Does violence within a non-violent social movement help or hurt the movement?

Evidence from the 2020 BlackLivesMatter Protests

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Keywords

Collective action, nonviolent protest, violence, prejudice

Abstract

The murder of George Floyd ignited one of the largest mass mobilizations in US history, including both non-violent and violent BlackLivesMatter protests in the summer of 2020. Many have since asked: did the violence within the largely non-violent movement help or hurt its goals? To answer this question, we used real-world data (ACLED, 2020) about the location of all BlackLivesMatter protests during the summer of 2020 to identify US counties that featured no protests, only nonviolent protests, or both nonviolent and violent protests. We then combined this data with survey data ($N = 494$, Study 1), data from the Congressional Cooperative Election Study ($N = 43,924$, Study 2A), and data from Project Implicit ($N = 180,480$, Study 2B), in order to examine how exposure (i.e. living in a county with) different types of protest affected both support for the key policy goals of the movement and prejudice towards Black Americans. We found that the 2020 BLM protests had no impact on prejudice among either liberals or conservatives. However, they were, even when violent, able to increase support for BlackLivesMatter's key policy goals among conservatives living in relatively liberal areas. As such, this research suggests that violent, disruptive actions within a broader non-violent movement may affect those likely to be resistant to the movement. We connect these findings to the notion of disruptive action, which explains why these effects do not materialize in reducing prejudice, but in generating support for important policy goals of the movement.

During the summer of 2020, the death of George Floyd at the hands of the police set off one of the largest mass mobilizations in US history, as hundreds of thousands of people protested against systematic racism under the banner of Black Lives Matter (BLM). While this movement was overwhelmingly nonviolent¹, a small minority of violent protests garnered significant attention and set off discussions both within and outside of the movement about the effectiveness of protests, particularly of violent protests within the larger (nonviolent) movement. This raises a key question at the core of the current paper: Does violent protest *hurt* or *help* the broader movement in terms of advancing its goals? Both public discourse²⁻⁴ and the current literature⁵⁻¹¹ offer mixed answers to this question. We aimed to shed additional light on this debate by combining survey data with a publicly available dataset of all BLM protest events in the summer of 2020. Thus, we expand on the literature in two key ways: First, by examining the effect of violence within in a larger nonviolent movement for equality by a minority group. And second, by examining effects on support for the movement's key policy goals along with prejudice towards the broader group.

Effectiveness of Protests in Terms of Policy Support or Prejudice?

The question of whether violence aids or hinders disadvantaged minority groups in their struggle for equality is one that has long been central to psychology^{11,12}, sociology^{13,14}, and political science^{5,6,15,16}. As the US has recently experienced a surge in protests by minority groups calling for greater equality, most notably the Black Lives Matter movement, many scholars have continued to examine this question specifically in the context of this movement¹⁷⁻¹⁹. The answer to the question of whether violence makes protests more or less effective, likely depends largely on what outcome is used to evaluate effectiveness. However, so far, studies that examined effects of BLM protests have focused only on one outcome: Whites' prejudice and negative attitudes towards African Americans. Perhaps as a result, these studies found that any effects of protests' are either very small in size^{18,19} or limited to those already sympathetic to the movement (e.g., liberals¹⁷). Little to no effects were found on

conservatives' prejudice, who tend to be more resistant to the goals of BLM^{18,19}. However, we suggest that this focus on prejudice and negative attitudes reflects an (at least implicit) assumption that in order to be effective, protests for racial equality need to succeed in reducing prejudice, or put differently, in making the advantaged like the disadvantaged more.²⁰

Drawing from social psychological understandings of collective action and prejudice reduction, we question this assumption. Research has shown that reducing prejudice relies often on positive contact with the relevant outgroup or other interventions focused on social harmony and commonality^{20,21}, whereas social protests are fundamentally an expression of social conflict that emphasize the differences (namely inequalities that exist) between the two groups²². This is why some argue that prejudice reduction and collective action rely on fundamentally different psychological processes²⁰. Thus, we may not expect protests to be very effective in prejudice reduction, but this may not mean that protests are not effective in other ways.

Based on sociological and social-psychological theorizing and research^{13,23–25}, disruptive protests may be able to generate support for making the policy changes demanded by the movement. Indeed, some theories on large scale mass protests argue that they derive their power from the ability to disrupt normally cooperative relations and the broader social order. Such disruption can thus incentivize even those who may not agree with the movement goals to make specific policy concessions. As such, a key consequence of the occurrence of protests may be their effect on the public's support for specific policies, rather than prejudice reduction toward the group as a whole.

To fully understand the impact of BLM protests and the potential role of violence within them, we believe it is important to look at their effect on support for their key policy goals (e.g., reducing and redirecting funding for the police to other social services), in addition to prejudice towards African Americans. In other words, while often any potentially

relevant outcome measure has been used as a measure of effectiveness, we will measure two outcomes in the current work: support for policies that advance equality, and prejudice. This enables us to look beyond prejudice and examine whether the BLM protests affected public opinion about specific policies.

How Effective is Violence?

This expansion of the focus of the outcomes of protest from reducing prejudice to increasing public support for the policy goals of the movement is particularly relevant to the question of the effectiveness of violence, as many of the studies that have shown violent protests can be effective have focused on policy support or related outcomes^{5-8,26}. While much contemporary scholarship has emphasized the effectiveness of nonviolence over violence, as people identify more with nonviolent protesters¹⁰, and thus nonviolent movements are more likely to mobilize large numbers of their sympathizers⁹, the literature is still divided. Moreover, recent work that reanalyzed some of the key data in this scholarship found that the link between nonviolence and movement success disappeared for minority groups¹⁶. In addition, there are notable examples that indicate that violence can increase support for a minority group's policy goals and help to achieve specific policy gains⁵⁻⁸. Of particular relevance is literature on the positive effects of a small amount of violence as a part of a larger nonviolent movement (sometimes known as a *radical flank*) on policy related outcomes. For example, Tompkins (2015) found that the presence of a violent radical flank was linked to short-term progress in achieving the movement's goals and winning concessions from the government. However, this work was based on a large dataset of many different movements and did not specifically consider protests by minority groups.

Importantly, such potentially positive effects of violent protests within the larger (nonviolent) movement may apply particularly to those resistant to the protest's goals. This is because (a) those who are already sympathetic to the movement are likely already high on support for its policy goals, and (b) the logic of disruptive action is that it produces pressure

leading to concessions among those resistant. Indeed, Gould and Klor (2010) found that exposure to moderate (but not high) levels of Palestinian violence increased support for concessions, particularly among right-wing Israelis⁷. Moreover, Shuman et al. (2020) found that disruptive protest was particularly effective for those resistant, as long as the protestors were perceived as having constructive intentions (thus producing “constructive disruption”)²⁵. Indeed, the larger nonviolent movement such as BLM may help balance the disruption produced by the violence with more positive perceptions of the protesting group, as well as provide a more moderate alternative with which to negotiate with and make concessions to²⁷. Thus, we suggest that violent protests within the larger (nonviolent) BLM movement may increase support for specific policies among those resistant to the movement goals (without necessarily reducing prejudice).

The Current Research

The aim of the current research was to examine the psychological impact of BLM protests that occurred in the wake of the murder of George Floyd and the role of violence within them on both (a) increasing support for key policy demands of the movement and (b) reducing prejudice. While these and other outcome measures (e.g. prejudice, support for the movement, support for policy changes, etc.) have often been used interchangeably as indicators of effectiveness based on the implicit assumption that they would move together, we argue that different effects of protest may be observed on different outcomes. Namely that while protests are unlikely to reduce prejudice, they may increase public support for the movement’s policy goals, and that some amount of violence may even increase this effect.

Furthermore, based on work showing that disruptive protests can be particularly relevant for those more resistant to the movement, we expect to find these effects mainly among conservatives, who are generally resistant to BLM¹⁷. Thus, we hypothesize that for conservatives, violence occurring alongside nonviolent protests implies greater disruption, which should increase support for the movement’s policy goals (but not reduce prejudice).

Against this backdrop, we do not expect to find clear effects of such protests on liberals. This is because we assume liberals to already be lower in prejudice towards African Americans²⁸, and generally already supportive of the cause¹⁷, and hence likely high in support for the movement's policy goals. As a result, both conceptually and statistically they have less room to move on our dependent variables. We therefore focus our results and discussion on conservatives as this is where we anticipate effects, but we include and present all participants in our analyses.

Overview of Methods, Studies, and Data Analysis Strategy

Data

In all studies, we combined survey data with a publicly available dataset (see ACLED 2020) of all BLM protest events in the summer of 2020 based on location. This dataset included an entry for each protest and variables describing that protest including location (what city it occurred in) and whether it was nonviolent or violent as coded by ACLED. Peaceful protests were coded as when “demonstrators are engaged in a protest while not engaging in violence or other forms of rioting behaviour” and violent protests were coded as “violent events where demonstrators or mobs engage in disruptive acts, including but not limited to rock throwing, property destruction, etc. They may target other individuals, property, businesses, other rioting groups” (for more detail see supplementary information and the ACLED codebook²⁹).

By combining this data with survey data where participants reported the zip code or county in which they lived, we were able to characterize the type of protests that occurred in the area where participants lived. Study 1 used survey data collected by the researchers during the George Floyd protests as an initial test of our hypotheses. However, given this study's small sample and our use of location-based data we felt it was important to replicate these results using large-scale nationally representative datasets. Therefore, we sought out large publicly available datasets that measured support for the BLM movement's policy goals, prejudice

towards black Americans, or both. While we were not able to find a single dataset that measured both these variables, we found two datasets that included at least one of our key variables. First, the 2020 version of the Cooperative Congressional Election Survey (CCES) measured support for the policy goals of the BLM movement³⁰, and was conducted between September 29 and November 2nd thus allowing us to measure the impact of the protest movement. In addition, Project Implicit³¹ posted their data collected for 2020 which included a feeling thermometer measure of prejudice. Both datasets also included location data per participant, allowing us to examine the effect of exposure to different types of protests on our dependent variables. Thus, we tested our hypotheses about policy support (Study 2A) and prejudice (Study 2B) in these two datasets.

Data Analysis Strategy

We adopted a quasi-experimental design and compared three groups: people living in areas featuring a) no protest events, b) only nonviolent protest events, and c) both nonviolent and violent protest events. As there were only 5 counties in the entire country that experienced *only* violent protests, and we had very few participants from these counties (Study 1 $n = 0$, Study 2A $n = 41$, Study 2B $n = 79$), which did not allow to draw reasonable inferences about these participants and hence excluded them from analyses (we present analyses including them in the supplementary information). We use categorical groups rather than a continuous measure of the amount of violence, as this variable was extremely skewed (see supplementary information) and there was no clear place for no protests on such a continuous measure. However we do present analyses with a continuous measure of violence (without the areas with no protest) in supplementary information.

Given the quasi-experimental design which lacked random assignment, we adopted a two-pronged approach to estimate the causal effects of protest type. First, we used regression analyses and controlled for potential confounding variables. Second, we used propensity score matching to better estimate the causal effect where possible. Propensity score matching which

balances covariates across treatment groups through creating matched pairs or subgroups, rather than controlling in regression, is generally considered the gold standard for estimating causal effects from observational data^{32,33} (for a detailed discussion of the advantages of propensity scores versus regression models with covariates see Schafer and Kang, 2008). One meaningful strength is that propensity scores are particularly useful when the distribution of covariates across the treatment groups is very dissimilar, as is the case in our data (see supplementary figures 3-29, 34-52, 61-78). However, propensity score matching requires additional assumptions to be met (e.g., adequate sample size to conduct matching, region of common support, etc.), which limits its applicability. As a result of lack of common support and sample size issues (for more details see supplementary information), we could only use propensity score matching to estimate the causal effect of the nonviolent only protests vs. violent and nonviolent protests comparison in studies 2A and 2B.

For both approaches, the selection of appropriate controls (i.e., potential confounds) is important. However, the variables measured in each dataset varied: some studies included additional variables that could affect responses to the George Floyd protests (e.g., exposure to COVID-19, perceptions of the BLM movement, etc.) where others only had demographics. Therefore, for the sake of consistency we present analyses including individual level and geographic level demographics in the main text of the article and analyses that included additional relevant covariates in the supplementary information.

Study 1: Method

Participants and procedure

Participants were 567 white Americans who completed a survey on MTurk. Sixteen participants were excluded because they failed a question designed to ensure they were not bots, 21 participants were excluded because they failed both attention check measures (these exclusion criteria were pre-registered see https://osf.io/pz9c2/?view_only=6d86d237ece548b9818869b55852d7e9). Additionally

because we had a small percent of missing cases, with excluded participants with missing data on the variables in our model ($n = 27$) on a listwise basis³⁹. And an additional 9 participants were excluded because they provided invalid zipcodes – preventing us from conducting the location matching. This left a final sample of 494 (291 male, 201 female, 2 other, $M_{age} = 39.5$, 47% conservative, 15% moderate, 38% liberal).

Participants were invited to take part in a study on current events. After completing the informed consent form, participants were told, “Following the killing of George Floyd by a Minneapolis police officer, crowds have filled the streets in cities across the U.S., protesting against police brutality and systemic racism. We are interested in your general perceptions of and reactions to these protests.” They then completed a survey including following measures, we display the measures here organized according to their role in the model, however they are displayed in the order viewed by the participants in the supplementary information¹:

Measures

Independent Variables

Protest Type in Participants Location. Participants were asked to report the zip-codes of the area where they lived and this was then cross-referenced with a publicly available dataset published by the Armed Conflict Location & Event Data (ACLED) project, which included a list of all the protest events that happened during the summer of 2020, with variables coding location (on the town/city level), organizations protesting, violence/nonviolence, date, and a news source reference (see <https://acleddata.com/2020/08/31/us-crisis-monitor-releases-full-data-for-summer-2020/>). We first cleaned the dataset so that it only included protests related to George Floyd/Black Lives Matter. Then based on this data we calculated the following variables per city: number of

¹ This project was part of a larger project designed to test a number of research questions related to the George Floyd protests. For a full list of measures and a pre-registration of the various research questions included in this survey see https://osf.io/pz9c2/?view_only=6d86d237ece548b9818869b55852d7e9. We note that these hypotheses were not pre-registered as at the time the study was conducted we did not know that we would have access to such detailed data on the location and type of real-world protests.

protest events, number of nonviolent protest events, and number of violent protest events, and used it to categorize cities as experiencing no protests, nonviolent protests, or both nonviolent and violent protests. We then linked this data to participants by connecting participants with the relevant city using participant provided zip-codes.

