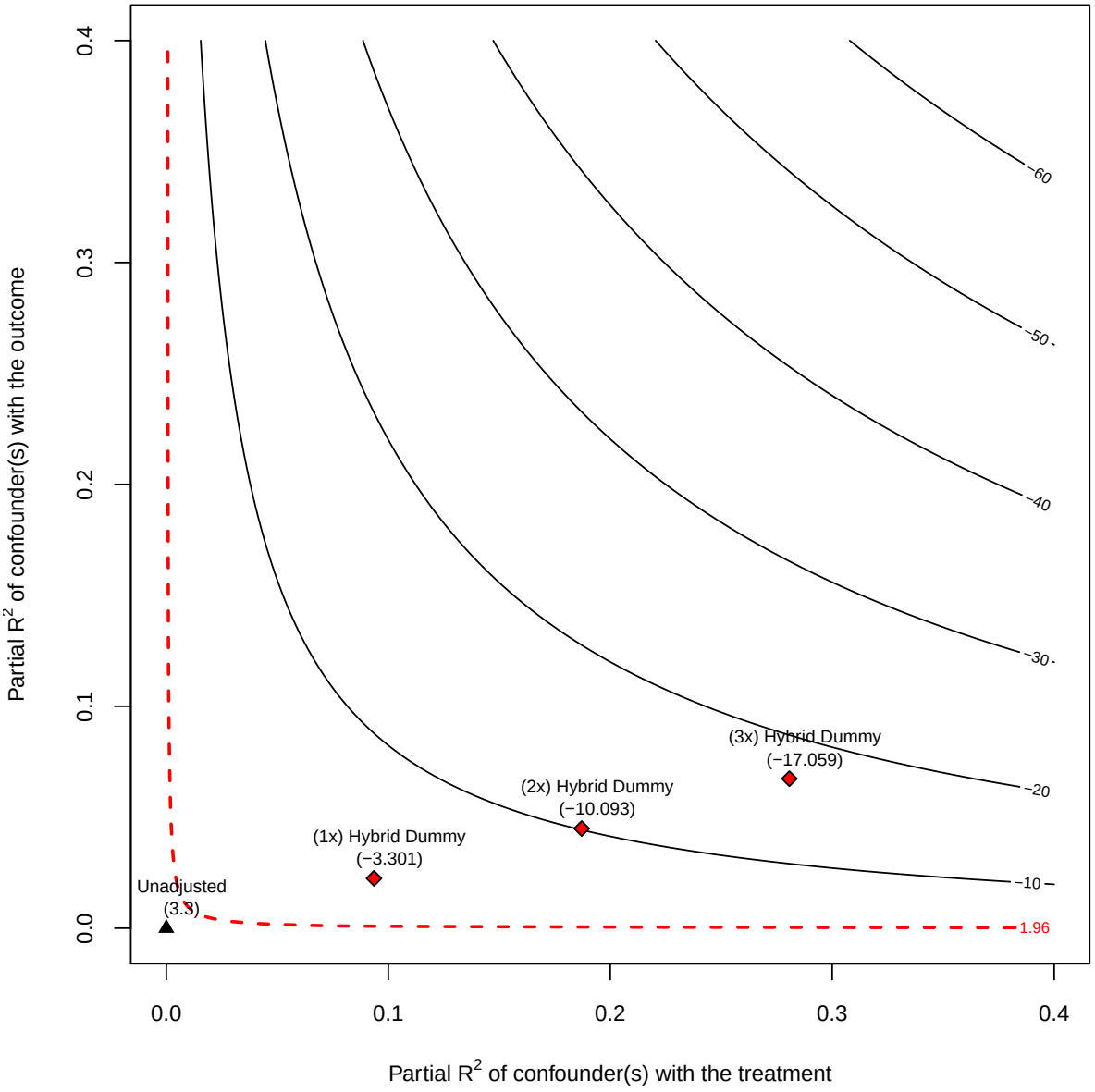
Figure 4.1: Sensitivity contour plot of treatment estimate using benchmark *Hybrid Dummy*



of a hypothetical vaccine to prevent the worst effects of COVID-19 infection would be among the top concerns of those considering whether or not to get vaccinated, as has been validated in multiple studies including in Kaplan and Milstein (2021); and *Pharma Favorability*, which somewhat surprisingly is strongly related to treatment, perhaps as a result of specific factors that influence Republican party identification and trust in pharmaceutical companies.

