Supporting Information for How Police Behavior Shapes Perceptions of Protests: Evidence from Black Lives Matter

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1 Construction of BLM Protest Dataset

1.1 Coding Details

We used a two-stage coding process to collect information about protest events. We describe that process here and then enclose the coding instructions we gave to RA's for the second round of coding (these instructions include detailed definitions of all of included variables).

First round: read a single source article We began our coding process by reading the news article associated with the protest event in the original elephrame.com database of BLM protests. We (and our research assistants) read each of these articles and did a preliminary coding of each event, leaving many of our columns blank when we could not determine the codings from this one article.

After this first round, we evaluated the dataset and noticed several things:

- First, there were several large protest "waves" in the dataset that had been collapsed to a single daily observation. On August 14, 2014, for example, activists held scores of protests across the country. The database we used as a starting point for our dataset included one row for all of these protests together, listing the protest location as "119+ cities". Before starting the second round of coding, we "expanded" these rows as best we could, using data from the news articles in the database (several of which included lists of dozens of cities that had protests on a given date), as well as manual inspection of the "map" tab at this website with a visualization of BLM protests over time: https://elephrame.com/textbook/BLM/ This yielded a dataset with (as far as possible) one row per individual city protest, even if there were many protests on the same day nationwide.

- Second, we found that some of the variables we had defined, particularly "mostlyblack-crowd", were largely missing after this first round. Very few news articles explicitly mention the race of protesters, so most coded observations left this column blank. We decided to introduce another variable where coders in the second round would examine available photos of protesters and attempt to guess the race of protesters; see the attached coding instructions for full detail.

Second round: search for more news coverage and fill in gaps Next, we sought out more news coverage on each of the protest observations in our dataset, reading additional articles and attempting to fill in missing information that had not been found in the first round of coding. See the included instructions (on the next page) for the details of the search process. At this stage, we also added in rows for any other protests that coders encountered in their search process.

After this coding process was complete, we wrote code that further standardized the database and made minor corrections such as fixing typos in placenames so that the dataset could be merged to Census geographic data.

Coding instructions for second coding pass
Protest Policing Project
[redacted]
February 2018

Basically, we want to search around for more news coverage of the protests in our database, to allow us to fill in any columns that are currently missing. In the first round of coding, students read the articles that are already linked to in the database, and filled in the columns as best they could with that information. Now, we're going to search for additional articles, and try to fill in any missing columns.

So, for a given column, you'll skim over and see whether there are any blank columns remaining. If there are, you'll search for news articles about that specific protest.

You'll want to search Google for some relevant keywords, then select "News" so you're looking only at news stories, then select "Tools" and rather than "recent", select "Custom Range" and put in a time range that should include the protest in question (maybe the date of the protest to a week or so later?). As for keywords, try things like [city name] + "protest", maybe including "BLM" or "Black Lives Matter" if you need to narrow down. But the city name and the date range should do a lot of the work here.

Once you have some news results, you'll want to open the first few articles, read through them, make sure they're about the correct protest, and see if they allow you to fill in any more protest characteristics in the spreadsheet (see coding rules below). You'll then also add links to those articles to the spreadsheet (copy-paste them into the "additionalarticles" column).

- If you don't find any relevant articles, try playing around with the keywords to see if you get anything.
- If you find a ton of relevant articles, read the first 5 articles and fill in the spreadsheet based on those-- no need to read dozens of articles about the same protests.
- Once you're done reading the articles, filling in as many columns as you can, and then copying the article URLs into the spreadsheet, you're done with that row: move on to the next protest.

As for the spreadsheet columns, they should be about the same as the first round; instructions for each column appear below. Anything you can't answer from the article(s) should be left blank (not 0, but empty).

howmanydemonstrators How many demonstrators were at the protest? Give us your best guess from the following options: <50, 50-100, 100-1000, 1000+, or leave it blank if you really can't tell.

policepresence Does the reporting indicate that the police were present at the protest? (0=no, 1=yes, blank=can't tell).

anyarrests Did anyone get arrested at the protest? (0=no, 1=yes, blank=can't tell)

howmanyarrests How many people got arrested? This should be a number, or blank if you can't tell.

crowdcontrol Were there reports of police using riot gear, shields, or any other tools like that? Were there reports of tear gas or other crowd control measures? (0=no, 1=yes, blank=can't tell)

whichcrowdcontrol If you marked "crowdcontrol"=1, use this space to fill in what kinds of gear/actions were reported.

anyprotesterinjuries Were there any injuries to protesters reported? (0=no, 1=yes, blank=can't tell)

anypoliceinjuries Were there any injuries to police reported? (0=no, 1=yes, blank=can't tell)

anyotheragencies Did any other agencies besides the municipal police show up at the protest, such as the national guard? (0=no, 1=yes, blank=can't tell)

whichotheragencies If you marked "anyotheragencies"=1, use this space to fill in what other agencies were there.