Political Ideology was measured with one item, “Please describe your political ideology using the following scale” with a scale of 1 – very conservative, 2- conservative, 3 – somewhat conservative, 4 – moderate, 5 – somewhat liberal, 6 – liberal, 7 – very liberal.

Outcome Variables

Support for the Movements Policy Goals. Five items measured participants’ support for policies advocated for by the protesters based on statements by protestors, movement leaders, and policy outlines (e.g. Campaign Zero), “There should be community oversight of police (i.e., local non-police government committees should decide when there has been police misconduct and determine the consequences)”, “Funding to the police should be reduced”, Funds that used to be directed to the police should be used to invest in social services (e.g. for mental health, domestic violence and homelessness, etc.) for disadvantaged communities”, “There should be large scale criminal justice reform to address racial inequalities in the justice system”, and “The government needs to invest more in closing racial gaps in education, employment, housing, and other areas” ($\alpha = .84$).

Prejudice. We measured prejudice with a simple feeling thermometer which asked participants to “Please rate your feelings towards people in the following groups from 0 (cold) to 100 (warm)” the list of groups included white and black Americans. We used participants ratings of black Americans (while controlling for their ratings of white Americans) as a measure of prejudice. The measure was reverse scored so that higher scores reflected more prejudice (rather than warmer feelings).

Control Variables

Person-Level Factors: Demographic Questionnaire. Participants completed a brief demographic questionnaire. Items included gender, age, education, employment, political ideology.

Area-Level Control Variables. Given that the demographics of a certain area may affect the number of protests, and the reactions of people who live there to such protests, we wanted to control for area level-demographics in addition to the individual demographics of our participants. Therefore, we downloaded demographic data from the 2019 American Communities Survey (ACS-19) using the *tidycensus* package in R. We used this variable to calculate the total population, percent female, percent white, percent African American, percent Hispanic, percent Asian American, percent other race, median age, and median income for the zip code of each participant. In addition, we obtained election data from the Harvard Dataverse (MIT Election Data and Science Lab, 2018), and used this to determine the vote share for Trump in each zip code where our participants lived.

Study 1 Results

Data and code for analyses can be found at https://osf.io/pz9c2/?view_only=6d86d237ece548b9818869b55852d7e9. We first examined the differences on all covariates between areas featuring a) no protest events ($n = 188$), b) only nonviolent protest events ($n = 162$), and c) both nonviolent and violent protest events, ($n = 144$), for details see supplementary information. To test our hypotheses, we examined the interactions between this categorical variable and political ideology on support for the movements policy goals and on prejudice. Since the independent variable was categorical it was coded into two dummy variables with the group who lived in areas with violence as the reference category.

Effects on Support for Policies

We ran a linear regression testing the interaction between type of protest and political ideology on support for policies, controlling for the variables described above. There was no

interaction between D1 (violent protests vs. no protest) and political ideology, however the interaction between D2 (violent protests vs. nonviolent protest only) and political ideology was marginally significant (see Table 1). Simple slopes analysis revealed that among conservatives, support for the movement's policy goals was significantly stronger where violent protests were present (alongside nonviolent protests) compared to where there were only nonviolent protests ($b = -0.57$, $SE = .22$, $t = -2.61$, $p = .01$, see Figure 1). Among liberals, there were no such difference ($p = .86$). Overall, the simple slope results are in line with our hypotheses, but we treat the overall pattern as suggestive for now, as the overall interaction effect was marginally significant. Although, we note that when additional relevant control variables (which were only measured in this study) are added to the model, the interaction effect is statistically significant (see supplementary information).

Figure 1. Interaction Between Protest Type and Ideology on Support for Policy Goals

Note. Error bars represent 95% confidence intervals.

No Effects on Prejudice

We ran the same model predicting prejudice as measured by the feeling thermometer towards black Americans. There were no significant interactions between either D1 (violent protests vs. no protest) or D2 (violent protests vs. nonviolent protest only) and political ideology (see Table S2), which aligned with our hypothesis that protests would be less effective at reducing prejudice. This held true regardless of whether we used the feeling thermometer towards black Americans as the outcome or difference scores between feeling thermometer ratings between black and white Americans, and regardless of whether a categorical or continuous measure of violent protest was used (for analysis details see supplementary information).

Study 1 Discussion

Study 1 found that conservatives who lived in areas where both violent and nonviolent protests occurred were more supportive of the movement's policy goals than those who lived in areas where only nonviolent protest occurred. There was no effect of protest type on conservatives or liberals' prejudice towards African Americans. This is in line with our reasoning that the disruption produced by some level of violence can pressure conservatives to be more supportive of the movement's policy goals, rather than reducing their prejudice.

An important limitation of the study is that almost all of the counties that experienced both nonviolent and violent protests were generally liberal counties (i.e. with low Trump voting; see Figure S12). Although we statistically controlled for this variable, it could present a boundary condition to the interpretation of the findings, especially given that a previous study³⁵ of exposure to disruptive civil rights protests using a similar methodology found that effects were limited to whites who lived in liberal areas. So perhaps disruptive protests that include violence only increase policy support among conservatives who live in relatively liberal areas. There are a number of reasons for why this might be the case: First, according to the logic of disruptive action^{23,24}, policy concessions reflect a way of pacifying the protestors

and ending the disruption. This may only seem a feasible option in liberal areas where there is some chance of concessions being made to the protestors. Alternatively, in areas where conservatives are in the majority, conservatives may feel less pressure to make concessions to minority group protests, even if these protests are more extreme, as they might feel less threat or pressure from the disruption. Finally, it might be that conservatives living in more liberal areas are more sympathetic to begin with, perhaps because they are less prejudiced in general. We consider these possibilities in the following study by 1) examining the local political context (i.e. vote share for Trump in 2016) as an additional moderator (in Studies 2A and 2B), and 2) comparing levels of prejudice among conservatives living in different areas (in Study 2B).

Study 2A: Method

Participants and procedure

The 2020 CES involved 60 teams, yielding a Common Content sample of 61,000 participants. Each research team purchased a 1000-person national sample survey, conducted by YouGov of Redwood City, CA. The questionnaire was in the field from September 29 to November 2. For each survey of 1,000 persons, half of the questionnaire was developed and controlled entirely by each individual research team, and half of the questionnaire is devoted to Common Content. The Common Content consists of the questions common to all team modules and has a sample size equal to the total sample size of all team modules combined. Because we were interested in protests effects on the advantaged group, we selected from this data set to include only white participants, this left a final sample of 43,924 (43.8% men, 56.1% women, $M_{age}= 51.3$, 31.3% conservative, 36.3% moderate/don't know, 32.4% liberal).

Independent Variables

Protest Type in Participants Location. We used the same ACLED dataset, however in this dataset participants did not report their zip-codes but rather only their county FIPS

(Federal Information Processing System) codes. So, we recoded the ACLED dataset to be at the county level, all analyses are now performed at the county level².

Political Ideology was measured with one item, “In general, how would you describe your own political viewpoint?” with a scale of 1 – very liberal, 2- liberal, 3 – moderate, 4 – conservative, 5 – very conservative, 6 – Not sure. Rather, than exclude those who answered not sure, we combined them with the category of moderate. 31.56% were liberal (1-2), 34.67% were moderate, and 33.77% were conservative (4-5). In all analyses we used the continuous measure and simply evaluated the simple slopes at 2 (liberal) and 4 (conservative).

Political Context was operationalized as the vote share for Trump in 2016 per county, data was collected from the Harvard Dataverse (MIT Election Data and Science Lab, 2018).

Outcome Variable

Support for the Movements Policy Goals. Eight items measured participants’ support for policies advocated for by the movement, e.g., “Eliminate mandatory minimum sentences for non-violent drug offenders.”, “Decrease the number of police on the street by 10 percent, and increase funding for other public services”, “Ban the use of choke holds by police”. Participants were asked to indicate whether or not they supported each proposal on a binary scale. Thus, we calculated total number of the movements policy goals that they supported as a measure of movement policy support.

Control Variables

Person-Level Demographics. Participants reported both their **gender** and **age**. **Education** was measured with the item “What is the highest level of education you have completed?” on the scale 1 - Did not graduate from high school, 2- High school graduate, 3 - Some college, but no degree (yet), 4 - 2-year college degree, 5 - 4-year college degree, 6- Postgraduate degree (MA, MBA, MD, JD, PhD, etc.). **Employment** was measured with one

² If we go back to the pilot study and reanalyze it at the county level all the patterns remain the same however the interactions were not significant. This is likely due to increased noise as counties are less specific locations than zip codes.

item with many response options (see supplementary information) for ease of analysis it was recoded into a variable that indicated if a person was unemployed.

Area-Level Control Variables. We controlled for the exact same variables but just at the county level rather than the zipcode (ZCTA) level.

Study 2A Results

Data and code for analyses can be found at https://osf.io/pz9c2/?view_only=6d86d237ece548b9818869b55852d7e9. We followed the same analysis plan as in Study 1. Specifically, we compared three groups: people living in counties where there were a) no protest events ($n = 5401$), b) only nonviolent protest events ($n = 21270$), and c) both nonviolent and violent protest events, ($n = 17253$). We examined the interactions between this categorical variable and political ideology, and county 2016 vote share for Trump, on support for the movements policy goals.

Regression Analysis

To test our hypothesis, we ran a linear mixed model to account for the nesting of participants within counties, and tested the interaction between type of protest, political ideology, and political context, controlling for all personal and county demographics (for models with additional controls see supplementary information). The interaction between D1 (violent protests vs. no protest), political ideology, and Trump vote share was significant, and the interaction between D2 (violent protests vs. nonviolent protest only), political ideology, and Trump vote share was significant as well (see Table 4). Simple slopes analysis revealed that among conservatives, policy support was significantly higher where violent and nonviolent protests were present compared to where there were only nonviolent protests ($b = -0.14$, $SE = .04$, $t = -3.30$, $p < .01$), and was also higher compared to where there were no protests ($b = -0.30$, $SE = .10$, $t = -3.06$, $p < .01$, see Figure 2), but only in relatively liberal areas (low Trump vote share counties). When Trump vote share was high, policy support was significantly lower where violent and nonviolent protests were present compared to where

there were only nonviolent protests ($b = 0.14$, $SE = .06$, $t = 2.53$, $p = .01$), but not compared to where there were no protests ($b = 0.08$, $SE = .06$, $t = 1.23$, $p = .22$). Among liberals, there were no differences on policy support between nonviolent and violent protest (p 's $> .06$). These findings replicate the findings of Study 1. Moreover, the large sample size of Study 2A enabled us to use propensity score analysis, which can reduce uncertainty about the presumed causality of the effect.

Figure 2. Interaction Between Protest Type and Ideology on Support for Policy Goals

Note. Error bars represent 95% confidence intervals.

Propensity Score Analysis

We present detailed information of how we conducted the propensity score matching in the supplementary information. Given that some covariates were not perfectly matched after matching (SMDs greater than .2), we included these confounders as covariates in the weighted outcome multi-level regression model to further control for them. However, results remain the same whether these or no covariates are included in the final model (see supplementary information). Results from the outcome model for estimating the effects of a mix of violent and nonviolent protests (vs. only nonviolent protests) replicated the three-way interaction found in the regression analyses (see Table 3). Similar to the earlier analyses, the

presence of violent and nonviolent protests increased support for policy concessions relative to only nonviolent protests among conservatives in areas where Trump received low support ($b = 0.18$, $SE = .04$, $t = 3.95$, $p < .01$, see Figure 7), and reduced support in areas where Trump received high support ($b = -0.15$, $SE = .07$, $t = -2.32$, $p = .02$). There were no effects of violent protests on liberals (p 's $> .11$).

Figure 3. Interaction Between Protest Type and Ideology on Support for Policy Goals Using Balanced Sample

Note. Error bars represent 95% confidence intervals.

In sum, these results supported our hypotheses. Exposure to a combination of both nonviolent and violent protests increased conservatives' support for policy concessions to the BLM movement compared to exposure to only nonviolent protests or no protests at all, but only in relatively liberal areas. Thus, this study also reveals an important boundary condition of this effect: that it only occurs in generally liberal areas. Rather in highly conservative areas, there is evidence that violence led to a decrease in support relative to purely nonviolent protests. A potential explanation for this is that conservatives in generally liberal areas are simply less prejudiced, and thus more open to the goals of the BLM movement. We examine this possibility and test our hypotheses regarding the effects of different types of protest on prejudice in the next study.

Study 2B: Method

Participants were visitors to the Project Implicit website (<https://implicit.harvard.edu>) who chose to complete the “Race IAT” between August 29, 2020 (after the last protest in the ACLED Dataset) and December 31, 2020. We didn’t include participants who completed the IAT during the protests as the type of protests that occurred on in the county where they lived was changing on a day to day basis as the protests unfolded. Also we didn’t have data from this period in the other datasets so we wanted to make this comparable to that data.

Participants completed the IAT, explicit attitude measures, as well as a few demographic questions. Only White participants who lived in the United States and who had location data were included in the final sample, which included 180, 480 participants (34% men, 65% women 1% other, $M_{age} = 34.5$, 24.1% conservative, 18.1% moderate, 57.8% liberal)

Independent Variables

For **Protest Type in Participants Location**, we used the same ACLED dataset, however in the project implicit dataset, participants location was also coded according to their county FIPS codes, so all protest exposure type was determined at the county level.

Political Ideology was measured with one item, “Please describe your political ideology using the following scale” with a scale of 1 – very conservative, 2- conservative, 3 – somewhat conservative, 4 – moderate, 5 – somewhat liberal, 6 – liberal, 7 – very liberal.

Political Context was operationalized as the vote share for Trump in 2016, data was collected from the Harvard Dataverse (MIT Election Data and Science Lab, 2018).

Outcome Variables

Prejudice. Prejudice was measured with a simple feeling thermometer which asked participants to “Please rate your feelings towards people in the following groups from 0 (very cold) to 10 (very warm)” the list of groups included white and black Americans. We used participants ratings of black Americans (while controlling for their ratings of white

Americans) as a measure of prejudice. We reversed scored this item so that higher scores reflected more prejudice.

