Online Appendix:

Images that Matter: Online Protests and the Mobilizing Role of Pictures

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A Appendix: Image Labeling Procedures

This appendix presents the questions used to manually label images, with two sample images and their labeling scores.

Variable	Question	Options
sign_slogan	Is there a protest sign or slogan in the picture? (e.g. Black Lives Matter; Hands Up, Don't Shoot!)	(0,1)
symbol	Is there any symbol in the picture? (e.g. flags, logos)	(0,1)
anger	How much anger does the image incite in you? If none, select 0.	(0, 1, ..., 10)
fear	How much anger does the image incite in you? If none, select 0.	(0, 1, ..., 10)
disgust	How much anger disgust the image incite in you? If none, select 0.	(0, 1, ..., 10)
sadness	How much sadness does the image incite in you? If none, select 0.	(0, 1, ..., 10)
enthusiasm	How much enthusiasm does the image incite in you? If none, select 0.	(0, 1, ..., 10)
peop_n	By your guess, how many people are in the picture? Leave blank if no people.	(number)
black	Check the box if this race/ethnicity is represented in the picture: Black	(0,1)
white	Check the box if this race/ethnicity is represented in the picture: White, non-Hispanic	(0,1)
latino	Check the box if this race/ethnicity is represented in the picture: Latino, Hispanic	(0,1)
asian	Check the box if this race/ethnicity is represented in the picture: Asian	(0,1)
native	Check the box if this race/ethnicity is represented in the picture: Native/Indigenous	(0,1)

(a) The Most Tweeted Image During the April 14 Protest

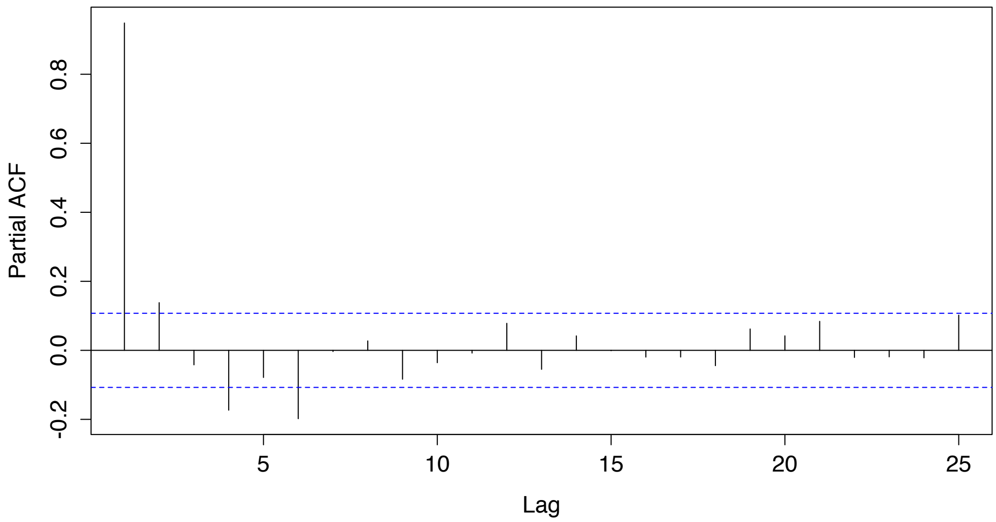
Research staff labeled this image as having 7 people (on average), no signs or slogans, and no symbols. On the emotions, the average scores were: anger: 2, fear: 1, disgust: 2, sadness: 3, enthusiasm: 1. Races/ethnicities identified were Black and White (non-Hispanic)

