Do Protests Shift Public Opinion? A Replication Study of the Reny and Newman Analysis of the 2020 George Floyd Protests

[redacted]

December 20, 2023

Contents

Introduction

In a November, 2021 article, the Washington Post reported that the number of protests globally increased by more than threefold between 2006 and 2020, leading the researchers who conducted the cited study to conclude that we may be in a "historic age of protest" (Washington Post, Adam Taylor). The authors of the study referred to the farmers' protests in India, protests in Brazil opposing the election of Bolsonaro, and climate protests around the world just to name a few. The reason for this surge in demonstration, they offer, is the growing feeling around the world of democratic failure. Populations increasingly hold the perspective that their opinions and positions on issues of public importance go unheard by elected officials or those with the institutional power to implement meaningful change (Taylor, 2021). Dr. Martin Luther King, Jr. once proclaimed that the riot is the language of the unheard. While a protest is not the same as a riot – in that a riot is the spontaneous reaction of acute oppression targeting the especially silenced – the protest does have a family resemblance. Being a more organized and coordinated, often larger scale, form of issuing a grassroots demand from below, yet still fairly immediate and responsive to sudden and charged events, protests, it would seem, hold greater potential to effect change.

This raises the obvious question: do protests actually contribute to bringing about democratic change? If the reason why demonstrations are rising globally is because populations feel that the political class disregards them, is protesting the right strategy to facilitate the change people wish to see? While this is an urgent question, there stands – I submit – a prior question that must be answered. Do protests change minds, and significantly and durably enough to open up the political conditions and create the political will to produce said change? This question motivates and is the central focus of the research described in this paper.

In this paper, I replicate a key finding from a paper by Tyler Reny of Claremont Graduate University and Benjamin Newman of the University of California, Riverside, titled "The Opinion-Mobilizing Effect of Social Protest against Police Violence: Evidence from the George Floyd Protests." This paper inquires about a specific instance of the question stated above – whether protests induce longstanding and significant change in public opinion. The question they examine is if the nationwide and heavily attended protests that sprung up in the aftermath of George Floyd's murder in 2020 influenced what the public thinks on the matters of race and policing. The authors pursue this question via two dependent variables: 1) attitude toward the institution of policing, and 2) perception of the level of discrimination faced by Black Americans. The pair of researchers wager that George Floyd's murder was an unexpected enough event that the protests that followed constitute an "as-if random" event to be able to make causal inferences about the impact of the protests on public opinion. Operating from this supposition, Remy and Newman conduct a regression discontinuity design (RDD) with a running time variable to measure public opinion on their two dependent variables before and after their cutoff date. Suspecting that changes in opinion may be driven by partisan commitments or racial attitudes, they also use a probit model to evaluate the outcomes for their dependent variables conditional on level of racial prejudice and identification as strongly Democrat or strongly Republican. In this replication project, I replicate only the first result from the RDD. The dataset that they use is the Nationscape survey (NS) which provides survey responses from a representative sample that is collected daily.

Reny and Newman find that following the cutoff, the opinions measured by the two dependent variables changed to a substantial degree. Disaggregating by race, they find that this shift was larger whites than for Black, Latino, and Asian Americans, although shorter lived. They also find that disaggregating for whites, that the shift was largely driven by those who were more progressive and those with lower racial prejudice. This finding suggests that people's prior ideological commitments determine to a large extent the impact the protest has on them. Which means, as Reny and Newman write, that protests may actually contribute to polarization.

The rest of this paper will explain the theory behind the research, going into detail about research that investigates the role and impact of protests. From there, I will discuss the data that was used and the design of the research. The results will be covered from there and then the paper will close with thoughts on the lessons gleaned from this exercise.

Theory and Expectations

Why study the protests that stormed the nation after George Floyd's murder? Ultimately, if racial justice and equality are something we as a society desire, then we must commit ourselves to the mechanisms of change that will accomplish this. Broadly, as stated in the introduction section, it appears that we are in a juncture in history where the will of the people does not easily translate into concrete policies that reflect the people's desire. As the incandescent energy of the people often coalesces into protest, it is worthwhile investigating whether these movements lead to substantive change. The implementation of change depends on the ability of these movements to alter opinion. In this regard, even though the immediate interest is the shift in opinion on the topic of systemic and persistent racism, this study has a wider applicability in terms of public opinion shift and democratic will in general.

Motivating this research for Reny and Newman is a body of literature that attempts to learn whether protests are an effective form of civic engagement. In their review, they surface several key findings that encourage their research direction. They cite Taeku Lee's 2002 work, "Mobilizing Public Opinion: Black Insurgency and Racial Attitudes in the Civil Rights Era," that indicates "that minority-led protest can serve as a grassroots 'bottom-up' factor that mobilizes liberal shifts in public opinion on racial issues (Reny and Newman, 2021)." Similarly, they also refer to Omar Wasow's paper, "Agenda Seeding: How 1960s Black Protests Moved Elites, Public Opinion and Voting," that protests led by people of color and other minoritized groups can alter what the news reports and how they report it (Reny and Newman, 2021), evincing that protests may shift opinion through impacting what the larger population sees and hears through the media as an intervening variable. From here, Reny and Newman report on findings that show that protests shift how liberal segments of the population vote as well as how Congress members may vote (Reny and Newman, 2021). Further, protests may have an effect on the way white people vote, the partisanship of the white population, their prejudice toward Black Americans, and their opinion on affirmative action (Reny and Newman, 2021).

In my own research on the topic, I have found work supporting the need for further investigation on this topic and also suggesting that studying protests can be a promising inquiry for learning how opinions change and how policy shifts. In 2019, Edwin Amenta and Francesca Polletta published the article, "The Cultural Impacts of Social Movements." While they studied social movements broadly, and not protests specifically, some of the evidence they presented has implications for our focus of concern. In this paper, they home in specifically on culture. They write that "rather than treating culture as a sphere of social life, one that lies outside the state and the economy, we have instead conceptualized culture as the meaning-making dimension of all policies and practices" (Amenta and Polletta, 291). This sets them up to investigate the impact of social movements via culture on four different nodes of society – public opinion, media coverage, nonpolitical institutions, and public policy and political institutions (Amenta and Polletta, 291). They find some evidence that social movements' most likely avenue for influencing culture and public opinion is through the interaction of the movements with institutions, particularly media (Amenta and Polletta, 291-2). While this research is on social movements broadly, this has import for protests since protests often garner significant media coverage and attention through social media platforms. This allows for the message of the protest to be carried to a wider audience and provides some degree of control to the movement to shape the narrative. Amenta and Polletta also lament the dearth of research on this topic, which provides some encouragement that the direction pursued here, through the work of Reny and Newman, is an area of study with high demand.

In other research from my own review of the literature, Jon Agnone's "Amplifying Public Opinion: The Policy Impact of the US Environmental Movement," seeks to answer questions about the relationship between protest, public opinion, and legislative activity. Agnone is interested in the mechanism by which protests impact public policy outcomes. He proposes that that protest and public opinion are best studied through an amplification model (Agnone, 1597). The idea is that the level of the effect of public opinion on legislative outcomes is impacted by the amount of protest activity (Agnone, 1597). To test this hypothesis, Agnone runs a Poisson regression analysis and uses an interaction term between environmental movement protests and public opinion on the environment to discern the effect of this interaction on Congressional activity pertaining to environment related policy. He finds that "increases in the support for environmental regulation have a greater impact on the passage of environmental legislation consistent with the goals of the environmental movement depending on the level of environmental protest" (Agnone, 1609). These findings by Agnone do not comment on whether protests sway public opinion, but the fact that protests bolster the effect of public opinion on legislative outcomes offers promise that the Reny and Newman direction of research is a fruitful one. Reny and Newman, however, also review literature that is more skeptical about a link between protest activity and public opinion. They cite Krosnick and Petty from 1995 and Sears from 1993 who find that political attitudes are so deeply embedded that protest has negligible effects on changing it. Because of this, they believe that their study provides an excellent opportunity to test a phenomenon that is under debate.

Reny and Newman also provide information as to why the George Floyd protests, in particular, and protests having to do with issues of race generally are of great importance. First, they believe that attitudes about police and policing are becoming evermore shaped by race and political affiliation. They cite Michael Tesler who finds that "racial attitudes have played an integral part of contemporary partisan sorting and polarization" (Reny and Newman, 1500). Further, they discuss the presence of counternarratives and counter-explanations for police killings of Black people, as well as counter-movements, embodied by slogans like "Blue Lives Matter." They see all of this as evidence that people's view of the institution of policing is increasingly racialized and partisan. With attitudes about policing and the killing of Black people highly determined by the level of anti-Black bias, particularly among whites, they understand attitudes about policing to be highly durable and partisan. These hypotheses accord with research on the topic that I have conducted. Researcher Ashley Jardina and her coauthor Trent Ollerenshaw examine survey data from the American National Election Studies dataset and find that while white Democrats are becoming more supportive of racial equality initiatives, white Republicans are becoming more entrenched in their opposition and in their levels of racial resentment (Jardina and Ollerenshaw, 2022).

Given these findings from the literature, Reny and Newman hypothesize that they might not find a broad effect on public opinion. Instead, they might find an effect of increased polarization, divided along the lines of racial attitude and political affiliation among whites. They make the Floyd protests the object of their research because of its scale, surmising that if they find no effect here, given the sheer magnitude of the protests, then it would cast doubt on the proposition that protests lead to shifts in opinion (Reny and Newman, 1500).

Theory and expectations also include theory about method. As stated previously, Reny and Newman employ an RDD to estimate the impact of the George Floyd protests on public opinion related to attitude toward policing and perception of discrimination against Black Americans. The thinking behind the RDD is that there is an arbitrary and random cutoff, often but not always temporal or geographic, on either side of which it is effectively random where observations land. This assumption is for observations close to the cutoff. The observations close to the cutoff should be similar to each other and should be balanced on key covariates, allowing for the RDD to produce a local average treatment effect on the like observations close to the cutoff.

In a 2018 paper titled, "When Does Regression Discontinuity Work? Evidence from Random Election Outcomes," Ari Hyytinen et al. attempt to compare the RDD method to an actual experiment to see how if each produces similar results. They use election data that contains ties between two or more candidates in municipal elections in Finland (Hyytinen et. al, 1020). They state that "the unique feature of [their] data is that ties were resolved via a lottery and that the random assignment occurs *right at the cutoff*" (Hyytinen et. al, 1020, italics in original). This is important because the treatment in the experiment is the same as the cutoff in the RDD, which is how they compare the RDD's effectiveness as a method to an experiment.