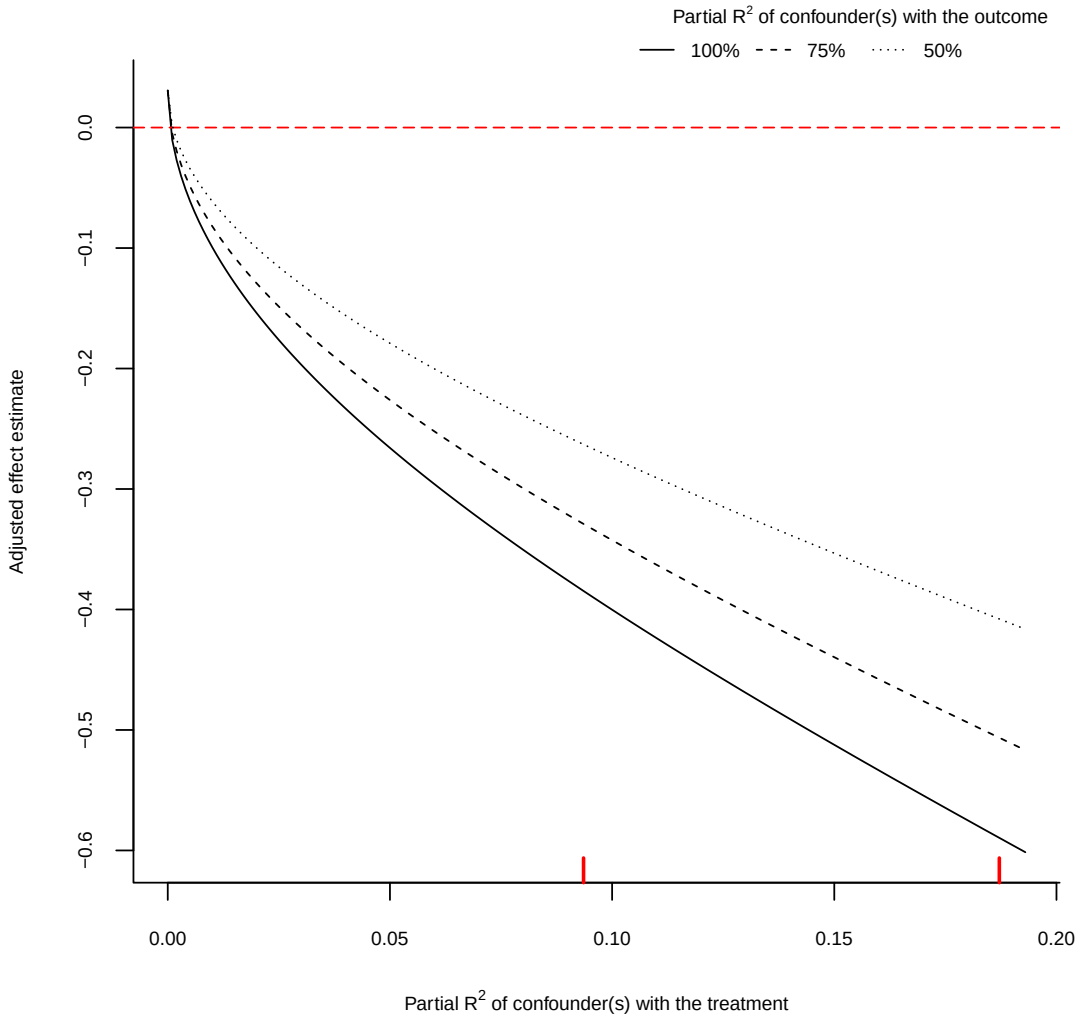
Finally, in order to better visualize how the *Republican* treatment effect estimate is mini-