(a) The Fifth Most Tweeted Image During the April 14 Protest

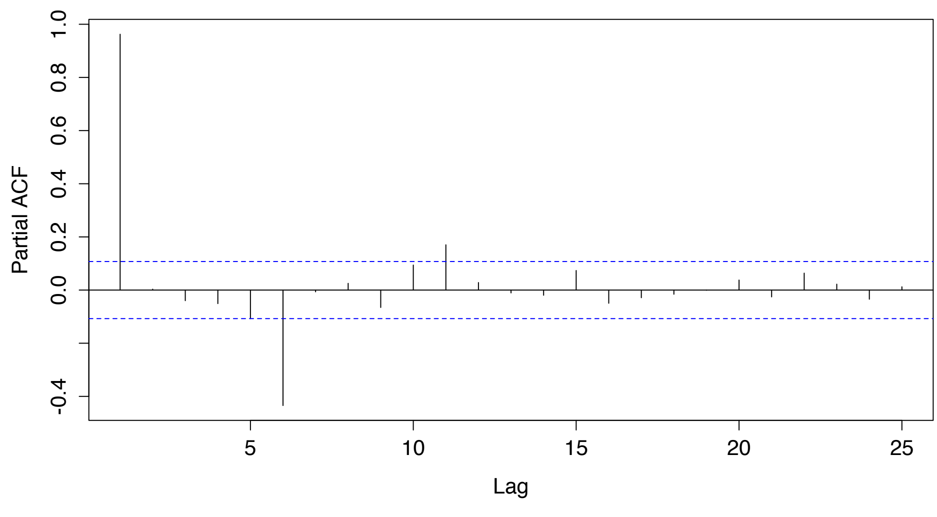
Research staff labeled this image as having 45 people (on average) and protest signs, but no slogans or symbols. On the emotions, the average scores were: anger: 2, fear: 1.5, disgust: 1, sadness: 1, enthusiasm: 2.5. Races/ethnicities identified were Black, White (non-Hispanic) and White (Hispanic).

B Appendix: Observational Dependent Variable PACFs

(a) Partial Autocorrelation Function plot for the dependent variable *Attention* (Number of messages with a BLM and/or A14 hashtag)



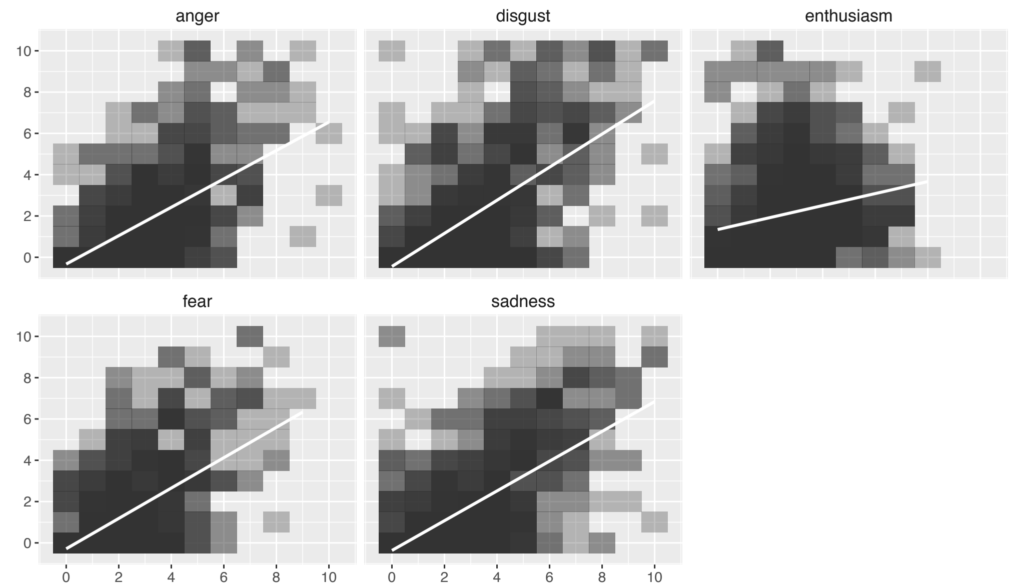
(b) Partial Autocorrelation Function plot for the dependent variable *Diffusion* (Number of new unique users tweeting about a particular BLM protest: Shutdown A14)