Control Variables

Person-Level Contextual Factors. In addition, we aimed to control for all potentially relevant variables that might explain the differences between the groups, since participants were not randomly assigned, we also tried to control for as similar variables as possible to the prior studies, so difference in control variables could not explain differences in results. Specifically, participants reported both their **gender** and **age**. **Education** was measured with the item “What is the highest level of education you have completed?” on a scale ranging between elementary school to PhD. **Employment** was measured with one item with many response options (see supplementary information) for ease of analysis it was recoded into a variable that indicated if a person was unemployed. Since these data were collected over a long period following the wave of the protests, we also controlled for time in days.

Area-Level Control Variables. We controlled for the exact same county level variables as Study 2A.

Study 2B Results

All data and code for analyses can be found at https://osf.io/pz9c2/?view_only=6d86d237ece548b9818869b55852d7e9. We followed the same analysis plan as in the previous study: we compared three groups: people living in counties where there were a) no protest events ($n = 12152$), b) only nonviolent protest events ($n = 82842$), and c) both nonviolent and violent protest events, ($n = 85486$).

Regression analysis

We ran a linear mixed model to account for the nesting of participants within counties, and tested the interaction between type of protest, political ideology, and political context, controlling for all personal and county demographics (for models with additional controls see supplementary information). Because we hypothesized that if any type of protest would

reduce prejudice it would be nonviolent protest, nonviolent protest was coded as the reference category in the dummy variables. There was a significant interaction between D1 (nonviolent protests vs. no protest), political ideology, and Trump vote share, and between D2 (violent protests vs. nonviolent protest only), political ideology, and Trump vote share (see Table 4). Simple slopes analysis revealed that among conservatives, prejudice was significantly lower where nonviolent protests were present compared to where there were no protests ($b = 0.35$, $SE = .07$, $t = 4.98$, $p < .01$), and was also lower compared to where there were violent and nonviolent protests ($b = 0.10$, $SE = .03$, $t = 3.96$, $p < .01$, see Figure 4, but only in relatively liberal areas (low Trump vote share counties). Where Trump vote share was high, there was no effect of protest type on conservatives' levels of prejudice. Among liberals, there was no effect of type of protest on prejudice (p 's $> .36$).

Figure 4. Interaction Between Protest Type and Ideology on Prejudice in Study 2B

Note. Error bars represent 95% confidence intervals.

Propensity Score Analysis

We present detailed information of how we conducted the propensity score matching in the supplementary information. Given that some covariates were not perfectly matched after matching (SMDs greater than .2), we included these confounders as covariates in the

weighted outcome regression model to further control for them. However, results remain the same whether these or no covariates are included in the final model (see supplementary information). Importantly, and unlike the results of the regression, results from the outcome model estimating the effects of a mix of violent and nonviolent protests on prejudice did *not* find any effects of protest type or interactions (see Table 5). Given the enhanced ability of this approach to estimate the causal effect, this finding suggests that the small difference observed in the regression analyses may not reflect a true causal effect, and hence we do not interpret it as such. Thus, in sum the only robust effect was that conservatives living in liberal areas with no protests were higher on prejudice than conservatives living in all other types of areas.

General Discussion

Did violent protests within the larger (nonviolent) movement *hurt* or *help* the BLM movement during the 2020 George Floyd protests? One answer to this question is that it seemed to have helped by increasing conservatives' (in liberal areas) support for the policies advocated for by the BLM movement. Another answer, however, is that it did not help -- as there was no evidence of prejudice reduction, and some evidence of a decrease in policy support for conservatives living in conservative areas. In this sense, our findings offer a nuanced view on the general tendency in the literature to depict violent protest as an ineffective, if not problematic, strategy for social movements^{9,10,15}, and raises the question of whether violent protests within a larger (nonviolent) movement can sometimes help movements to successfully earn concessions for specific policy goals. Most of all, our findings --- uniquely combining subjective and objective data --- suggest that we need to better understand not only *whether*, but more importantly *when* and *how* violent protests might positively (or negatively) influence those who are not sympathizers.

More specifically, we found across three studies that violent protests within the larger (nonviolent) movement increased conservatives' support for policy concessions to the BLM movement (compared to exposure to only nonviolent protests or no protests), but only in

relatively liberal areas. These findings fit nicely with sociological and psychological work^{7,8,23} suggesting that the disruption produced by violent protest against the backdrop of nonviolent protests can create pressure for those resistant (in this case conservatives) to support policy concessions to the movement's goals. Importantly, these findings offer a more contextualized view on the question of whether violence can be an effective social movement tactic, suggesting that it is pivotal to take into account both local context and level of exposure to protests. Indeed, conservatives' policy concessions can be viewed as a response to end the disruption caused by the protests in liberal areas, where there is some chance to make such concessions and appease the protestors. Yet in areas where conservatives are in the majority, they may feel less threatened by the protests, or that they have other means to end the disruption. Future research should further study these psychological mechanisms that can explain when and why conservatives are willing to make concessions (see Shuman et al., 2020). Indeed, we want to emphasize that our findings should first be better understood scientifically before using them for practical applications.

We note that our findings regarding policy support acquire even more relevance given that we did not find similar effects of protest types on prejudice. This suggests that when we think or talk about the "effectiveness" or "effects" of a protest, it is absolutely pivotal to specify on which outcome variable(s) we are expecting to find such effects, and why. We interpret our findings as suggesting that these two different outcomes reflect different ways to think about how social movements can have psychological effects on public opinion. Reducing prejudice, although important in its own right, may be less likely to occur through conflict- or disruption-based actions, and perhaps more likely to occur through well-designed social harmony interventions (such as intergroup contact) than through forms of social conflict^{20,36}.

This diversity in effects also suggests a potential framework for making sense of potentially conflicting findings in the literature regarding the effectiveness of nonviolence vs.

violence. Many of the studies showing that nonviolence is more effective focus on more attitudinal outcomes such as identification with the protestors, attitudinal support, and mobilization in support of the movement.^{10,37,38} Whereas, many of the studies that have found positive effects of violence have used more policy related outcomes^{5-8,25}. Thus, it may be that different types of protest are effective for different goals. Future research should explore these differential effects and how they interact to determine a movement's overall impact. Such general considerations about what goal to target through social protests may of course be of prime importance for social movement organizers and practitioners. We need more research that can examine when and how which goals might be realistically achieved through which type of protest.

The studies reported have a number of strengths and limitations. As far as we know, this is the first set of studies to combine subjective psychological data and objective data with objective data about the location and type of protests to examine the effects of the BLM movement. While we took great efforts to estimate causality, using both regression and propensity score matching, our data was observational and thus we cannot be completely confident that these findings are causal in nature. Future research might try to replicate these findings in more controlled lab settings where participants are randomly assigned to read news articles describing different types of protests and their reactions measured. In addition, although our results point to the important role of local political context places in moderating the effects of disruptive collective action (particularly violence), all these results came from the same protest movement and political context in the US. Thus, research should examine these processes in other movement and national contexts.

This research revealed that the BlackLivesMatter movement can have positive effects even on majority group members are more resistant to their goals. However, following the logic of disruptive action, these positive effects are not in reducing prejudice towards the minority group, but rather in generating support for important policy goals of the movement.

In this context, it seems that some amount of violence mixed with a largely nonviolent protest movement can in some cases increase the effectiveness of the protests of minority groups in their struggle for equality, by increasing the disruption and thus pressure for policy concessions.

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Table 1. Study 1 Model Predicting Policy Support

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.22	4.99 – 5.45	<0.001
Gender D1 (Men vs. Women)	-0.19	-0.42 – 0.04	0.107
Gender D2 (Men vs. Other)	0.96	-0.87 – 2.79	0.303
Participant Age	-0.14	-0.25 – -0.02	0.018
Participant Education	0.21	0.09 – 0.33	0.001
Participant Employment	-0.31	-0.79 – 0.17	0.207
ZCTA Population	-0.06	-0.20 – 0.08	0.427
ZCTA Median Age	-0.05	-0.19 – 0.09	0.466
ZCTA Median Income	-0.09	-0.25 – 0.06	0.224
ZCTA Percent Female	0.07	-0.04 – 0.19	0.227
ZCTA Percent White	0.14	-0.28 – 0.55	0.515
ZCTA Percent Black	0.18	-0.15 – 0.51	0.285
ZCTA Percent Asian American	0.14	-0.11 – 0.38	0.283
ZCTA Percent Hispanic	0.04	-0.15 – 0.22	0.714
ZCTA Percent Race Other	0.04	-0.18 – 0.25	0.730
ZCTA Trump Vote Share	-0.02	-0.18 – 0.13	0.763
Protest Type D1: Violent vs. No Protests	-0.11	-0.44 – 0.21	0.486
Protest Type D2: Violent vs. Nonviolent Only	-0.32	-0.63 – -0.01	0.044
Political Ideology	0.56	0.35 – 0.77	<0.001
Protest Type D1 X Political Ideology	0.07	-0.22 – 0.35	0.649
Protest Type D2 X Political Ideology	0.26	-0.02 – 0.55	0.072
Observations	494		
R ² / R ² adjusted	0.278 / 0.247		

Table 2. Study 2A Model Predicting Policy Support

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.34	5.30 – 5.39	<0.001
County Population	-0.01	-0.05 – 0.03	0.586
County Median Age	-0.04	-0.06 – -0.02	<0.001
County Median Income	-0.01	-0.03 – 0.01	0.402
County Percent Female	-0.02	-0.04 – -0.01	0.014
County Percent White	-0.06	-0.15 – 0.03	0.206
County Percent Black	-0.09	-0.15 – -0.02	0.012
County Percent Asian American	-0.03	-0.08 – 0.02	0.215
County Percent Race Other	-0.07	-0.12 – -0.03	0.001
County Percent Hispanic	-0.01	-0.04 – 0.02	0.598
Gender	-0.00	-0.02 – 0.01	0.835
Age	-0.21	-0.23 – -0.19	<0.001
Education	0.15	0.13 – 0.17	<0.001
Employment	-0.10	-0.12 – -0.08	<0.001
Protest Type D1 (Violent and Nonviolent Protests vs. No Protests)	-0.11	-0.21 – -0.00	0.043
Protest Type D2 (Violent and Nonviolent Protests vs. Nonviolent)	-0.02	-0.07 – 0.04	0.532
Trump Vote Share	-0.12	-0.18 – -0.07	<0.001
Political Ideology	-1.36	-1.40 – -1.33	<0.001
Protest Type D1 X Trump Vote Share	0.07	-0.01 – 0.16	0.099
Protest Type D2 X Trump Vote Share	0.06	0.01 – 0.12	0.032
Protest Type D1 X Political Ideology	-0.01	-0.11 – 0.09	0.887
Protest Type D2 X Political Ideology	0.02	-0.02 – 0.06	0.347
Trump Vote Share * Political Ideology	-0.04	-0.07 – -0.00	0.028
Protest Type D1 X Trump Vote Share X Political Ideology	0.14	0.06 – 0.22	0.001

Protest Type D2 X Trump Vote Share X Political Ideology	0.10	0.05 – 0.14	<0.001
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Random Effects

σ^2	2.87
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τ_{00} countyfips	0.02
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ICC	0.01
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N countyfips	2565
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Observations	43924
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Marginal R^2 / Conditional R^2	0.413 / 0.416
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Table 3. Study 2A Propensity Score Balance Model Comparing Only Nonviolent and Both Nonviolent and Violent Protests

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.43	5.38 – 5.47	<0.001
Total Population	-0.01	-0.07 – 0.04	0.588
Percent Female	-0.10	-0.14 – -0.07	<0.001
Percent White	0.17	0.11 – 0.22	<0.001
Percent African American	0.13	0.09 – 0.18	<0.001
Percent Asian American	0.07	0.03 – 0.11	0.002
Percent Hispanic	-0.04	-0.07 – -0.00	0.029
Gender	-0.00	-0.02 – 0.01	0.687
Employment	0.02	-0.00 – 0.03	0.053
Protest Type: Violent vs. Nonviolent Only	-0.04	-0.11 – 0.02	0.178
Trump Vote Share	-0.14	-0.20 – -0.08	<0.001
Political Ideology	-1.42	-1.45 – -1.39	<0.001
Protest Type X Trump Vote Share	0.05	-0.01 – 0.12	0.121
Protest Type X Political Ideology	0.01	-0.03 – 0.06	0.486
Trump Vote Share X Political Ideology	-0.04	-0.07 – -0.01	0.009
Protest Type X Trump Vote Share X Political Ideology	0.12	0.08 – 0.16	<0.001
Random Effects			
σ^2	2.36		
τ_{00} countyfips	0.04		
ICC	0.02		
N _{countyfips}	1328		
Observations	38523		
Marginal R ² / Conditional R ²	0.451 / 0.460		

Table 4. Study 2B Model Predicting Prejudice

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.75	4.65 – 4.85	<0.001
County Population	0.01	-0.01 – 0.03	0.243
County Median Age	0.02	0.01 – 0.03	<0.001
County Median Income	0.01	-0.01 – 0.02	0.277
County Percent Female	-0.02	-0.02 – -0.01	0.001
County Percent White	0.11	0.06 – 0.16	<0.001
County Percent Black	0.07	0.03 – 0.11	0.001
County Percent Asian American	0.05	0.03 – 0.07	<0.001
County Percent Race Other	0.03	0.01 – 0.05	0.002
County Percent Hispanic	-0.06	-0.07 – -0.05	<0.001
Gender D1: Male vs. Female	0.33	0.28 – 0.38	<0.001
Gender D1: Male vs. Other	-0.50	-0.55 – -0.45	<0.001
Age	0.04	0.03 – 0.05	<0.001
Education	0.05	0.04 – 0.05	<0.001
Employment	-0.00	-0.01 – 0.01	0.949
Feeling Thermometer White	-1.32	-1.32 – -1.31	<0.001
Protest Type D1 (Nonviolent vs. No Protests)	-0.29	-0.43 – -0.14	<0.001
Protest Type D2 (Nonviolent vs. Violent and Nonviolent Protests)	-0.53	-0.79 – -0.27	<0.001
Trump Vote Share	-0.18	-0.19 – -0.16	<0.001
Political Ideology	-0.71	-1.28 – -0.14	0.015
Protest Type D1 X Trump Vote Share	0.53	0.21 – 0.84	0.001
Protest Type D2 X Trump Vote Share	-0.12	-0.19 – -0.04	0.002
Protest Type D1 X Political Ideology	0.04	0.02 – 0.07	0.001
Protest Type D2 X Political Ideology	0.06	0.01 – 0.10	0.009

