Reluctant Republicans? Partisan Non-Response and the Accuracy of 2020 Presidential Pre-Election Polls

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Using the registration-based samples and disposition codes of state level exit polls conducted by the National Election Pool in 12 states we determine whether likely Democrats were more likely to cooperate with the National Exit Poll than likely Republicans and independents. Controlling for individual and geographic features plausibly related to non-response (e.g., age, gender, race, urban/rural, community support for President Trump, and effects of COVID-19) that are available for both respondents and non-respondents, we find that Democrats are more likely to cooperate with telephone interviewers than Republicans and independents by 3 and 6 percentage points respectively. Using post-stratification to equalize the partisan cooperation rates decreases the average polling error on the margin of victory by 4 percentage points in the polls we examine, but sizable errors remain in critical swing states because of within-party differences in who responds and/or errors in the available partisanship measures in the voter file.

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After four years of President Trump and his supporters decrying "fake polls" and "fake news," some worried whether his supporters would still participate in the "fake polls" being done by "fake news" organizations (e.g., Matthews 2020; Musto 2020). Emblematic of the language he often used to describe polls and pollsters, in an interview in the closing weeks of the 2020 campaign, President Trump commented: "It's a shame they [pollsters] can get away with it. If you think about it, it's almost like a campaign contribution to the DNC. The good news is our people understand it. They understand it very well." (Smith-Schowenwalder, 2020).

The 2020 pre-election polls generally failed to predict the level of support for Republican candidates in the 2020 election (Clinton et al 2021), and some early evidence suggests that a portion of this error resulted from differential partisan response caused by the politicization of survey participation (Von Hagen-Jamar et al. 2021; Keeter et al. 2021; McAullife et al. 2021; Yan and Barlas 2021). Partisan elites can certainly affect public opinion and behavior (e.g., Zaller 1992), but it is unknown whether pre-election polls were impacted by a decreased willingness of President Trump's supporters to take political surveys – and an *increased* willingness on the part of President Biden's supporters. This politicization has the potential to create *differential partisan response*: a situation where an individuals partisanship affects the degree to which they cooperate with the survey conditional on being contacted. Because partisanship is so often related to the outcomes of interest and only weakly related to the variables commonly used to correct for differential response bias via post-stratification (e.g., Keeter et al. 2017; Keeter 2018), the presence of differential partisan response would adversely affect the accuracy of political surveys (Bethlehem 2002; Groves et al. 2012).

Using the registration-based samples and disposition codes of telephone exit poll poll surveys conducted by the 2020 National Election Pool in the 12 states of Alabama, Arizona, Colorado, Florida, Iowa, Michigan, Minnesota, North Carolina, Nevada, Pennsylvania, Texas, and Wisconsin we examine whether likely Democrats were more likely to cooperate with survey interviewers than likely Republicans and independents. Controlling for individual-level and geographic-level characteristics related to survey participation (e.g., age, race, past presidential vote in the zip code, urban/rural/suburban geography, and the impact of COVID 19), we show that Republicans were 3 percentage points less likely to participate in the telephone portions of the National Exit Poll than Democrats and independents were 5 percentage points less likely. This difference points to either Republican and independent reluctance to take polls, Democratic enthusiasm, or some combination of the two.[1]

Post-stratifying the sample of completed interviews using observable demographics fails to fully eliminate the pro-Biden error in the margin among respondents, but weighting by the inverse of the partisan cooperation rate to equalize the cooperation rates across partisan groups reduces the average error on the final certified margin by 4 percentage points in the 6 states where a sizable pre-election phone poll of the electorate was completed.

While encouraging, considerable errors remain after equalizing the cooperation rate across partisanship – especially in the swing states of MI, WI, and PA. The remaining error suggests either that the opinions of Republicans and independents who cooperate differ from those who do not – as might be the case if participating in a survey is considered a partisan act – or else that the voter-file measure of partisanship is less reliable in these swing states. Even though accounting for partisan-related differences in cooperation *between* partisan groups improves the accuracy of the surveys we examine, it is no panacea.

1 Differential Partisan Response?

Survey researchers have been increasingly worried about the potential effects of differential partisan response bias. When analyzing differential partisan response in 2016 and before, Keeter et. al. (2017) note that "affiliation with a particular political party does not appear to affect the likelihood that a person will participate in telephone polls" among public opinion

[1] Unfortunately, the lack of information on the opinions of non-responders prevents us from determining precise how – or why – those who respond differ from those who do not beyond the demographic and geographic characteristics we examine.

polls conducted by Pew between 1997 and 2016. Possibly reflecting increased antagonism towards polls from Republican elites following the election of President Trump, in 2018, a comparison of RDD and RBS samples by Kennedy et. al. (2018) concludes: "registration-based poll tilted slightly less politically conservative than the random-digit-dial poll [which] raises the possibility that the RBS poll suffered from differential partisan nonresponse, with the Republicans called in the RBS poll being less likely to participate than Democrats."[2]

Others have also shown that partisans' willingness to participate in surveys can vary depending on campaign events and media coverage. Examining the daily cooperation of partisans throughout the 2012 election, Gelman et. al. (2016) show that partisans are less likely to participate when media coverage is negative towards their candidates. In a follow-up study focusing on the 2016 election, Rivers and Lauderdale (2016) note "the willingness of Clinton and Trump supporters to participate in our polls varied by a significant amount depending upon what was happening at the time of the poll: when things are going badly for a candidate, their supporters tend to stop participating in polls." If respondents in 2012 and 2016 were less likely to participate in surveys when their candidate was being criticized, it seems reasonable to question whether the conditions in the 2020 election were especially ripe for differential partisan response given the politicization of the media and the polls by President Trump and his supporters.

Research thus far has found mixed evidence of the degree to which differential partisan response affected the polls in 2020. Several reports looking at traditional sampling have indeed found that one component of the substantial over-estimate in Biden's support in the pre-election polls was an under-sampling of Republicans/conservatives and an over-sampling of Democrats/liberals (Von Hagen-Jamar et al. 2021; Keeter et al. 2021; McAullife et al. 2021; Yan and Barlas 2021). At the same time, Cohn (2020) found that respondents who had voted in Republican primaries were *more* likely to participate in polls, though the difference

[2] Republicans contacted via RDD may be more willing to participate than those contacted via RBS if registered Republicans have a stronger commitment to partisan messaging about "fake polls" and "fake news" than unregistered (and therefore less engaged) Republicans.

disappeared after controlling for demographics. Consistent with this, the analysis of Yan and Barlas (2021) found that Republicans were no more likely to drop out of their panel study than Democrats, nor were they more likely to switch their party affiliation.

2 Data & Research Design

To examine the extent to which differential partisan response may have affected the accuracy of pre-election polls in the 2020 election we examine the registration based samples used by Edison Research to conduct the telephone component of the National Exit Poll in: Alabama, Arizona, Colorado, Florida, Iowa, Michigan, Minnesota, North Carolina, Nevada, Pennsylvania, Texas, and Wisconsin. Samples in these states were drawn from registered voters, and the surveys were administered at similar times using similar procedures and questionnaires.[3] Moreover, seven of these polls were intended to be fully representative of the state's electorate. (The other 4 polls focused on early voters and were intended to be used in conjunction with in-person exit polls). Nearly 1-million phone calls were made in these 12 states to yield just under 14,000 completed survey responses.

Because the voter files used to select the numbers to be called contain individual-level and geographic-level information on every attempted contact, we can use that information to estimate the probability of cooperation – that is, the probability an individual completed the survey conditional on being successfully contacted.[4] In particular, for each sampled voter file record i we estimate:

$$Pr_i(Cooperation) = \alpha_s + \beta_R R_i + \beta_I I_i + \beta X_i + \gamma G_i + \epsilon_i \quad (1)$$

where R_i and I_i are indicators for whether the voter in record i is identified as being a

[3] Like many survey research firms, the state-level exit polls looked to increase the efficiency of its outreach effort by deliberately sampling likely voters based on their voting history. As such, the sample of those called is not a random sample of individuals in the voter file. However, because all individuals in the analysis below were reached via the same sampling frame, the differences in cooperation rates by party are instructive.

[4] Appendix C reports the results of predicting the probability of contact using the same specification.

State	Total	Contacted	Refused	Completed	Cooperation	Party Source	Final Poll
AL	20975	4415	3887	528	12.0%	Imputed	No
AZ	103987	5597	4010	1587	28.4%	Registration	Yes
CO	88237	9230	7633	1597	17.3%	Registration	Yes
FL	130846	6473	5257	1216	18.8%	Registration	No
IA	71927	11538	10535	1003	8.7%	Registration	Yes
MI	159829	12326	11094	1232	10.0%	Imputed	Yes
MN	52395	4521	3516	1005	22.2%	Imputed	Yes
NC	32772	2116	1330	786	37.1%	Registration	No
NV	59938	3651	2737	914	25.0%	Registration	No
PA	98548	21736	19931	1805	8.3%	Registration	Yes
TX	86454	5179	4246	933	18.0%	Imputed	No
WI	86484	4559	3155	1404	30.8%	Imputed	Yes

Table 1: *Total Calls* is the total number of calls from the voter file sample, *Contacted* are the number of respondents that were successfully contacted, *Refused* are number of Hard Refusals, Soft Refusals, and Break-offs, *Completed* are the number of completed interviews, *Cooperation* is the cooperation rate among those contacted, *Party Source* is whether partisanship is based on voter registration data or imputation, and *Final Poll* is whether we are able to use the poll in Section 3 to examine the effect of a non-response adjustment. Appendix A summarizes the disposition codes in more detail.

"likely" Republican or independent/other respectively, X_i is a vector of demographic indicators denoting the age, gender, and race (sometimes imputed) of the respondent according to the voter file, and G_i is a vector of characteristics based on the voter's address: whether their zip-code is Urban/Rural/Suburban, the percentage of the county-level vote President Trump received in 2020, and the incidence of COVID-19 in the respondent's county as of Election Day. The covariates we control for in specification (1) are useful for isolating the effect of partisanship above and beyond other aspects that may affect the probability of cooperation (e.g. Keeter 2006; Yeager et a. 2011). State fixed effects (α_s) are used to control for any unmeasured between-state differences in culture, politics, or demographics that may affect response rates when estimating an overall average affect by pooling the state samples.

As Table 1 reveals, the measure of partisanship available in the voter file varies by state. State-sourced party registration information is available in Arizona, Colorado, Florida, Iowa, North Carolina, Nevada and Pennsylvania, but imputed measures are required in Alabama, Michigan, Minnesota, Texas, and Wisconsin. Partisanship is imputed based on previous participation in party primaries, or, lacking this information, an estimate based on the surrounding precinct and voter demographics. Prior investigations have show the imputation to be fairly accurate (e.g., Igielnik et. al. 2018) – see also Table 5 in Appendix G – and replicating our analyses for states with and without party registration data results in substantively similar results. (Although we identify some notable exceptions below).

3 Characterizing Differential Cooperation

The first question of interest is: how much does survey cooperation vary between partisans after controlling for demographic and geographic differences? To summarize the overall effect across all states, Figure 1 plots the estimated coefficients (and 95% confidence intervals) from specification (1) using state fixed effects to control for unmeasured between-state differences. The statistically significant negative coefficients for both *Likely Republicans* (-0.032) and *Independents* (-0.058) indicate that these individuals are significantly less likely to cooperate relative to *Likely Democrats* (the omitted category) by 3.2 percentage points and 5.8 percentage points respectively. Because these differences are being estimated conditional on all other included covariates, the partisan differences we identify are above and beyond any differences related to the age, gender, race, and rural/urban/suburban location of the contacted individuals.