C Appendix: Evidence of Stable Emotions Labeling

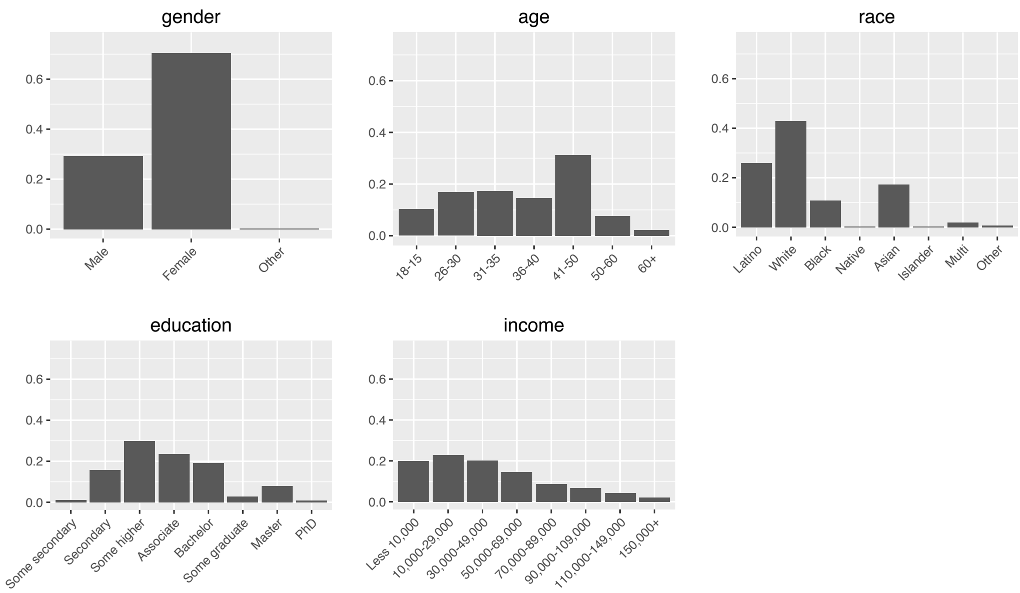
In this Appendix we provide extra information showing that although emotions are subjective, on average the top 1,000 images (which account for more than 50% of the messages with images) triggered very similar emotions to different people. This is important because when modeling the data we give to each unique image a single score per emotion (in a 10 points scale). Each image has been labeled by five different people and for each image and emotion we averaged the scores given by the five individuals. In a first iteration two research assistants labeled the top 1,000 images. We had weekly meetings with them during the labeling process, they were aware of the substance and goals of the project, and they helped us improve other parts of the labeling form. Figure 1 shows the correlation between the emotional scores given by the two research assistants to the same images. The correlation is very strong in all the cases. The *enthusiasm* score shows the weakest correlation but it is still strong.

Figure 1: Correlation between the emotion scores given by 2 research assistants to the same images (top 1,000)



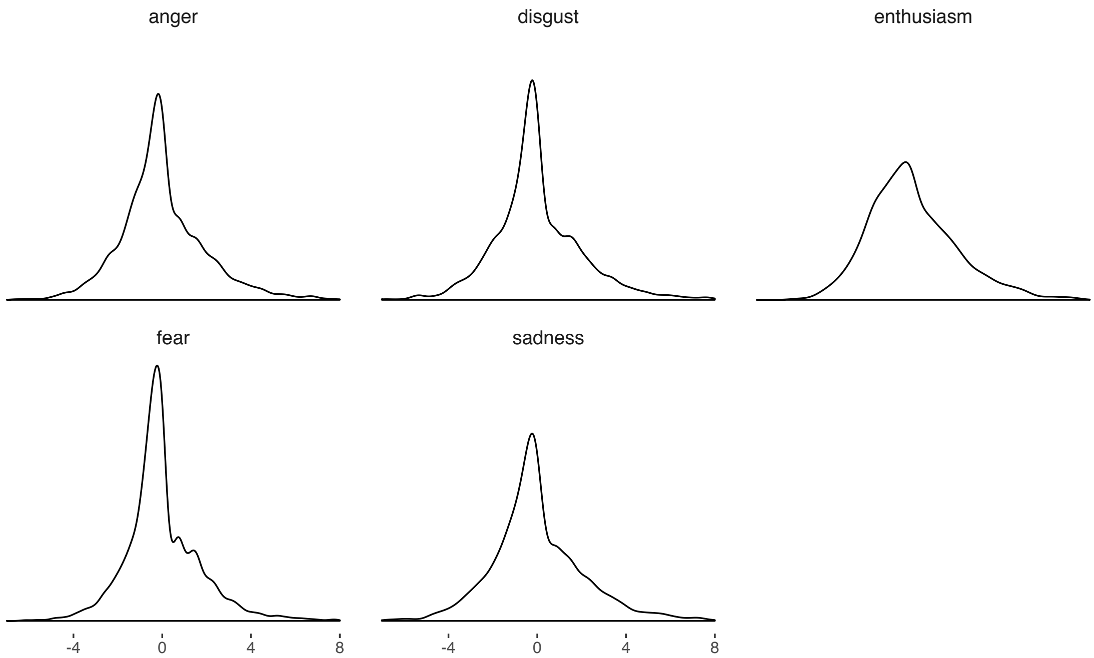
In a second iteration we used Mechanical Turk (MT) to label three more times the top 1,000 images. We decided to do so not only to have more emotion labels per image but also to get scores from people with different backgrounds, since our two research assistants were both undergraduate students, male, and white. We set it up so that only MT workers from the United States could participate and we also set it up so that workers could label more than one image but never the same image twice. Figure 2 presents summary statistics for the MT workers that participated to the labeling process. The figure shows how workers had a very diverse background.