publicstreet Did the protest take place primarily on a public street/sidewalk? (0=no, 1=yes, blank=can't tell)

otherpublicspace Did the protest take place primarily in some other public space (a park, a transit station, etc.)? (0=no, 1=yes, blank=can't tell)

afterdark Did any part of this protest take place after dark? (0=no, 1=yes, blank=can't tell)

shutitdown Did protesters use any tactics such as blocking traffic on local streets or chaining themselves to objects? (0=no, 1=yes, blank=can't tell)

highwayblockage Did protesters attempt to move onto a highway and block traffic there? (0=no, 1=yes, blank=can't tell)

mostlyblackcrowd Was the crowd mostly Black? (0=no, 1=yes, blank=can't tell)

mostlyblackphoto If you find one main news article, look at the photos: if there are more than 10 individual protesters visible, make your best guess about their race; if more than 50% appear to be Black (so, 6/10 but NOT 5/10) mark 1. If 50% or fewer are Black, mark 0. If there are no photos, you can't identify the race of enough people, or there are too few people visible in photos, leave this column blank.

if you find many news articles, make your best assessment. At a minimum count the people in one photo. There is research evidence that people who aren't used to seeing majority-Black (or majority-female) crowds systematically overestimate the share of people who are Black (or female, or otherwise less visible in media portrayals), so it's worth actually counting rather than following one's initial guess of the proportion.

Race is a social construct and guessing where other people fit into it is really unpleasant, so it's ok for this to feel uncomfortable, but this data is important enough to be worth the discomfort.

mostlyblackphotonotes Any notes about weird or difficult aspects of coding photos go in this column.

clergyorganizers Did the protest have substantial visible support from, or organizers who are, clergy members (of any religious tradition)? (0=no, 1=yes, blank=can't tell)

spontaneous Was the protest planned well in advance (like for MLK day), or was it relatively spontaneous in response to an event like a police killing or a non-indictment of an officer? (0=planned, 1=spontaneous, blank=can't tell)

permitsforrally Did the protest have a permit? (0=no, 1=yes, blank=can't tell)

aboutpolicing Was the protest explicitly about policing issues? (0=no, 1=yes, blank=can't tell)

othernotes Use this space to note anything you think was especially weird about any of the prior answers.

changedround2 Did you change anything from the previous round? Only mark yes if you *changed* data rather than filling in missingness (0=no, 1=yes)

1.2 Completeness of Protest Dataset

The protest dataset presented in this paper covers BLM protests from summer 2014 through spring 2017, a period that included several major waves of BLM protest (and captured the most widespread protest activity prior to the summer 2020 BLM protests that followed the death of George Floyd). This time period allows us to examine protest policing of various types of protest—that is, it includes a range of actions from vigils to marches to highway blockages—and covers the key moments of the first portion of BLM protest mobilization. It also represents a period of time for which we could find media coverage of protests and could undergo the labor-intensive process of coding various protest features and supplementing the dataset with additional web searches as needed.[1]

As noted in the paper, we began this project by building on a dataset of BLM protests compiled by Robinson (2017). We then amended that dataset in several ways. We added observations to the dataset: where a given row of the dataset was based on an article reporting on protests in multiple locations, we split it out to have one row per protest event and sought out additional news coverage of each of those individual protests. If coders encountered reports of any additional protests in their news searches, we also incorporated those protests as new rows in the dataset.

At the same time, we also removed many observations from the dataset because they did not align with this project's focus on street protests in the US. We omitted protests that occurred outside the United States, as well as those that were only virtual events. And given our focus on public protests that would tend to be subject to policing, we omitted campus protests (since those are often not open to the public or occurring in public spaces, and likely also face different policing dynamics).

There is no way to ensure perfect completeness of this dataset in capturing all BLM protests over the time period of interest. But we undertake several validation approaches. First, we plot protests over time in Figure A1, noting that we see large spikes in protest volume associated with major events (such as the Ferguson protests in August 2014 and the killing of Philando Castile in July 2016), as expected.

We also compare our dataset to that of Williamson, Trump and Einstein (2018) for the one-year period covered by the dataset used in that paper. Williamson, Trump and Einstein (2018) also began with the Robinson dataset as a starting point, but then undertook a process of cleaning and supplementing that dataset, including independently searching Google News for evidence of any other BLM protests that might not have been included in the original dataset. For the one-year period running from August 9, 2014-August 9, 2015 (the coverage of their dataset), we compare our dataset to the one included in that paper's replication package to get a sense of coverage and completeness. Williamson and Trump include a total of 780 protests from that one-year period in their dataset. Our final cleaned dataset includes 662 protests over the same time period, but the two datasets have slightly different inclusion criteria because Williamson and Trump do not exclude campus protests as we do here. Prior to the exclusion of campus protests, our cleaned/amended dataset includes 721 protests for that same time period, capturing over 90% as many protests as reported by Williamson and Trump.[2] We thus conclude that for the period where it is possible to

[1]We did not have the resources to continue this exercise up through the 2020 wave of protest, but we direct readers to the work of the ACLED project for protest data from this period.