Consistent with past results, Hispanic, Black, and those individuals who are coded as having a race/ethnicity as "Other" are less likely to cooperate compared to White individuals, and older individuals are also generally more likely to cooperate. Conditional on the individual level controls, there are no differences in cooperation based on whether contacted voters are thought to live in rural, urban, or suburban zip-codes. The percentage of the county voting for President Trump in 2020 also has no effect on individuals' cooperation, but individuals living in a county with a larger (logged) number of total COVID-19 cases

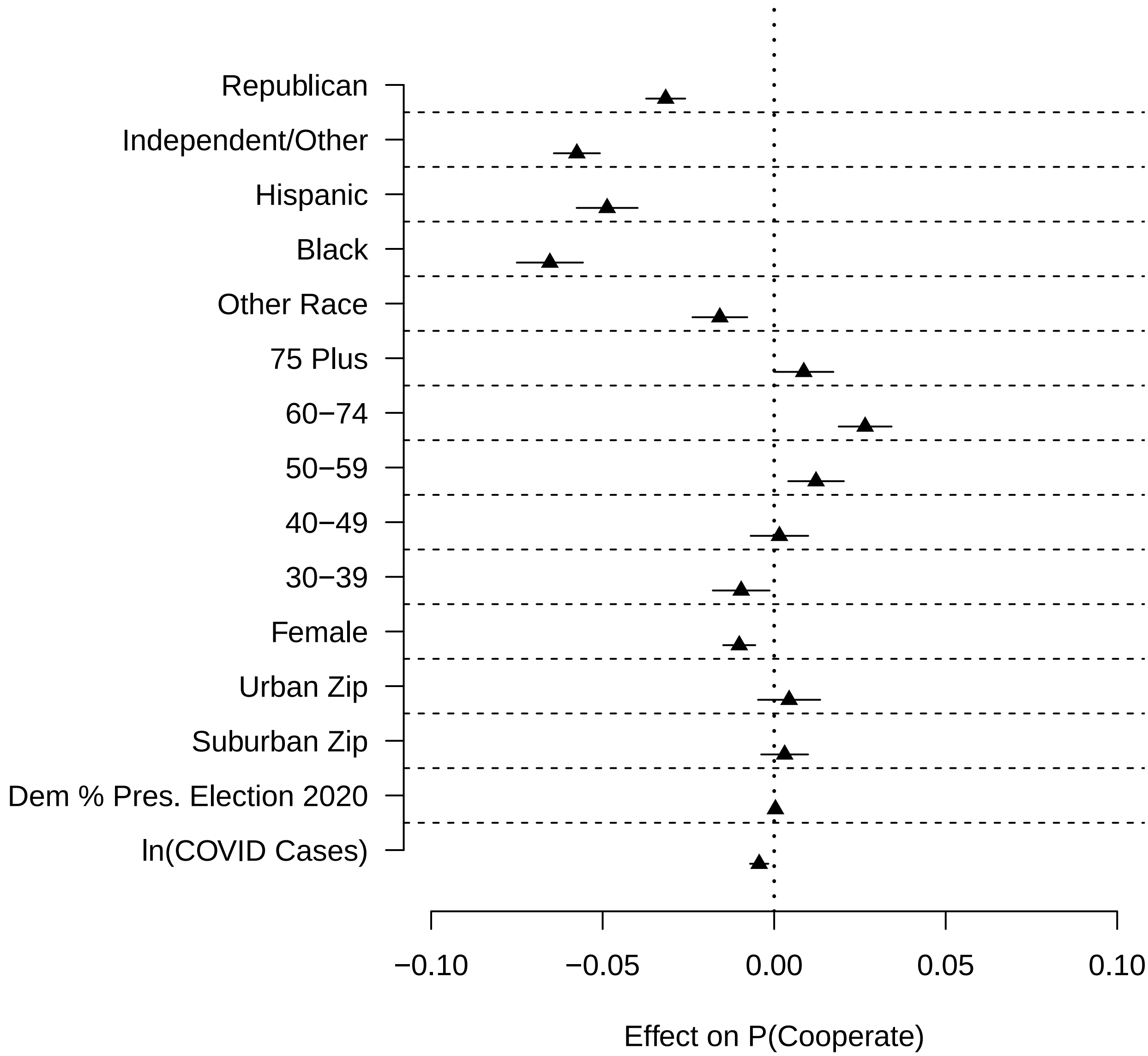

Figure 1: **Estimated Marginal Effect on Pr(Cooperate)**: Coefficients are from estimating specification (1) via Ordinary Least Squares regression with state fixed effects using the pooled sampling frame across states. Error bars represent 95% Confidence Intervals from standard errors clustered at the state level. Full results are in Appendix B.

as of election Day are slightly less likely to cooperate. (Appendix J considers the impact of COVID-19 in more detail.)

To allow the effects of differential partisan response to vary by state, Figure 2 decomposes the overall differences in Figure 1 by state and plots the estimated differences in partisan cooperation probabilities (with 95% confidence intervals) relative to Democrats. Because Figure 2 plots the results from separately estimating specification (1) for each state, the effect of every included covariate is allowed to vary between states. In Alabama, for example, likely Republicans were 6% less likely to cooperate than likely Democrats, and likely Independents were nearly 12% less likely. In Wisconsin, likely Republicans were 8% less likely and likely independents were 10.5% less likely to cooperate than Democrats.

Figure 2 reveals that Republicans are less likely to cooperate than Democrats in every state except for Texas. Moreover, not only are the differences statistically distinguishable in Alabama, Arizona, Colorado Florida, Iowa, Michigan, Nevada, Pennsylvania, and Wisconsin (only in Minnesota and North Carolina are the differences statistically indistinguishable from zero), but the substantive magnitudes of the partisan effects are often sizable.[5]

Among independents, the lack of cooperation relative to Democrats is both larger and harder to interpret than the difference between Republicans and Democrats given the ambiguity of what it means to be classified as an independent according to the voter file (Keith et al. 1986; Klar & Krupnikov 2016). Consider, for example, the case of North Carolina where independents were 14% less likely than Democrats to cooperate. Does the higher refusal rate among independents reflect the fact that independents are less politically engaged than registered partisans on average and therefore less willing to participate in a political survey? Or, does this reflect an extreme lack of cooperation among independent-leaning supporters of President Trump? It is difficult, if not impossible, to determine why the differences we

[5]One theory of systematic non-response was that Democrats in areas where the COVID-19 crisis was particularly severe may be more likely to be available due to more stringent adherence to stay-at-home orders. Figure 2 and Figure 5 in the Appendix do not suggest much difference in the magnitude of effects from state to state. We test this more formally in Appendix J by interacting party with local incidence of COVID-19 and find no significant differences of partisan effects when COVID is more or less severe in a respondent's county.

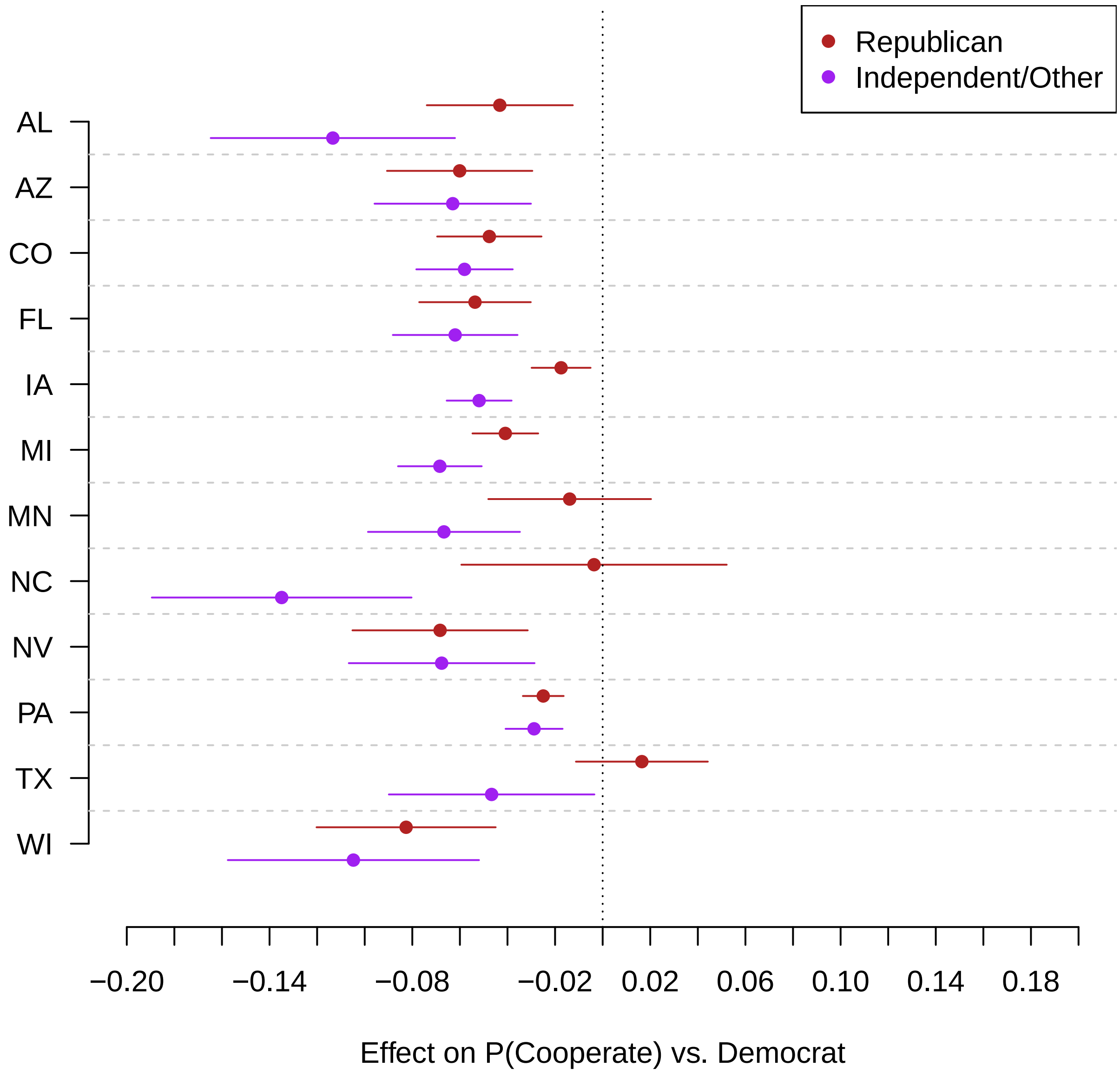

Figure 2: **Difference in Cooperation Relative to Democrats by State**: Coefficients are a result of applying specification (1) via OLS separately to each state's voter file sample. Bars represent 95% confidence intervals. Full results are reported in Appendix H.

detect might exist given the available data.

While the differences we document in Figure 2 are suggestive, it remains to be seen whether these partisan differences in cooperation affect the accuracy of the surveys after using conventional post-stratification weights based on age, gender, education, race, and geographic stratum. If, for example, the likelihood of voting affects the probability of survey cooperation – or else a common feature affects both – then the differences in Figure 2 may simply reflect partisan-related differences in the likelihood of voting. But if Republicans and independents who ultimately vote are less likely to cooperate with survey interviewers than Democratic voters all else being equal, than the sample of completed interviews may contain too few Republicans and independents relative to Democrats. If so, the overall results would be biased towards the opinions of Democrats and away from the opinions of Republicans and independents.

4 Correcting for Differential Partisan Response

To quantify how the partisan differences in survey cooperation graphed in Figure 1 affect survey accuracy we compare the margin of victory in the certified election results to the estimated margin of victory in the post-stratified polls with and without accounting for the partisan differences in cooperation rates.