Trump Vote Share * Political Ideology	0.15	0.03 – 0.27	0.012
Protest Type D1 X Trump Vote Share X Political Ideology	-0.08	-0.14 – -0.03	0.005
Protest Type D2 X Trump Vote Share X Political Ideology	-1.32	-1.32 – -1.31	<0.001
SD (Intercept)	0.07		
SD (Observations)	1.13		
Random Effects			
σ^2	1.66		
τ_{00} countyfips	0.00		
ICC	0.00		
N countyfips	2448		
Observations	180480		
Marginal R ² / Conditional R ²	0.516 / 0.517		

Table 5. Propensity Score Balance Model Comparing Only Nonviolent and Both Nonviolent and Violent Protests in Study 2 B

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.38	4.21 – 4.55	<0.001
Total Population	0.01	-0.03 – 0.05	0.515
Median Income	0.01	-0.02 – 0.03	0.503
Percent Race Other	-0.01	-0.03 – 0.02	0.615
Percent White	0.06	0.01 – 0.11	0.017
Percent African American	0.03	-0.02 – 0.07	0.239
Protest Type: Violent vs. Nonviolent Only	-0.07	-0.28 – 0.13	0.498
Trump Vote Share	-0.62	-1.04 – -0.20	0.004
Political Ideology	-0.11	-0.13 – -0.08	<0.001
Protest Type X Trump Vote Share	0.05	-0.43 – 0.53	0.845
Protest Type X Political Ideology	0.01	-0.02 – 0.04	0.460
Trump Vote Share X Political Ideology	0.03	-0.03 – 0.09	0.375
Protest Type X Trump Vote Share X Political Ideology	0.00	-0.07 – 0.08	0.983
SD (Intercept)	0.16		
SD (Observations)	1.35		
Random Effects			
σ^2	3.34		
τ_{00} countyfips	0.03		
ICC	0.01		
N countyfips	1022		
Observations	167141		
Marginal R ² / Conditional R ²	0.007 / 0.015		

Supplementary Information

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ACLED Protest Data Coding Details

The fundamental unit of observation in the ACLED dataset is the event. Events involve designated actors – e.g. a named protest group, a militia or state forces. They occur at a specific named location (identified by name and geographic coordinates) and on a specific day. Researchers work to ensure that the most specific location and time possible are recorded. They are categorized into six types: protests, riots, battles, violence against civilians, and strategic developments, explosions/violence remote (for more detail see below and the ACLED codebook). The ACLED dataset contained all events that occurred in the US between May 24, 2020 and August 22, 2020, which all fell into the first five categories.

Definitions of Types of Events.

A **protest** is defined as a public demonstration in which the participants do not engage in violence, though violence may be used against them. Events include individuals and groups who peacefully demonstrate against a political entity, government institution, policy, group, tradition, businesses or other private institutions. Events that are not coded as protests are symbolic public acts such as displays of flags or public prayers (unless they are accompanied by a demonstration), protests in legislatures such as parliamentary walkouts or MPs staying silent, strikes (unless they are accompanied by a demonstration), and individual acts such as self-harm actions (e.g. individual immolations or hunger strikes).

‘Riots’ are violent events where demonstrators or mobs engage in disruptive acts, including but not limited to rock throwing, property destruction, etc. They may target other individuals, property, businesses, other rioting groups or armed actors. Rioters are noted by generic terms (e.g. ‘Rioters (Country)’); if representing a group, the name of that group is recorded in the respective ‘Associated actor’ column. Rioters may begin as peaceful protesters,

or may be intent on engaging in spontaneous and disorganized violence from the beginning of their actions. Contrary to armed groups, rioters do not use sophisticated weapons such as guns, knives or swords. “Crude bombs” (e.g. Molotov cocktails, petrol bombs, firecrackers) may be used in rioting behaviour.

ACLED defines a **battle** as “a violent interaction between two politically organized armed groups at a particular time and location.” Battles can occur between armed and organized state, non-state, and external groups, and in any combination therein.

ACLED defines ‘**Violence against civilians**’ as violent events where an organized armed group deliberately inflicts violence upon unarmed non-combatants. By definition, civilians are unarmed and cannot engage in political violence. The perpetrators of such acts include state forces and their affiliates, rebels, militias, and external/other forces.

Strategic developments capture contextually important information regarding the activities of violent groups that is not itself recorded as political violence, yet may trigger future events or contribute to political dynamics within and across states. The inclusion of such events is limited, as its purpose is to capture pivotal events within campaigns of political violence. They typically include a disparate range of events, such as recruitment drives, looting, incursions, as well as the location and date of peace talks and the arrests of high- ranking officials or large groups.

Data Reduction

We first reduced the dataset to only those events that were related to BlackLivesMatter (i.e. BlackLivesMatter was listed as one of the actors involved for details about how actors were determined see the ACLED codebook). In this dataset, there were no battles, one event of violence against civilians, and 6 strategic developments. As our focus was on the effects of

protests, and there were too few of these events to analyze we focused on protests ($n = 7490$) and riots ($n = 553$). These two types of events are also subcategorized indicating for example whether the police used force against protestors ($n = 51$) and differentiating violent protests from mob violence ($n = 3$, i.e. when rioters violently interact with other rioters, another armed group, or civilians). Because of the very low rate of occurrence of these subtypes, we did not feel we could make meaningful inferences about their effects. Therefore, we focused on simply on the protests (i.e. nonviolent protests) vs. riots (violent protests) distinction. For Study 1 (which was conducted in mid July), we then further reduced the dataset to only those events that had occurred prior to the start of data collection for that study.

We then calculated the number of nonviolent protests and violent protests that occurred in each zip-code area (Study 1) or county (Study 2A & 2B), and used this to determine whether an area had both nonviolent and violent protests, only nonviolent protests, or no protests.

Study 1

Additional Relevant Measures

Perceptions of the COVID-19 Pandemic. We measured participants perceived threat from the pandemic (“I think that the coronavirus is a serious threat”), the perceived severity of the pandemic (“How serious is the COVID-19 outbreak in your city?”), job loss as a result of the pandemic (“I’ve lost my job as a result of the COVID-19 pandemic”), and financial hardship as a result of the pandemic (“The COVID-19 pandemic has significantly harmed my financial situation”).

Exposure to Protest News was measured with the item “I see news about the recent protests almost every day” on a scale of 1 (strongly disagree) to 7 (strongly agree).

Protest Participation was measured with the yes or no question “Have you participated (been physically present) in any of the recent protests following the death of George Floyd?” with 0 indicating no and 1 indicating yes.

General Perceptions of the Overall Movement were measured in order to control for the effect of the nationwide protests. Since we were interested in comparing the effects of different types of local action, we wanted to control for perceptions of the nationwide protest movement more broadly, and demonstrate that the specific types of protest that occurred where a participant lived had effects above and beyond how they perceived the broader movement¹. Participants were told that “Following the killing of George Floyd by a Minneapolis police officer, crowds have filled the streets in cities across the U.S., protesting against police brutality and systemic racism. We are interested in your general perceptions of and reactions to these protests.” We then measured *Perceived Violence* with one item: “To what extent do you think the protests have been violent/nonviolent?”, on a scale ranging from 1 (completely nonviolent) to 7 (completely violent). *Perceived Normativity* was measured with one item: “I think the recent protests fall within widely accepted societal norms for expressing protest and discontent”, on a scale ranging from 1 (strongly disagree) to 7 (strongly agree). We measured the extent to which participants perceived the movement as involving both white and black participants with two items: “To what extent do the protests involve both Black and White participants?” on a scale from 1 (none of the protests) to 7 (all of the protests) and “What percent of the protestors do you think are White vs. Black Americans?” on a scale of 0 to 100. While we had originally intended to make a scale with this items, we found that they were not strongly correlated ($r = .21$). Upon

¹ While it is possible that these perceptions were also influenced by local protests, because we wanted to estimate causal effects of the local type of protest we felt it was important to control for these perceptions of the national movement. Even if some of this variance would be explaining the effects we are trying to estimate this only makes it a more conservative test of our hypotheses.

second thought this made sense, as it is possible to think that there are many white protestors (high score on the second item), but relatively few protest events where both black and white protestors are present together (low score on the first item). Therefore, in the analyses we considered these items separately.

Distribution of All Protest Events

Figure S1.

Figure S2.

Note. The 199 participants who lived in cities with no protests are not included in this graph, as it is not really possible to calculate a logical percentage for these participants.

Group Differences on All Covariates

Note. All figures were generated using the *ggstatsplot* package (Patil, 2021).

Figure S3. Differences Between Zip Code Areas with Different Protest Types on Total Population

Figure S4. Differences Between Zip Code Areas with Different Protest Types on Median Age

Figure S5. Differences Between Zip Code Areas with Different Protest Types on Median Income

Figure S6. Differences Between Zip Code Areas with Different Protest Types on Gender

Figure S7. Differences Between Zip Code Areas with Different Protest Types on White Population

Figure S8. Differences Between Zip Code Areas with Different Protest Types on Black Population

Figure S9. Differences Between Zip Code Areas with Different Protest Types on Asian American Population

Figure S10. Differences Between Zip Code Areas with Different Protest Types on Hispanic Population

Figure S11. Differences Between Zip Code Areas with Different Protest Types on Other Racial Population

Figure S12. Differences Between Zip Code Areas with Different Protest Types on Trump Vote Share

Figure S13. Differences Between Zip Code Areas with Different Protest Types on Participant Age

Figure S14. Differences Between Zip Code Areas with Different Protest Types on Participant Education

Figure S15. Differences Between Zip Code Areas with Different Protest Types on Participant Ideology

Figure S16. Differences Between Zip Code Areas with Different Protest Types on Participant's Perceptions of COVID-19's Severity

Figure S17. Differences Between Zip Code Areas with Different Protest Types on Participant's Perceived Threat from COVID-19

Figure S18. Differences Between Zip Code Areas with Different Protest Types on COVID-19's Impact on Participant's Finances

Figure S19. Differences Between Zip Code Areas with Different Protest Types on COVID-19's Impact on Participant's Job

Figure S20. Differences Between Zip Code Areas with Different Protest Types on Participant's Exposure to News about the George Floyd Protests

Figure S21. Differences Between Zip Code Areas with Different Protest Types on Participant's Feeling Thermometer Scores towards White Americans

Figure S22. Differences Between Zip Code Areas with Different Protest Types on Participant's Feeling Thermometer Scores towards Black Americans

Figure S23. Differences Between Zip Code Areas with Different Protest Types on Participant's Perceptions of the BlackLivesMatter Protests as Violent

Figure S24. Differences Between Zip Code Areas with Different Protest Types on Participant's Perceptions of the BlackLivesMatter Protests as Normative

Figure S25. Differences Between Zip Code Areas with Different Protest Types on Participant's Perceptions of the amount of Joint (Black And White) BLM Protests

Figure S26. Differences Between Zip Code Areas with Different Protest Types on Participant’s Perceptions of the Percentage of BLM Protesters who were white

Figure S27. Differences Between Zip Code Areas with Different Protest Types on Participant’s Gender

Figure S28. Differences Between Zip Code Areas with Different Protest Types on Participant’s Employment

$\chi^2_{\text{Pearson}}(2) = 4.06, p = 0.132, \hat{V}_{\text{Cramer}} = 0.06, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 494$

$\log_e(\text{BF}_{01}) = 0.43, \hat{V}_{\text{Cramer}}^{\text{posterior}} = 0.10, \text{CI}_{95\%}^{\text{HDI}} [0.03, 0.17], a_{\text{Gunnel-Dickey}} = 1.00$

Figure S29. Differences Between Zip Code Areas with Different Protest Types on Participant's Participation in the BLM movement following the murder of George Floyd

$\chi^2_{\text{Pearson}}(2) = 0.10, p = 0.949, \hat{V}_{\text{Cramer}} = 0.00, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 494$

$\log_e(\text{BF}_{01}) = 3.86, \hat{V}_{\text{Cramer}}^{\text{posterior}} = 0.05, \text{CI}_{95\%}^{\text{HDI}} [4.45\text{e-}03, 0.11], a_{\text{Gunnel-Dickey}} = 1.00$

Full Details of Prejudice Analysis in Main Text

Table S1. Study 1 Model Predicting Prejudice

<i>Predictors</i>	<i>Estimates</i>	<i>s</i>	
		<i>CI</i>	<i>p</i>
(Intercept)	30.47	26.29 – 34.66	<0.001
Gender (Men vs. Women)	-3.27	-7.45 – 0.92	0.126
Gender (Men vs. Other)	-21.27	-54.15 – 11.61	0.204
Participant Age	-0.36	-2.41 – 1.69	0.732
Participant Education	-0.35	-2.48 – 1.77	0.744
Participant Employment	1.45	-7.23 – 10.13	0.743
ZCTA Population	-1.36	-3.89 – 1.17	0.290
ZCTA Median Age	-0.47	-2.99 – 2.04	0.712
ZCTA Median Income	1.90	-0.85 – 4.64	0.176
ZCTA Percent Female	-1.44	-3.53 – 0.66	0.179
ZCTA Percent White	3.77	-3.62 – 11.17	0.316
ZCTA Percent Black	3.65	-2.30 – 9.60	0.229
ZCTA Percent Asian American	2.03	-2.41 – 6.48	0.369
ZCTA Percent Hispanic	0.51	-2.88 – 3.91	0.767
ZCTA Percent Race Other	1.80	-1.99 – 5.60	0.351
ZCTA Trump Vote Share	-0.79	-3.65 – 2.07	0.587
Feeling Thermometer: White	-10.34	-12.41 – -8.27	<0.001
Protest Type D1: Violent vs. No Protests	4.75	-1.04 – 10.54	0.108
Protest Type D2: Violent vs. Nonviolent Only	4.44	-1.18 – 10.07	0.121
Political Ideology	-2.83	-6.61 – 0.94	0.141
Protest Type D1 X Political Ideology	-2.71	-7.80 – 2.39	0.297