[2]Readers may also wonder whether the two datasets are automatically similar in size given their shared starting point (the Robinson dataset). But both teams amend and extend that dataset substantially, so the comparison is still

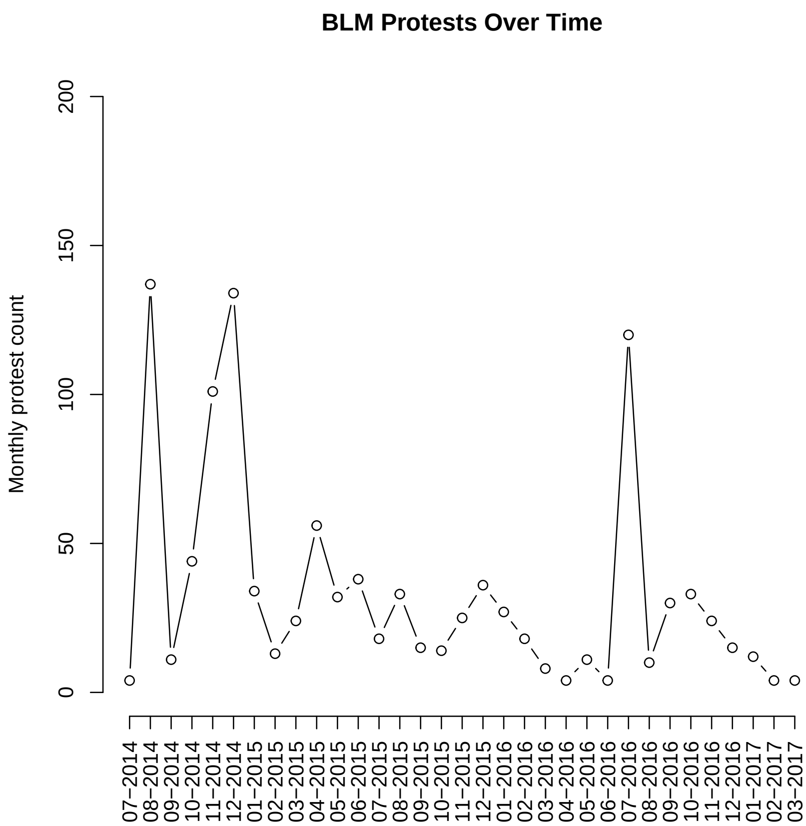


Figure A1: Events included in the observational BLM protest dataset, by month validate our approach against a different team's efforts to build a complete accounting of protest activity (or at least publicly-visible protest activity that drew some media attention), our dataset is relatively complete.

2 Additional descriptive tables for BLM Protest Dataset

Table A1 presents additional specifications that add state fixed effects, as well as municipality size, to the specifications shown in Table 1 of the main paper. Table A2 adds county and month fixed effects, as well as variables capturing whether media coverage reported any protester or police injuries occurring at a given protest, though we note that these injury variables are best thought of as post-treatment variables (for example, it is very unlikely to see police injuries at a protest where the police do not turn up). Table A3 presents some descriptive statistics for various subsets of the observational dataset.

As noted in the paper, some readers may wonder about "Bayesian updating" by respondents in our experimental sample. Respondents are shown a vignette about a protest with limited information about whether that protest is violent (no explicit description of violence but also no statement that it was nonviolent). The treatment condition adds a sentence about, and a photo of, a large police deployment at the protest. In the real world, does heavy police presence provide additional information about whether a protest is actually violent? Readers curious about this question may be interested in the correlations shown in these tables constructed with observational data, particularly table A2 given that it includes information on protest injuries where those were recorded. We are hesitant, however, to use these correlations to construct an empirical benchmark of what we think the ”right” amount of updating would be in these contexts, given limits of both the protest dataset and our survey data. While we think the empirical data presented here can establish, as we say in the paper, that policing varies across time and space in ways that are not fully explained by visible protest characteristics, we do not think that they allow for an assessment of all included protests as either ”violent” or ”nonviolent.” For one thing, even where injury data is reported in media coverage of protests, it is rarely possible to trace protester or police injuries directly back to the choices of either protesters or police (or the dynamic interplay of the two groups). Further, our survey experimental respondents live in various jurisdictions, making it difficult to determine the appropriate frame of reference for such a benchmark: respondents may infer different things from police deployments because their local police departments pursue different protest-policing strategies. We do not have enough information to estimate the benchmark described by the reviewer.

useful. The raw Robinson dataset included just 583 protest observations over this time period, including some international/online protests.

Table A1: Protest Characteristics and Police Response (Extra Specifications)

	Dependent variable:								
	Any Police Presence			Any Arrests Made			Crowd Control Measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Highway Blockage	0.124*	0.089	0.090	0.182*	0.169*	0.197*	0.104*	0.090	0.114*
	(0.052)	(0.059)	(0.059)	(0.042)	(0.050)	(0.051)	(0.041)	(0.047)	(0.048)
Other Disruption	0.352*	0.315*	0.303*	0.207*	0.195*	0.205*	0.089*	0.076*	0.082*
	(0.030)	(0.033)	(0.034)	(0.024)	(0.028)	(0.029)	(0.023)	(0.027)	(0.028)
After Dark	0.076*	0.084*	0.078*	0.055*	0.055	0.028	0.122*	0.129*	0.114*
	(0.030)	(0.033)	(0.034)	(0.024)	(0.028)	(0.029)	(0.023)	(0.027)	(0.028)
Protest Size Under 50		−0.219*	−0.163*		−0.081	−0.040		−0.164*	−0.131*
		(0.059)	(0.060)		(0.050)	(0.052)		(0.048)	(0.049)
Protest Size 50-100		−0.143*	−0.106		−0.062	−0.029		−0.109*	−0.082
		(0.060)	(0.060)		(0.050)	(0.051)		(0.048)	(0.049)
Protest Size 100-1000		−0.051	−0.033		−0.072	−0.047		−0.062	−0.042
		(0.056)	(0.057)		(0.048)	(0.048)		(0.045)	(0.046)
Majority-Black Protesters		−0.017	−0.035		−0.034	−0.060*		−0.007	−0.023
		(0.031)	(0.033)		(0.026)	(0.028)		(0.025)	(0.027)
Policing-focused Protest		0.025	0.009		−0.035	−0.063		−0.074*	−0.086*
		(0.044)	(0.046)		(0.038)	(0.040)		(0.037)	(0.039)
Municipal Population (Thousands)			0.00003*			0.00003*			0.00002
			(0.00001)			(0.00001)			(0.00001)
Constant	0.504*	0.628*	0.059	0.052*	0.171*	0.113	0.049*	0.230*	0.121
	(0.019)	(0.064)	(0.297)	(0.015)	(0.055)	(0.254)	(0.015)	(0.052)	(0.243)
State FE			X			X			X
Observations	977	778	778	980	780	780	951	767	767
R^2	0.177	0.207	0.282	0.132	0.125	0.197	0.074	0.101	0.163
Adjusted R^2	0.174	0.199	0.229	0.129	0.116	0.138	0.071	0.092	0.101