To do so we measure the partisan cooperate rates p_i using the fraction of partisans who complete the survey relative to the number who complete or refuse the survey (i.e., we separately calculate the cooperation rate reported in Table 1 for Democrats, Republicans, and independents in each state).[6]

In each state we multiply the inverse of these partisan cooperation rates (i.e., $\frac{1}{p_i}$) by the original post-stratification weights w_i based on age, race, sex, education, and geographic

[6]Appendix F replicates the results using the inverse of the predicted probability that results from using the results of estimating specification (1) rather than just the partisan cooperation rates. So doing allows demographics to affect both the cooperation weight and the post-stratification weight, but the results are largely unchanged.

stratum to produce the compound weight $\frac{w_i}{p_i}$. (A related approach would simply include the partisan distribution of contacted voters as a weighting parameter when constructing the original differential response weight w_i, but we calculate the partisan cooperation rates separately from the post-stratification weights to compare the effect of the adjustment relative to the using the original post-stratification weights for the purposes of exposition.)[7]

Unlike other methods that weight based on partisanship, our correction based on the cooperation rates of partisans doesn't require us to specify the distribution of partisanship in the electorate in advance. Instead, it uses the distribution of partisanship in the sampling frame to equalize the cooperation rate of of contacted partisan respondents. Our approach is similar to work leveraging low-propensity respondents to estimate the opinions of those who do note respond (Bailey 2018, Peress 2010), or using Multilevel Regression with Post-Stratification to convert unrepresentative survey estimates to be representative of the broader voting public (Ghitza & Gelman 2020; Wang et al. 2015). Our approach differs, however, in that we use information on actual non-responders (i.e. likely partisanship) to estimate how their response would have affected the overall poll results.

To quantify the nature and impact of differential partisan response we focus on the 7 state telephone polls of: Arizona, Colorado, Iowa, Michigan, Minnesota, Pennsylvania, and Michigan. The remaining 4 states have a high level of early in-person voting (FL, NC, NV, TX) and the phone poll was consequently designed to be combined with in-person early and Election Day exit polls. Although Alabama also had a stand-alone telephone poll design, there were only 11 independents in the sample – far too few to trust the adjustment we examine.

Following prior assessments of polling error (e.g., Kennedy et. al. 2018), the outcome of

[7]Using the product of the original post-stratification weights w_i and the inverse of the partisan cooperation rates p_i as we do in the text equalizes the importance of each adjustment. Including the partisan cooperation rate as a weighting parameter in the post-stratification results in the cooperation adjustment being equally important with every other demographic adjustment (e.g., distribution of partisanship is as important as the distribution of age). While it does not matter for the results, weighting partisan cooperation on par with demographic-based post-stratification weights as we do in the text is defensible given the importance of partisanship relative to other demographics for the outcomes of interest.

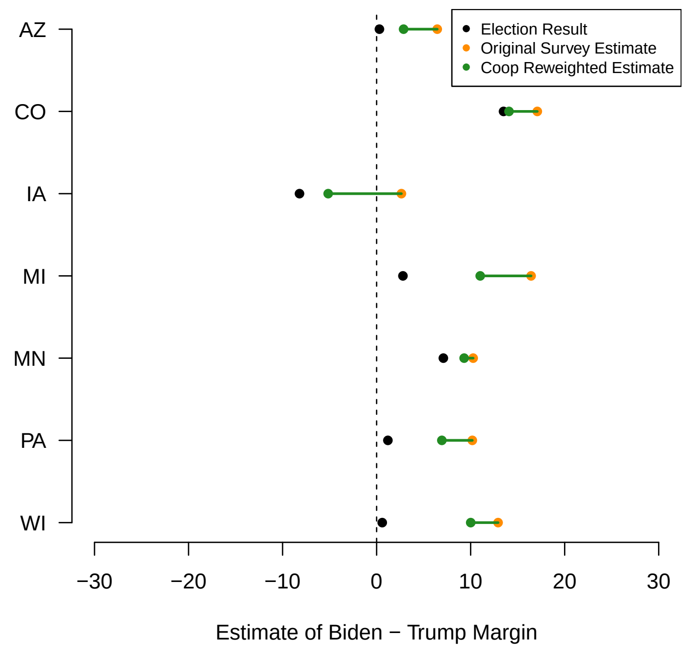

Figure 3: Effect of Equalizing Partisan Cooperation Rates. For each state we denote the final certified margin (black), the Biden-Trump marginal using the original post-stratification weights (orange), and the product of the cooperation-adjustment and the original post-stratification weights (green).

primary interest is how the estimated margin of victory in each poll compares to the margin in the certified vote. Figure 3 presents the results of these comparisons: black dots indicate the Biden-Trump certified vote margin in each state, orange dots denote the estimated Biden-Trump margin using demographic-based post-stratification weights, and green dots indicate the estimated margin after adjusting the same post-stratification weights with the cooperation-adjustment noted above.

As the results make clear, the accuracy in all 7 states was improved by the cooperation adjustment we employ. The overall average improvement in survey accuracy – measured using the signed error (and weighted by sample size) – was approximately 4 points. The largest improvements were in Iowa (a 7.8 point improvement) and Michigan (a 5.4 point improvement). In Colorado, the 3 point adjustment produces a survey estimate which closely matches the final margin.

While encouraging, it is important to highlight that there is heterogeneity in the degree to which errors remain after the adjustment – especially in the key battleground states of Michigan, Pennsylvania, and Wisconsin. To help understand this heterogeneity, Figure 4 investigates the relationship between likely partisanship, self-reported partisanship, and self-reported vote choice for the survey respondents in the 7 states for which we make a differential partisan response adjustment (Appendix G displays the full joint probability distribution for these variables).

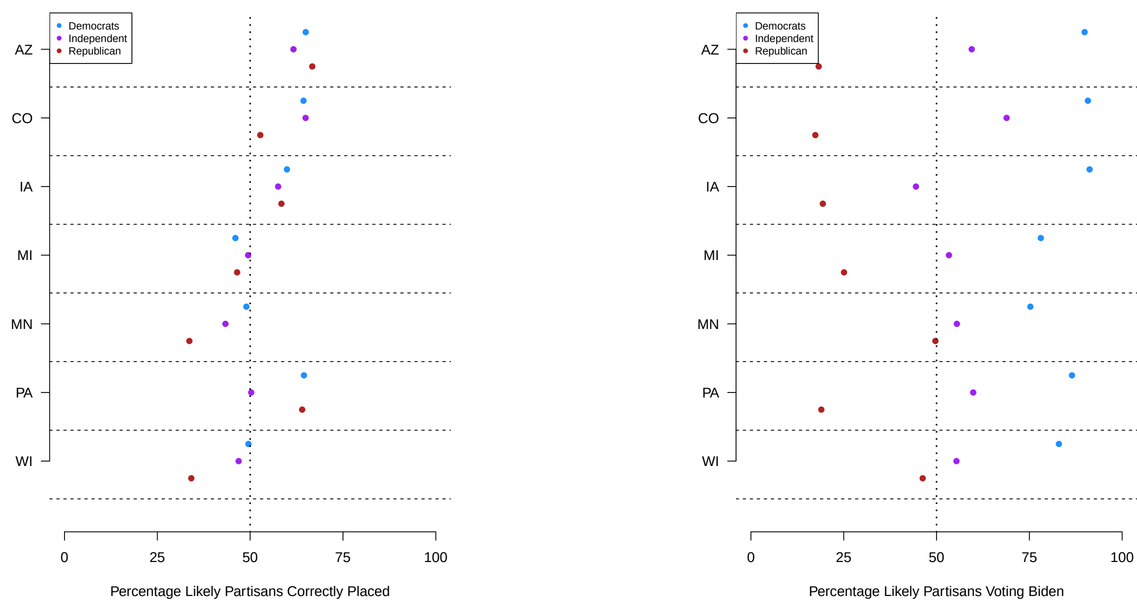

Figure 4: Relationship between Voter File Partisanship and Self-Reported Partisanship (Left) and Vote Choice (Right) by State. Among survey respondents, the left figure plots the percentage of respondents whose voter file partisanship matches their self-reported partisanship and the right figure plots the percentage who report voting for Biden among each voter file partisan group.

In Arizona, Colorado, and Iowa, not only does the cooperation adjustment reduce, if not nearly eliminate, the amount of survey error, but it is also the case that the voter file measures of partisanship predict self-reported partisanship and self-reported vote-choice quite well. Using the voter file measures of partisanship to equalize the cooperation rates of partisans in these states is consequently very effective.

In Wisconsin, however, a different conclusion seems likely. Figure 3 reveals that there is nearly a 10 percentage point error on the margin even after the differential partisan response adjustment and Figure 4 reveals that the voter file measures of partisanship are only weakly related to self-reported partisanship and vote-choice. In fact, less than half of those imputed to be of a certain partisanship in Wisconsin self-identify with the imputed partisanship and only a third of those that were thought to be Republicans in the voter file self-identified as Republicans when interviewed. Moreover, nearly 50% of those who are thought to be Republican in the voter file report voting for President Biden – far higher than the support among likely Republicans in other states. Somewhat similar patterns occur in Minnesota and Michigan.

There are two possibilities for the weak correlations that in Figure 4 which drive the under-corrections in Figure 3. These low correlations could result from: 1) error in the measurement of likely partisanship in the voter file; or 2) systematic non-responsiveness *within* partisan groups.

First, it may be that "likely" (and especially imputed) partisanship may be a worse measure of self-reported partisanship in certain states. The ability to account for differential response using voter file information obviously depends on the measure of partisanship being sufficiently accurate. The lower the correlation between actual partisanship and the voter file measure of partisanship, the less effective the adjustment will be. To take an extreme example, if the voter file measure is independent of voters' partisanship then any adjustments that are made based on that measure will simply add random noise to post-stratification weights. The fact that there is a positive relationship between self-reported partisanship and the measure of partisanship in the voter file means that although the measurement error may limit the effectiveness of the adjustment, the adjustment will sill have an effect. Only if the voter file measures were *negatively* related to partisanship – i.e., imputed Democrats are actually Republicans and imputed Republicans are actually Democrats – would larger errors result from using the voter file measure. Weak correlations seem much more plausible than negative correlations. Further, it would be unlikely we would find the differences we found in Section 3 if measurement error was purely random.

A second, more potentially concerning, problem is the possibility of differential partisan response *within* parties. Correcting for differential partisan response by equalizing the cooperation rates *between* partisan respondents assumes that respondents and non-respondents *within* partisan groupings have similar views. But if those that answer differ from those that do not then the correction will fail. In Wisconsin, likely Republicans according to the voter file were less likely to cooperate with the survey, less likely to self-identify with the Republican party, and nearly 50% reported having voted for Biden. In the absence of measurement error in the voter file partisanship measure, it would seem likely that the likely Republicans who cooperated with the poll must differ from those who did not. In particular, likely Republicans who cooperated were more independent and more supportive of Biden relative to the likely Republicans who refused to cooperate (given the ultimately close race in that state).[8]

Unlike the effects of measurement error in the voter file partisanship measures, within-party differences of opinion that are correlated with survey cooperation would not only make the differential partisan response adjustment less effective, but it may even make it worse. To take an extreme example, if the independents who respond all support President Biden and the independents who refuse all support President Trump then increasing the weight being given to the included independents will make the survey results less accurate by moving the survey estimates further away from the truth.

Altogether, the effects of the partisan cooperation adjustment we employ graphed in Figure 3 suggests that differential partisan response is only partially corrected by re-weighting

[8]We focus here on the possibility that Republicans (and Independents) who choose not to cooperate may be different than those that do, resulting in still-large errors when weighting those groups higher to account for the lower cooperation rate. It is worth noting that another potential source of within-party differences is the sampling frame itself. Like many survey firms, the National Exit Poll deliberately over-samples likely voters based on their voting history. If this sampling frame omits, for example, new enthusiastic Trump voters at the expense of traditional Trump-wary Republicans, this would also lead to within-party missingness.

polls to equalize partisans' cooperation rates. The fact that every poll becomes more accurate after applying the cooperation adjustment suggests that the differential response *between* parties likely resulted in too few Republicans (and Republican-supporting independents) being included relative to Democrats. However, the fact that sizable errors sometimes remain suggests that the average opinion of the likely Republicans and independents who responded did not match the average opinions of those who did not – particularly in the swing states of Michigan, Wisconsin and Pennsylvania – either due to measurement error or within-party non-response. If polls reach a biased group of Republicans (or Democrats, or independents) no amount of weighting will return an accurate estimate of the final election result.