Figure 2: Summary of the socio demographic characteristics of Mechanical Turk workers that labeled the images



To see whether people gave very different emotion scores to the same images, for each image and emotion we calculated the average score given by the five annotators (the two research assistants and three people from MT), and then for each of the five scores we calculated the difference between them and the mean score. Figure 3 shows again that the same images triggered very similar emotions to different people, with most individual scores being around 1 or 2 points from the five-scores mean. *Enthusiasm* is again the emotion that presents the most variation.

Figure 3: Distribution of the difference between emotions scores for the same top 1,000 images



D Appendix: Observational Data Analysis Regression Table

The following table presents the coefficients and standard errors in parentheses for the Negative Binomial models predicting *attention* (number of Twitter messages about Black Lives Matter and/or the Shutdown-A14 protest) and *diffusion* (new unique users tweeting about the Shutdown-A14 protest). Models 1 and 2 are the basic models that show larger percentage of messages with images increase *attention* and *diffusion* (variable *Percent Images*). In Models 2 and 3 we substitute the variable of interest *Percent Images* for the mechanisms variables. See Figure 2 and Figure 4 in the paper for a visual representation of the standardized coefficients and 95% confidence intervals around them.

	Model1 (Attention)	Model2 (Diffusion)	Model3 (Attention)	Model4 (Diffuison)
Percent Images	1.659^{***} (0.287)	2.238^{***} (0.656)		
Percent Images (1 lag)	-0.270 (0.288)	1.363^{**} (0.645)	-0.418 (0.273)	0.692 (0.612)
Followers	0.000 (0.000)	0.00000^{*} (0.00000)	0.000 (0.000)	0.00000^{*} (0.00000)
Followers (1 lag)	-0.00000^{***} (0.000)	-0.00000 (0.00000)	-0.00000^{***} (0.000)	-0.00000^{**} (0.00000)
BLM tweets (1 lag)	0.002^{***} (0.0002)		0.001^{***} (0.0002)	
BLM tweets (2 lag)	-0.00005 (0.0002)		0.00002 (0.0002)	
A14 tweets		0.0003 (0.001)		-0.0003 (0.001)
A14 new users (1 lag)		0.005^{***} (0.001)		0.005^{***} (0.001)
Black			1.419^{*} (0.842)	-3.260^{*} (1.978)
White			2.279^{**} (0.923)	9.143^{***} (2.154)
Latino			-1.022 (1.686)	-2.231 (3.890)
Asian			2.156 (3.221)	4.562 (7.470)
Native			-7.203 (5.416)	21.617^{*} (12.728)
People protesting			-0.013^{***} (0.003)	-0.004 (0.008)
Symbol			1.161 (1.782)	10.155^{**} (4.094)
Anger			-0.170 (0.278)	-0.208 (0.642)
Fear			-0.624^{***} (0.182)	-2.052^{***} (0.435)
Disgust			0.107 (0.244)	0.298 (0.570)
Sadness			0.116 (0.137)	0.879^{***} (0.318)
Enthusiasm			0.352^{**} (0.151)	-0.066 (0.346)
Constant	4.753^{***} (0.104)	1.552^{***} (0.245)	5.195^{***} (0.098)	2.319^{***} (0.231)
Observations	333	333	332	332
Log Likelihood	$-2{,}123.403$	$-1{,}447.979$	$-2{,}091.140$	$-1{,}417.735$
Akaike Inf. Crit.	4,260.805	2,909.958	4,218.281	2,871.471

Note: *p<0.1; **p<0.05; ***p<0.01

E Appendix: Observational Data Analysis Robustness Checks

This appendix discusses the robustness of our main observational finding: that images shared online increase rates of protest attention and diffusion (H_1). In particular, we are concerned about two aspects that may challenge the findings. First, the estimated *General Image Effect* may simply be capturing the mobilizing effect of a particular event that took place during the Shutdown-A14 protest; and second, the results may be conditional on some modeling choices such as using 30 minutes breaks as a unit of analysis. We address these potential challenges in three different ways. First we estimate Models 1 and 2 (from Figure **??**) using two different samples: the first 50 and the second 50 observations in our data set. Observations 1 to 50 go from the afternoon of April 13 to the afternoon of April 14, 2015. Observations 51 to 100 go until the afternoon-evening of April 15. The organizations behind the Shutdown A14 action demonstrated on the streets on April 14. However, no protest or mobilization happened on April 15. If we still observe the key variable *Percent Images* to have a significant effect when estimating the models using the second sample (observations 51 to 100), then we would find evidence suggesting the mobilizing effect of images is not dependent of a very particular event or accident that could had happened during the protest.