Note: $^{*}p<0.05$

Table A2: Protest Characteristics and Police Response (Further Specifications)

	Dependent variable:		
	Any Police Presence	Any Arrests Made	Crowd Control Measures
	(1)	(2)	(3)
Highway Blockage	0.102	0.176*	0.110*
	(0.056)	(0.049)	(0.043)
Other Disruption	0.215*	0.159*	0.022
	(0.035)	(0.030)	(0.027)
After Dark	0.019	−0.007	0.057*
	(0.035)	(0.030)	(0.026)
Protest Size Under 50	−0.195*	−0.056	−0.150*
	(0.060)	(0.052)	(0.046)
Protest Size 50-100	−0.103	−0.031	−0.130*
	(0.060)	(0.052)	(0.045)
Protest Size 100-1000	−0.056	−0.079	−0.098*
	(0.056)	(0.048)	(0.042)
Policing-focused Protest	0.056	0.010	0.043
	(0.058)	(0.050)	(0.044)
Municipal Population (Thousands)	0.0001	0.00004	0.00003
	(0.00004)	(0.00004)	(0.00003)
Protester Injuries Reported (0/1)	0.072	0.421*	0.422*
	(0.072)	(0.062)	(0.055)
Police Injuries Reported (0/1)	0.085	0.302*	0.212*
	(0.081)	(0.070)	(0.062)
Constant	0.112	−0.002	0.007
	(0.411)	(0.354)	(0.309)
County FE	X	X	X
Month FE	X	X	X
Observations	954	959	936
R^2	0.484	0.382	0.423
Adjusted R^2	0.301	0.162	0.215

Note: $^{*}p<0.05$

Table A3: Outcome Variable Means by Protest Features

	Police Presence	Any Arrests	Other Crowd Control
All Protests (1095)	0.67	0.17	0.14
Highway-Blockage Protests (90)	0.99	0.48	0.35
Other-Disruption Protests (390)	0.92	0.33	0.22
After-Dark Protests (347)	0.78	0.25	0.24
Policing-Focused Protests (911)	0.69	0.17	0.13

3 MTurk Experimental Pilot (Fall 2019)

In fall 2019, we ran a small pilot experiment on Mechanical Turk using the same treatment text/photos as in the main study reported in the paper, and some of the same outcome measures. We collected 772 responses (dropping people who left the survey prior to treatment assignment, and keeping anyone who was assigned to treatment even if they did not complete all portions of the study).

This pilot encountered several challenges: we received some open-ended text responses that suggested participation by either bots or very inattentive humans, and several participants told us they did not see the treatment article.[3] We present intent-to-treat estimates without excluding any of these problem observations, noting that such problems should tend to make it harder to distinguish between experimental arms.

The following table describes all the outcome measures included in the pilot study as well as the experimental treatment effects observed. The "diff" column presents the difference in means between the "heavy police presence" and "no police photo" conditions, and the "p-value" column presents the p-values of those differences, adjusted to control the false discovery rate using the Benjamini-Hochberg approach.

The estimates in the pilot are generally consistent with our theoretical predictions, though we urge caution in interpreting them given the limited pilot sample size and implementation problems discussed above. People exposed to the police imagery were significantly more likely to say that the protesters had violent intentions or were out to cause trouble. They were significantly less likely to say that the protesters' actions were justified or that they would consider getting involved with a group that supported similar causes. These differences range from about a quarter to a third of a point on a five-point scale, which is usually about a third of a standard deviation.

Several other outcomes, such as whether people report that they would go to a protest like this or whether it is important to listen to these protesters, have effects that are either null (substantively small coefficients indistinguishable from zero) or quite noisily-estimated.