5 Conclusion and Implications

There are many potential sources of survey error in a pre-election survey – e.g., assuming the wrong electoral composition when constructing post-stratification weights or incorrectly identifying likely voters – but an increased willingness of Democrats to cooperate with pre-election polls relative to Republicans and independents suggests a troubling additional issue that could affect the accuracy of pre-election polls. It is also a possibility that has taken on new importance given the emergence of partisan-based attacks on polling and the fact that the 2020 pre-election polls did not accurately estimate the support that Republicans received.

We demonstrate that differential partisan response exists in the 12 pre-election telephone polls conducted for the National Election Pool by Edison Research. In the 12 states, the average Republican was 3.2 percentage points less likely to cooperate than the average Democrat, and the average independent was 5.8 percentage points less likely to participate even after taking into account a wide range of demographics. To be clear, we are only able to reveal here the relative cooperation rates among partisans. As such, it is impossible to conclude whether the differences we find here are due to Republican hesitancy to take polls, Democratic enthusiasm to take polls, or some combination of the two.

Regardless of the source, these differences have real consequences for using those polls to predict the final certified margin in the 7 states for which the telephone polls were intended to be representative of the statewide electorate. Although post-stratification is widely used to correct for non-response related to known demographic characteristics (e.g., gender, age, race, and education), accounting for differential partisan response likely requires an additional correction because partisanship is only weakly correlated with the variables being currently used in post-stratification weighting. As Gelman et. al. (2016) note: "Demographic post-stratification, similar to that used in most academic and media polls, is inadequate, but the addition of attitudinal variables (party identification, ideological self-placement, and past vote) appears to make selection ignorable in our data."

Suggesting that at least some of this error is due to too few Republicans and Republican-supporting independents, applying the cooperation adjustment decreases the overall average error by 4 percentage points across the seven states we examine. The fact that large errors sometimes remain even after the correction – nearly 10 percentage points in the critical swing states of Michigan and Wisconsin and nearly 5 percentage points in Pennsylvania – suggests either that the partisans who are responding in these states may have different opinions than those who are not or else that the measures of partisanship being used from the voter file to adjust for non-responses are not up to the task.

Moreover, although the adjustment we use always improves the performance of the surveys we examine, this need not be the case. Because the adjustment relies on the assumption that the partisans who respond share the opinions of those that do not, if the opinions of respondents differ from non-respondents – as would be the case if a candidate's supporters are less likely to respond to a poll conditional on partisanship – then increasing the weight being given to the partisans that do respond may not improve survey accuracy and it may even make it worse.

Our studies focuses only on the state-level telephone exit polls conducted by the National

Election Pool, but there is no reason to suspect that the issues we identify are limited to those polls given the standard polling practices that were used and the fact that the performance of the telephone portion of the National Exit Polls we examine were not terribly dissimilar to the performance of the other pre-election polls being conducted at the time. It seems likely that the issues we identify likely impacted other pre-election polls in 2020 – perhaps partially explaining why the polls systematically underpredicted Republican support.

What is less clear is whether the problems we identify will generalize beyond 2020. If the impact was due to the prominent cues "anti-polling" cues provided by President Trump then perhaps future elections will be less impacted. Or perhaps the issue was due to newly mobilized voters who were voting to support President Trump specifically and who might not vote if he was not on the ballot – if so, the problems we note may be less severe in less-salient elections (e.g., midterm elections) when President Trump is not on the ballot. While it is too early to know for certain, it does seem possible that the increased politicization that many have noted may be starting to have non-trivial consequences of polling. If participating in a public opinion poll is seen as a political act as is being suggested by many partisan elites, then we may worry about whether the views of those who respond can reflect the views of those who do not and what might be done by pollsters in response.

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Appendix

A Full List of Disposition Codes

The following table displays the disposition codes that we received from the data vendor in each state and records how we coded those into 4 categories: (1) Completed survey (2) Refused Survey (3) Not contacted (4) Disqualified.

When the data vendor is unable to get the individual from the voter file on the phone, this is coded as (3) Not Contacted. This could because, for example, the vendor got an answering machine, the phone was disconnected, the individual is on a Do Not Call list, or the individual was not home.

If the data vendor is able to get the specified individual on the phone, the individual can be coded either (1), (2), or (4). Individuals with code (1) are those that completed the survey. Individuals with code (2) are those that did not complete the survey through their own choice: for example if they break off, continually ask to be called back (but never complete the survey), or hung-up. Individuals with code (4) are those that did not complete the survey, but not through their own choices: for example if there was a language barrier, if the individual was not registered to vote, or if they failed several screening questions for likely voters.

State	Code	Text
AL	1	Complete
AL	2	Break-Off, Callback, Hung up during introduction, Partial Interview - Callback, Refusal, Refused who will vote for
AL	3	Answering Machine, Blocked Call Privacy Manager, Busy, Disconnected/Non-Working, Do not call list, Don not call list, Fax/Computer Tone, No adult at number, No Answer, Non-Residential
AL	4	Language Barrier, Non registered to vote, Not likely to vote in Presidential Election, Undecided, Will not vote on election day, ZIP Code out of area
AZ	1	Complete
AZ	2	Callback, Hard Refusal, Interviewer Terminate, Monitoring Refusal, Put On Do Not Call List, Respondent Terminate, Soft Refusal, Suspend
AZ	3	Business / Non-Residence, Busy Signal, Dead Air, Fax/Data Line, No Answer, Non-Working/Disconnected, Not Available, Privacy Manager / Tech Barrier, Technical Phone Problems, Telephone Answering Device
AZ	4	Dropped Call, Language Barrier, QS1:Term, QS3:Term, QS4:Term, QZ1:Term, Term logic before QC1
CO	1	Completed
CO	2	Answered and dropped, Cell Phone Complaint, Initial Refusal, Mid-Interview Terminate, Schedule Callback
CO	3	Answering machine, Blocked Call / Privacy Manager, Business / Government, Child's phone line, Disconnected, Fax / Modem, In Do Not Call List, No answer, No ring, Phone Busy, Respondent not available
CO	4	Language Problems, Not 18+, Over Quota, S1: Not registered in CO, S3: Unlikely to vote, S4: Voting preference, V_series: No candidates favored, Z1: Zip out of area

FL	1	Complete
FL	2	Callback, Refusal
FL	3	Answering machine, Business, Busy, Disconnect/Not in Service, Do Not Call List, Fax or modem, No answer
FL	4	DQS1, DQS3, DQS4, DQVP, DQZ1, Language Barrier
IA	1	Completed Survey
IA	2	Declined To Take Survey, Do Not Call Again, Early Hangup, Partially Completed Survey, Survey Terminated
IA	3	Answering machine, Busy, No Answer, Tri-tone/No longer in service, Wrong Number
IA	4	Language Barrier
MI	1	Complete
MI	2	Break-Off, Callback, Hung up during introduction, Partial Interview - Callback, Refusal, Refused who will vote for
MI	3	Answering Machine, Blocked Call Privacy Manager, Busy, Disconnected/Non-Working, Do not call list, Fax/Computer Tone, No Answer, Others
MI	4	Language Barrier, No adult at number, Non registered to vote, Non-Residential, Not likely to vote in Presidential Election, Undecided, Will not vote on election day, Will/Did not vote for President, ZIP Code out of area
MN	1	(001) Complete
MN	2	(015) Respondent Hard Refusal or 2x Soft RF, (104) Callback (Specified), (105) Callback (Unspecified), (189) Soft Refusal (Bucket 9)
MN	3	(005) Non Working, (006) Business, (009) Fax, (014) Number added to DNC List, (060) Spam Blocker (Busy Signal on Cell), (101) No Answer, (103) Busy to No Answer, (107) Answering Machine/VM, (182) Busy2NA, (198) (Special=8) Dialer got 4 No Answers in a Row, (199) (Special=9) Respondent Not Available for Study Duration, (807) Dialer Bad Number (was 77), (809) Dialer Disconnected (was 79), (819) Dialer No Connect, (851) Dialer No Answer (was 101), (853) Dialer Busy To Na (was 103), (854) Dialer Trunk-line Busy (was 104 then 157), (856) Dialer Nuisance Call (was 106), (857) Dialer Answering Machine (was 107), (953) Server Found # In 'DNC' List, don't call (was 96)(stack 330)
MN	4	(003) Language, (010) INTV Coded as Duplicate Number, (017) Over quota - Question Driven, (021) Question TQ (See Statcode in QPX), (022) Question TQ (See Statcode in QPX), (023) Question TQ (See Statcode in QPX), (024) Question TQ (See Statcode in QPX), (025) Question TQ (See Statcode in QPX), (196) (Special=6) Gatekeeper ACP, (951) Server Found Duplicate, don't call (was 91) (stack 316)
NC	1	Complete
NC	2	Callback, Callback - Call to Complete, Not Interested
NC	3	Answering Machine, Busy, DNC, Invalid - Business Residential, Invalid - FaxModem, Invalid - Not In Service, Invalid - Phone Congestion, Invalid Other Phone Issue, No Answer
NC	4	DQ - Did not vote cant vote, DQ - Language Barrier, DQ - Not in North Carolina, DQ - Quota Full
NV	1	Complete

NV 2	Callback, Hard Refusal, Interviewer Terminate, Monitoring Refusal, Put On Do Not Call List, Respondent Terminate, Soft Refusal, Suspend
NV 3	Business / Non-Residence, Busy Signal, Dead Air, Fax/Data Line, Language Barrier, No Answer, Non-Working/Disconnected, Not Available, Privacy Manager / Tech Barrier, Technical Phone Problems, Telephone Answering Device
NV 4	Dropped Call, QS1:Term, QS3:Term, QS4:Term, QZ1:Term, Term logic before QC1
PA 1	Completed Survey
PA 2	Declined To Take Survey, Do Not Call Again, Early Hangup, Partially Completed Survey, Survey Terminated
PA 3	Answering machine, Busy, No Answer, Tri-tone/No longer in service, Wrong Number
PA 4	Language Barrier
TX 1	Complete
TX 2	CB - Not specific time, CB - Specific time, Refusal, Refused - called too many times, Refused - Death in family
TX 3	Answering machine, Business #, Call blocked, Dialer answering machine, Dialer change number, Dialer modem, Dialer no answer, Dialer not in service, Do not call list, Fax/Modem, No answer, Number change
TX 4	LB Not Spanish, LB-Spanish, Term S, Term Zip
WI 1	Complete
WI 2	Callback, Hard Refusal, Interviewer Terminate, Monitoring Refusal, Put On Do Not Call List, Respondent Terminate, Soft Refusal, Suspend
WI 3	Business / Non-Residence, Busy Signal, Dead Air, Fax/Data Line, Language Barrier, No Answer, Non-Working/Disconnected, Not Available, Privacy Manager / Tech Barrier, Technical Phone Problems, Telephone Answering Device
WI 4	before QC1 term, Dropped Call, QS1 not 1, QS3 not 1, QS4 not 1,2,3, QZ1 TERM

B Full Table of Main Results

Table 3 presents the full results predicting both P(Cooperate) and P(Contact) amongst all respondents contacted for the National Exit Poll. The regression is estimated via a Linear Probability Model with fixed effects for states. Standard errors are clustered by state.

Table 3: Full Results predicting P(Cooperation) and P(Contact)

	P(Contact)	P(Cooperate)
	(1)	(2)
ln(COVID Cases)	-0.003^{**}	-0.004^{**}
	(0.001)	(0.002)
Dem % Pres. Election 2020	0.0001	0.0004
	(0.0001)	(0.0002)
Suburban Zip	-0.006^{**}	0.003
	(0.002)	(0.004)
Urban Zip	-0.003	0.004
	(0.002)	(0.006)
Female	-0.003^{***}	-0.010^{***}
	(0.001)	(0.003)
30-39	0.001	-0.010
	(0.001)	(0.006)
40-49	0.0003	0.002
	(0.002)	(0.004)
50-59	0.004^{*}	0.012^{***}
	(0.002)	(0.003)
60-74	0.025^{***}	0.027^{***}
	(0.003)	(0.006)
75 Plus	0.077^{***}	0.009
	(0.012)	(0.009)
Other Race	-0.0005	-0.016^{***}
	(0.001)	(0.005)
Black	0.003	-0.065^{***}
	(0.005)	(0.009)
Hispanic	-0.002	-0.049^{***}
	(0.002)	(0.007)
Independent/Other	-0.005^{***}	-0.058^{***}
	(0.001)	(0.007)
Republican	-0.002	-0.032^{***}
	(0.001)	(0.006)
State F.E.	Yes	Yes
N	864,134	86,108
R^2	0.041	0.055
Adjusted R^2	0.041	0.055
Residual Std. Error	0.293 (df = 864107)	0.347 (df = 86081)

*p < .1; **p < .05; ***p < .01

As is discussed in the main body of the paper, the important coefficients here are for "Independent/Other" and "Republican", which display the change in the probability of being contacted or cooperating versus being a democrat while holding constant the other variables in the model and state fixed effects.