Protest Type D2 X Political Ideology	-2.89	-8.00 – 2.21	0.266
Observations	494		
R ² / R ² adjusted	0.228 / 0.193		

Effects of Prejudice with Difference Score as Outcome

Table S2. Study 1 Model Predicting Prejudice (as Difference Score of Feeling Thermometers)

<i>Predictors</i>	PrejudiceDiffScore		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	2.49	-2.12 – 7.11	0.289
Gender	-1.79	-6.40 – 2.82	0.445
Participant Age	0.78	-1.47 – 3.02	0.498
Participant Education	-0.28	-2.63 – 2.07	0.813
Participant Employment	-0.55	-10.07 – 8.97	0.910
ZCTA Population	-1.32	-4.10 – 1.47	0.353
ZCTA Median Age	-1.68	-4.43 – 1.07	0.230
ZCTA Median Income	2.10	-0.93 – 5.13	0.175
ZCTA Percent Female	-0.79	-3.11 – 1.52	0.499
ZCTA Percent White	2.85	-5.31 – 11.02	0.493
ZCTA Percent Black	2.86	-3.71 – 9.42	0.393
ZCTA Percent Asian American	0.91	-3.99 – 5.81	0.716
ZCTA Percent Hispanic	0.15	-3.60 – 3.90	0.936
ZCTA Percent Race Other	2.62	-1.56 – 6.81	0.219
ZCTA Trump Vote Share	0.09	-3.05 – 3.22	0.956
Protest Type D1: Violent vs. No Protests	6.18	-0.20 – 12.56	0.058
Protest Type D2: Violent vs. Nonviolent Only	4.86	-1.35 – 11.07	0.125
Political Ideology	-5.37	-9.49 – -1.24	0.011

Protest Type D1 X Political Ideology	-0.37	-5.97 – 5.23	0.897
Protest Type D2 X Political Ideology	-1.64	-7.26 – 3.98	0.566
Observations	494		
R ² / R ² adjusted	0.082 / 0.045		

Main Analyses with All Additional Covariates

Effects on Support for Policy Goals

We ran the same model described in the main paper, however we included additional control variables that we had measured (only in this study) that might be relevant for estimating the causal effect. There was no interaction between D1 (violent protests vs. no protest) and political ideology, however the interaction between D2 (violent protests vs. nonviolent protest only) and political ideology was significant (see Table SX). Simple slopes analysis revealed that among conservatives, support for policy concessions was significantly higher where violent protests were present compared to where there were only nonviolent protests ($b = -0.55$, $SE = .17$, $t = -3.14$, $p < .01$), and was also higher compared to where there were no protests ($b = -0.41$, $SE = .17$, $t = -2.35$, $p = .02$, see Figure 1). However, among liberals, there were no differences on policy support according to types of protest (p 's $> .44$).

Figure S30. Interaction Between Protest Type and Ideology on Support for Policy Goals

Table S3. Study 1 Model Predicting Policy Support with all covariates

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.27	5.09 – 5.46	<0.001
Gender (Men vs. Women)	-0.08	-0.26 – 0.11	0.429
Gender (Men vs. Other)	0.21	-1.25 – 1.67	0.775
Participant Age	-0.10	-0.19 – -0.01	0.031
Participant Education	0.04	-0.06 – 0.14	0.455
Participant Employment	-0.34	-0.74 – 0.06	0.093
ZCTA Population	-0.05	-0.16 – 0.06	0.372
ZCTA Median Age	-0.02	-0.13 – 0.09	0.701
ZCTA Median Income	-0.10	-0.22 – 0.03	0.122
ZCTA Percent Female	0.06	-0.03 – 0.15	0.197
ZCTA Percent White	0.08	-0.25 – 0.41	0.626

ZCTA Percent Black	0.09	-0.18 – 0.35	0.521
ZCTA Percent Asian American	0.08	-0.12 – 0.27	0.438
ZCTA Percent Hispanic	0.07	-0.08 – 0.22	0.377
ZCTA Percent Race Other	-0.08	-0.24 – 0.09	0.374
ZCTA Trump Vote Share	-0.03	-0.16 – 0.09	0.624
Corona Severe	-0.01	-0.13 – 0.11	0.874
Corona Threat	0.39	0.27 – 0.51	<0.001
Corona Financial	-0.05	-0.17 – 0.08	0.444
Corona Lost Job	0.01	-0.13 – 0.14	0.936
Exposure News	0.08	-0.02 – 0.18	0.108
Participant Protest Participation	0.08	-0.02 – 0.19	0.102
General Perceptions of Violence	-0.27	-0.38 – -0.16	<0.001
General Perceptions of Normativity	0.37	0.26 – 0.47	<0.001
General Perceptions of Number of Mixed-Race Protests	0.17	0.07 – 0.27	0.001
General Perceptions of Amount White Protesters	0.18	0.07 – 0.28	0.001
Protest Type D1: Violent vs. No Protests	-0.30	-0.55 – -0.04	0.023
Protest Type D2: Violent vs. Nonviolent Only	-0.28	-0.53 – -0.03	0.026
Political Ideology	0.24	0.05 – 0.42	0.011
Protest Type D1 X Political Ideology	0.12	-0.11 – 0.34	0.309
Protest Type D2 X Political Ideology	0.27	0.04 – 0.49	0.019
Observations	494		
R ² / R ² adjusted	0.566 / 0.538		

Effects on Prejudice

Table S4. Study 1 Model Predicting Prejudice with all covariates

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	30.79	26.39 – 35.20	<0.001
Gender (Men vs. Women)	-4.21	-8.70 – 0.29	0.066
Gender (Men vs. Other)	-1.32	-36.30 – 33.67	0.941
Participant Age	-1.13	-3.34 – 1.08	0.315
Participant Education	0.34	-2.02 – 2.70	0.777
Participant Employment	3.28	-6.25 – 12.80	0.499
ZCTA Population	-1.40	-4.06 – 1.27	0.304
ZCTA Median Age	-0.33	-2.98 – 2.33	0.810
ZCTA Median Income	0.96	-1.98 – 3.90	0.521
ZCTA Percent Female	-2.05	-4.25 – 0.16	0.069
ZCTA Percent White	4.92	-2.95 – 12.79	0.220
ZCTA Percent Black	3.99	-2.39 – 10.37	0.220
ZCTA Percent Asian American	3.22	-1.50 – 7.94	0.180
ZCTA Percent Hispanic	-0.57	-4.22 – 3.07	0.757
ZCTA Percent Race Other	2.01	-2.03 – 6.04	0.330
ZCTA Trump Vote Share	-1.56	-4.59 – 1.48	0.313
Corona Severe	3.17	0.23 – 6.11	0.035
Corona Threat	-5.58	-8.42 – -2.74	<0.001
Corona Financial	-1.60	-4.62 – 1.41	0.296
Corona Lost Job	2.63	-0.63 – 5.89	0.113
Exposure News	-0.22	-2.56 – 2.11	0.852

Participant Protest Participation	0.63	-1.81 – 3.07	0.612
General Perceptions of Violence	1.80	-0.89 – 4.49	0.188
General Perceptions of Normativity	-2.08	-4.66 – 0.50	0.114
General Perceptions of Number of Mixed-Race Protests	-3.79	-6.17 – -1.40	0.002
General Perceptions of Amount White Protesters	-2.65	-5.20 – -0.10	0.042
Protest Type D1: Violent vs. No Protests	4.51	-1.61 – 10.62	0.149
Protest Type D2: Violent vs. Nonviolent Only	3.41	-2.53 – 9.35	0.260
Political Ideology	2.48	-1.91 – 6.86	0.267
Protest Type D1 X Political Ideology	-5.31	-10.71 – 0.09	0.054
Protest Type D2 X Political Ideology	-3.06	-8.47 – 2.35	0.267
Observations	494		
R ² / R ² adjusted	0.168 / 0.114		

Main Analyses with Continuous Measure of Violence

Effects on Support for Policy Goals

We decided to do a follow-up analysis on just this difference using a continuous measure of violent protests, the percent of protests in an area that were violent, which was cube root transformed to correct for skew (we used the cube root transformation because it was most successful at normalizing the data). We conducted the same analysis as above except that the dummy variables were replaced with this continuous measure of violent protests (this analysis was conducted on the subset of participants who lived in areas with protests, $n = 305$). The interaction percentage of violent protests and political ideology was marginally significant ($p = .08$, see Table SX). Simple slopes analysis revealed that among conservatives, policy support was positively predicted by the percent of violent protests ($b = 0.98$, $SE = .40$, $t = 2.43$, $p = .02$, see Figure 2). However, among liberals, there was no effect ($p = .87$).

Figure S31. Interaction Between Percent of Violence Protests and Political Ideology on Support for the Movement's Policy Goals

Note. The figure uses untransformed values for ease of interpretation.

Table S5. Study 1 Model Predicting Policy Support with Continuous Measure of Violent Protests

<i>Predictors</i>	GenConPol_sc		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.89	4.68 – 5.10	<0.001
Gender D1 (Men vs. Women)	-0.24	-0.55 – 0.07	0.129
Gender D2 (Men vs. Other)	0.23	-2.65 – 3.10	0.876

Participant Age	-0.24	-0.40 – -0.09	0.002
Participant Education	0.26	0.10 – 0.41	0.001
Participant Employment	-0.41	-1.10 – 0.28	0.245
ZCTA Population	-0.03	-0.22 – 0.16	0.787
ZCTA Median Age	-0.00	-0.19 – 0.19	0.995
ZCTA Median Income	-0.09	-0.29 – 0.11	0.378
ZCTA Percent Female	0.07	-0.08 – 0.23	0.356
ZCTA Percent White	0.42	-0.61 – 1.44	0.428
ZCTA Percent Black	0.39	-0.43 – 1.20	0.349
ZCTA Percent Asian American	0.25	-0.29 – 0.80	0.355
ZCTA Percent Hispanic	-0.02	-0.26 – 0.22	0.870
ZCTA Percent Race Other	0.16	-0.22 – 0.54	0.415
ZCTA Trump Vote Share	-0.04	-0.25 – 0.18	0.747
Percent of Violent Protests	0.56	-0.03 – 1.14	0.064
Political Ideology	0.83	0.63 – 1.03	<0.001
Percent of Violent Protests X Political Ideology	-0.45	-0.96 – 0.05	0.080
Observations	306		
R ² / R ² adjusted	0.316 / 0.273		

Effects on Support for Prejudice

Table S6. Continuous Measure of Violence in Model Predicting Prejudice

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	34.54	30.60 – 38.48	<0.001
Gender D1 (Men vs. Women)	-3.59	-9.46 – 2.27	0.229
Gender D2 (Men vs. Other)	-0.81	-54.89 – 53.26	0.976

Participant Age	-0.72	-3.63 – 2.19	0.625
Participant Education	-1.34	-4.27 – 1.58	0.368
Participant Employment	1.85	-11.09 – 14.80	0.778
ZCTA Population	-0.31	-3.89 – 3.27	0.866
ZCTA Median Age	-1.53	-5.16 – 2.09	0.407
ZCTA Median Income	1.64	-2.10 – 5.38	0.389
ZCTA Percent Female	-1.19	-4.19 – 1.80	0.434
ZCTA Percent White	9.63	-9.75 – 29.01	0.329
ZCTA Percent Black	8.51	-6.82 – 23.84	0.276
ZCTA Percent Asian American	6.72	-3.47 – 16.91	0.195
ZCTA Percent Hispanic	0.04	-4.45 – 4.53	0.986
ZCTA Percent Race Other	2.68	-4.49 – 9.86	0.462
ZCTA Trump Vote Share	-1.00	-5.11 – 3.11	0.633
Percent of Violent Protests	-7.81	-18.89 – 3.26	0.166
Political Ideology	-4.76	-8.51 – -1.00	0.013
Percent of Violent Protests X Political Ideology	7.40	-2.13 – 16.93	0.128
Observations	306		
R ² / R ² adjusted	0.060 / 0.001		

Study 2A

Additional Relevant Measures

Perceptions of the economy were measured with one item, “Would you say that over the past year the nation's economy has . . . “ on a scale of 1 – “Gotten much worse” to 6 – “Gotten much better”.

Personal financial status was measured with one item, “Over the past year, has your household's annual income . . . “ on a scale of 1 – “Decreased a lot much worse” to 5 – “Increased a lot”.

Variables related to the COVID-19 Pandemic. Participants were asked “Have you or someone you know been diagnosed with the novel coronavirus (COVID-19) during the past year?” with the following options: “Yes, I have”, “Yes, a family member”, “Yes, a friend”, “Yes, a co-worker”, “No, I do not know anyone who has been diagnosed”. This was recoded into two binary variables reflecting 1) whether the participant had had COVID-19 and 2) whether they knew someone who had had COVID-19.

Distribution of All Protest Events

Figure S32.

Figure S33.

Note. The 5401 participants who lived in cities with no protests are not included in this graph, as it is not really possible to calculate a logical percentage for these participants.