The reason I am citing this paper is not for the highly interesting and creative comparison they are attempting, but because of their description of what the RDD does. This explication should be helpful to our theoretical purposes of understanding why Reny and Newman choose an RDD design in their study. Hyytinen et al. explain that "in a regression discontinuity design, individuals are assigned dichotomously to a treatment if they cross a given cutoff of an observable and continuous forcing variable, whereas those who fail to cross the cutoff form the control group" (Hyytinen et. al, 1020). They next state that "if the conditional expectation of the potential outcome is continuous in the forcing variable at the cutoff, correctly approximating a regression function for the treated and control groups at the cutoff gives the average treatment effect at the cutoff" (Hyytinen et. al, 1020). To understand what this means, we should unpack a few of the terms they use.

In The Effect: An Introduction to Research Design and Causality, author Nick Huntington-Klein explains that the forcing variable is also sometimes referred to as the running variable and that this variable determines whether an observation receives or doesn't receive the "treatment." The cutoff, he goes on to state, is the value of the running variable that determines who gets the treatment. In order for the design to be valid, the cutoff has to be random, meaning the observations shouldn't be able to choose which side of the cutoff they are on and the researchers determining the cutoff shouldn't be influenced by where they see certain observations when deciding what the cutoff is (Huntington-Klein, 2021). Huntington-Klein also states that a major assumption of the RDD is that if there had been no treatment at all at the cutoff, the trend in the data would have stayed the same. This is what is often referred to as "smooth at the cutoff" (Huntington-Klein, 2021). Having all of these concepts squared away should make the above sentences from Hyytinen clearer. If there had otherwise been a smooth trend in the data, if there is a cutoff implemented that acts as a treatment, then we can compare the observations on either side of the cutoff (who should be fairly similar to each other) to determine a local average treatment effect.

In terms of the RDD that Reny and Newman run, time is the running variable and May 28, 2020 is the cutoff, the “treatment” being the protests that occurred as a result of George Floyd’s murder. The assumption is that had his death and the protests not occurred, there would have been no change in opinion at the time. This RDD is a little different from how most that I’ve encountered in the literature are designed. Instead of having a control group and a treatment group, we are comparing a sample representative of the entire adult population of the US from before the cutoff and after the cutoff. They are different people being surveyed, but we are to act as if they are basically one representation of the population being surveyed before and after. In other scenarios, we would have one discrete control group and one discrete treatment group that we would compare on either side of the cutoff. Also, for Reny and Newman, the bandwidth is less important than for most RDDs. They are interested in how large of an effect the protests have at the cutoff, but they also want to know how long the change in opinion lasts and for which population groups the change fades. With this theoretical discussion helping to underpin and clarify what the study is attempting to learn and how it is attempting to accomplish that learning, we can now turn to the data, design, and results.

Data

As stated previously, this replication study uses the NS, or Nationscape, dataset that Reny and Newman use for their analysis. As the authors state in their paper, the NS is a survey that is conducted on a weekly basis. It surveys 6,250 people a week and is weighted to be representative of the adult population of the US. The surveyors interview people daily, conducting 900 surveys a day. Reny and Newman argue that this allows them to estimate attitude changes as a product of random and isolated occurrences like the George Floyd protests. For their analysis, they use the first 60 iterations of the NS, which started in July, 2019. They therefore have data from July, 2019 to September, 2020.

Exploring the data from Reny and Newman’s replication file, I find that they have not included every variable from the NS, but only the variables relevant to the study. This gives us 42 variables and 364,727 observations. The unit of analysis is the individual and the outcome variables we are interested in are attitude toward police and perception of discrimination against Black Americans. These attitude measures are derived from Likert-scale questions. Reny and Newman have recoded the answers so that a 4 equals the most unfavorable attitude toward police and a 5 equals a perception of greater discrimination against Black Americans. I offer some descriptive statistics to provide a closer understanding of the data set below:

Table 1 presents a descriptive overview of the individuals in the NS dataset, giving us an idea of the distribution on a number of key covariates. The average age in this subset of the NS that Reny and Newman use is 44 years old, and the dataset is 55 percent female. The mean income is 9.38, which is a scale that the NS uses to code a range of incomes. The digit ‘9’ corresponds to incomes between \$50,000 and \$54,999 annually. Political ideology is a variable measured on a Likert scale between 1, which equals ‘very liberal,’ and 5, which equals ‘very conservative.’ The mean political ideology in this subset of the NS is 3.02, which corresponds to ‘moderate’ on the Likert scale for the variable.

In terms of the outcomes that are measured in the primary analysis of this study, the mean attitude toward police is 2.05 and the mean perception of discrimination toward Black people is 3.68. Both of these variables are measured on a Likert scale, with police attitude ranging from 1 to 4 and perception of anti-Black discrimination ranging from 1 to 5. The scale is kept the same for police favorability in the original NS and in the subset used for this analysis, meaning 1 equals ‘very favorable’ and 4 equals ‘very unfavorable.’ The discrimination scale, however, was reordered by Reny and Newman so that 1 equals a perception that Black people face very little discrimination and 5 indicates a perception that Black people face a great deal of discrimination. A mean attitude toward police of 2.05 indicates that surveyed individuals have a more favorable attitude toward police. This makes intuitive sense, as Reny and Newman point out in their paper that policing is a highly trusted institution in the US. But this statistic is also of great interest for what it might indicate when unpacked further. As we can see in Table 2 of the descriptive statistics, the dataset is made up of mostly white survey takers. Reny and Newman emphasize that trust in policing is strong among whites, and for whites, attitudes toward policing are becoming more polarized (Reny and Newman, 1500). This makes it an appealing outcome variable, because it may speak to several expectations for the results. For instance, Reny and Newman write that because police trust is durable, the protests may not shift it or since police attitudes are racialized, a backlash effect may be detected if attitudes toward police strengthen (Reny and Newman, 1500). A weakening of attitudes would provide strong evidence of a relationship between the protests and shifts in public opinion based on the protests' messaging. The same is true for perceptions of discrimination. A mean of 3.68 shows that respondents have a perception that discrimination faced by Black people is slightly higher than a moderate amount. But any movement here could indicate the effectiveness of protests, that this perception is hard to alter, or a backlash effect.

Table 1: Descriptive Statistics

Variable	min	mean	sd	max
Covariates				
Age	18	44.67	16.57	99
Percent Female	0	0.55	0.50	1
Income	1	9.38	7.06	24
Political Ideology	1	3.02	1.08	5
Outcomes				
Attitude to Police	1	2.05	1.02	4
Perception of Discrimination	1	3.68	1.21	5

Regarding the racial makeup of respondents, the dataset is overwhelmingly white. The survey takers are 69 percent white and only 11 percent Black, 15 percent Latino, and 5 percent Asian. This indicates that any findings could be driven largely by white respondents and could be a product of attitudes and beliefs that one is more likely to hold if socialized as white. This is one reason why the results are disaggregated by race. It is also why the extension focuses on white attitudes toward whites. Since the main interest of this research is shifting public opinions, if whites remain a majority of voters due to population share, then understanding what is driving shifts in white attitudes might provide useful insights into influencing or harnessing shifts in public opinion. The results, discussed later, of a shift in white attitudes toward whites is crucial to consider in terms of its interaction with Reny and Newman's outcome variables of interest.

Table 2: Percentages by Race

Variable	mean
Percentages	
Percent White	0.69
Percent Black	0.11
Percent Latino	0.15
Percent Asian	0.05

The next figure (Figure 1) disaggregates pre-cutoff attitudes toward police by race. We can see that whites have the most favorable attitude toward police (1 = very favorable, 5 = very unfavorable), which makes sense for the reasons discussed above. Black respondents having the least favorable attitude also makes intuitive sense given the level of police brutality faced by this population.

Having reviewed a summary of the descriptive statistics for this study, we can now turn to the design of the analysis.

Design

The design for this analysis is a regression discontinuity design (RDD). This type of design uses a variable called a running variable. A value of the running variable is chosen as a cutoff point. The units of analysis

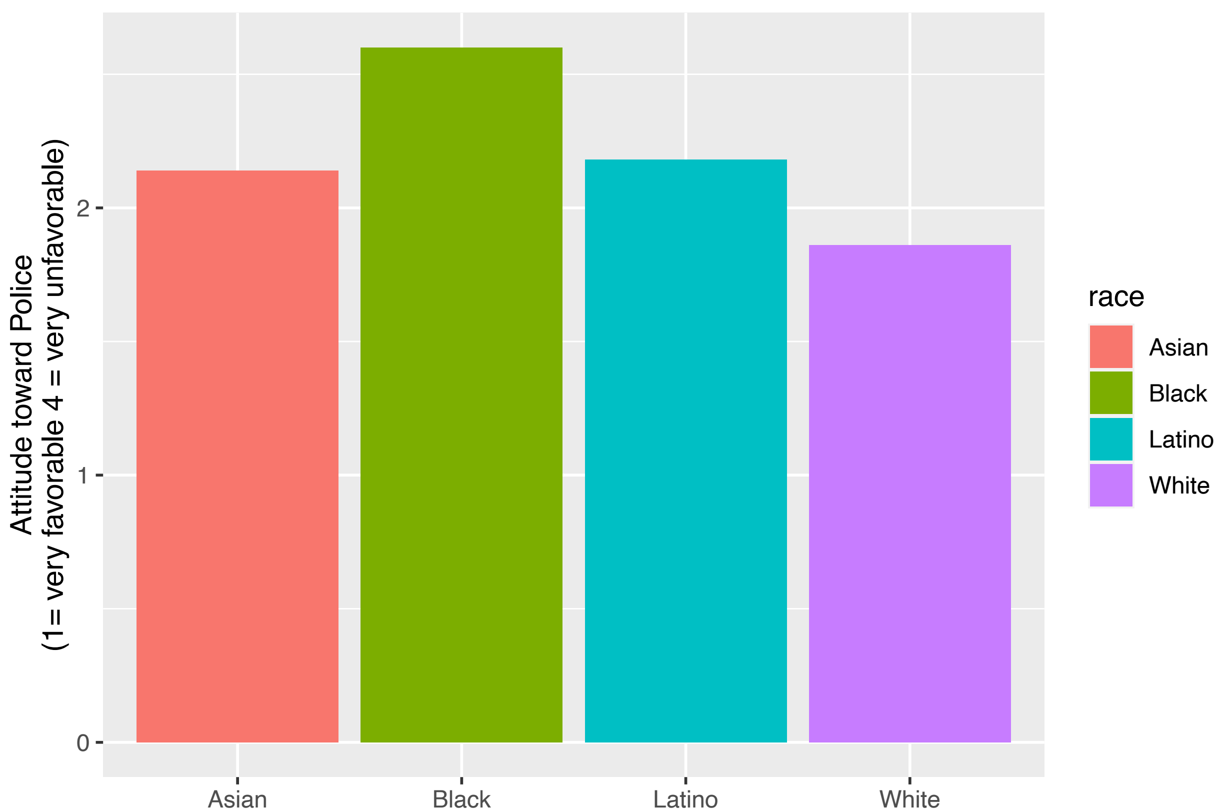


Figure 1: Graph of Attitude toward Police Pre-Cutoff

above the cutoff receive the treatment and those below do not. The logic of the RDD is that units close to the cutoff are comparable, therefore, the RDD produces a local average treatment effect which is the difference in outcome variables for those similar units on either side of the cutoff. In Research Design in the Social Sciences: Declaration, Diagnosis, and Redesign, Blair et al. remark that because researchers know that everyone below the cutoff did not receive treatment and everyone above did, "knowledge about the threshold serves as a basis for a strong causal identification claim" (Blair et. al).