Individuals who are independent or hold a third-party affiliation are around 0.5% less likely to be contacted then Democrats. Republicans, are around 0.2% less likely to be contacted than Democrats, though this coefficient is not reliably different from 0.

Individuals who are independent or hold a third-party affiliation are around 5.8% less likely to cooperate with surveys as compared to Democrats. Republicans are around 3.2% less likely to cooperate with surveys then are Democrats.

C Probability of Contact by Partisanship by State

Figure 5 displays the results of using specification (1) to predict the probability of contact separately for each state. For simplicity, we focus on the coefficients for Republican and independent that measure the difference in the probability of contact relative to Democrats. Although there are sometimes non-zero differences, the magnitude of the effects are far smaller effect than the effects we find when predicting cooperation – suggesting that its' effect is relatively minor. Moreover, the differences in contact rates in the states with the largest remaining errors after applying the correction to equalize cooperation (MI, PA, WI) are not sufficiently large to account for those differences. While there may be some variation in contact rates by party and by state, the magnitude of those differences is minor.

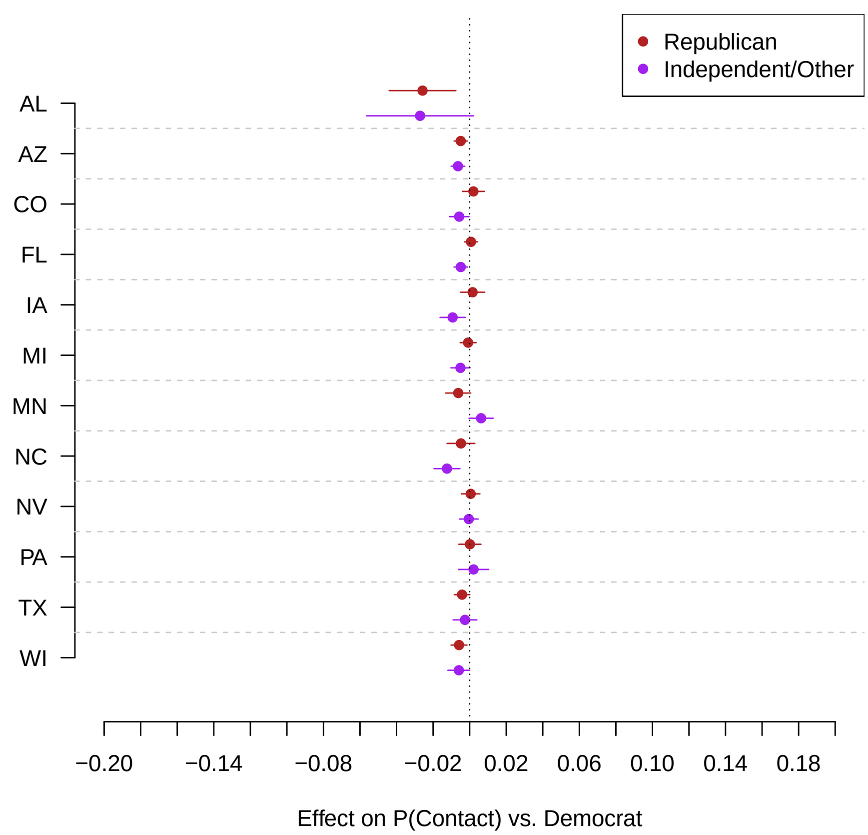

Figure 5: **Difference in Contact Relative to Democrats by State**: Coefficients are a result of applying specification (1) separately to each state's voter file sample.

D Comparison of Registration and Imputation Party States

Table 4 displays the results of specification (1) predicting P(Cooperation) separately in states where voter files display party registration (column 1) and states where voter files display imputed partisanship (column 2).

Table 4: Predicting P(Cooperation) Across Different Voter File Partisanship Types

	P(Cooperate)	
	Party Registration States	Imputed Party States
	(1)	(2)
Independent/Other	-0.054^{***}	-0.073^{***}
	(0.009)	(0.007)
Republican	-0.034^{***}	-0.030^{*}
	(0.007)	(0.013)
ln(COVID Cases)	-0.004^{*}	-0.005
	(0.002)	(0.003)
Dem % Pres. Election 2020	0.0003	0.0004
	(0.0003)	(0.0002)
Suburban Zip	-0.0002	0.011
	(0.003)	(0.011)
Urban Zip	0.001	0.012
	(0.004)	(0.018)
Female	-0.011^{**}	-0.009^{**}
	(0.004)	(0.003)
30-39	-0.005	-0.015
	(0.008)	(0.007)
40-49	0.002	0.002
	(0.007)	(0.007)
50-59	0.010^{**}	0.017^{***}
	(0.004)	(0.003)
60-74	0.022^{**}	0.038^{***}
	(0.007)	(0.007)
75 Plus	0.002	0.024
	(0.012)	(0.013)
Other Race	-0.011^{**}	-0.029^{*}
	(0.003)	(0.012)
Black	-0.057^{***}	-0.079^{***}
	(0.008)	(0.017)
Hispanic	-0.043^{***}	-0.068^{***}
	(0.008)	(0.012)
N	58,000	28,108
R^2	0.059	0.047
Adjusted R^2	0.059	0.047
Residual Std. Error	0.341 (df = 57978)	0.358 (df = 28088)

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

The results for the two partisanship variables indicate that classify respondents based on their imputed and registered partisanship has little effect on the substantive conclusions above. Likely Republicans and independents are less likely to cooperate with a survey regardless of the method of partisan classification. Those who are imputed as independents are slightly more affected (relative to Democrats) than are those who are registered as independents (or a third party), though the difference is marginal.

E Comparison of Original and Cooperation-Adjusted Weights

Figure 6 displays, for the seven states we make weighting corrections, the relationship between the original weights W_i on the x-axis and the cooperation-adjusted weights on the y-axis. The cooperation-adjusted weight for individual i is simply: $\frac{1}{Pr(Coop_i|PID_i)} \times W_i$.

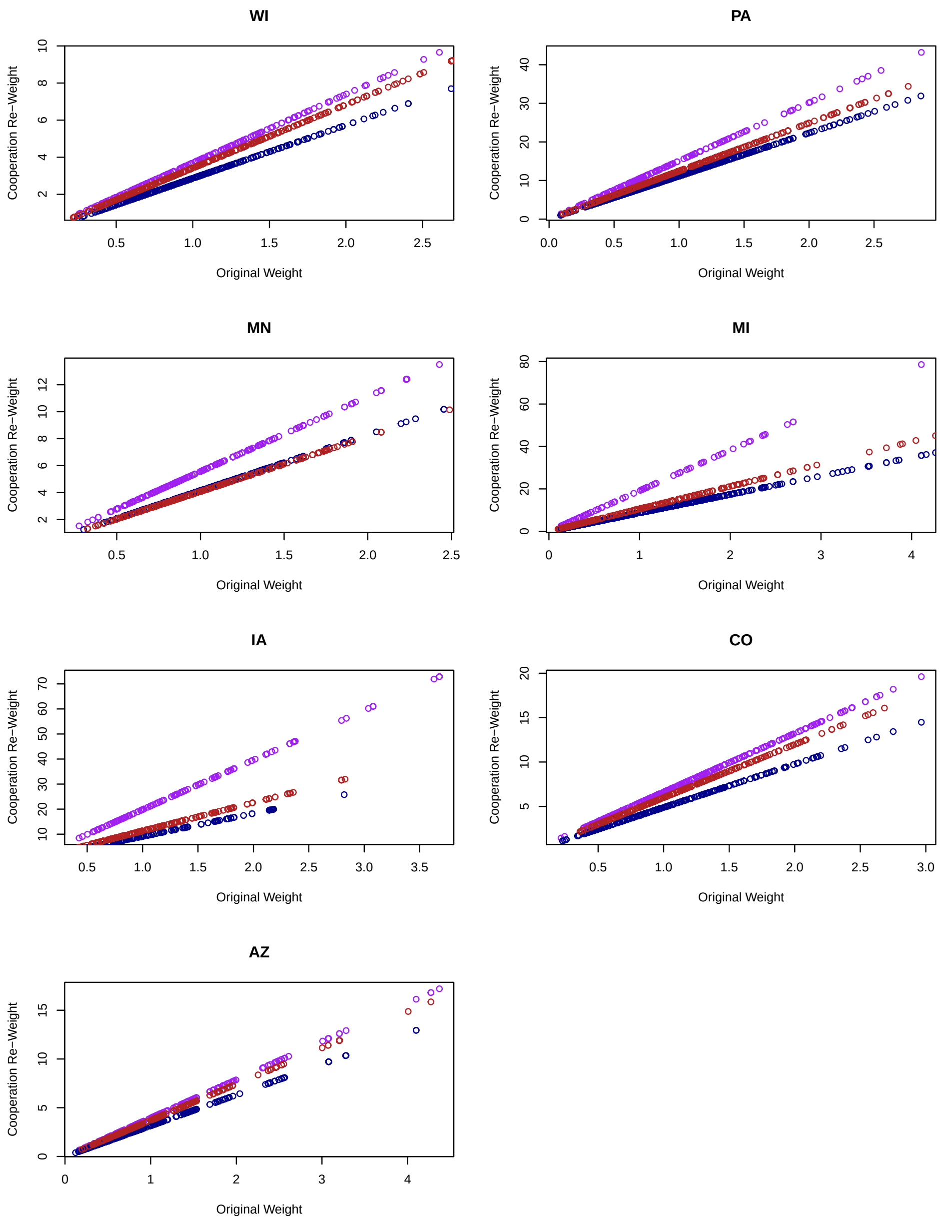

Figure 6: **Comparison of Original and Re-weighting based on Partisanship**

F Cooperation Adjustment with full Demographics

Figure 6 displays, for the seven states we make weighting corrections, the relationship between the original weights (on the x axis) and the cooperation-adjusted weights (on the y axis). The results are substantively identical to the results in the text that are obtained by using only voter file partisanship to adjust for non-response.