Group Differences on All Covariates

Figure S34. Differences Between Counties with Different Protest Types on County Population (Log10 Transformed)

Figure S35. Differences Between Counties with Different Protest Types on County Median Age

Figure S36. Differences Between Counties with Different Protest Types on County Median Income

Figure S37. Differences Between Counties with Different Protest Types on County Gender

Figure S38. Differences Between Counties with Different Protest Types on White Population

Figure S39. Differences Between Counties with Different Protest Types on Black Population

Figure S40. Differences Between Counties with Different Protest Types on Asian American Population

Figure S41. Differences Between Counties with Different Protest Types on Other Race Population

Figure S42. Differences Between Counties with Different Protest Types on Hispanic Population

Figure S43. Differences Between Counties with Different Protest Types on Trump Vote Share

Figure S44. Differences Between Counties with Different Protest Types on Participant's Age

Figure S45. Differences Between Counties with Different Protest Types on Participant's Education

Figure S46. Differences Between Counties with Different Protest Types on Participant's Ideology

Figure S47. Differences Between Counties with Different Protest Types on Participant's Perceptions of the Economy

Figure S48. Differences Between Counties with Different Protest Types on Participant's Increase in Income in the Past 6 Months

Figure S49. Differences Between Counties with Different Protest Types on Participants’ Gender

Figure S50. Differences Between Counties with Different Protest Types on Participants’ Employment

Figure S51. Differences Between Counties with Different Protest Types on Whether Participants Had COVID-19

Figure S52. Differences Between Counties with Different Protest Types on Whether Participants Knew Someone who got COVID-19

Main Analysis with All Additional Covariates

We ran a linear regression testing the interaction between type of protest and political ideology, controlling for the variables described above and demographics. As hypothesized the interaction between D1 (violent protests vs. no protest), political ideology, and Trump vote share was significant, and the interaction between D2 (violent protests vs. nonviolent protest only),

political ideology, and Trump vote share was significant as well (see Table 4). Simple slopes analysis revealed that among conservatives, policy support was significantly higher where violent and nonviolent protests were present compared to where there were only nonviolent protests ($b = -0.13$, $SE = .04$, $t = -3.02$, $p < .01$), and was also higher compared to where there were no protests ($b = -0.30$, $SE = .10$, $t = -3.15$, $p < .01$, see Figure 2), but only in relatively liberal areas (low Trump vote share counties). When Trump vote share was high, violent and nonviolent protests decreased policy support compared to nonviolent protests ($b = 0.11$, $SE = .05$, $t = 2.07$, $p = .04$), but compared to no protests ($p = .49$). Among liberals, there were no differences on policy support between nonviolent and violent protest (p 's $> .36$), however for liberals living in conservative areas (high Trump vote share counties), violent and nonviolent protests were associated with higher policy support compared to no protests ($b = -0.14$, $SE = .06$, $t = -2.27$, $p = .02$).

Figure S53. Interaction Between Protest Type and Ideology on Support for Policy Goals

Table S7. Study 2A Model Including Additional Covariates

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.34	5.30 – 5.39	<0.001
County Population	-0.00	-0.04 – 0.03	0.914
County Median Age	-0.03	-0.05 – -0.01	0.002
County Median Income	-0.01	-0.04 – 0.01	0.222
County Percent Female	-0.02	-0.04 – -0.00	0.028
County Percent White	-0.06	-0.14 – 0.03	0.173
County Percent Black	-0.07	-0.14 – -0.01	0.030
County Percent Asian American	-0.02	-0.07 – 0.02	0.294

County Percent Race Other	-0.08	-0.12 – -0.03	<0.001
County Percent Hispanic	0.00	-0.03 – 0.03	0.981
Gender D1: Male vs. Female	-0.02	-0.04 – -0.01	0.010
Gender D1: Male vs. Other	-0.22	-0.24 – -0.21	<0.001
Age	0.12	0.10 – 0.13	<0.001
Education	-0.08	-0.10 – -0.06	<0.001
Overall Economic Perceptions	0.49	0.48 – 0.51	<0.001
Income Increase	-0.06	-0.08 – -0.04	<0.001
Had COVID	0.02	0.00 – 0.03	0.031
Knew COVID	0.08	0.07 – 0.10	<0.001
Protest Type D1: Violent vs. No Protests	-0.12	-0.22 – -0.02	0.023
Protest Type D2: Violent vs. Nonviolent Only	-0.02	-0.07 – 0.04	0.561
Trump Vote Share	-0.09	-0.14 – -0.04	<0.001
Political Ideology	-1.10	-1.13 – -1.06	<0.001
Protest Type D1 X Trump Vote Share	0.07	-0.01 – 0.15	0.105
Protest Type D2 X Trump Vote Share	0.05	-0.01 – 0.10	0.088
Protest Type D1 X Political Ideology	-0.02	-0.11 – 0.08	0.740
Protest Type D2 X Political Ideology	0.01	-0.03 – 0.05	0.626
Trump Vote Share * Political Ideology	-0.02	-0.06 – 0.01	0.176
Protest Type D1 X Trump Vote Share X Political Ideology	0.12	0.05 – 0.20	0.002
Protest Type D2 X Trump Vote Share X Political Ideology	0.08	0.04 – 0.13	<0.001
Random Effects			
σ^2	2.66		
τ_{00} countyfips	0.01		
ICC	0.00		
N countyfips	2564		

Observations	43866
Marginal R ² / Conditional R ²	0.457 / 0.459

Main Analyses Including Counties with Only Violent Protests

We conducted the same analysis as in the main text, but included those participants who lived in counties with only violent protests. Overall the results do not really change, and there are significant effects involving those who live in counties with only violent protests (likely because there are not enough participants).

Table S8. Study 2A Model Including Participants who Lived in Areas with Only Violent Protests

<i>Predictors</i>	GenConPol_sc		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.34	5.30 – 5.39	<0.001
County Population	-0.01	-0.05 – 0.03	0.582
County Median Age	-0.04	-0.06 – -0.02	<0.001
County Median Income	-0.01	-0.03 – 0.01	0.402
County Percent Female	-0.02	-0.04 – -0.01	0.014
County Percent White	-0.06	-0.15 – 0.03	0.206
County Percent Black	-0.09	-0.15 – -0.02	0.012
County Percent Asian American	-0.03	-0.08 – 0.02	0.214
County Percent Race Other	-0.07	-0.12 – -0.03	0.001
County Percent Hispanic	-0.01	-0.04 – 0.02	0.603
Gender	-0.00	-0.02 – 0.01	0.832
Age	-0.21	-0.23 – -0.19	<0.001
Education	0.15	0.13 – 0.17	<0.001

Employment	-0.10	-0.12 – -0.08	<0.001
Protest Type D1 (Violent and Nonviolent Protests vs. No Protests)	-0.11	-0.21 – -0.00	0.043
Protest Type D2 (Violent and Nonviolent Protests vs. Nonviolent)	-0.02	-0.07 – 0.04	0.535
Protest Type D3 (Violent and Nonviolent Protests vs. Violent)	-0.51	-1.88 – 0.86	0.464
Trump Vote Share	-0.12	-0.18 – -0.07	<0.001
Political Ideology	-1.36	-1.40 – -1.33	<0.001
Protest Type D1 X Trump Vote Share	0.07	-0.01 – 0.16	0.098
Protest Type D2 X Trump Vote Share	0.06	0.01 – 0.12	0.032
Protest Type D3 X Trump Vote Share	0.60	-0.39 – 1.59	0.235
Protest Type D1 X Political Ideology	-0.01	-0.11 – 0.09	0.890
Protest Type D2 X Political Ideology	0.02	-0.02 – 0.06	0.344
Protest Type D3 X Political Ideology	0.36	-0.98 – 1.70	0.599
Trump Vote Share * Political Ideology	-0.04	-0.07 – -0.00	0.028
Protest Type D1 X Trump Vote Share X Political Ideology	0.14	0.06 – 0.22	0.001
Protest Type D2 X Trump Vote Share X Political Ideology	0.10	0.05 – 0.14	<0.001
Protest Type D3 X Trump Vote Share X Political Ideology	0.05	-0.93 – 1.02	0.925
Random Effects			
σ^2	2.87		
τ_{00} countyfips	0.02		
ICC	0.01		
N countyfips	2569		
Observations	43975		
Marginal R ² / Conditional R ²	0.413 / 0.416		

Main Analysis with Continuous Measure of Violence

We conducted the same analysis as above except that the dummy variables were replaced with a continuous measure of violent protests (the percentage of violent protests cube root transformed). The interaction percentage of violent protests, political ideology, and Trump vote share was significant (see Table S9). Simple slopes analysis revealed that among conservatives who lived in more liberal areas, policy support was positively predicted by the percent of violent protests ($b = 0.30$, $SE = .08$, $t = 3.70$, $p < .01$, see Figure 4), however in more conservative areas there was the effect of violence tended to be negative ($b = -0.27$, $SE = .10$, $t = -2.57$, $p = .01$). Also among liberals, there was no effect (p 's $> .17$) of violent protests.

Figure S54. Interaction Between Percent of Violence Protests and Political Ideology on Support for the Movement's Policy Goals

Note. The figure uses untransformed values for ease of interpretation.

Table S9. Study 2A Model Predicting Policy Support with Continuous Measure of Violence

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	5.32	5.29 – 5.35	<0.001
County Population	-0.00	-0.04 – 0.03	0.863
County Median Age	-0.05	-0.07 – - 0.02	<0.001
County Median Income	-0.01	-0.03 – 0.02	0.677
County Percent Female	-0.04	-0.07 – - 0.02	0.002
County Percent White	-0.04	-0.15 – 0.06	0.425
County Percent Black	-0.07	-0.16 – 0.01	0.087
County Percent Asian American	-0.03	-0.09 – 0.02	0.260
County Percent Race Other	-0.07	-0.11 – - 0.02	0.008
County Percent Hispanic	-0.02	-0.06 – 0.01	0.171
Gender	0.00	-0.02 – 0.02	0.847
Age	-0.22	-0.23 – - 0.20	<0.001
Education	0.15	0.14 – 0.17	<0.001
Employment	-0.10	-0.11 – - 0.08	<0.001
Percent of Violent Protests	0.05	-0.05 – 0.16	0.321
Trump Vote Share	-0.06	-0.09 – - 0.02	0.001
Political Ideology	-1.34	-1.36 – - 1.31	<0.001
Percent of Violent Protests X Trump Vote Share	-0.14	-0.24 – - 0.03	0.011

Percent of Violent Protests X Political Ideology	-0.04	-0.13 – 0.04	0.315
Trump Vote Share X Political Ideology	0.05	0.03 – 0.08	< 0.001
Percent of Violent Protests X Trump Vote Share X Political Ideology	-0.18	-0.26 – -0.10	< 0.001
Random Effects			
σ^2	2.84		
τ_{00} countyfips	0.01		
ICC	0.00		
N countyfips	1328		
Observations	38523		
Marginal R ² / Conditional R ²	0.419 / 0.421		

Propensity Score Matching Analysis with Same Covariates as the Main Text

We began by examining the overlap in the range of propensity scores across the groups (common support), which is an important precondition for propensity score analysis (see Dong, 2012; Harris & Horst, 2016), for the three possible comparisons: no protest vs. only nonviolent protests, only nonviolent vs. violent and nonviolent protests, and no protests vs. violent and nonviolent protests. These analyses revealed that there was virtually no common support for the no protest vs. violent and nonviolent protests comparison (see Figure S55). There was common support only for the no protest vs. only nonviolent protests comparison (see Figure S56) and the nonviolent vs. violent and nonviolent protests comparisons, despite relatively different distribution of the propensity scores (see Figure S57).

Common Support Figures

Figure S55. Common Support for the No Protest vs. Violent & Nonviolent Protests Comparison

Figure S56. Common Support for the No Protest vs. Nonviolent Protests Comparison

Figure S57. Common Support for the Nonviolent Protests vs. Violent & Nonviolent Protests Comparison

Propensity Score Matching Method Details (Including SMD Table)

As a result of the lack of common support in the no protest vs. violence comparison we decided not to try to estimate this causal comparison via propensity score matching, or to use methods that conduct propensity score matching with multiple categories (Burgette et al., 2021), as the counties where no protests occurred and where violent protests occurred were simply too different (see Tables S34-54). In addition, while there was common support for the no protest vs. nonviolent protest only comparison, the sample sizes for these two groups were extremely different (the no protest group was only 24% the size of the nonviolent only group). This would result in either dropping large amounts of the nonviolent group or giving the no protests participants extremely high weights, which can bias results (Harris & Horst, 2016). Therefore,

we conducted propensity score matching only for the comparison of both violent and nonviolent protests relative to only nonviolent protests.

Propensity score matching was conducted using the *MatchIt* package in R according to the methods laid out in Ho et al., (2011). When there are many covariates, covariates have a large range of potential values, and the two groups vary greatly on the covariates, exact matching and other methods involving pairwise matching can become impossible or ineffective (Ho et al., 2011). Therefore, we chose to use subclass matching, which forms subclasses such that in each class the distribution (rather than the exact values) of covariates for the treated and control groups are as similar as possible. It is also preferable to methods that achieve balance by dropping observations that do not have an adequate match, as this can produce bias in the matched sample. Thus, we matched based on all covariates included in the original model, using a subclass matching algorithm with 7 classes², and estimating for the average treatment effect on the treated (ATT). We then assessed whether the propensity score matching improved the balance across the two groups by comparing the standardized mean difference (SMD) on all covariates before and after the matching.

In general, SMD's less than .2 are considered balanced (Coffman et al., 2016; Harris & Horst, 2016), yet some covariates may be impossible to adequately balance, especially if they were extremely unbalanced to begin with (Schafer & Kang, 2008). These variables can be included as covariates in the final analysis, and some scholars argue that including all covariates in the final matched analysis is advisable (Nguyen et al., 2017). Including covariates in the outcome model after matching has several functions: it can increase precision in the estimates of effects, it can reduce any biases due to residual imbalances, and finally it can make the estimates

² 7 classes were selected because they produced the lowest standardized mean differences on the covariates after matching.

“doubly robust,” so that they are consistent if either the matching reduces sufficient imbalance in the covariates or if the outcome model is correct. In our analysis, matching reduced the SMD, especially on variables where there was a large SMD pre-matching. The average SMD between the nonviolent only and violent and nonviolent conditions was reduced from .59 to .28, with 9 of 15 covariates remaining with SMDs above .2 (versus 13 prior to matching see Table SX). Given the large differences that existed between conditions on many of our covariates, we were generally satisfied with the balance produced by this match.

Table S10. Mean Differences Before and After Matching

	Before Matching			After Matching		
	Means Treated	Means Control	Std. Mean Diff.	Means Treated	Means Control	Std. Mean Diff.
County Population	0.51	-0.41	0.7	0.51	-0.15	0.5
County Median Age	-0.37	0.3	-0.96	-0.37	-0.43	0.1
County Median Income	0.11	-0.09	0.24	0.11	0.17	-0.07
County Percent Female	0.2	-0.16	0.42	0.2	0.38	-0.22
County Percent White	-0.55	0.45	-1.12	-0.55	-1.38	0.94
County Percent Black	0.35	-0.28	0.6	0.35	0.66	-0.29
County Percent Asian American	0.34	-0.28	0.57	0.34	0.09	0.23
County Percent Race Other	0.43	-0.35	0.68	0.43	0.36	0.06
County Percent Hispanic	0.38	-0.31	0.63	0.38	-0.05	0.4
Gender	-0.05	0.04	-0.08	-0.05	-0.32	0.28
Age	-0.03	0.02	-0.05	-0.03	0.16	-0.19
Education	0.12	-0.09	0.21	0.12	0.25	-0.13
Employment	0.06	-0.05	0.12	0.06	0.41	-0.34
Trump Vote Share	-0.61	0.49	-1.41	-0.61	-0.9	0.38
Political Ideology	-0.12	0.1	-0.22	-0.12	0.04	-0.16

Final Analysis with No Controls

In the main paper, we control for covariates with SMD's over .2 after matching. Below we present the same analysis without any covariates.