The RDD utilizes several types of variables. It has a running variable, a cutoff point, a treatment variable, and an outcome (Blaire et. al) The RDD's key assumption is that the outcome variable is continuous at the cutoff (Blaire et. al). This means that there is a clear trend in the outcome variable and that for every value of the running variable there is a defined value for the outcome so that it can be claimed that nothing else besides the cutoff interrupted or changed the trend of the outcome variable.

The RDD that produces the main result of this analysis uses time as the running variable. May 28, 2020 is the cutoff point, which is the date that most of the first major protests after George Floyd's death occurred. The design, disaggregated by race, plots the two outcome variables – police attitude and perception of discrimination – with time on the x-axis and the outcome variable on the y-axis. It then fits a line of best fit to the plotted data. The line is plotted before and after the cutoff to see if there is a significant difference between the trends of each of the lines. Because the NS survey is collected daily, the dataset has a value of the outcome for each unit (day) of the running variable, which fulfills the assumption of a continuous conditional expectation function.

This specific design is different from most RDDs who analyze differences on either side of the cutoff between discrete control and treatment groups. The reason is because the NS survey is a nationally representative sample that acts as if those sampled are the same (as far as their representation of the nation as a whole). Because of this, and because Reny and Newman are fairly certain that the unplanned and unpredictable timing of the protests constitute an as-if random event, this design can be said to be making a selection on observables. Also, because this analysis does not have to worry about categorically different groups on either side of the cutoff and is also interested in how long shifts in opinion last, the bandwidth issue central to most RDD studies is not salient here.

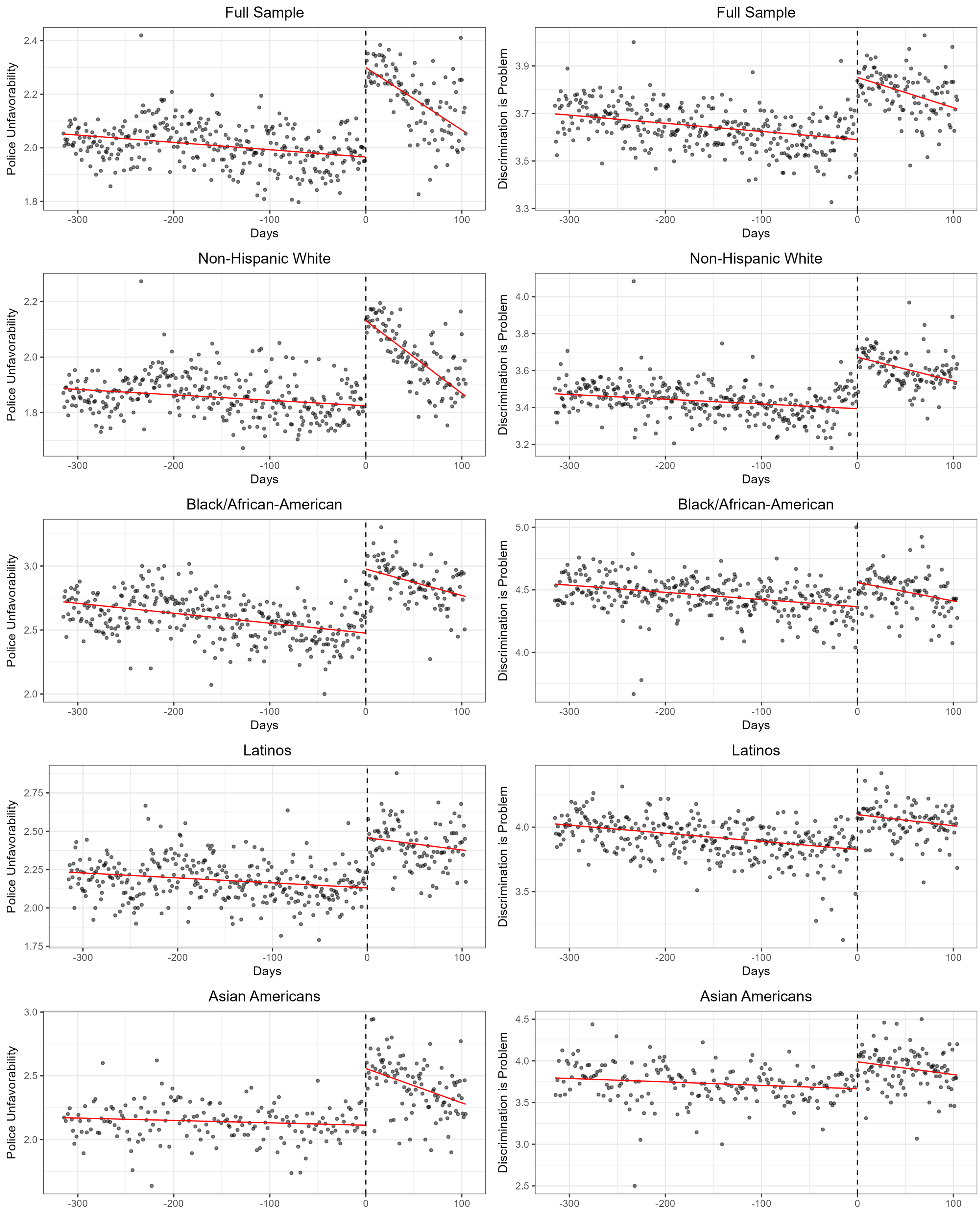
In terms of how to interpret the model, any discontinuity indicates some type of effect presumably attributable to the treatment at the cutoff if our assumptions about the design hold – that is, if we are confident that the treatment is the only factor that impacted the outcome variables. The larger the discontinuity, the larger the local average treatment effect. The steeper the trend line in the post period, the sharper the decline in the effect over time (if the trend line is negative). This speaks to the lack of salience of the bandwidth. If we were concerned with units right around the cutoff, then our focus would be tightly hugged to the cutoff. But since we are interested in shifts in opinion over time, the post period trend line and its slope are of interest. Specific to the results in this study, a jump upward after the cutoff means an increase in unfavorability toward police and an increase in the perception of the severity of anti-Black discrimination.

Results

The results display a discontinuity at the cutoff point which suggests that the 'treatment' of the protests' occurrence has a relationship to a shift in attitudes toward police and perception of discrimination toward Black Americans. Since we know that there is a continuous conditional expectation function, as we have a response on these two outcome variables for every day of the running time variable, we can say with some confidence that this strongly suggests a causal relationship.

These results are presented in two forms. One (Figure 2) is a visual representation of the discontinuities, showing breaks in the plotted trend lines in the pre- and post-periods. The other is a table (Table 3) that shows the point-difference on either side of the threshold for the coefficients on the outcome variables. For instance, for the full sample, the difference in the coefficient on police attitude was a 0.29 point increase from the pre- to the post-period, the implication being that this jump was likely caused by the protests. These coefficients are reported with standard errors. A standard error (SE) is the standard deviation of the sampling distribution, meaning that if this RDD was run numerous times with a different sample, hypothetically, the SE is the amount of typical variation from the coefficient there would be. These SEs are lower for the full sample and for whites because there are more people in these two groups.

For both outcome variables, there is a large shift between the two trend lines of the pre- and post-periods for the full sample. As we might expect from the descriptive statistics showing us that whites make up 69 percent of the dataset, the size of the discontinuity is largely driven by whites. This is evidenced in the disaggregated results where whites have the largest shift in the outcome variable trend lines. Though whites had the largest shift, they started at lower starting points than the respondents of other races. As in, whites had a higher favorability toward police and a perception of lower levels of discrimination faced by Black people than did the other races surveyed. In some cases, even though the white shift was the largest, it still did not reach the pre-treatment value of the outcome variables for other races. For instance, whites had a shift of 0.29 points for police attitude and 0.18 points for discrimination but this raised them to a police attitude level of just below 2.2 and a discrimination perception level of around 3.7 whereas Black respondents had a pre-cutoff level of roughly 2.7 for police attitude and just above 4.5 for perception of discrimination. Black respondents had the smallest shifts but the highest pre-cutoff starting points for each outcome variable.



These findings suggest that the George Floyd protests served as somewhat of a wakeup call for white Americans. It perhaps exposed them to the realities for nonwhites and particularly Black Americans that whites had no connection to or were able to ignore. This speaks to the earlier point about white socialization. Because whites do not experience policing in the same way, it is easier for them to have a higher degree of trust in the institution and favorability toward police. Therefore, the difference in the response levels in the descriptive statistics as well as in the analysis results are not a product of some innate quality of race but the socialization that shapes and defines race. Further, these findings can aid us in thinking about how race is structural and institutions like policing are forces of racialization.

Another result is that the slopes of the trend lines in the post period are steeper for whites than for nonwhites. The post period that the data displays is 100 days after the cutoff. This finding demonstrates that the shift in opinion had less durability for whites than for people of color, perhaps suggesting a quicker return to a social reality that allows for a disengagement with the structural conditions faced by Black people and other nonwhites. The shallower slope for people of color might indicate a confirmation of their expectations as well as a belief that conditions have worsened with no immediate prospects of improving.

Table 3: RD Estimates

coef	se	pv	sample	outcome
0.29	0.02	0.00	Full	Police
0.29	0.02	0.00	Full	Police
0.29	0.03	0.00	Full	Police
0.29	0.03	0.00	White	Police
0.29	0.03	0.00	White	Police
0.29	0.03	0.00	White	Police
0.20	0.08	0.02	Black	Police
0.18	0.08	0.03	Black	Police
0.18	0.10	0.07	Black	Police
0.24	0.05	0.00	Latino	Police
0.24	0.05	0.00	Latino	Police
0.24	0.07	0.00	Latino	Police
0.25	0.10	0.01	Asian American	Police
0.22	0.10	0.02	Asian American	Police
0.22	0.12	0.06	Asian American	Police
0.20	0.03	0.00	Full	Discrim
0.21	0.03	0.00	Full	Discrim
0.21	0.03	0.00	Full	Discrim
0.18	0.03	0.00	White	Discrim
0.18	0.03	0.00	White	Discrim
0.18	0.04	0.00	White	Discrim
0.12	0.08	0.15	Black	Discrim
0.10	0.08	0.24	Black	Discrim
0.10	0.10	0.33	Black	Discrim
0.22	0.06	0.00	Latino	Discrim
0.23	0.06	0.00	Latino	Discrim
0.23	0.07	0.00	Latino	Discrim
0.21	0.08	0.01	Asian American	Discrim
0.20	0.08	0.02	Asian American	Discrim
0.20	0.10	0.05	Asian American	Discrim

Extensions

The first extension conducted was a balance test on key covariates before and after the cutoff. This extension is essentially a robustness check to strengthen our confidence that we can attribute the findings to the ‘treatment’ of the protests that happened at the cutoff point. The rationale is that if these covariates are not of similar value, then it could be due to that difference that we observe a shift in the trend line between the pre- and post-period. Our confidence in being able to attribute the difference to the protests would be undermined. This extension looked at the covariates of party affiliation, political ideology, the percentage of each race, and gender. Figure 3 presents the findings of the balance test. Blue dots indicate values for the pre-period and red dots for the post. The significant overlap among the dots for each covariate shows high balance and increases our confidence that the protests have a strong case for being the causal factor.