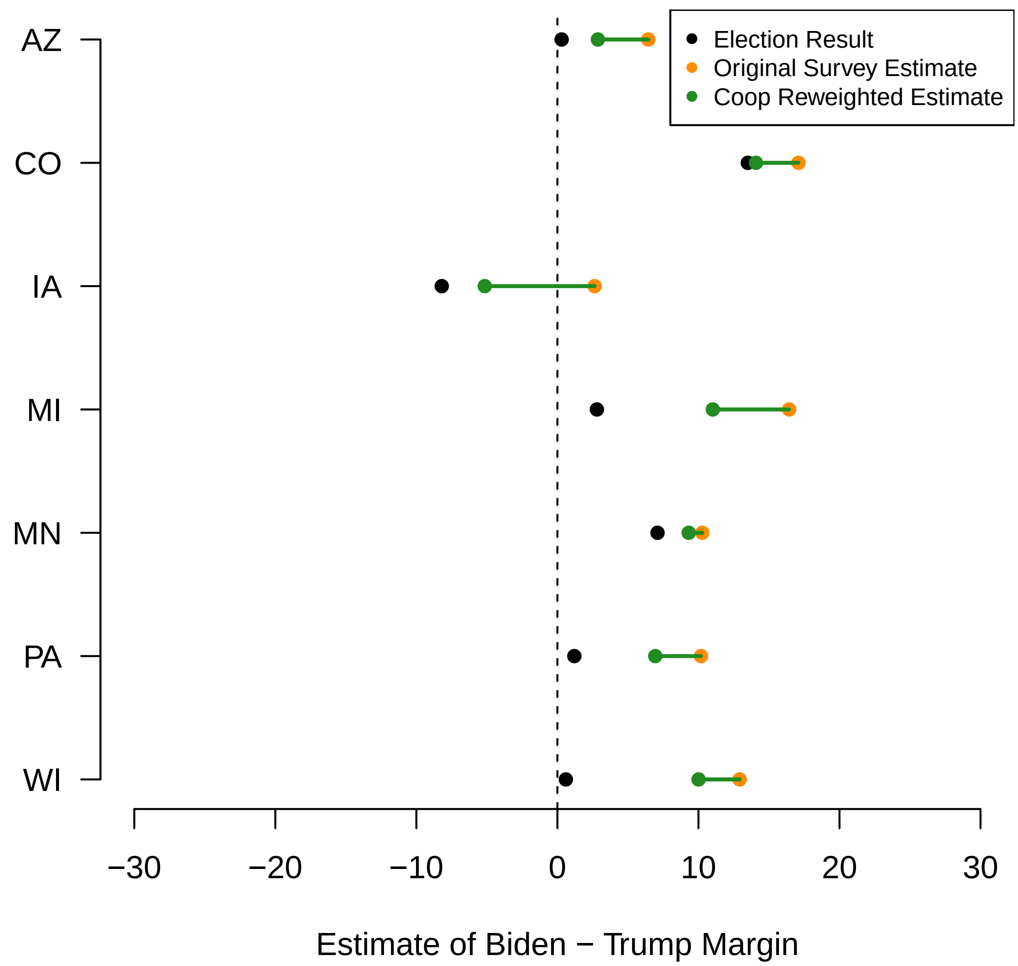

Figure 7: Effects on Polling Estimates Correcting for Partisan Cooperation Rates

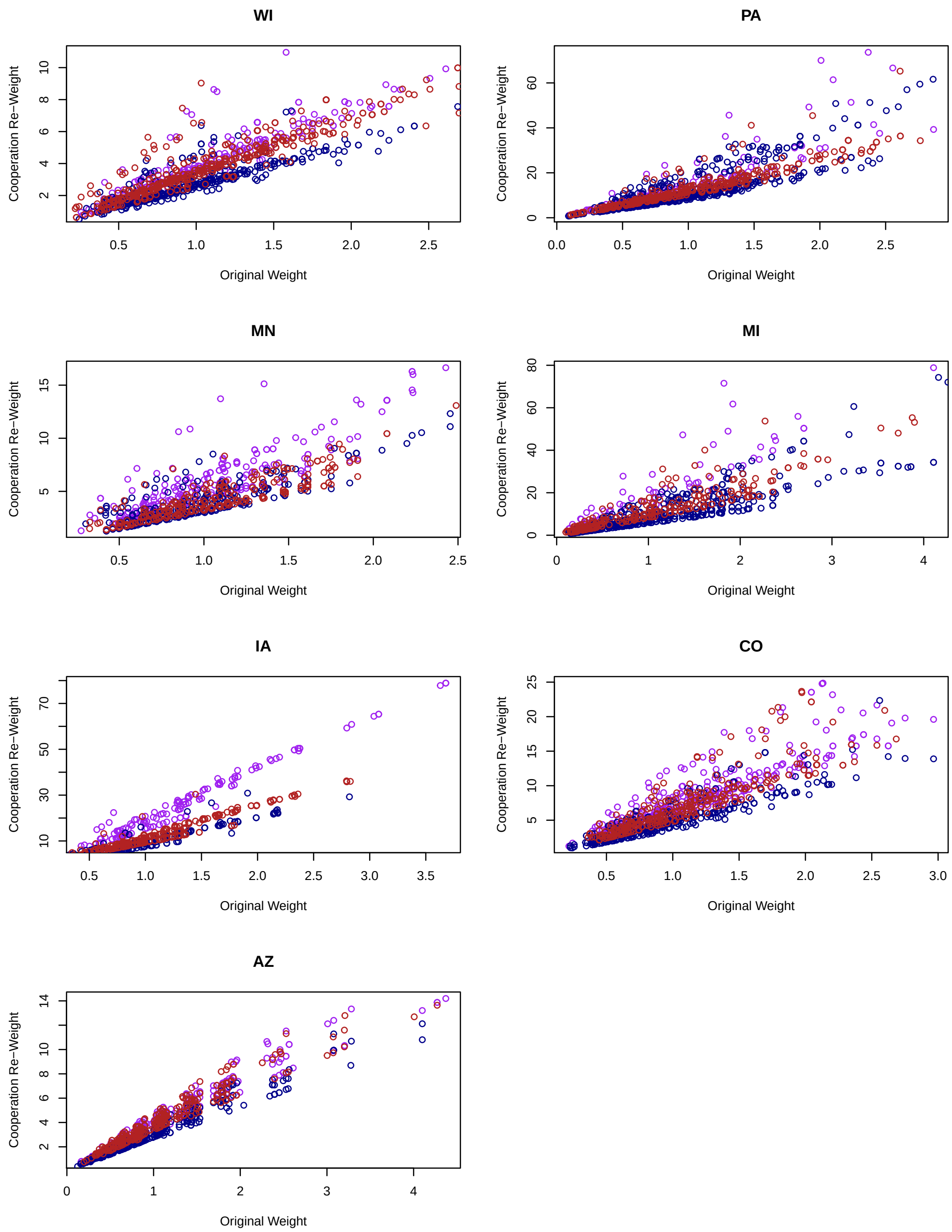

Figure 8: **Comparison of Original and Re-weighting based on Full Demographic Model**

G Relationship Between Likely Party and Partisan Self Identification

Table 5 displays the relationship between respondents' likely partisanship (in the columns) and self reported partisanship (in the rows). Percentages are calculated down the columns, and therefore indicate (for example) the percentage of likely Democrats in the voter file who self report as Democrats, Independents, or Republicans.

There is not a 1:1 matching of likely partisanship and how a respondent self identifies. While the majority of likely Republicans and Democrats self report as being members of those parties, a fair number also identify as independent. While this survey did not ask independent identifiers whether they "leaned" closer to one of the two parties, evidence from previous work suggests that most of these self-identifying independents will lean towards the major party which they are likely to be a member of.

Table 5: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	57.7%	23.7%	11.6%
Ind ID	33.6%	55.8%	35.7%
Rep ID	8.7%	20.5%	52.7%

To confirm this, Table 6 displays the unweighted percentage of each cell that indicates that they will vote for Biden for President. Self-reported independents who are thought to be likely Democrats and Republicans are very different from one another, with over 80% of the former group voting for Biden while only 32% of the latter group does.

Table 6: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	97.56%	94.71%	90.85%
Ind ID	81.02%	61.73%	32.51%
Rep ID	18.85%	13.85%	7.12%

What follows it the joint probability functions for each state for which we make non-response corrections:

Arizona

Table 7: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	64.95%	17.22%	6.76%
Ind ID	29.31%	61.67%	26.51%
Rep ID	5.74%	21.11%	66.73%

Table 8: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	97.65%	100%	86.49%
Ind ID	84.07%	62.12%	25%
Rep ID	27.78%	18.42%	8.43%

Colorado

Table 9: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	64.36%	21.39%	5.03%
Ind ID	29.76%	64.93%	42.23%
Rep ID	5.88%	13.68%	52.74%

Table 10: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	98.65%	95.41%	100%
Ind ID	85.99%	70.39%	24.29%
Rep ID	24.24%	20.29%	4.72%

Iowa

Table 11: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	59.91%	17.81%	8.97%
Ind ID	33.55%	57.53%	32.61%
Rep ID	6.54%	24.66%	58.42%

Table 12: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	97.81%	88%	78.79%
Ind ID	91.84%	45.95%	22.73%
Rep ID	27.59%	11.43%	8.21%

Michigan

Table 13: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	46.03%	28.57%	12.28%
Ind ID	41.11%	49.45%	41.23%
Rep ID	12.86%	21.98%	46.49%

Table 14: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	98.9%	88%	88.1%
Ind ID	74.26%	53.49%	28.12%
Rep ID	15%	10%	5.81%

Minnesota

Table 15: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	49.98%	34.22%	22.92%
Ind ID	37.24%	43.35%	43.45%
Rep ID	13.78%	22.43%	33.63%

Table 16: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	98.44%	94.32%	97.33%
Ind ID	66.41%	51.89%	52.24%
Rep ID	9.8%	6.78%	12.26%

Pennsylvania

Table 17: Likely vs. Reported Partisanship

	Likely Dem	Likely Ind	Likely Rep
Dem ID	64.49%	27.75%	9.73%
Ind ID	27.67%	50.29%	26.25%
Rep ID	7.84%	21.97%	64.01%

Table 18: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	Likely Ind	Likely Rep
Dem ID	95.25%	100%	84.85%
Ind ID	82.45%	58.67%	23.35%
Rep ID	28.17%	13.51%	7.64%

Wisconsin

Table 19: Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	49.53%	25.66%	22.39%
Ind ID	40.34%	46.90%	43.46%
Rep ID	10.13%	27.43%	34.15%

Table 20: Percent Voting for Biden among Likely vs. Reported Partisanship

	Likely Dem	**Likely Ind**	**Likely Rep**
Dem ID	98.09%	89.66%	96.35%
Ind ID	83.09%	63.37%	50%
Rep ID	7.55%	11.48%	8.17%