Table S12. Study 2A Propensity Score Balance Model Comparing Only Nonviolent and Both Nonviolent and Violent Protests with No Covariates

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	8.91	8.70 – 9.13	< 0.001
Protest Type: Violent vs. Nonviolent Only	0.65	0.34 – 0.97	< 0.001
Trump Vote Share	0.06	-0.51 – 0.63	0.846
Political Ideology	-1.09	-1.16 – -1.03	< 0.001
Protest Type X Trump Vote Share	-1.53	-2.31 – -0.75	< 0.001
Protest Type X Political Ideology	-0.29	-0.38 – -0.20	< 0.001
Trump Vote Share X Political Ideology	-0.21	-0.38 – -0.05	0.011
Protest Type X Trump Vote Share X Political Ideology	0.65	0.43 – 0.87	< 0.001
Random Effects			
σ^2	2.36		
τ_{00} countyfips	0.06		
ICC	0.02		
N _{countyfips}	1328		
Observations	38523		
Marginal R ² / Conditional R ²	0.448 / 0.460		

Propensity Score Matching Analysis with Additional Covariates

We repeated the main analysis from the paper comparing the nonviolent to the violent and violent protest counties including all potentially relevant variables in this dataset (see

description of additional measures above). The average SMD between the nonviolent only and violent and nonviolent conditions was reduced from .59 to .28, with 9 of 15 covariates remaining with SMDs above .2 (versus 13 prior to matching, see Table S11). Given the large differences that existed between conditions on many of our covariates, we were generally satisfied with the balance produced by this match.

Table S11. Mean Differences Before and After Matching

	Before Matching			After Matching		
	Means Treated	Means Control	Std. Mean Diff.	Means Treated	Means Control	Std. Mean Diff.
County Population	0.75	0.2	1.95	0.75	0.73	0.07
County Median Age	0.51	-0.41	0.7	0.51	-0.15	0.5
County Median Income	-0.37	0.3	-0.96	-0.37	-0.43	0.1
County Percent Female	0.11	-0.09	0.24	0.11	0.17	-0.07
County Percent White	0.2	-0.16	0.42	0.2	0.38	-0.22
County Percent Black	-0.55	0.45	-1.12	-0.55	-1.38	0.94
County Percent Asian American	0.35	-0.28	0.6	0.35	0.66	-0.29
County Percent Race Other	0.34	-0.28	0.57	0.34	0.09	0.24
County Percent Hispanic	0.43	-0.35	0.68	0.43	0.36	0.06
Gender	0.38	-0.31	0.63	0.38	-0.05	0.4
Age	-0.05	0.04	-0.08	-0.05	-0.33	0.28
Education	-0.03	0.02	-0.05	-0.03	0.16	-0.19
Employment	0.12	-0.09	0.21	0.12	0.25	-0.14
Overall Economic Perceptions	0.06	-0.05	0.11	0.06	0.41	-0.34
Income Increase	0.07	-0.06	0.13	0.07	0.13	-0.06
Had COVID	-0.02	0.01	-0.03	-0.02	0.19	-0.2
Knew COVID	0.02	-0.02	0.04	0.02	-0.06	0.08
Trump Vote Share	0.03	-0.03	0.06	0.03	0.02	0.01
Political Ideology	-0.61	0.49	-1.41	-0.61	-0.9	0.38

Given that there were variables with SMDs greater than .2 post matching we included these confounders as covariates in the weighted outcome regression model to further control for

them. However, results remain the same whether these, all, or no covariates are included in the final model. Results from the outcome model for estimating the effects of a mix of violent and nonviolent protests (vs. only nonviolent protests) replicated the three-way interaction found in the regression analyses (see Table 5). Similarly, to the earlier analyses, the presence of violent and nonviolent protests increased support for policy concessions relative to only nonviolent protests among conservatives in areas where Trump received low support ($b = 0.14$, $SE = .05$, $t = 3.03$, $p < .01$, see Figure 7), but this analysis revealed violent protests had the opposite effects where he received high support ($b = -0.14$, $SE = .07$, $t = -2.09$, $p = .04$). There were no effects of violent protests on liberals (p 's $> .28$).

Figure S58. Interaction Between Protest Type and Ideology on Support for Policy Goals Using Balanced Sample With Additional Covariates

Table S12. Study 2A Model Including Additional Covariates in Balanced Sample

<i>Predictors</i>	Policy Support		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	9.72	9.49 – 9.96	< 0.001
Total Population	-0.01	-0.07 – 0.04	0.574
Percent Female	-0.10	-0.13 – -0.06	< 0.001
Percent White	0.17	0.11 – 0.23	< 0.001
Percent African American	0.13	0.08 – 0.18	< 0.001
Percent Asian American	0.07	0.03 – 0.11	0.001
Percent Hispanic	-0.04	-0.07 – -0.00	0.038
Gender	-0.00	-0.02 – 0.01	0.588
Employment	0.02	0.00 – 0.03	0.046
Protest Type: Violent vs. Nonviolent Only	-0.65	-0.95 – -0.34	< 0.001
Trump Vote Share	-1.84	-2.39 – -1.30	< 0.001
Political Ideology	-1.37	-1.43 – -1.31	< 0.001
Protest Type X Trump Vote Share	1.57	0.81 – 2.32	< 0.001
Protest Type X Political Ideology	0.28	0.19 – 0.37	< 0.001
Trump Vote Share X Political Ideology	0.43	0.28 – 0.57	< 0.001
Protest Type X Trump Vote Share X Political Ideology	-0.63	-0.85 – -0.42	< 0.001
Random Effects			
σ^2	2.36		
τ_{00} countyfips	0.04		
ICC	0.02		
N countyfips	1328		
Observations	38476		
Marginal R ² / Conditional R ²	0.451 / 0.459		

Study 2B

Additional Relevant Measures

Area-Level Control Variables. In the supplementary analyses, we also controlled for counties mean prejudice levels in 2020 prior to the death of George Floyd, as well as the time amount of time that had passed between the death of George Floyd and when the participant completed the IAT survey (as this dataset was collected over the entirety of 2020).

Distribution of All Protest Events

Figure S59.

Figure S60.

Group Differences on All Covariates

Figure S61. Differences Between Counties with Different Protest Types on County Population (Log10 Transformed)

Figure S62. Differences Between Counties with Different Protest Types on County Median Age

Figure S63. Differences Between Counties with Different Protest Types on County Median Income

Figure S64. Differences Between Counties with Different Protest Types on County Gender

Figure S65. Differences Between Counties with Different Protest Types on White Population

Figure S66. Differences Between Counties with Different Protest Types on Black Population

Figure S67. Differences Between Counties with Different Protest Types on Asian American Population

Figure S68. Differences Between Counties with Different Protest Types on Other Race Population

Figure S69. Differences Between Counties with Different Protest Types on Hispanic Population

Figure S70. Differences Between Counties with Different Protest Types on Trump Vote Share

Figure S71. Differences Between Counties with Different Protest Types on Counties Mean Level of Prejudice Prior to the Death of George Floyd

Figure S72. Differences Between Counties with Different Protest Types on Participant's Age

Figure S73. Differences Between Counties with Different Protest Types on Participant's Education

Figure S74. Differences Between Counties with Different Protest Types on Participant’s Ideology

Figure S75. Differences Between Counties with Different Protest Types on White Feeling Thermometer

Figure S76. Differences Between Counties with Different Protest Types on Days Following End of Protests in ACLED Dataset

Figure S77. Differences Between Counties with Different Protest Types on Participants' Gender

Figure S78. Differences Between Counties with Different Protest Types on Participants' Employment

Main Analysis with All Additional Covariates

We ran a linear regression testing the interaction between type of protest, political ideology, and Trump vote share, controlling for the variables described above. Because we hypothesized that if any type of protest would reduce prejudice it would be nonviolent protest, nonviolent protest was coded as the reference category in the dummy variables. There was a significant interaction between D1 (nonviolent protests vs. no protest), political ideology, and Trump vote share, and between D2 (violent protests vs. nonviolent protest only), political ideology, and Trump vote share (see Table 4). Simple slopes analysis revealed that among conservatives, prejudice was significantly lower where nonviolent protests were present compared to where there were no protests ($b = 0.28, SE = .08, t = 3.45, p < .01$), and was also lower compared to where there were violent and nonviolent protests ($b = 0.10, SE = .03, t = 3.81, p < .01$, see Figure 8), but only in relatively liberal areas (low Trump vote share counties). Where Trump vote share was high, there was no effect of protest type on conservatives' levels of prejudice. Among liberals, there was no effect of type of protest on prejudice (p 's $> .36$).

Figure S79. Study 2B Model with Additional Covariates

Table S13. Study 2B Model with Additional Covariates

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.47	4.37 – 4.58	<0.001
County Population	0.01	-0.01 – 0.03	0.248
County Median Age	0.01	0.01 – 0.02	0.002
County Median Income	0.00	-0.01 – 0.02	0.421
County Percent Female	-0.02	-0.03 – -0.01	0.003
County Percent White	0.13	0.07 – 0.19	<0.001
County Percent Black	0.09	0.04 – 0.13	<0.001
County Percent Asian American	0.06	0.03 – 0.09	<0.001
County Percent Race Other	0.04	0.02 – 0.06	<0.001

County Percent Hispanic	-0.06	-0.08 – -0.05	<0.001
Gender D1: Male vs. Female	0.33	0.27 – 0.38	<0.001
Gender D1: Male vs. Other	-0.50	-0.55 – -0.45	<0.001
Age	0.04	0.03 – 0.04	<0.001
Education	0.05	0.04 – 0.06	<0.001
Employment	0.00	-0.01 – 0.01	0.928
Days Since End of Protests	0.00	-0.00 – 0.01	0.625
Feeling Thermometer White	-1.32	-1.32 – -1.31	<0.001
County Mean on Prejudice Prior to George Floyd's Death	-0.01	-0.01 – -0.00	0.047
Protest Type D1 (Nonviolent vs. No Protests)	0.70	0.28 – 1.12	0.001
Protest Type D2 (Nonviolent vs. Violent and Nonviolent Protests)	0.27	0.13 – 0.42	<0.001
Trump Vote Share	-0.03	-0.22 – 0.17	0.789
Political Ideology	-0.13	-0.15 – -0.12	<0.001
Protest Type D1 X Trump Vote Share	-0.97	-1.63 – -0.32	0.004
Protest Type D2 X Trump Vote Share	-0.49	-0.81 – -0.17	0.003
Protest Type D1 X Political Ideology	-0.13	-0.22 – -0.04	0.004
Protest Type D2 X Political Ideology	-0.04	-0.07 – -0.02	0.001
Trump Vote Share * Political Ideology	-0.02	-0.06 – 0.02	0.316
Protest Type D1 X Trump Vote Share X Political Ideology	0.19	0.05 – 0.33	0.009
Protest Type D2 X Trump Vote Share X Political Ideology	0.08	0.02 – 0.13	0.008
Random Effects			
σ^2	1.65		
τ_{00} countyfips	0.00		
ICC	0.00		
N countyfips	1435		
Observations	176195		

Marginal R² / Conditional R²

0.516 / 0.517

Main Analysis Including Counties with Only Violent Protests

We conducted the same analysis as in the main text, but included those participants who lived in counties with only violent protests. Overall the results do not really change, and there are significant effects involving those who live in counties with only violent protests (likely because there are not enough participants).

Table S14. Study 2B Model Including Participants who Lived in Areas with Only Violent Protests

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.75	4.65 – 4.85	<0.001
County Population	0.01	-0.01 – 0.03	0.245
County Median Age	0.02	0.01 – 0.03	<0.001
County Median Income	0.01	-0.01 – 0.02	0.277
County Percent Female	-0.02	-0.02 – -0.01	0.001
County Percent White	0.11	0.06 – 0.16	<0.001
County Percent Black	0.07	0.03 – 0.11	0.001
County Percent Asian American	0.05	0.03 – 0.07	<0.001
County Percent Race Other	0.03	0.01 – 0.05	0.002
County Percent Hispanic	-0.06	-0.07 – -0.05	<0.001
Gender (Men vs. Women)	0.33	0.28 – 0.38	<0.001
Gender (Men vs. Other)	-0.50	-0.55 – -0.45	<0.001
Age	0.04	0.03 – 0.05	<0.001
Education	0.05	0.04 – 0.05	<0.001
Employment	-0.00	-0.01 – 0.01	0.975

Feeling Thermometer White	-1.32	-1.32 – -1.31	<0.001
Protest Type D1 (Violent and Nonviolent Protests vs. No Protests)	0.59	0.23 – 0.94	0.001
Protest Type D2 (Violent and Nonviolent Protests vs. Nonviolent)	-0.29	-0.43 – -0.14	<0.001
Protest Type D3 (Violent and Nonviolent Protests vs. Violent)	6.84	- 1.50 – 15.18	0.108
Trump Vote Share	-0.53	-0.79 – -0.27	<0.001
Political Ideology	-0.18	-0.19 – -0.16	<0.001
Protest Type D1 X Trump Vote Share	-0.71	-1.28 – -0.14	0.015
Protest Type D2 X Trump Vote Share	0.52	0.21 – 0.84	0.001
Protest Type D3 X Trump Vote Share	-9.19	- 20.75 – -2.36	0.119
Protest Type D1 X Political Ideology	-0.12	-0.19 – -0.04	0.002
Protest Type D2 X Political Ideology	0.04	0.02 – 0.07	0.001
Protest Type D3 X Political Ideology	-1.46	-3.28 – -0.36	0.116
Trump Vote Share * Political Ideology	0.06	0.01 – 0.10	0.009
Protest Type D1 X Trump Vote Share X Political Ideology	0.15	0.03 – 0.27	0.012
Protest Type D2 X Trump Vote Share X Political Ideology	-0.08	-0.14 – -0.03	0.005
Protest Type D3 X Trump Vote Share X Political Ideology	1.94	-0.59 – 4.47	0.132
Random Effects			
σ^2	1.66		
τ_{00} countyfips	0.00		
ICC	0.00		
N countyfips	2452		
Observations	180559		
Marginal R ² / Conditional R ²	0.516 / 0.517		

Figure S80. Study 2B Model Including Participants who Lived in Areas with Only Violent Protests

Main Analysis with Continuous Measure of Violence

We conducted a follow-up analysis using a continuous measure of violent protests, the percent of protests in an area that were violent, which was cube root transformed to correct for skew. The interaction percentage of violent protests, political ideology, and Trump vote share was marginally significant ($p = .07$, see Table 7). Simple slopes analysis revealed that among conservatives who lived in more liberal areas, prejudice was positively predicted by the percent of violent protests ($b = 0.12$, $SE = .04$, $t = 3.08$, $p < .01$, see Figure 6), however in more conservative areas there was no effect of the amount of protest violence on conservatives' levels of prejudice ($p = .53$). Also among liberals, there was no effect (p 's $> .81$) of the amount of violent protests.