Figure 4.2: Sensitivity contour plot of treatment t-statistic using benchmark *Hybrid Dummy*



mized in the case where a large proportion of the residual variance in the outcome is explained by the unobserved confounder, an "extreme scenario" plot is presented in Figure 4.3. The red x-axis tick marks show the bounds of the partial R^2 of the unobserved confounder which is k times as strong as the benchmark variable; (1x) and (2x) as strong, reading the tick marks from left to right. When we have a poor understanding of the strength of potential confounders relative to the observed covariates (or in this case, a postulated hybrid variable

Figure 4.3: Extreme Scenario plot of treatment estimate using benchmark *Hybrid Dummy*



of two observed covariates), an extreme scenario plot such as this can provide insight into whether it is feasible to believe that sufficiently strong unobserved confounders relative to our observed covariates exist to better understand the robustness of the treatment effect under study. However, in this case, it appears from Figure 4.3 and others prior to it that, given this hybrid benchmark, even "weak" confounding would be sufficient to nullify the treatment effect estimate.

4.3 Discussion

From the results above presented, we see that under our parsimonious model, the conclusion that those who identify themselves as Republican are nearly 3 percentage points significantly more likely to accept a hypothetical COVID-19 vaccine, as compared with members of other groups, cannot be strongly accepted given that even minor unobserved confounding is likely sufficient to nullify the treatment effect estimate. The methods utilized herein from Cinelli and Hazlett (2020) provide a framework to study, in a more principled and transparent way, the effects of potential confounders on our model results. We now note some caveats of the sensitivity analysis and of this paper in general.

4.3.1 Plausibility of Confounding as Strong as *Hybrid Dummy*

The *Hybrid Dummy* variable used in the analysis to bound the strength of confounding is not an observed covariate, but rather a combination of characteristics of the randomized *Efficacy: 90%* and non-randomized *Pharma Favorability* covariates in the parsimonious model. However, it is unclear as to whether or not a confounder with these characteristics exists and is omitted from our analysis. An assortment of variables was included in the modeling based on the results of Model 2 from Kreps et al. (2020), yet few, if any, displayed as strong an effect on the treatment as *Pharma Favorability* or as strong an effect on the outcome as *Efficacy: 90%*; these two observed covariates were outliers in this regard. A number of additional, self-reported demographic characteristics were collected in Kreps et al. (2020) as well, such as job status, location, ability to work remotely and belief in overall vaccine safety; the influence of these factors on vaccination willingness was not controlled for in our analysis or in Kreps et al. (2020) and could have biased our conclusions. While we lack expert knowledge to hypothesize whether or not the omission of such variables is significant enough to bias our results (or affect the results of Kreps et al. (2020) upon which our analysis is partially based), subsequent analyses should be conducted to ascertain whether their

inclusion would alter the treatment effect estimate under our parsimonious model.

4.3.2 Factors Influencing *Republican* Party Identification

Studying *Republican* party identification as a treatment effect poses potential problems. Considering this as a treatment is unusual as a person cannot surgically change his/her party identification without changing other characteristics about himself/herself; in reality, party identification is likely due to a combination of experiences. For example, Kreps et al. (2020) collected other characteristics from participants in the study, such as support for Joe Biden or Donald Trump and political ideology, which could influence party identification and thereby instead be at least partially responsible for our observed treatment effect estimate rather than the treatment itself; these other self-reported demographic characteristics were likewise omitted from our analysis as we based our parsimonious model on the discrete choice question Model 2 of Kreps et al. (2020). Additionally, a variable that was not collected in Kreps et al. (2020) (or by us) was *trust*, or the degree to which a respondent trusts that the government is providing all information (if not full transparency in general) regarding the pandemic and the development of vaccines to combat it. General surveys such as Lazarus et al. (2021) have found that, at least in other countries, trust in information from government sources was correlated with an individual's increased willingness to be vaccinated. Furthermore, Baumgaertner, Carlisle, and Justwan (2018) proposes that differing degrees of *trust* in medical professionals based on political ideology, rather than political party identification, may cause disparities in vaccination willingness. Ultimately, *Republican* party identification is an imperfect treatment to study, both due to its inability to be randomly assigned to participants as well as its being an imperfect proxy for the partisan beliefs that one holds; yet analyzing the sensitivity of this "treatment" effect estimate is nonetheless useful.