H State by State Results

Table 21: Predicting Survey Cooperation, by State

	Dependent variable:											
	P(Cooperate)											
	AL	AZ	CO	FL	IA	MI	MN	NC	NV	PA	TX	WI
Independent/Other	−0.113***	−0.063***	−0.058***	−0.062***	−0.052***	−0.068***	−0.067***	−0.135***	−0.068***	−0.029***	−0.047**	−0.105***
	(0.026)	(0.017)	(0.010)	(0.013)	(0.007)	(0.009)	(0.016)	(0.028)	(0.020)	(0.006)	(0.022)	(0.027)
Republican	−0.043***	−0.060***	−0.048***	−0.054***	−0.017***	−0.041***	−0.014	−0.004	−0.068***	−0.025***	0.016	−0.083***
	(0.016)	(0.016)	(0.011)	(0.012)	(0.006)	(0.007)	(0.017)	(0.028)	(0.019)	(0.004)	(0.014)	(0.019)
ln(COVID Cases)	−0.002	−0.001	−0.008*	−0.010	0.003	−0.002	0.008	−0.016	−0.009	−0.002	−0.008	0.001
	(0.006)	(0.006)	(0.005)	(0.007)	(0.004)	(0.003)	(0.009)	(0.013)	(0.011)	(0.003)	(0.006)	(0.010)
Dem % Pres. Election 2020	0.0003	0.001	0.001**	0.001*	0.0005	0.001*	0.0005	0.001	0.001	−0.0003	−0.0003	0.001
	(0.0004)	(0.001)	(0.0003)	(0.001)	(0.0004)	(0.0003)	(0.001)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.001)
Suburban Zip	0.032**	0.015	−0.002	−0.002	0.001	0.00002	−0.044**	−0.027	−0.028	0.0001	0.027	0.004
	(0.014)	(0.023)	(0.015)	(0.015)	(0.008)	(0.008)	(0.022)	(0.029)	(0.032)	(0.005)	(0.018)	(0.021)
Urban Zip	0.041	−0.013	−0.002	0.014	0.005	−0.015	−0.035	0.018	−0.011	0.004	0.048**	−0.006
	(0.025)	(0.027)	(0.017)	(0.018)	(0.011)	(0.012)	(0.029)	(0.041)	(0.034)	(0.008)	(0.021)	(0.036)
Female	−0.005	−0.002	−0.015*	−0.037***	−0.001	−0.005	−0.009	−0.025	0.004	−0.009**	−0.018*	−0.015
	(0.010)	(0.013)	(0.008)	(0.010)	(0.005)	(0.006)	(0.013)	(0.021)	(0.015)	(0.004)	(0.011)	(0.016)
30-39	0.001	−0.067**	−0.014	−0.023	0.0002	−0.007	−0.040**	0.063	−0.059**	0.008	−0.023	−0.024
	(0.019)	(0.028)	(0.015)	(0.019)	(0.009)	(0.009)	(0.020)	(0.040)	(0.028)	(0.007)	(0.018)	(0.037)
40-49	0.006	−0.059**	−0.013	−0.015	0.003	0.004	−0.029	0.019	0.023	0.012*	0.003	0.011
	(0.019)	(0.027)	(0.015)	(0.019)	(0.010)	(0.010)	(0.021)	(0.039)	(0.028)	(0.007)	(0.018)	(0.034)
50-59	0.031*	−0.038	−0.003	0.012	0.010	0.016*	0.007	0.040	0.025	0.014**	0.024	−0.003
	(0.019)	(0.026)	(0.015)	(0.017)	(0.009)	(0.009)	(0.021)	(0.037)	(0.026)	(0.006)	(0.020)	(0.033)
60-74	0.045***	−0.021	0.030**	−0.016	0.032***	0.044***	0.061***	0.117***	−0.024	0.022***	0.033*	−0.015
	(0.017)	(0.023)	(0.014)	(0.017)	(0.009)	(0.010)	(0.021)	(0.034)	(0.026)	(0.006)	(0.018)	(0.033)
75 Plus	0.044**	−0.077***	−0.015	−0.030*	0.016*	0.024**	0.052**	0.145***	−0.044	0.019***	0.032	−0.062*
	(0.019)	(0.025)	(0.016)	(0.018)	(0.009)	(0.011)	(0.023)	(0.039)	(0.031)	(0.007)	(0.020)	(0.035)
Other Race	0.016	−0.035	−0.039*	−0.019	−0.005	−0.041***	−0.022	−0.027	−0.009	−0.007	−0.086***	0.068
	(0.022)	(0.034)	(0.022)	(0.017)	(0.008)	(0.013)	(0.016)	(0.040)	(0.034)	(0.005)	(0.027)	(0.050)
Black	−0.110***	−0.027	−0.020	−0.089***	−0.026	−0.057***	−0.103**	−0.062**	−0.061	−0.042***	−0.038*	−0.174***
	(0.018)	(0.055)	(0.032)	(0.016)	(0.023)	(0.010)	(0.043)	(0.029)	(0.040)	(0.007)	(0.022)	(0.048)
Hispanic	−0.061	−0.041***	−0.079***	−0.050***	−0.036**	−0.031**	−0.102***	0.029	−0.034	−0.043***	−0.046***	−0.135***
	(0.039)	(0.016)	(0.013)	(0.014)	(0.016)	(0.016)	(0.036)	(0.050)	(0.021)	(0.009)	(0.015)	(0.050)
Constant	0.141***	0.324***	0.252***	0.318***	0.052**	0.108***	0.194***	0.446***	0.379***	0.129***	0.262***	0.347***
	(0.052)	(0.062)	(0.033)	(0.052)	(0.023)	(0.021)	(0.053)	(0.101)	(0.055)	(0.017)	(0.039)	(0.077)
Observations	4,407	5,002	8,162	6,433	11,434	11,019	4,468	2,114	3,236	21,619	4,811	3,403
R^2	0.020	0.009	0.012	0.012	0.010	0.014	0.018	0.037	0.011	0.006	0.015	0.014
Adjusted R^2	0.017	0.006	0.010	0.009	0.009	0.013	0.015	0.030	0.006	0.005	0.012	0.010
Residual Std. Error	0.322 (df = 4391)	0.450 (df = 4986)	0.374 (df = 8146)	0.389 (df = 6417)	0.280 (df = 11418)	0.296 (df = 11003)	0.413 (df = 4452)	0.476 (df = 2098)	0.430 (df = 3220)	0.275 (df = 21603)	0.381 (df = 4795)	0.458 (df = 3387)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Estimates from OLS regression. Republicans are less likely to cooperate than Democrats in every state except for Texas. Moreover, not only are the differences statistically distinguishable in Alabama, Arizona, Colorado Florida, Iowa, Michigan, Nevada, Pennsylvania, and Wisconsin (only in Minnesota and North Carolina are the differences statistically indistinguishable from zero), but the substantive magnitudes of the partisan effects are often sizable.

I Weighting to Distribution of Partisanship in the Voter File

The purpose of the re-weighting in the paper was to consider the implications of knowing that partisans respond at different rates to election surveys. The ultimate goal of this was to create a set of weights which more accurately reflect the electorate in terms of partisanship. There are other methods, however, that look to accomplish the same goal.

Figure 9 considers the effect of re-weighting polls based on the distribution of likely partisanship in the voter file on election day. To achieve these results the original survey weights were further post-stratified such that the distribution of likely partisanship in the sample equaled the distribution of likely partisanship in the voter file at-large. The results of this procedure show that this makes a much smaller, and oftentimes counterproductive, effect on the polling average. This is due to the fact that the distribution of partisanship in the voter file is not a good representation of the partisanship of the electorate.

Figure 10 displays the distribution of likely partisanship in the voter file, the disposition file, and in the exit poll after weighting to the correct outcome in each state (i.e. a reasonable measure of the actual distribution of partisanship in the electorate. There is a large difference in the distribution of partisanship in the voter file compared to the distribution of partisanship in the individuals actually called (regardless of whether they were contacted or completed the survey). While survey firms make use of the voter file in an RBS poll, they do not randomly sample from that file, but increase their efficiency by attempting to contact likely voters. This can lead to large discrepancies in the distribution of partisanship. Indeed, the distribution of partisanship of those called is much closer to the distribution of partisanship in the electorate. For this reason, weighting to the distribution of partisanship in the electorate is not a reasonable method of correcting for between-party non-response.

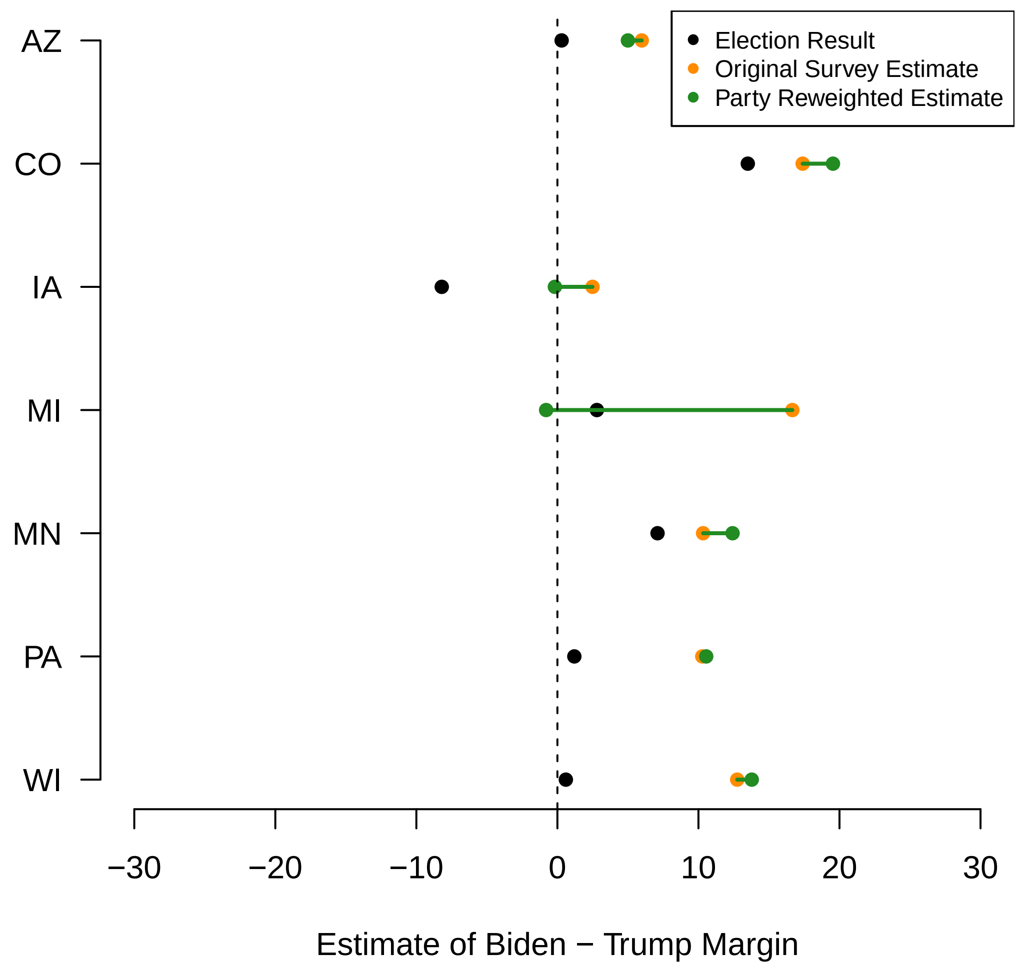

Figure 9: Effects on Polling Estimates Correcting for Partisan Composition in Voter File

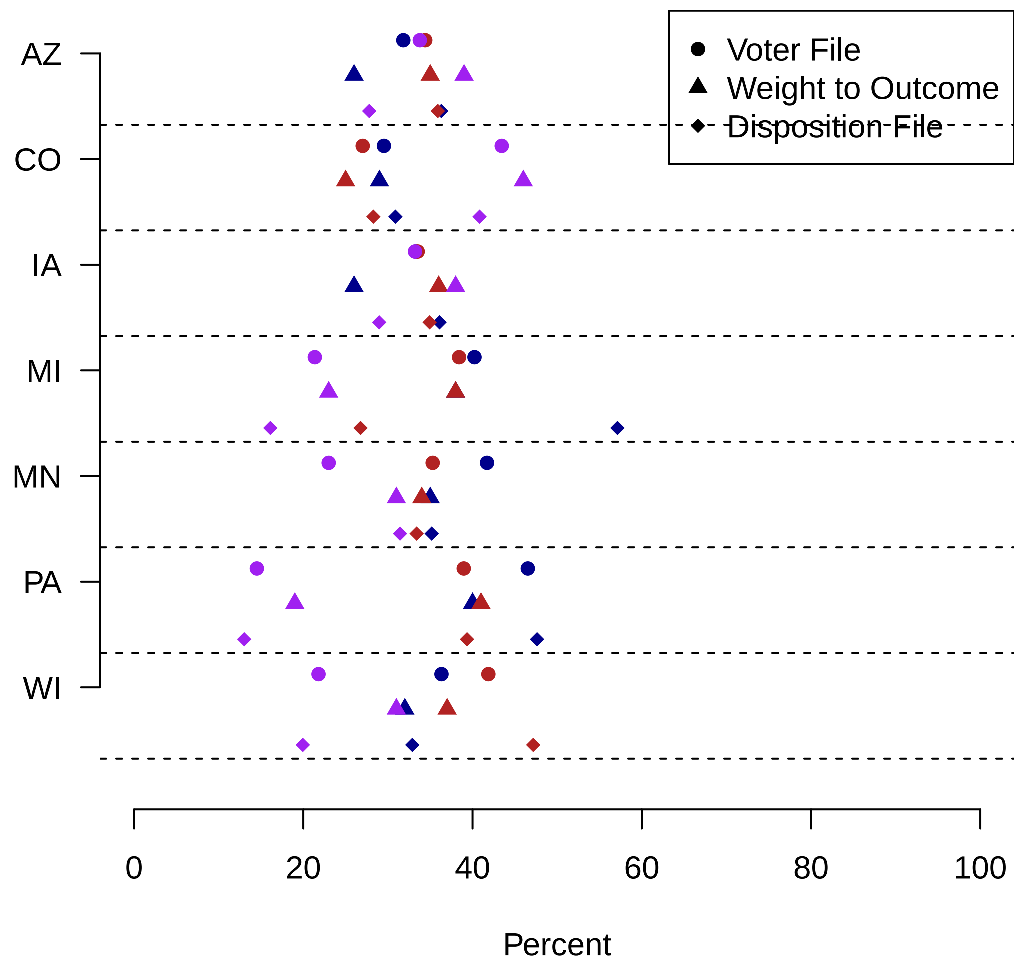

Figure 10: Distribution of Partisanship Across Adjustment Methods

J Is the impact of partisanship driven by high-COVID areas?