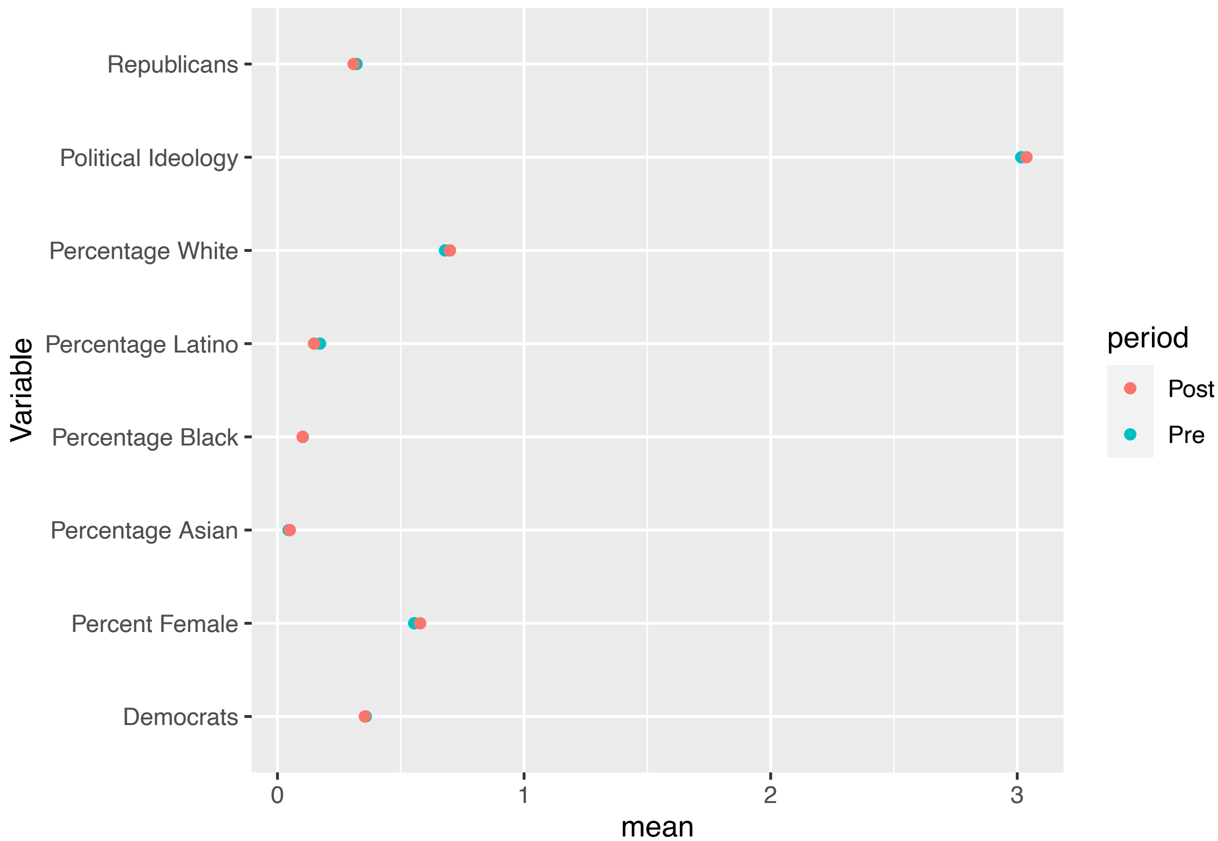


Figure 2: Pre and Post Balance Test

The second extension examines whether white group favorability changed for whites from one side of the cutoff to the other. The logic behind asking this question is related to learning more about the sizeable coefficients on the outcome variables for white people or, stated differently, the sizeable shift in the trend lines between the pre- and post-periods. Since whites are the largest racial group in the data and largely drive the full sample shift we observe, and because the white RDD results are different from the results for people of color in that whites had a larger jump but steeper decline, it is worth digging into what is happening here. The intuition behind testing white group favorability is that there could be a white guilt factor at play. In other words, if white people have less of a direct experience with police brutality and racial discrimination and thus have a more favorable opinion of police and perceive less discrimination faced by Black people, as the results potentially suggest, then it is worth asking if the shift is driven by guilt about racial status and a feeling of helplessness to personally undo a structural problem. Such a feeling may manifest as a drop in favorability toward whites as a group for white people.

Because Reny and Newman surmise that police attitude is racialized and that racial attitudes drive political polarization, this test of white group favorability was disaggregated by political ideology. The belief is that if conservatives have stronger racial biases as well, they would be less likely to feel this sense of white guilt and therefore be less likely to show a drop in white favorability in the post-period. Before the RDDs were run, a regression was run to see if there is a relationship between political ideology and white group favorability among whites.

The regression equation is given as:

$$WhiteFavorability = \beta_0 + \beta_1 ideology + \beta_2 age + \beta_3 female + \beta_4 income + \epsilon$$

Where Beta-Naught is the intercept and the predictor variable is political ideology and the dependent variable is white group favorability. The model includes the covariates of age (Beta-Two), proportion female (Beta-Three), and income (Beta-Four). Regression analysis is used to discern and demonstrate a relationship between two variables. It shows how one variable changes as changes in another occur. For the model in this extension analysis, we are examining whether political ideology explains variation in white group favorability. Regression does this by choosing a line of best fit in a scatter plot of the independent and dependent variable. The line is chosen in a way that minimizes the sum of the squared residuals. Residuals, or the error terms, are the difference between an observed value of the outcome variable for a certain value of the independent variable and the predicted value at this point. Squaring the error terms treats negative and positive values the same. This best fit line is what is used to describe the relationship between the independent and dependent variables. Adding in covariates answers the question: if these other predictors are held constant, or if we take into account the additional variance these added covariates account for, how much does the dependent variable vary in relation to changes in the primary independent variable? In our model, we are reasoning that age, gender, and income might account for some variation so if we hold these constant, we are interested in how much of a relationship exists between ideology and white group favorability.

The regression analysis shows that a coefficient of 0.12 for ideology. This means that as political ideology gets more conservative, the model predicts that attitude toward whites for whites would become more favorable. This is what we would expect if we believe that conservatives are less racially open and that political ideology is racialized so that conservative identity is strongly tied to white identity. Table 4 and Table 5 present the results of the regression analysis. The tables are the same with the exception that Table 4 presents P-Values and Table five presents confidence intervals. A P-Value is the probability of getting the produced result if the null hypothesis that there is actually no effect is true. The coefficient on ideology is significant at the .001 level, meaning that there is a .1 percent chance we would have this result if the null of zero effect were true. In other words, if you centered a normal distribution around zero, this result would be way out in the tail in an area where we see almost no data. The likelihood of having a result out here is .1 percent. A confidence interval of 95 percent means that if we did repeated random sampling, we would expect that the interval would contain the true value of the parameter we are interested in 95 percent of the time. The true parameter has an equal likelihood of being any value within the interval. Here, we see that the coefficient of 0.12 on ideology is within the very narrow confidence interval and so it is within the interval that 95 percent of the time should contain the true value of the variation in white group favorability explained by political ideology.

With this relationship between ideology and white group favorability established, we can look at the RDD plots for white group favorability among whites at different ideologies. Although very small, we do observe a shift downward for white democrats, liberals, and moderates. This suggests that there could be a white guilt effect occurring but this shift may be too small to be meaningful. If it is meaningful, however, then perhaps it can help explain the shift in the outcome variables in the main analysis. Although visually we see a shift for white conservatives, looking at the scale on the y-axis, we see that this shift is probably negligible, which would align with our expectations that conservatives would likely not feel less favorable to whites after the protest events.

	Ideology's Impact on White Favorability
(Intercept)	2.73***
	(0.01)
Ideology	0.12***
	(0.00)
Age	0.00***
	(0.00)
Gender (female)	0.00
	(0.00)
Household Income	0.00***
	(0.00)
R^2	0.04
Adj. R^2	0.04
Num. obs.	202703

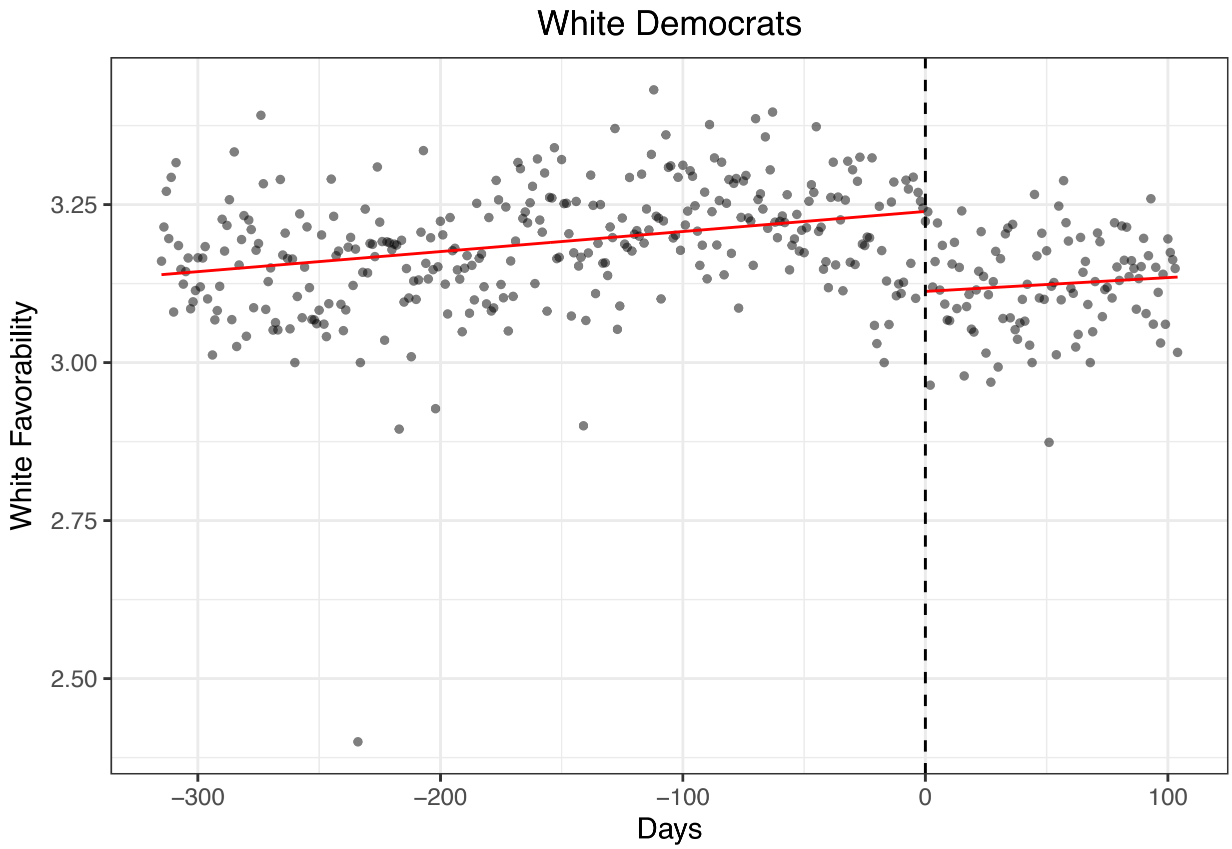
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