[3] We could not replicate this problem on any computer/browser combination we tried, but we think it may be related to the "timing" feature in Qualtrics, which we were using to track whether people went through the study more quickly than expected.

question_text	question_scale	ctrl_mean	trt_mean	diff	pvalue
The protesters had violent intentions	5-pt Likert agreement (Strongly disagree, somewhat disagree, neither agree nor disagree, somewhat agree, strongly agree)	1.93	2.30	0.36	0.00
These protesters were out to cause trouble	5-pt Likert agreement	2.13	2.46	0.33	0.00
It is important to listen to these protesters	5-pt Likert agreement	4.29	4.25	-0.04	0.58
The protesters' actions were justified	5-pt Likert agreement	4.25	3.97	-0.28	0.00
I would consider getting involved with a group who supported causes similar to those of the protesters	5-pt Likert agreement	3.46	3.26	-0.20	0.10
On the following scale, how close are your beliefs to those of the protesters you just read about?	4-point closeness (Not at all close, not too close, somewhat close, very close)	2.91	2.82	-0.09	0.22
How likely would you be to take the following actions? Go to a protest like this one	0-100 probability slider	49.25	44.58	-4.67	0.11
How likely would you be to take the following actions? Post something positive about a protest like this on social media	0-100 probability slider	56.22	51.23	-4.99	0.11

Table A4: Outcome measures and differences-of-means from pilot study (adjusted p-values)

4 Descriptive Statistics: Prolific Sample

	All	Control	Militarized-Police Treatment
Female	0.504	0.499	0.508
Asian	0.060	0.058	0.061
Black	0.122	0.120	0.124
Hispanic	0.041	0.043	0.038
White	0.740	0.735	0.746
Democrat	0.492	0.486	0.497
Republican	0.193	0.183	0.203
Independent	0.280	0.285	0.275
Under 18	0.001	0.001	0.000
18-29	0.236	0.237	0.236
30-39	0.206	0.203	0.209
40-49	0.169	0.172	0.166
50-59	0.173	0.164	0.183
60+	0.208	0.210	0.207

Table A5: Covariate Means, April 2022 Prolific Sample

5 Experimental Study: Ethical Considerations

This section describes how our experimental study adheres to APSA's Principles and Guidance for Human Subjects Research.

Voluntary and Informed Consent

Participants for our experimental study were recruited from Prolific, an Oxford University-based platform for opt-in survey research. Before the survey, we informed participants about the research study and asked for their voluntary and informed consent. We used the following text to inform participants about the research study and ask for consent: "I agree to participate in a research study conducted by researchers from the Massachusetts Institute of Technology. In order to analyze responses to the questionnaire, my answers will be recorded. No identifying information about me will be made public and any views I express will be kept completely confidential. Findings from this study will be reported in scholarly journals, at academic seminars, and at research association meetings. The data will be stored in a secured location and retained indefinitely. My participation is voluntary. I am free to withdraw from the study at any time."

Compensation

Participants were compensated for our four minute survey in exchange for \$0.95 (a rate recommended by Prolific).

Impact

The experimental study did not directly intervene in political processes. However, it is possible that our treatments indirectly affected the political opinions or behaviors of participants by providing information about protests and/or policing. This is possibility is unlikely because the treatments are similar to what individuals encounter in their daily lives. Moreover, the study was not done at a scale liable to alter electoral outcomes or inject false information into political processes. For these reasons, we deemed the risk of impacting political outcomes to be minimal.

6 Regression Tables for Main Estimates

Table A6 reports the estimated effects of heavy police presence on perceptions of protest violence. Table A7 presents the estimates for the outcomes about support for Black Lives Matter protests.

Table A8 reports the estimated effects of our heavy-police-presence treatment on perceptions of protest violence, as in Table A6, but the different columns subset the sample by race. Table A9 similarly presents treatment effects by race for the outcomes about support for BLM protests. Then, Table A10 includes an interaction term testing for different treatment effects between Black respondents and the rest of the sample, for all outcomes shown in both Tables A8 and A9.

Table A6: Effect of Heavy Police Presence on Violence Perception: Regressions

	Dependent variable:		
	Event Violent	Intentions Violent	Cause Trouble
Heavy Police Presence	0.151^{*}	0.214^{*}	0.147^{*}
	(0.047)	(0.040)	(0.044)
Constant	1.832^{*}	1.628^{*}	1.792^{*}
	(0.033)	(0.028)	(0.031)
Observations	2,644	2,646	2,646
Note:			*p<0.05

Table A7: Effect of Heavy Police Presence on BLM Support: Regressions

	Dependent variable:			
	Get Involved	Go Protest	Social Media	Support
Heavy Police Presence	−0.016	−0.883	−0.605	−0.018
	(0.056)	(1.361)	(1.474)	(0.052)
Constant	3.165^{*}	36.927^{*}	43.923^{*}	3.839^{*}
	(0.040)	(0.973)	(1.053)	(0.037)
Observations	2,640	2,637	2,637	2,637
Note:				*p<0.05

Table A8: Effect of Heavy Police Presence on Violence Perceptions by Race: Regressions

	EventViolent			IntentionsViolent			CauseTrouble		
	Black	White	Other	Black	White	Other	Black	White	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Heavy Police Presence	−0.050	0.163*	0.272*	−0.033	0.250*	0.247*	−0.0003	0.191*	0.047
	(0.120)	(0.055)	(0.126)	(0.080)	(0.048)	(0.099)	(0.086)	(0.052)	(0.116)
Constant	1.646*	1.888*	1.682*	1.354*	1.696*	1.497*	1.405*	1.864*	1.743*
	(0.086)	(0.039)	(0.090)	(0.057)	(0.034)	(0.071)	(0.062)	(0.037)	(0.083)
N	326	1,972	346	326	1,973	347	326	1,973	347