4.3.3 Bias and the Generalizability of Results

Our conclusions above set forth possibly apply only to the specific group studied and thus can provide no clarity with respect to any other group chosen. The quota-based, convenience sampling method used in Kreps et al. (2020) to recruit participants that are representative of the national population demographic, while shown to afford similar informative benefits as national probability surveys (Coppock & McClellan, 2019), can still introduce biases depending on how each population subgroup is chosen and their relative weights, thereby potentially affecting our model conclusions. Moreover, the method by which the *vaxbin* outcome variable was generated from the *vaxord* outcome variable for the data in Kreps et al. (2020) leaves room for subjectivity, consequently leading us to reach potentially different conclusions depending on the assignment of Likert-Scale numbers to binary outcomes.

Chapter 5

Conclusion

Understanding the factors that influence one's choice to ultimately accept a COVID-19 vaccination has important implications for public health in the United States, and can provide clarity on the justifiability of the argument that once a vaccine for COVID-19 is widely available, the pandemic will quickly abate. While many studies to date have probed a variety of factors and their influence on vaccine hesitancy and willingness, confounding concerns have only recently begun to be rigorously studied in the medical and public health literature. This paper presents the finding of our model, which was constructed using data and insights from Kreps et al. (2020), that the effect of Republican political party identification on COVID-19 vaccination willingness is likely not statistically significant in the case of even minor confounding. This conclusion is supported by the structured approach to understanding robustness as delineated by Cinelli and Hazlett (2020), which provides greater clarity into discussions concerning the threat of unobserved confounding to our results. As a consequence, we cannot be confident in the results of our model that persons identifying as Republican are nearly 3 percentage points more likely to agree to be vaccinated against COVID-19 as compared to members of other groups, given the data used.

Additionally, as noted earlier, the results of our analysis must be considered in light of certain limitations. The potential for bias in our results cannot be ignored, due to the lack of transparency as to why specific observed covariates were included in modeling in Kreps et al. (2020) upon which our analysis is based, our study's limited scope, and the imperfectness in using Republican party identification as the treatment to study COVID-19 vaccination willingness since such identification cannot be randomly assigned to survey participants as in the traditional case for a treatment. Nevertheless, our decision to utilize the extension of

the OVB framework to sensitivity analysis that is proposed by Cinelli and Hazlett (2020) was prudent in order to impart greater transparency and confidence into the conclusions we reached in this paper, and should be integrated into future studies in the literature to ensure that the question of confounding is adequately and rigorously addressed.

More research would be beneficial, whether using the additional data collected by Kreps et al. (2020), completely new data or a combination thereof. Until such studies are conducted, policymakers and public health officials should refer to previous studies, such as Baumgaertner et al. (2018) and Hornsey, Finlayson, Chatwood, and Begeny (2020), which point to a potential connection between political identity and COVID-19 vaccination hesitancy, in order to fashion policy measures and programs at the local, state, and federal levels to address vaccination inclination disparities. While our finding in this paper cannot state for certain that Republican party identification in and of itself is responsible for a lower rate of willingness to accept a hypothetical COVID-19 vaccine, at least when compared with members of other groups, it remains useful to target and reach out to self-identified Republicans to increase their vaccination willingness, in line with prior research as in the findings of Baum et al. (2020) and Mesch and Schwirian (2015b).

As the COVID-19 vaccination rate in the United States slows, concerted vaccination outreach programs and campaigns targeting persons identifying as Republican is crucial for ultimately containing the current pandemic in our country. The detailed sensitivity analysis presented in this paper provides a blueprint for future evaluation of hypothetical confounders in the context of OLS results, to hopefully become more broadly adopted in the scientific literature. While the framework used in this paper does not provide definitive answers regarding the significance of potential confounders, it posits a principled approach to confounding that can standardize the discussion of confounding throughout the field.

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