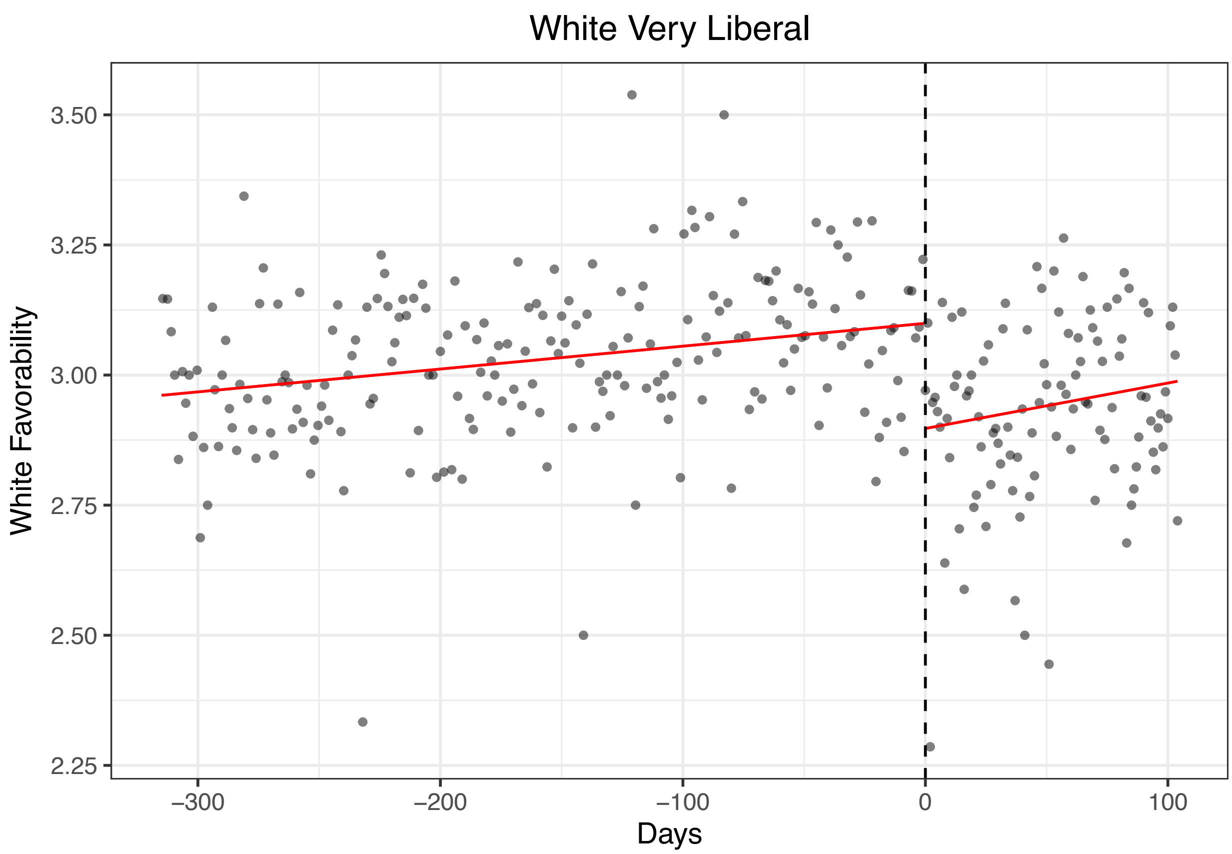
Table 4: Extension 2 Model

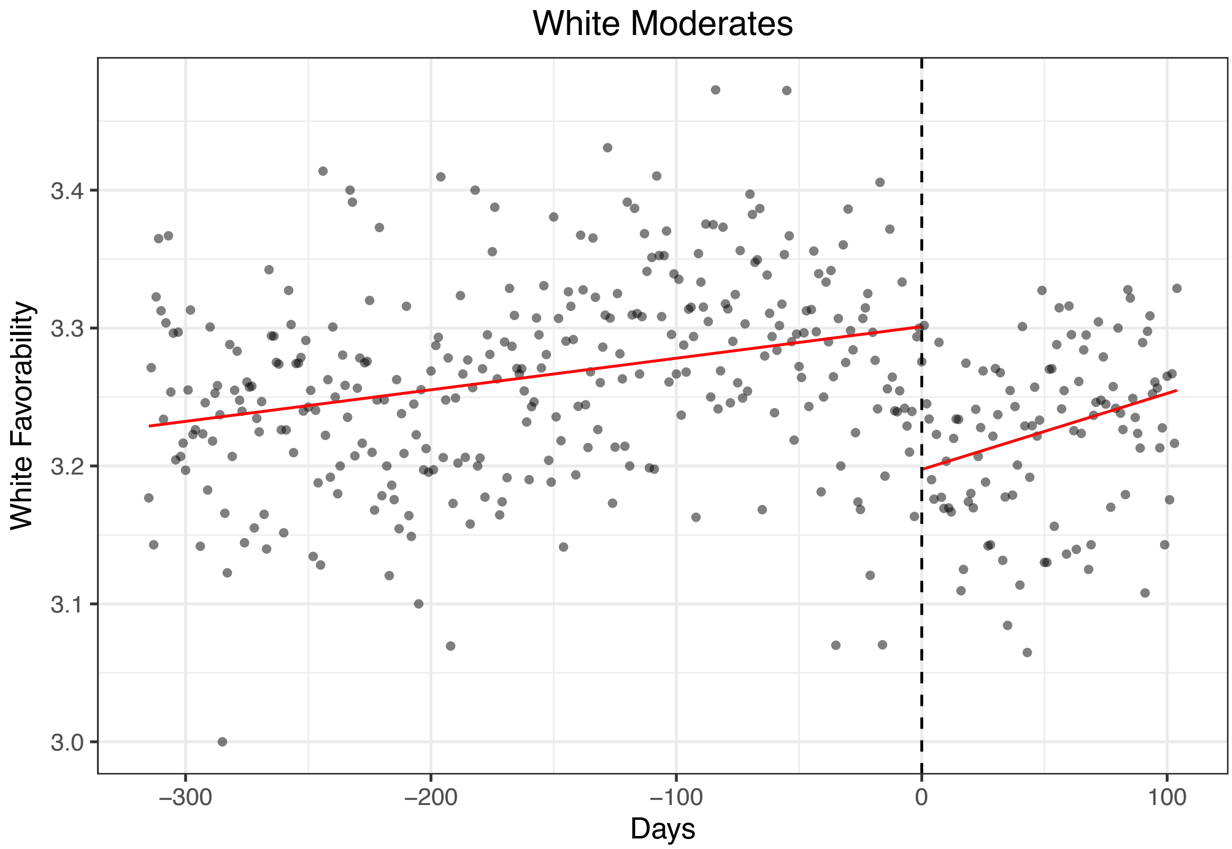
	Ideology's Impact on White Favorability
(Intercept)	2.73*
	[2.72; 2.74]
Ideology	0.12*
	[0.11; 0.12]
Age	0.00*
	[0.00; 0.00]
Gender (female)	0.00
	[−0.00; 0.01]
Household Income	0.00*
	[0.00; 0.00]
R^2	0.04
Adj. R^2	0.04
Num. obs.	202703

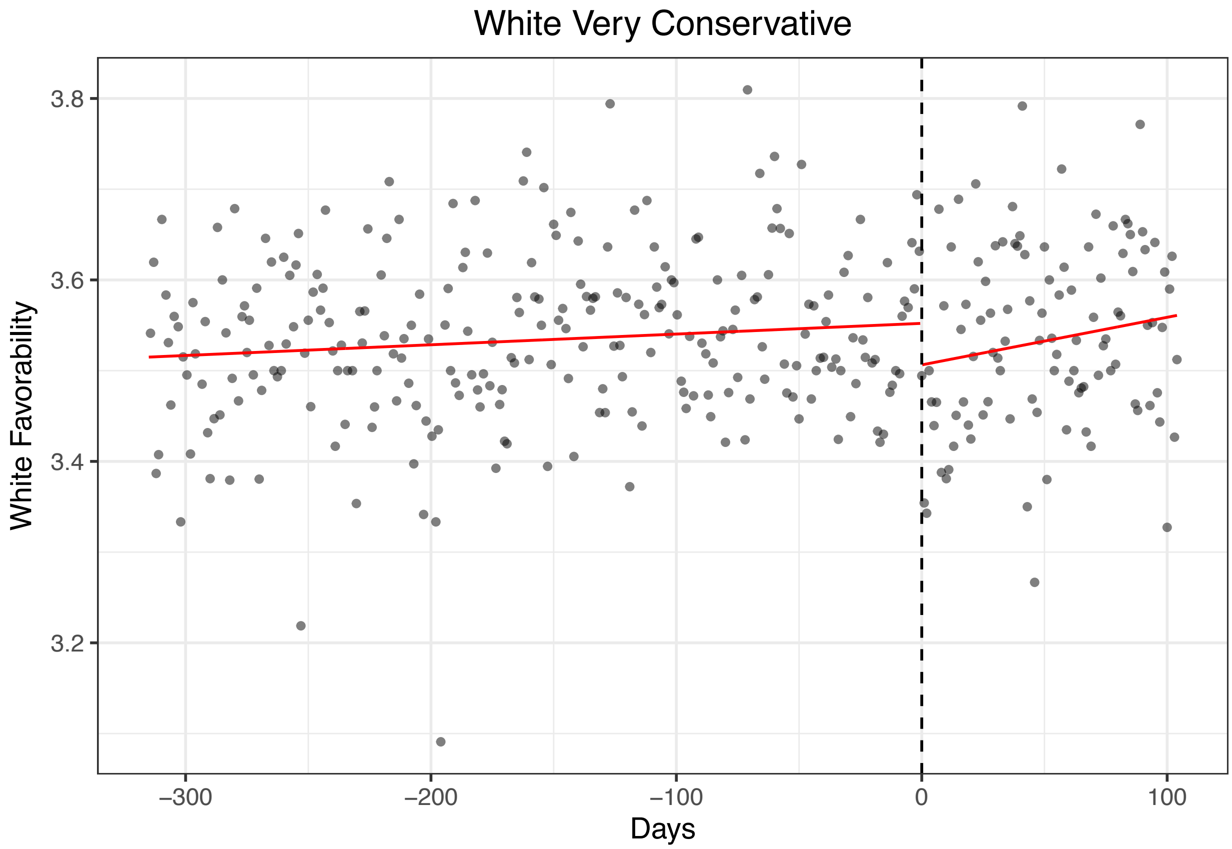
* 0 outside the confidence interval.