*$p<0.05$

Table A9: Effect of Heavy Police Presence on Protester Support by Race: Regressions

	SupportProtest			GetInvolved			GoProtest			SocialMedia		
	Black	White	Other	Black	White	Other	Black	White	Other	Black	White	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Heavy Police Presence	−0.069	−0.019	0.024	0.034	−0.015	−0.085	−2.345	0.104	−5.388	−1.729	−0.577	−0.131
	(0.105)	(0.062)	(0.130)	(0.138)	(0.066)	(0.149)	(3.902)	(1.557)	(3.711)	(3.954)	(1.691)	(3.878)
Constant	4.414*	3.721*	3.976*	3.669*	3.046*	3.376*	48.541*	33.593*	45.154*	62.771*	39.793*	49.976*
	(0.076)	(0.045)	(0.093)	(0.099)	(0.047)	(0.106)	(2.805)	(1.112)	(2.647)	(2.843)	(1.208)	(2.766)
N	325	1,968	344	325	1,970	345	325	1,968	344	325	1,968	344

*$p<0.05$

Table A10: Effect of Heavy Police Presence on Violence Perceptions and Protester Support: Black respondents compared to the rest of the sample

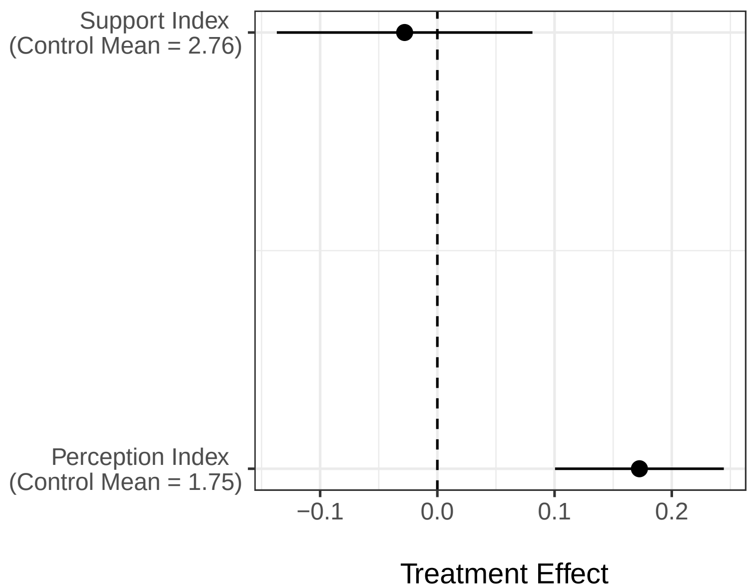
	EventViolent	IntentionsViolent	CauseTrouble	SupportProtest	GetInvolved	GoProtest	SocialMedia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Heavy Police Presence	0.180*	0.250*	0.170*	−0.013	−0.026	−0.720	−0.519
	(0.050)	(0.042)	(0.046)	(0.055)	(0.060)	(1.444)	(1.549)
Black	−0.212*	−0.312*	−0.440*	0.655*	0.574*	13.224*	21.459*
	(0.102)	(0.086)	(0.094)	(0.112)	(0.122)	(2.957)	(3.170)
Heavy Police Presence X Black	−0.230	−0.283*	−0.170	−0.056	0.059	−1.625	−1.211
	(0.142)	(0.119)	(0.131)	(0.156)	(0.170)	(4.116)	(4.413)
Constant	1.858*	1.666*	1.845*	3.759*	3.095*	35.318*	41.312*
	(0.035)	(0.030)	(0.033)	(0.039)	(0.043)	(1.031)	(1.106)
N	2,644	2,646	2,646	2,637	2,640	2,637	2,637

*$p<0.05$

7 Difference-in-Means for Index Variables

Figure A2 presents the estimated effects of militarized police on an index variable composed of our three perceptions of violence outcomes and an index variable composed of our four BLM support outcomes. To create this second index, we re-scaled respondents' willingness to "Go to a protest like this one" and "Post something positive about a protest like this on social media" from 1-100 to 1-5 scales so that all four survey items were scaled the same before combining. Consistent with the item-specific estimates shown in the main paper, we see that respondents shown the "militarized-police" treatment were more likely to view the protest as violent and appear to be less likely to support a protest of this sort (though this estimate is noisier and not statistically distinguishable from 0).

Figure A2: Effects of Militarized Police on Index Variables (Violence Perceptions and Support for BLM Protesters)



8 Pre-Analysis Plan as filed with EGAP at OSF

This is a blinded copy of the pre-analysis plan filed prior to fielding the survey experimental study described in the paper. The original copy is available at: `https://osf.io/beuzc`.

Pre-Analysis Plan:
How Police Behavior Frames Protest

[redacted]

April 25, 2022

1. Study Design Overview

The objective of the study is to understand how police responses to Black Lives Matter (BLM) protests shape public perceptions of protest violence and public support for the BLM movement.

We use an online survey experiment to evaluate the effect of *police responses to BLM protests* (Explanatory variable) on *perceptions of protest violence* (Outcome 1) and *support for BLM* (Outcome 2). We conduct this experiment in the United States, where Black Lives Matter protests have been widespread, and police reactions varied.