Figure S81. Interaction Between Percent of Violence Protests and Political Ideology on Support for the Movement's Policy Goals

Note. The figure uses untransformed values for ease of interpretation.

Table S15. Study 2B Model with Continuous Measure of Violence

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	3.78	3.76 – 3.80	<0.001
County Population	0.01	-0.01 – 0.03	0.282
County Median Age	0.02	0.01 – 0.03	<0.001
County Median Income	0.00	-0.01 – 0.01	0.605
County Percent Female	-0.02	-0.03 – -0.01	<0.001
County Percent White	0.10	0.04 – 0.15	0.001
County Percent Black	0.07	0.02 – 0.11	0.003

County Percent Asian American	0.05	0.03 – 0.08	<0.001
County Percent Race Other	0.03	0.01 – 0.05	0.007
County Percent Hispanic	-0.06	-0.07 – -0.05	<0.001
Gender (Men vs. Women)	0.32	0.27 – 0.38	<0.001
Gender (Men vs. Other)	-0.50	-0.55 – -0.45	<0.001
Age	0.04	0.03 – 0.05	<0.001
Education	0.05	0.04 – 0.06	<0.001
Employment	-0.00	-0.01 – 0.01	0.930
Feeling Thermometer White	-1.31	-1.32 – -1.31	<0.001
Percent of Violent Protests	0.03	-0.01 – 0.08	0.151
Trump Vote Share	-0.02	-0.03 – -0.00	0.024
Political Ideology	-0.25	-0.26 – -0.24	<0.001
Percent of Violent Protests X Trump Vote Share	-0.02	-0.07 – 0.02	0.286
Percent of Violent Protests X Political Ideology	-0.03	-0.06 – -0.00	0.041
Trump Vote Share X Political Ideology	-0.00	-0.01 – 0.01	0.513
Percent of Violent Protests X Trump Vote Share X Political Ideology	0.03	-0.00 – 0.06	0.051
Random Effects			
σ^2	1.66		
τ_{00} countyfips	0.00		
ICC	0.00		
N countyfips	1197		
Observations	168328		
Marginal R ² / Conditional R ²	0.513 / 0.514		

Main Analysis with Feeling Thermometer Difference Score

We conducted the same analysis as in the main text, with the difference score between the white and black feeling thermometers as a measure of prejudice. Overall, the results are essentially the same.

Table 16. Study 2B Model with Feeling Thermometer Difference Score

<i>Predictors</i>	Feeling Thermometer Difference Score		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	0.91	0.80 – 1.02	<0.001
County Population	0.02	-0.00 – 0.04	0.054
County Median Age	0.01	-0.00 – 0.02	0.097
County Median Income	0.02	0.01 – 0.03	0.001
County Percent Female	-0.01	-0.02 – -0.00	0.016
County Percent White	0.14	0.08 – 0.19	<0.001
County Percent Black	0.09	0.05 – 0.14	<0.001
County Percent Asian American	0.06	0.03 – 0.08	<0.001
County Percent Race Other	0.05	0.03 – 0.07	<0.001
County Percent Hispanic	-0.10	-0.11 – -0.08	<0.001
Gender (Men vs. Women)	0.63	0.57 – 0.68	<0.001
Gender (Men vs. Other)	-0.71	-0.76 – -0.65	<0.001
Age	0.03	0.02 – 0.04	<0.001
Education	0.05	0.04 – 0.06	<0.001
Employment	-0.01	-0.02 – -0.00	0.004
Protest Type D1 (Nonviolent vs. No Protests)	0.78	0.39 – 1.17	<0.001
Protest Type D2 (Nonviolent vs. Violent and Nonviolent Protests)	0.26	0.10 – 0.42	0.001

Trump Vote Share	-0.05	-0.27 – 0.16	0.633
Political Ideology	-0.17	-0.19 – -0.15	<0.001
Protest Type D1 X Trump Vote Share	-1.10	-1.70 – -0.50	<0.001
Protest Type D2 X Trump Vote Share	-0.49	-0.84 – -0.13	0.007
Protest Type D1 X Political Ideology	-0.13	-0.21 – -0.05	0.002
Protest Type D2 X Political Ideology	-0.04	-0.07 – -0.02	0.002
Trump Vote Share * Political Ideology	-0.01	-0.05 – 0.03	0.557
Protest Type D1 X Trump Vote Share X Political Ideology	0.19	0.06 – 0.31	0.005
Protest Type D2 X Trump Vote Share X Political Ideology	0.09	0.02 – 0.15	0.007
Random Effects			
σ^2	2.01		
τ_{00} countyfips	0.01		
ICC	0.00		
N _{countyfips}	2448		
Observations	180480		
Marginal R ² / Conditional R ²	0.058 / 0.061		

Propensity Score Matching Analysis

Common Support Figures

Figure S82. Common Support for the No Protest vs. Violent & Nonviolent Protests Comparison

Figure S83. Common Support for the No Protest vs. Nonviolent Protests Comparison

Figure S84. Common Support for the Nonviolent Protests vs. Violent & Nonviolent Protests Comparison

Propensity Score Matching Method Details (Including SMD Table)

We conducted a propensity score analysis following the same methods as in Study 2A. As again there was a lack of common support for the no protests vs. violent and nonviolent protests comparison and a large discrepancy between the sample sizes of the no protest and nonviolent only groups, we focused only on the nonviolent only vs. both violent and nonviolent comparison. We matched based on all covariates included in the original model, using a subclass matching algorithm with 5 classes³, and estimating for the average treatment effect on the treated (ATT). In general, matching reduced the SMD, especially on variables where there

³ 5 classes were selected because they produced the lowest standardized mean differences on the covariates after matching.

was a large SMD pre-matching. The average SMD between the nonviolent only and violent and nonviolent conditions was reduced from .40 to .19, with only 5 of 17 covariates remaining with SMDs above .2 (versus 10 prior to matching, see Table S17). Given the large differences that existed between conditions on many of our covariates, we were generally satisfied with the balance produced by this match.

Table S17. Mean Differences Before and After Matching

	Before Matching			After Matching		
	Means Treated	Means Control	Std. Mean Diff.	Means Treated	Means Control	Std. Mean Diff.
County Population	0.43	-0.45	0.73	0.43	-0.12	0.45
County Median Age	-0.26	0.27	-0.71	-0.26	-0.13	-0.17
County Median Income	-0.06	0.06	-0.14	-0.06	0.12	-0.22
County Percent Female	0.23	-0.24	0.51	0.23	0.3	-0.08
County Percent White	-0.45	0.47	-1	-0.45	-1.03	0.63
County Percent Black	0.39	-0.41	0.77	0.39	1.02	-0.6
County Percent Asian American	0.14	-0.15	0.33	0.14	-0.01	0.17
County Percent Race Other	0.3	-0.32	0.57	0.3	0.67	-0.34
County Percent Hispanic	0.23	-0.24	0.43	0.23	0.12	0.1
Gender (Men vs. Women)	0.64	0.65	-0.02	0.64	0.65	-0.02
Gender (Men vs. Other)	0.66	0.67	-0.02	0.66	0.66	-0.02
Age	0.01	-0.01	0.02	0.01	-0.03	0.04
Education	0.07	-0.07	0.14	0.07	0	0.07
Employment	0.02	-0.02	0.04	0.02	-0.07	0.09
Feeling Thermometer White	-0.02	0.02	-0.04	-0.02	0	-0.01
Trump Vote Share	-0.46	0.48	-1.15	-0.46	-0.6	0.16
Political Ideology	0.11	-0.12	0.24	0.11	0.07	0.05

Final Analysis with No Controls

In the main paper, we control for covariates with SMD's over .2 after matching. Below we present the same analysis without any covariates.

Table S18. Study 2B Analysis with No Covariates

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.30	4.14 – 4.46	<0.001
Protest Type (Mix Violent and Nonviolent vs. Nonviolent)	-0.06	-0.27 – 0.14	0.532
Trump Vote Share	-0.44	-0.84 – -0.03	0.033
Political Ideology	-0.11	-0.13 – -0.08	<0.001
Protest Type (Mix Violent and Nonviolent vs. Nonviolent) X Trump Vote Share	0.02	-0.46 – 0.51	0.919
Protest Type (Mix Violent and Nonviolent vs. Nonviolent) X Political Ideology	0.01	-0.02 – 0.04	0.449
Trump Vote Share * Political Ideology	0.03	-0.03 – 0.09	0.347
Protest Type (Mix Violent and Nonviolent vs. Nonviolent) X Trump Vote Share * Political Ideology	0.00	-0.07 – 0.08	0.968
Random Effects			
σ^2	3.34		
τ_{00} countyfips	0.03		
ICC	0.01		
N countyfips	1022		
Observations	167141		
Marginal R ² / Conditional R ²	0.007 / 0.015		

Propensity Score Matching Analysis with Additional Covariates

We repeated the main analysis from the paper comparing the nonviolent to the violent and violent protest counties including all potentially relevant variables in this dataset (see description of additional measures above). The average SMD between the nonviolent only and violent and nonviolent conditions was reduced from .41 to .17, with only 6 of 19 covariates remaining with SMDs above .2 (versus 10 prior to matching, see Table S19).

Table S19. Mean Differences Before and After Matching

	Before Matching			After Matching		
	Means Treated	Means Control	Std. Mean Diff.	Means Treated	Means Control	Std. Mean Diff.
County Population	0.43	-0.45	0.73	0.74	0.69	0.17
County Median Age	-0.26	0.27	-0.71	0.43	-0.09	0.43
County Median Income	-0.06	0.06	-0.14	-0.26	-0.1	-0.22
County Percent Female	0.23	-0.24	0.51	-0.06	0.18	-0.29
County Percent White	-0.45	0.47	-1	0.23	0.27	-0.05
County Percent Black	0.39	-0.41	0.77	-0.45	-1.05	0.65
County Percent Asian American	0.14	-0.15	0.33	0.39	1.03	-0.62
County Percent Race Other	0.3	-0.32	0.57	0.14	0.05	0.11
County Percent Hispanic	0.23	-0.24	0.43	0.3	0.65	-0.33
Gender (Men vs. Women)	0.64	0.65	-0.02	0.23	0.1	0.12
Gender (Men vs. Other)	0.66	0.67	-0.02	0.64	0.65	-0.02
Age	0.01	-0.01	0.02	0.66	0.67	-0.02
Education	0.07	-0.07	0.14	0.01	-0.02	0.03
Employment	0.02	-0.02	0.04	0.07	0.01	0.05
Time Since End of Protests	0.01	-0.02	0.03	0.02	-0.07	0.09
White Feeling Thermometer	-0.02	0.02	-0.04	0.01	0.07	-0.05
County Mean Prejudice	0.05	-0.06	0.18	-0.02	-0.01	-0.01
Trump Vote Share	-0.46	0.48	-1.15	0.05	0.13	-0.12
Political Ideology	0.11	-0.12	0.24	-0.46	-0.63	0.2

Given that some covariates were not perfectly matched after matching (SMDs greater than .2), we included these confounders as covariates in the weighted outcome regression model to further control for them. Specifically, results from the outcome model estimating the effects of a mix of violent and nonviolent protests did *not* find any effects of protest type or interactions (see Table SX) unlike the results of the regression. Given the enhanced ability of this approach to estimate the causal effect, this finding suggests that the small difference observed in the regression analyses may not reflect a true causal effect, and hence we do not interpret it as such.

Table S20. Study 2B Propensity Score Matching with Additional Covariates

<i>Predictors</i>	Prejudice		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	4.36	4.19 – 4.53	<0.001
County Median Age	0.05	0.02 – 0.07	<0.001
County Median Income	-0.02	-0.05 – 0.00	0.101
County Percent Female	-0.03	-0.05 – - 0.01	0.015
County Percent Black	-0.00	-0.02 – 0.02	0.985
County Percent Asian American	0.03	-0.01 – 0.06	0.101
County Percent Hispanic	-0.00	-0.02 – 0.02	0.694
Protest Type (Mix Violent and Nonviolent vs. Nonviolent)	-0.05	-0.25 – 0.16	0.659
Trump Vote Share	-0.57	-0.99 – - 0.15	0.008
Political Ideology	-0.11	-0.13 – - 0.08	<0.001
Protest Type (Mix Violent and Nonviolent vs. Nonviolent) X Trump Vote Share	0.05	-0.43 – 0.53	0.833
Protest Type (Mix Violent and Nonviolent vs. Nonviolent) X Political Ideology	0.01	-0.02 – 0.04	0.581

Trump Vote Share * Political Ideology	0.03	-0.03 – 0.09	0.364
Protest Type (Mix Violent and Nonviolent vs. Nonviolent)	-0.01	-0.09 – 0.06	0.780
X			
Trump Vote Share * Political Ideology			

Random Effects

σ^2	3.34
τ_{00} countyfips	0.03
ICC	0.01
N countyfips	1022
<hr/>	
Observations	167141
Marginal R ² / Conditional R ²	0.008 / 0.015