Table 5: White Favorability Regression with Confidence Intervals


White Democrats
White Favorability
3.25
3.00
2.75
2.50
−300
−200
−100
0
100
Days


White Very Liberal
White Favorability
3.50
3.25
3.00
2.75
2.50
2.25
−300
−200
−100
0
100
Days


White Moderates
White Favorability
3.0
3.1
3.2
3.3
3.4
−300
−200
−100
0
100
Days



Conclusion

The goal of this replication project was to learn about the impact of protests. The central question asked if protests shift public opinion. With protest movements rising globally because populations in each corner of the world feel that they have less political influence through normal democratic channels, this is an important inquiry to grapple with. Reny and Newman, in their study ask specifically if the protests following George Floyd's murder moved public opinion on attitudes toward police and perceptions of discrimination against Black Americans. They pulled on past studies about protest movements led by marginalized groups and the impact on public opinion. They grounded their investigation in literature that finds a relationship between policing, racial attitudes, and political polarization. Armed with the knowledge from these earlier works, they anticipated a relationship between political affiliation and the magnitude of the shift in opinion. They also contended that given the size of the Floyd protests, that if they did not see an effect here, there would be little evidence that protests lead to a real shift in opinion.

This research question was put to the test with the analytical method of the regression discontinuity design (RDD). The RDD utilizes a running variable and a cutoff point to estimate a local average treatment effect on either side of the cutoff threshold, comparing like units within a specified bandwidth around the cutoff. The design for this analysis used the protests occurring on May 28, 2020, as the cutoff and analyzed the difference in outcome variables on either side of this point. The assumption is that the protests were not predictable so acted as a random intervention, allowing the researchers to make causal claims about their results.

In running this replication study, we have found that following the protest date cutoff, there exists a discontinuity between the trend lines on either side of the threshold for the full sample. Disaggregating by race, we see a larger shift for whites for both police attitude and perception of discrimination. However, even in the post period, whites remained lower than the starting values for people of color. In extending the analysis, we observed balance in key covariates in the pre- and post-periods, making the causal claims of the study more credible. We also witnessed a small but visible shift in whites' attitude toward other whites, with the effect increasing with more liberal political ideologies.

The RDD was a strong methodological fit for this analysis because the NS survey provided a response for every day which allowed for the core assumption of a continuous conditional expectation function to be met. The NS survey also provided extremely high balance in the pre- and post-periods and the as-if random assumption of the spontaneous nature of the protests is highly credible. However, there are still a number of areas for improvement. Reny and Newman state that in their robustness checks, they used attitudes toward whites to make sure that there were no opinion shifts on variables that should not have been affected by the protests. However, when looking specifically at whites, we did observe a shift toward a less favorable opinion. Reny and Newman likely ran the robustness check on the full sample. Yet they missed an opportunity to analyze whether there is also an effect of white guilt happening. Or it could be that the shift that we did observe in the extension is so small (albeit visible) that it doesn't actually constitute a significant shift and thus still operates as a successful robustness check. More research can be done here to figure out more about what is happening here. Another weakness is the lack of disaggregation by income, particularly among whites. We discussed earlier how the results we found for whites could be an indication that their social reality does not expose them to the structural brutalities faced by nonwhites. However, lower-class whites may face higher levels of police brutality and other related hardships than middle and upper-class whites. It would be interesting to see whether this class-inflected relationship to the institute of policing or an allegiance to whiteness and the racializing function of policing proves more salient.

This analysis produced several interesting and generative findings and also has pointed in several directions for further research to take. In addition to the aforementioned class disaggregation, another direction for research can be to more closely examine the durability of the opinion shifts. Perhaps exploring what interventions might make a shift in opinion last longer. Additionally, the purpose of studying shifts in public opinion is to ultimately see if they translate into changes in public policy. One area of research that could be interesting is to see what types of bills are introduced during the period of time when opinion shifts are still high and to see the fate of the bill as opinion shifts wane. In the aftermath of the racial justice protests of 2020, many municipalities introduced police reform bills and some even considered police abolition or significant reallocation of police funding to other areas of public spending. However, many of these bills were never enacted and eventually abandoned. If opinion durability had been stronger, what would have become of these legislative proposals? This is a fruitful direction for research.

Overall, this replication study produced thought-provoking findings about the nature and mechanisms of public opinion shifts, and examined the creative deployment by Reny and Newman of the RDD, allowing for the exercise to act as an instructive teaching tool about the research method. In this way, the project has served as the initial first steps toward new portals of discovery.

References

Please find here a list of works cited:

- Agnone, J. (2007). Amplifying Public Opinion: The Policy Impact of the U.S. Environmental Movement. *Social Forces*, 85(4), 1593-1620.
- Amenta, E., & Polletta, F. (2019). The Cultural Impacts of Social Movements. *American Review of Sociology*, 45, 279-299.
- Blair, Graham, Coppock, Alexander, and Humphreys, Macartan. (2023) *Research Design in the Social Sciences: Declaration, Diagnosis, and Redesign.* Princeton University Press, 2023.
- Huntington-Klein, Nick. (2022) *The Effect: An Introduction to Research Design and Causality.* Routledge, 2022.

- Hyytinen, A., Merilainen, J., Saarimaa, T., Toivanen, O., & Tukiainen, J. (2018). When Does Regression Discontinuity Design Work? Evidence from Random Election Outcomes. *Quantitative Economics*, 9, 1019-1051.
- Jardina, A., & Ollerenshaw, T. (2022). The Polls - Trends: The Polarization of White Racial Attitudes and Support for Racial Equality in the US. *Public Opinion Quarterly*, 86(1), 576-587.
- Reny, T., & Newman, B. (2021). The Opinion-Mobilizing Effect of Social Protest against Police Violence: Evidence from the 2020 George Floyd Protests. *American Political Science Review*, 115(4), 1499-1507.
- Taylor, A. (2021). Why is the World Protesting So Much? A New Study Claims to Have Some Answers. *The Washington Post*, November 4, 2021, https://www.washingtonpost.com/world/2021/11/04/protests-global-study/

Appendix

This appendix includes the following:

- Codebook
- Code Appendix.

Code book

The code book includes the following:

- Outcome
- Key Predictor
- Covariates

Outcome Variables

- `group_favorability_the_police` | Attitude toward Police
  - **Question:** "Here are the names of some groups that are in the news from time to time. How favorable is your impression of each group or haven't you heard enough to say? - The Police"
  - **Recoding:** reverse coded so that in `group_favorability_the_police`, 1 = "Very Favorable", 2 = "Somewhat Favorable", 3 = "Somewhat Unfavorable", and 4 = "Very Unfavorable"
  - **Range:** 1 ("Very Favorable") to 4 ("Very Unfavorable")
- `discrimination_blacks` | Perception of Anti-Black Discrimination
  - **Question:** "How much discrimination is there in the United States today against each of the following groups? - Blacks"
  - **Recoding:** reverse coded so that in `discrimination_blacks`, 1 = "Not at all", 2 = "A little", 3 = "A moderate amount", 4 = "A lot" and 5 = "A great deal"
  - **Range:** 1 ("Not at all") to 5 ("A great deal")
- `group_favorability_whites` | Attitude to Whites
  - **Question:** "Here are the names of some groups that are in the news from time to time. How favorable is your impression of each group or haven't you heard enough to say? - Whites"
  - **Recoding:** reverse coded so that in `group_favorability_whites`, 1 = "Very unfavorable", 2 = "Somewhat unfavorable", 3 = "Somewhat favorable", and 4 = "Very favorable"

  - **Range:** 1 (“Very unfavorable”) to 4 (“Very favorable”)

Key Predictor

- `ideo5` | Political Ideology
  - **Question:** “In general, how would you describe your own political viewpoint?”
  - **Coding:** coded so that in `ideo5`, 1 = “Very liberal”, 2 = “Liberal”, 3 = “Moderate”, 4 = “Conservative” and 5 = “Very conservative”
  - **Range:** 1 (“Very liberal”) to 5 (“Very conservative”)

Covariates

- `household_income` | Income
  - **Question:** “What is your current annual household income before taxes?”
  - **Coding:** `V201233`coded so that in `household_income`, 1 = “Less than $14,999”, and 24 = “$250,000 and above”, there are 24 categories, 9 = “$50,000 to $54,999”
  - **Range:** 1 (“Less than $14,999”) to 24 (“$250,000 and above”)

Code Appendix

Finally, in your code appendix you will display the all the code from the previous code chunks in one single code chunk by:

- setting `echo = T, eval = F` in the code chunk’s header
- typing the `<<chunk_label>>` for each of your code chunks sequentially where `chunk_label` is replaced with the of the corresponding code chunk (e.g. ‘<>)

```r
# Set global options for knitr
knitr::opts_chunk$set(error = TRUE,
                      echo = F,
                      results = "hide",
                      comment = NA,
                      warning = FALSE,
                      error = FALSE,
                      message = FALSE,
                      cache = T,
                      tidy = FALSE,
                      fig.pos = 'H')

# ---- Packages ----

setwd('/Users/Eloy/Documents/POLS 2580/Final Project')

# Packages used in analysis
the_packages <- c(
  ## R Markdown
  "kableExtra","DT","texreg","htmltools",
  ## Tidyverse
  "tidyverse", "lubridate", "forcats", "haven", "labelled",
  "modelr", "purrr",
```

```r
  ## Extensions for ggplot
  "ggmap","ggrepel", "ggridges", "ggthemes", "ggpubr",
  "GGally", "scales", "dagitty", "ggdag", "ggforce",
  # Data
  "COVID19","maps","mapdata","qss","tidycensus", "dataverse",
  # Analysis
  "DeclareDesign", "boot"
)

# Define function to load packages
ipak <- function(pkg){
    new.pkg <- pkg[!(pkg %in% installed.packages()[, "Package"])]
    if (length(new.pkg))
        install.packages(new.pkg, dependencies = TRUE)
    sapply(pkg, require, character.only = TRUE)
}

ipak(the_packages)

library(tidyverse)
library(haven)
library(lubridate)
library(rdrobust)
library(MASS)
library(broom)
library(simcf)
library(ggrepel)




df <- read_dta('C:/Users/Eloy/Documents/POLS 2580/Final Project/nationscape_clean_replication.dta')



# recode vars of interest
blacks <- df %>% filter(race_ethnicity == 2 & hispanic == 1)
whites <- df %>% filter(race_ethnicity == 1 & hispanic == 1)
latinos <- df %>% filter(hispanic > 1)
asians <- df %>% filter(race_ethnicity %in% c(4:14))

# scale for converting X-axis
conversion = df %>%
  dplyr::select(wave, day) %>%
  group_by(wave) %>%
  slice(which.min(day))


returnPlot <- function(full_plot, yaxis, title){
  plot <- full_plot$vars_bins %>%
    na.omit() %>%
    filter(rdplot_N != 1) %>%
```

```
    ggplot(aes(rdplot_mean_x, rdplot_mean_y)) +
    geom_point(size=1, alpha=0.5) +
    geom_line(data=full_plot$vars_poly[full_plot$vars_poly<0,],
              aes(rdplot_x, rdplot_y),
              color='red', size=0.5) +
    geom_line(data=full_plot$vars_poly[full_plot$vars_poly>0,],
              aes(rdplot_x, rdplot_y),
              color='red', size=0.5) +
    geom_vline(xintercept=0, linetype=2) +
    theme_bw() +
    labs(x='Days',y=yaxis,title=title) +
    theme(plot.title = element_text(hjust=0.5),
          axis.title.y = element_text(margin = margin(t = 0, r = 5, b = 0, l = 0)))
  return(plot)
}

# ---- Check Recodes ----

ns_check <- read_dta('C:/Users/Eloy/Documents/POLS 2580/Final Project/ns20190718.dta')


df_check <- subset(df, day_running >= -315 & day_running <= -309, select = c(race_ethnicity:cand_favora

table(ns_check$ideo5)

table(df_check$ideo5)

table(ns_check$group_favorability_whites)

table(df_check$group_favorability_whites)

#they reversed white_favorability. In original, 1 is very favorable and 4 is very unfavorable. In their

#table(ns_check$group_favorability_whites)

#   1    2    3    4  999
# 2145 2379  727  293  795

# table(df_check$group_favorability_whites)

#   1    2    3    4
# 293  726 2379 2145

#ideo5 is the same in both

# table(ns_check$group_favorability_the_police)
#
#    1    2    3    4  999
# 2139 2065  954  674  506
#
# table(df_check$group_favorability_the_police)
#
#   1    2    3    4
```

```
# 2138 2065  954  673 - 4 is very unfavorable
#
#
# table(ns_check$discrimination_blacks)
#
#    1    2    3    4    5
# 2147 1290 1695  921  311
#
# table(df_check$discrimination_blacks)
#
#    1    2    3    4    5
#  311  921 1694 1290 2146
#They've reversed it here so in theirs 5 is a great deal of discrimination.

table(ns_check$group_favorability_whites)

table(df_check$group_favorability_whites)





# ---- Descriptive Statistics ----

df %>%
  mutate(
    race = case_when(
      race_ethnicity == 2 & hispanic == 1 ~ "blk",
      race_ethnicity == 1 & hispanic == 1 ~ "whte",
      hispanic > 1 ~ "latino",
      race_ethnicity %in% c(4:14) ~ "asian",))-> df

df %>%
  mutate(
    num_white <- ifelse(race == "whte", 1, 0),
    num_black <- ifelse(race == "blk", 1, 0),
    num_latino <- ifelse(race == "latino", 1, 0),
    num_asian <- ifelse(race == "asian", 1, 0)
  ) -> df

df %>%
  rename(
    num_white = `num_white <- ifelse(race == "whte", 1, 0)`,
    num_black = `num_black <- ifelse(race == "blk", 1, 0)`,
    num_latino = `num_latino <- ifelse(race == "latino", 1, 0)`,
    num_asian = `num_asian <- ifelse(race == "asian", 1, 0)`,
  ) -> df

view(df)

# Variables for table of descriptive statistics:
the_vars <- c("age","female",
```

```r
              "household_income", "ideo5",
              "group_favorability_the_police", "discrimination_blacks")

# Create table of summary statistics

df %>%
  dplyr::select(all_of(the_vars))%>%
  pivot_longer(
    cols = all_of(the_vars),
    names_to = "Variable"
  )%>%
  mutate(
    Variable = factor(Variable, levels = the_vars)
  )%>%
  arrange(Variable)%>%
  dplyr::group_by(Variable)%>%
  dplyr::summarise(
    min = min(value, na.rm=T),
    mean = mean(value, na.rm=T),
    sd = sd(value, na.rm=T),
    max = max(value, na.rm = T)
  ) %>%
  mutate(
    Variable = case_when(
      Variable == "age" ~ "Age",
      Variable == "female" ~ "Percent Female",
      Variable == "household_income" ~ "Income",
      Variable == "ideo5" ~ "Political Ideology",
      Variable == "group_favorability_the_police" ~ "Attitude to Police",
      Variable == "discrimination_blacks" ~ "Perception of Discrimination",
    )
  ) -> sum_df

sum_df

# ---- Table for Percentage Race ----

race_vars <- c("num_white","num_black",
              "num_latino", "num_asian")

# Create table of summary statistics

df %>%
  dplyr::select(all_of(race_vars))%>%
  pivot_longer(
    cols = all_of(race_vars),
    names_to = "Variable"
  )%>%
  mutate(
    Variable = factor(Variable, levels = race_vars)
  )%>%
  arrange(Variable)%>%
  dplyr::group_by(Variable)%>%
```

```
  dplyr::summarise(
    mean = mean(value, na.rm=T)
  ) %>%
  mutate(
    Variable = case_when(
      Variable == "num_white" ~ "Percent White",
      Variable == "num_black" ~ "Percent Black",
      Variable == "num_latino" ~ "Percent Latino",
      Variable == "num_asian" ~ "Percent Asian",
    )
  ) -> sum_race

sum_race

# ---- Descriptive Figures ----

pre_whites <- subset(whites, day_running < 0, select = c(race_ethnicity:cand_favorability_obama))

pre_blacks <- subset(blacks, day_running < 0, select = c(race_ethnicity:cand_favorability_obama))

pre_latinos <- subset(latinos, day_running < 0, select = c(race_ethnicity:cand_favorability_obama))

pre_asians <- subset(asians, day_running < 0, select = c(race_ethnicity:cand_favorability_obama))

mean(pre_whites$group_favorability_the_police, na.rm = T)
mean(pre_blacks$group_favorability_the_police, na.rm = T)
mean(pre_latinos$group_favorability_the_police, na.rm = T)
mean(pre_asians$group_favorability_the_police, na.rm = T)


race <- c("White", "Black", "Latino", "Asian")
police_attidue <- c(1.86, 2.6, 2.18, 2.14)

df_hist <- data.frame(race, police_attidue)

## Bar Graph of Police Attitude by Race
bar_fig1 <- df_hist %>%
  ggplot(aes(x = race, y= police_attidue, fill = race))+
  geom_bar(stat = "identity")+
  labs(
    y = "Attitude toward Police\n(1= very favorable 4 = very unfavorable)", x = ""
  )



# library(kableExtra)
# # Table of descriptive statistics

view(sum_df)

knitr::kable(sum_df,
             caption = "Descriptive Statistics",
             format = "latex",
```

```r
            booktabs = T,
            digits = 2) %>%
  kableExtra::kable_styling(latex_options = "hold_position") %>%
  kableExtra::pack_rows("Covariates", start_row = 1, end_row =4) %>%
  kableExtra::pack_rows("Outcomes", start_row = 5, end_row = 6)
```

```r
knitr::kable(sum_race,
             caption = "Percentages by Race",
             format = "latex",
             booktabs = T,
             digits = 2) %>%
  kableExtra::kable_styling(latex_options = "hold_position") %>%
  kableExtra::pack_rows("Percentages", start_row = 1, end_row =4)
```

```r
# Bar Graph Figure 1

bar_fig1
```

```r
# FULL SAMPLE
full_plot <- rdplot(df$group_favorability_the_police,df$day_running,
                    hide = T,
                    p=1,kernel = 'uniform')
p1 <- returnPlot(full_plot,yaxis='Police Unfavorability',title='Full Sample')

full_plot <- rdplot(df$discrimination_blacks,df$day_running,
                      hide = T,
                    p=1,kernel = 'uniform')
p2 <-returnPlot(full_plot=full_plot,yaxis='Discrimination is Problem',title='Full Sample')

# White sample
full_plot <- rdplot(whites$group_favorability_the_police,whites$day_running,
                      hide = T,
                    p=1,kernel = 'uniform')
p3 <- returnPlot(full_plot,yaxis='Police Unfavorability',title='Non-Hispanic White')

full_plot <- rdplot(whites$discrimination_blacks,whites$day_running,
                      hide = T,
                    p=1,kernel = 'uniform')
p4 <- returnPlot(full_plot=full_plot,yaxis='Discrimination is Problem',title='Non-Hispanic White')

# Black sample
full_plot <- rdplot(blacks$group_favorability_the_police,blacks$day_running,
                      hide = T,
                    p=1,kernel = 'uniform')
p5 <- returnPlot(full_plot,yaxis='Police Unfavorability',title='Black/African-American')
```

```r
full_plot <- rdplot(blacks$discrimination_blacks,blacks$day_running,
                     hide = T,
                   p=1,kernel = 'uniform')
p6 <- returnPlot(full_plot=full_plot,yaxis='Discrimination is Problem',title='Black/African-American')

# Latino sample
full_plot <- rdplot(latinos$group_favorability_the_police,latinos$day_running,
                     hide = T,
                   p=1,kernel = 'uniform')
p7 <- returnPlot(full_plot,yaxis='Police Unfavorability',title='Latinos')

full_plot <- rdplot(latinos$discrimination_blacks,latinos$day_running,
                     hide = T,
                   p=1,kernel = 'uniform')
p8 <- returnPlot(full_plot=full_plot,yaxis='Discrimination is Problem',title='Latinos')

# Asians
full_plot <- rdplot(asians$group_favorability_the_police,asians$day_running,
                     hide = T,
                   p=1,kernel = 'uniform')
p9 <- returnPlot(full_plot,yaxis='Police Unfavorability',title='Asian Americans')