2. Conditions

We present respondents with different versions of truthful news stories describing a BLM protest. First, participants read the following introductory text:

We're interested in your views on current events in the United States. First, please take a look at the information provided below about a real protest that occurred recently.

In the news stories, we randomly vary the police response to the protest. Some respondents see a news story accompanied only by a photograph of peaceful protestors ("no police" condition), while

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[redacted]

others see the story with an additional photo illustrating a heavy police presence at the protest ("militarized police" condition). All other details remain the same. Below are the descriptions and photos used for each condition. The red text indicates the militarized police condition.

Protesters rallied in front of City Hall on May 2 after a young man died in police custody, demanding action by city officials. Local organizers and members of the Black Lives Matter movement are asking that charges be brought against officers, since the man died of an injury suffered after his arrest. The crowds began to assemble around noon near the site of the man's arrest, then marched to City Hall. Police responded with a large deployment.

Figure 1: No Police Condition

Note: The figure shows pictures used in the experiment's "no police" condition

Figure 2: Militarized Police Condition

Note: The figure shows pictures used in the experiment's "militarized police" condition

3. Outcomes

Our two outcomes of interest are (1) perceptions of protest violence and (2) public support for the Black Lives Matter movement. We measure these outcomes and close with a brief free-text response that asks for respondents' thoughts about the protest. This section describes the measurement of the two outcomes and the covariates.

Outcome 1. We measure perceptions of protest violence with three measures. First, we ask respondents to read the following introductory text:

Next, we would like to ask your opinion of the protest you just read about. For each statement below, please indicate whether you agree or disagree with it.

Then, we ask respondents to indicate whether they "strongly agree," "somewhat agree," "neither agree nor disagree," "somewhat disagree," or "strongly disagree" with the following three statements: (1) "The event in question was violent," (2) "The protesters had violent intentions," and (3) "These protesters were out to cause trouble." These questions create three five-point outcome measures of protest violence.

Outcome 2. We measure public support for Black Lives Matter with four measures. First, we ask respondents to indicate whether they "strongly agree," "somewhat agree," "neither agree nor disagree," "somewhat disagree," or "strongly disagree" with the following statement: "I would consider getting involved with a group who supported causes similar to those of the protesters." Second and third, we ask respondents to indicate their willingness to "Go to a protest like this one" and to "Post something positive about a protest like this on social media" on a scale of 1–100, where 0 means that a respondent would "absolutely not take that action" and 100 means that a respondent would "definitely take that action." Fourth, we ask respondents whether they "strongly agree," "somewhat agree," "neither agree nor disagree," "somewhat disagree," or "strongly disagree" with the following statement: "I support these protestors."

Covariates. We collect a set of demographic covariates on gender, race, age, and political affiliation. We also include an attention check after the demographic questions, and a manipulation check after the treatment.

4. Hypotheses

We specify our two main hypotheses as follows:

> H1: Protests met with a militarized police response are more likely to be perceived as violent than identical protests without a militarized police response.
>
> H2: Protests met with a militarized police response are more likely to reduce public support for the social movement than identical protests without a militarized police response.

5. Estimation Procedure

First, we use a difference in means to test both hypotheses. We take the expected difference in perceptions of protest violence (Outcome 1) and public support for Black Lives Matter (Outcome 2) between respondents who received the "militarized police" and "no police" conditions.

Second, we use OLS to regress (1) perceptions of protest violence and (2) public support for the movement on a treatment indicator for the militarized police condition. The linear regression estimations take the form of:

$$Outcome_i = \alpha_1 + \beta_1 Police_i + \delta_1 X_i + \epsilon_i$$

where $Outcome_i$ is the perception of protest violence or support for BLM by respondent i, $Treatment_i$is the assignment status for the "militarized police" or "no police" condition for respondent i, and $X_i$is a vector of pre-treatment individual characteristics. For both hypotheses, the estimand is β_1: the average treatment effect (ATE). The baseline are respondents assigned to the “no police” condition.

For the first set of regressions (i.e., those that pertain to Outcome 1), the data will provide support for Hypothesis 1 if β_1 is greater than zero at a conventional threshold for statistical significance (α = 0.05). We expect the respondents in the “militarized police” condition to perceive the protest as more violent than the control group. For the set of regressions that pertain to Outcome 2, the data will provide support for Hypothesis 2 if β_1 is less than zero at a conventional threshold for statistical significance (α = 0.05). We expect respondents in the “militarized police” condition to view BLM less favorably than the control group. We use two-tailed tests for both sets of regressions ($H_1 = H_0$).

We estimate separate regressions for each outcome measure (i.e., separate regressions for the three measures of perceptions of protest violence, and for the four measures of support for BLM). We will also estimate regressions with indices for perceptions of protest violence (Outcome 1), and for support for BLM (Outcome 2). To correct for multiple testing, we will control the false discovery rate using the approach described in Benjamini and Hochberg (1995).

6. Sample

We aim to recruit 2,500 respondents via Prolific, an Oxford University-based platform for opt-in survey research. When participants agree to take the survey, they will be directed toward the external Qualtrics website where our survey is hosted. Participants will receive monetary compensation when they complete the survey and return to Prolific.