One possible explanation for the lower Cooperation and Contact rates among Republicans and Independents may be that they are more likely to have been living in areas more affected by the COVID-19 pandemic in the Fall of 2020. These individuals were more socially mobile throughout the pandemic, and thus were perhaps less likely to be home to take the call of survey research firms. Alternatively, these individuals may have been more affected by COVID-19 (whether personally or within their family) and perhaps had less time to answer a survey if contacted.

To understand this, we re-estimate our main model which pools all states. However, we also interact the party indicators with the logged number of COVID-19 cases in each individual's county. This allows us to estimate how the effect of partisanship varies as the number of COVID cases increases in an individuals areas. Again, this model is estimated with state fixed effects, so we are only comparing individuals (and their counties) within states.

Table 22 displays the result for estimating this specification for both the probability that an individual is contacted and whether they cooperate (conditional on being contacted). Figures 11 and 12 display the marginal effects of being a Republican or Independent/Other relative to being a Democrat across levels of COVID-19 cases in an individual's county.

The red line in Figure 11 displays the probability of contact for Republicans as compared to Democrats. The probability an individual is contacted if they are a likely Republican compared to a likely Democrat is lower regardless of the level of COVID-19.There is a slight negative slope to this line, which suggests that as COVID cases increase the likelihood of contacting Republicans as compared to Democrats decreases, but this slope is not statistically distinguishable from zero. In other words: there is not sufficient evidence in these data to overturn the null hypothesis that levels of COVID-19 does not change the relationship between being a Republican and being contacted.

The purple line in 11 displays the probability of contact for Independents as compared to

Democrats across levels of COVID-19 cases. Again, this line is persistently negative, suggesting that Independents are less likely to cooperate with surveys than Democrats regardless of the level of COVID-19. This line slopes upwards, and this slope is indeed statistically distinguishable from zero. In other words, as COVID rates increase, the difference in the probability of contact between Democrats and Independents decreases.

In Figure 12 there is little evidence that rates of COVID changes the relationship between partisanship and probability of cooperating for either Republicans or Independents. Both groups persistently cooperate less than Democrats, and that negative relationship is relatively stable as the number of COVID cases in a county increases.

Table 22: Modeling Contact and Cooperation, COVID/Party Interaction

	P(Contact)	P(Cooperate)
	(1)	(2)
ln(COVID Cases)	-0.113^{***}	-0.063^{***}
	(0.026)	(0.017)
Independent/Other	-0.043^{***}	-0.060^{***}
	(0.016)	(0.016)
Republican	-0.002	-0.001
	(0.006)	(0.006)
Dem	(0.0004)	(0.001)
Suburban Zip	0.032^{**}	0.015
	(0.014)	(0.023)
Urban Zip	0.041	-0.013
	(0.025)	(0.027)
Female	-0.005	-0.002
	(0.010)	(0.013)
30-39	0.001	-0.067^{**}
	(0.019)	(0.028)
40-49	0.006	-0.059^{**}
	(0.019)	(0.027)
50-59	0.031^{*}	-0.038
	(0.019)	(0.026)
60-74	0.045^{***}	-0.021
	(0.017)	(0.023)
75 Plus	0.044^{**}	-0.077^{***}
	(0.019)	(0.025)
Other Race	0.016	-0.035
	(0.022)	(0.034)
Black	-0.110^{***}	-0.027
	(0.018)	(0.055)
Hispanic	-0.061	-0.041^{***}
	(0.039)	(0.016)
ln(COVID Cases)*Independent/Other	0.141^{***}	0.324^{***}
	(0.052)	(0.062)
N	4,407	5,002
R^2	0.020	0.009
Adjusted R^2	0.017	0.006
Residual Std. Error	0.322 (df = 4391)	0.450 (df = 4986)

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

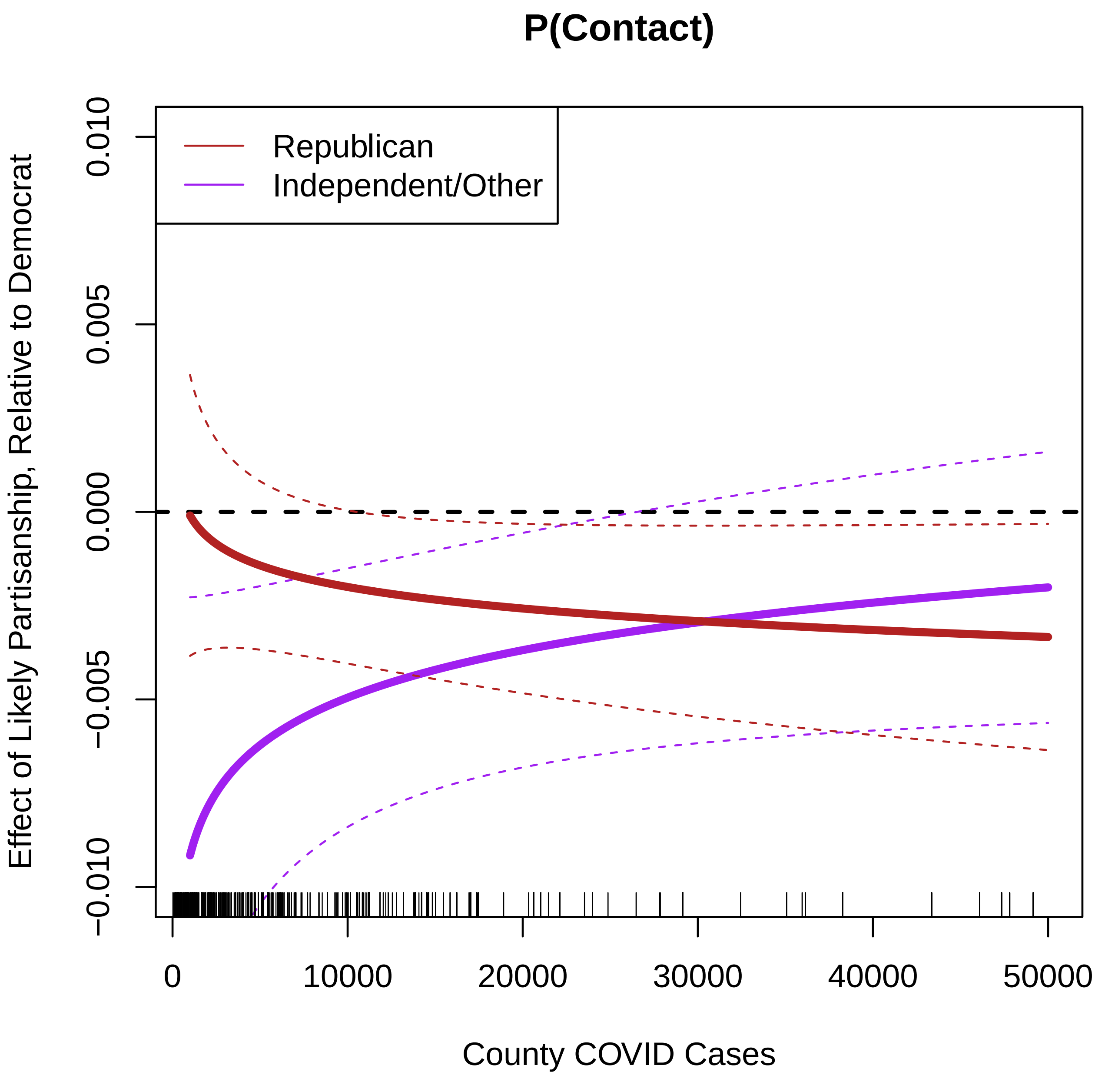

Figure 11: **Marginal Effect of Partisanship Across levels of COVID-19 in Respondent's County**

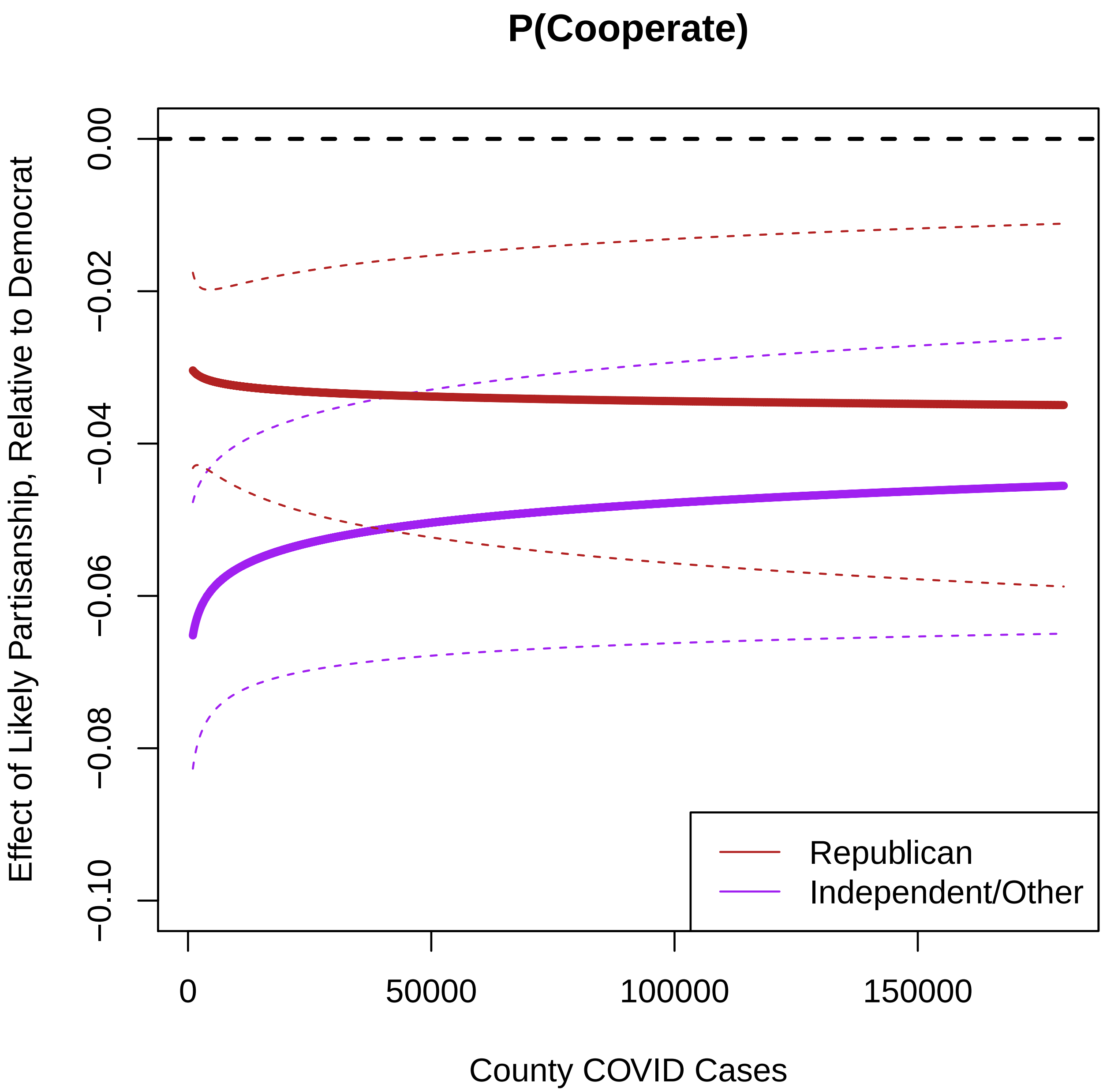

Figure 12: **Marginal Effect of Partisanship Across levels of COVID-19 in Respondent's County**