full_plot <- rdplot(asians$discrimination_blacks,asians$day_running,
                     hide = T,
                   p=1,kernel = 'uniform')
p10 <- returnPlot(full_plot=full_plot,yaxis='Discrimination is Problem',title='Asian Americans')

grobz <- gridExtra::arrangeGrob(p1,p2,p3,p4,p5,
                                p6,p7,p8,p9,p10,
                                ncol=2)



ggsave(grobz,
       width=12,
       height=15,
       filename='mainfigure_final.png')





# \begin{figure}
# \caption{yada yad}
# \includegraphics[width = .8\textwidth]{mainfigure_final.png}
# \end{figure}




full_plot_est <- rdrobust(df$group_favorability_the_police,df$day_running,
                          p=1,kernel = 'triangular')
full_police <- tibble(coef=full_plot_est$coef,
```

```r
                      se=full_plot_est$se,
                      pv=full_plot_est$pv) %>%
  mutate(sample='Full',
         outcome='Police')

full_plot_est_discrim <- rdrobust(df$discrimination_blacks,df$day_running,
                                  p=1,kernel = 'triangular')
full_discrim <- tibble(coef=full_plot_est_discrim$coef,
                       se=full_plot_est_discrim$se,
                       pv=full_plot_est_discrim$pv) %>%
  mutate(sample='Full',
         outcome='Discrim')

fav_bws <- full_plot_est
dis_bws <- full_plot_est_discrim


# White Respondents Only
full_plot_est <- rdrobust(whites$group_favorability_the_police,whites$day_running,
                          p=1,kernel = 'triangular')
whites_police <- tibble(coef=full_plot_est$coef,
                        se=full_plot_est$se,
                        pv=full_plot_est$pv) %>%
  mutate(sample='White',
         outcome='Police')

full_plot_est_discrim <- rdrobust(whites$discrimination_blacks,whites$day_running,
                                  p=1,kernel = 'triangular')
whites_discrim <- tibble(coef=full_plot_est_discrim$coef,
                         se=full_plot_est_discrim$se,
                         pv=full_plot_est_discrim$pv) %>%
  mutate(sample='White',
         outcome='Discrim')

# Black Respondents Only
full_plot_est <- rdrobust(blacks$group_favorability_the_police,blacks$day_running,
                          p=1,kernel = 'triangular')
blacks_police <- tibble(coef=full_plot_est$coef,
                        se=full_plot_est$se,
                        pv=full_plot_est$pv) %>%
  mutate(sample='Black',
         outcome='Police')

full_plot_est_discrim <- rdrobust(blacks$discrimination_blacks,blacks$day_running,
                                  p=1,kernel = 'triangular')
blacks_discrim <- tibble(coef=full_plot_est_discrim$coef,
                         se=full_plot_est_discrim$se,
                         pv=full_plot_est_discrim$pv) %>%
  mutate(sample='Black',
         outcome='Discrim')

# Latino Responents Only
full_plot_est <- rdrobust(latinos$group_favorability_the_police,latinos$day_running,
```

```
                          p=1,kernel = 'triangular')
latinos_police <- tibble(coef=full_plot_est$coef,
                         se=full_plot_est$se,
                         pv=full_plot_est$pv) %>%
  mutate(sample='Latino',
         outcome='Police')

full_plot_est_discrim <- rdrobust(latinos$discrimination_blacks,latinos$day_running,
                                  p=1,kernel = 'triangular')
latinos_discrim <- tibble(coef=full_plot_est_discrim$coef,
                          se=full_plot_est_discrim$se,
                          pv=full_plot_est_discrim$pv) %>%
  mutate(sample='Latino',
         outcome='Discrim')

# Asian Respondents Only
full_plot_est <- rdrobust(asians$group_favorability_the_police,asians$day_running,
                          p=1,kernel = 'triangular')
asians_police <- tibble(coef=full_plot_est$coef,
                        se=full_plot_est$se,
                        pv=full_plot_est$pv) %>%
  mutate(sample='Asian American',
         outcome='Police')

full_plot_est_discrim <- rdrobust(asians$discrimination_blacks,asians$day_running,
                                  p=1,kernel = 'triangular')
asians_discrim <- tibble(coef=full_plot_est_discrim$coef,
                         se=full_plot_est_discrim$se,
                         pv=full_plot_est_discrim$pv) %>%
  mutate(sample='Asian American',
         outcome='Discrim')

bind_rows(
  full_police, whites_police, blacks_police,latinos_police,asians_police,
  full_discrim, whites_discrim, blacks_discrim, latinos_discrim, asians_discrim
) %>%
  as.data.frame() %>%
  mutate_at(c('coef', 'se', 'pv'),
            function(x) round(x,2)) -> tableb1_df
```

```
knitr::kable(tableb1_df,
             caption = "RD Estimates",
             format = "latex",
             booktabs = T,
             digits = 2) %>%
  kableExtra::kable_styling(latex_options = "HOLD_position")
```

```
df_extension_pre <- subset(df, day_running >= -21 & day_running < 0, select = c(age, ideo5, republican,
```

```r
df_extension_post <- subset(df, day_running > 0 & day_running <= 21, select = c(age, ideo5, republican,

# Variables for table of descriptive statistics:
extension_vars <- c("age","ideo5",
              "republican", "democrat",
              "female", "num_white", "num_black", "num_latino", "num_asian")

# Create table of summary statistics

# ---- First Pre ----

df_extension_pre %>%
  dplyr::select(all_of(extension_vars))%>%
  pivot_longer(
    cols = all_of(extension_vars),
    names_to = "Variable"
  )%>%
  mutate(
    Variable = factor(Variable, levels = extension_vars)
  )%>%
  arrange(Variable)%>%
  dplyr::group_by(Variable)%>%
  dplyr::summarise(
    mean = mean(value, na.rm=T),
  ) %>%
  mutate(
    Variable = case_when(
      Variable == "age" ~ "Age",
      Variable == "ideo5" ~ "Political Ideology",
      Variable == "republican" ~ "Republicans",
      Variable == "democrat" ~ "Democrats",
      Variable == "female" ~ "Percent Female",
      Variable == "num_white" ~ "Percentage White",
      Variable == "num_black" ~ "Percentage Black",
      Variable == "num_latino" ~ "Percentage Latino",
      Variable == "num_asian" ~ "Percentage Asian",
    ),
    period = "Pre"
  ) -> sum_pre_extension_df


# ---- Now Post ----

df_extension_post %>%
  dplyr::select(all_of(extension_vars))%>%
  pivot_longer(
    cols = all_of(extension_vars),
    names_to = "Variable"
  )%>%
  mutate(
    Variable = factor(Variable, levels = extension_vars)
  )%>%
  arrange(Variable)%>%
```

```r
  dplyr::group_by(Variable)%>%
  dplyr::summarise(
    mean = mean(value, na.rm=T),
  ) %>%
  mutate(
    Variable = case_when(
      Variable == "age" ~ "Age",
      Variable == "ideo5" ~ "Political Ideology",
      Variable == "republican" ~ "Republicans",
      Variable == "democrat" ~ "Democrats",
      Variable == "female" ~ "Percent Female",
      Variable == "num_white" ~ "Percentage White",
      Variable == "num_black" ~ "Percentage Black",
      Variable == "num_latino" ~ "Percentage Latino",
      Variable == "num_asian" ~ "Percentage Asian",
    ),
    period = "Post"
  ) -> sum_post_extension_df


extension1_fig_df <- bind_rows(sum_pre_extension_df, sum_post_extension_df)

balance_fig <- extension1_fig_df %>%
  filter(Variable != "Age") %>%
ggplot(
       aes(
         y = Variable, x = mean, col = period
       )) + geom_point()




balance_fig


# ---- Regression ----


m1 <- lm(group_favorability_whites ~ ideo5 + age + female + household_income, whites)

texreg::texreg(
  list(m1),
  custom.coef.names = c("(Intercept)",
                        "Ideology", "Age",
                        "Gender (female)",
                        "Household Income"),
  custom.model.names = c("Ideology's Impact on White Favorability"),
  caption = "Extension 2 Model"

)


texreg::texreg(
```

```
  list(m1),
  custom.coef.names = c("(Intercept)",
                        "Ideology", "Age",
                        "Gender (female)",
                        "Household Income"),
  custom.model.names = c("Ideology's Impact on White Favorability"),
   ci.force = T,
  caption = "White Favorability Regression\n with Confidence Intervals"

)




#reg_fig2




# ---- White Dems ----


white_dems <- subset(whites, democrat == 1, select = c(race_ethnicity:cand_favorability_obama))

# conversion = white_dems %>%
#   dplyr::select(wave, day) %>%
#   group_by(wave) %>%
#   slice(which.min(day))


# White sample
full_plot_whitedem <- rdplot(white_dems$group_favorability_whites,white_dems$day_running,
                             hide = T,
                    p=1,kernel = 'uniform')
p1_whitedem <- returnPlot(full_plot_whitedem,yaxis='White Favorability',title='White Democrats')

fig_whitedems <- gridExtra::arrangeGrob(p1_whitedem,
                                ncol=1)

ggsave(fig_whitedems,
       width=12,
       height=15,
       filename='whitedem_figure.png')

p1_whitedem




white_libs <- subset(whites, ideo5 == 1, select = c(race_ethnicity:cand_favorability_obama))

# White sample
full_plot_whitelibs <- rdplot(white_libs$group_favorability_whites,white_libs$day_running,
                              hide = T,
```

```r
                    p=1,kernel = 'uniform')
p1_whitelibs <- returnPlot(full_plot_whitelibs,yaxis='White Favorability',title='White Very Liberal')

fig_whitelibs <- gridExtra::arrangeGrob(p1_whitelibs,
                                ncol=1)

ggsave(fig_whitelibs,
       width=12,
       height=15,
       filename='whitelibs_figure.png')

p1_whitelibs



# ---- White Moderates ----

white_mods <- subset(whites, ideo5 == 3, select = c(race_ethnicity:cand_favorability_obama))

# White sample
full_plot_whitemods <- rdplot(white_mods$group_favorability_whites,white_mods$day_running,
                              hide = T,
                    p=1,kernel = 'uniform')
p1_whitemods <- returnPlot(full_plot_whitemods,yaxis='White Favorability',title='White Moderates')

fig_whitemods <- gridExtra::arrangeGrob(p1_whitemods,
                                ncol=1)

ggsave(fig_whitemods,
       width=12,
       height=15,
       filename='whitemods_figure.png')

p1_whitemods




# ---- White Conservatives ----

white_cons <- subset(whites, ideo5 == 5, select = c(race_ethnicity:cand_favorability_obama))

# White sample
full_plot_whitecons <- rdplot(white_cons$group_favorability_whites,white_cons$day_running,
                              hide = T,
                    p=1,kernel = 'uniform')
p1_whitecons <- returnPlot(full_plot_whitecons,yaxis='White Favorability',title='White Very Conservativ

fig_whitecons <- gridExtra::arrangeGrob(p1_whitecons,
                                ncol=1)

ggsave(fig_whitecons,
       width=12,
```

```
       height=15,
       filename='whitecons_figure.png')

p1_whitecons
```