The main analysis will include all respondents except those who drop out before the treatment. We will also report robustness tests limiting the analyses to those respondents who pass the attention check.

7. Power Analysis

We conduct power calculations using results from a pilot survey. This survey was administered to 772 respondents in 2019 on Mechanical Turk. The pilot survey used the conditions described in Section 2.

We base the power calculations on two outcomes from the pilot survey. First, we use the question asking respondents to agree or disagree with the statement, "The protesters had violent intentions," on a 5-point scale from "Strongly agree" to "Strongly disagree." This outcome is one of our proposed questions for perceptions of protest violence (Outcome 1). Second, we use the question that asked, "How likely would you be to go to a protest like this one?" on a scale from 0 ("absolutely not") to 100 ("definitely"). This outcome is one of our proposed questions for support for BLM (Outcome 2).

Figures 3 and 4 report the power calculations for different sample sizes, based on the treatment effects and standard deviations of the dependent variables from the pilot. The red line indicates the conventional target power level (0.8). Figure 3 shows that a sample of ~420 is powered to detect effects for the first dependent variable ("The protesters had violent intentions"). Figure 4 shows that a sample of ~1700 is powered to detect effects for the second dependent variable ("How likely would you be to go to a protest like this one?").

Figure 3: Power Calculations for Outcome 1

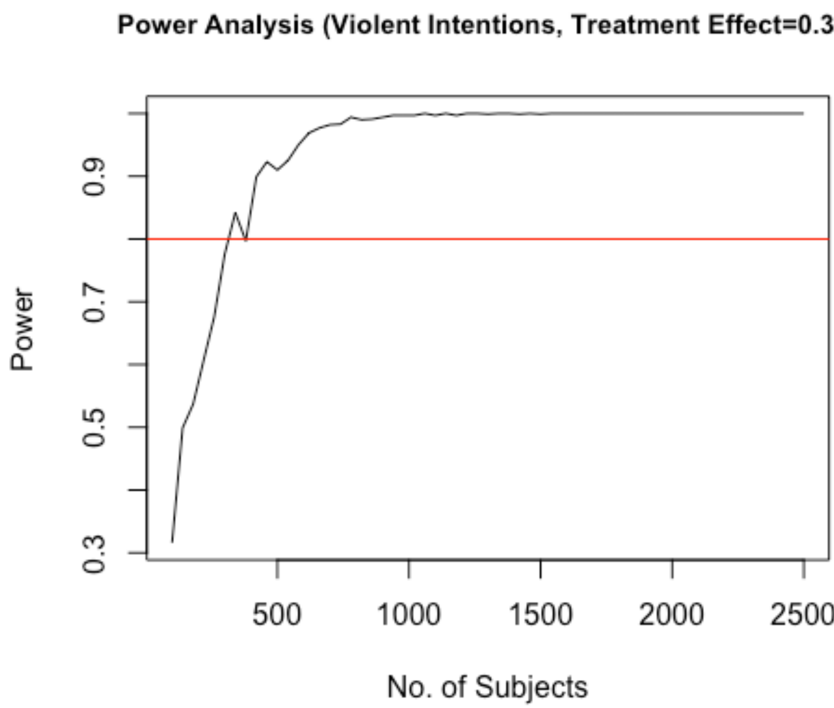
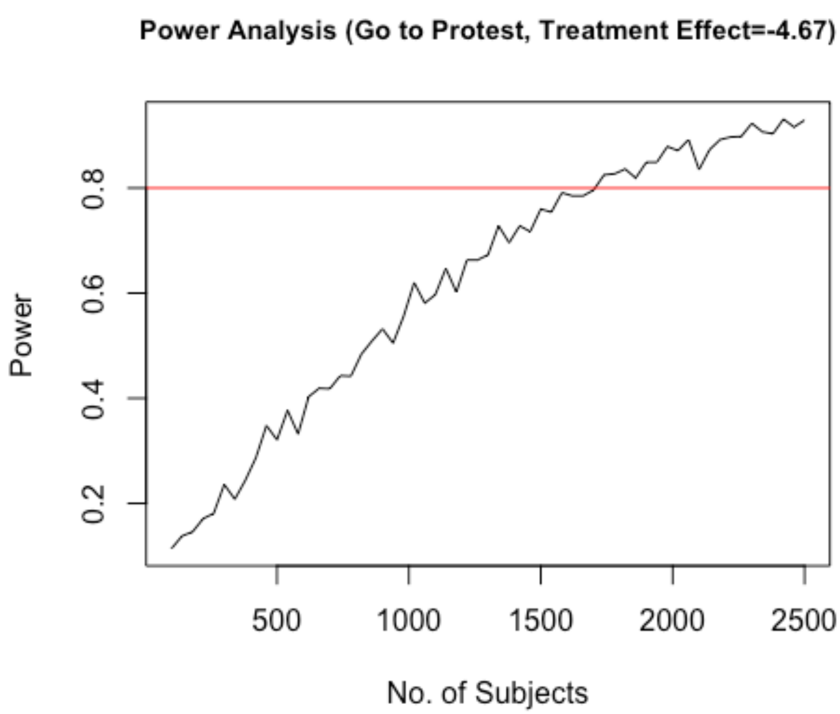


Figure 4: Power Calculations for Outcome 2



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