Second we also replicate Models 1 and 2 by using 10 minutes instead of 30 minutes breaks as a unit of analysis to see if the findings still hold and do not dependent on using a particular n-minutes break. Finally, to address this same issue we model the data in a completely new way. For all the unique users in the dataset, we collect the Twitter IDs of all their followers and we check whether they also tweeted during the protest. Then, for each unique user, we calculate the percentage of their followers that started messaging about the BLM movement and/or the A14 action after they tweeted for the first time during our period of analysis. For example, if a user had 100 followers, 30 of them were also in our dataset, and 15 of the 30 started messaging after the user tweeted for the first time, the value of interest would be 15%. We then estimate a model predicting this quantity, with the unit of analysis being individual users and the key explanatory variable being the percentage of the total messages by a user that had an image. We add the number of followers and the number of messages sent by each user as controls. We exclude from the dataset users that only tweeted once since they provide very little information while drastically driving the results.

Models 1a, 1b, 2a, and 2c in Table 1 show the results for the first robustness check. We observe very similar results despite using samples from different time periods to estimate the effect that images have on increasing attention to and diffusion of protests online: no matter whether we use observations from April 13 to April 14, or observations from April 14 to April 15. This evidence supports the argument that the *General Image Effect* is not simply capturing the diffusion effect of a particular event that took place during the protests. Second, Models 1c and 2c in the same Table show that when modeling data using 10 minutes instead of a 30 minutes breaks we also see the variable of interest *Percent Image* to have a positive and significant effect of a similar magnitude. This robustness check suggests that the result do not depend on the modeling choice of using periods of time of 30 minutes as unit of analysis. Finally, Model 5 in Figure 4 and Table 1 shows that we observe an image effect even when using a different modeling strategy. Followers of individuals that included an image to a larger percentage of their tweets were more likely to start tweeting about the BLM movement.

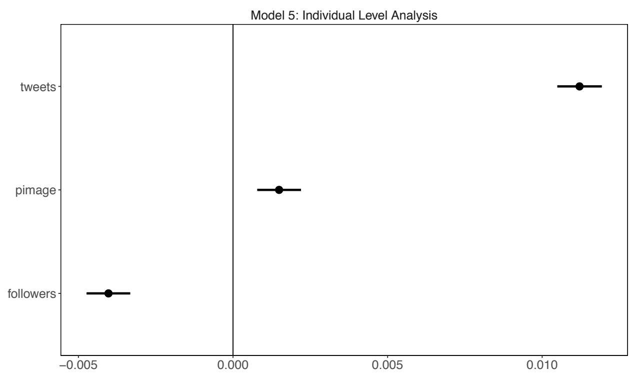
Table 1 Description: The following table presents the coefficients and standard errors in parentheses for the models we use to check the robustness of the findings (Models 1a, 1b, 1c, 2a, 2b, 2c, and 5). All models but the last one are Negative Binomials. Model 5 is a Linear Model (OLS). The dependent variable for Models 1a, 1b, and 1c is *attention* (number of Twitter messages about Black Lives Matter and/or the Shutdown-A14 protest). The dependent variable for Models 2a, 2b, and 2c is *diffusion* (new unique users tweeting about the Shutdown-A14 protest), and the dependent variable for Model 5 is the percentage of the total followers for each unique user that started messaging about the protest after that user did. The unit of analysis for Models 1a, 1b, 2a, and 2b are periods of 30 minutes: the first 50 observations were used to estimate Models 1a and 2a and the second 50 for Models 1b and 2b. The unit of analysis for Models 1c and 2c are periods of 10 minutes, and the unit of analysis for Model 5 are unique users that tweeted more than one message.

Table 1: Robustness Checks Models

	Dependent variable:						
	Model1a (Att.) (NB)	Model1b (Att.) (NB)	Model2a (Diff.) (NB)	Model2b (Diff.) (NB)	Model1c (Att.) (NB)	Model2c (Diff.) (NB)	Model5 (OLS)
Percent Images	2.106***	2.512***	2.046**	3.285***	0.757***	1.389***	0.004***
	(0.782)	(0.871)	(0.873)	(0.942)	(0.135)	(0.339)	(0.001)
Percent Images (1lag)	−0.286	−0.271	0.414	−1.090	0.166	1.260***	
	(0.687)	(0.934)	(0.722)	(1.016)	(0.136)	(0.338)	
Followers	0.00000***	0.000	0.00000	0.000	−0.000	0.00000	−0.00000***
	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.000)	(0.00000)	(0.00000)
Followers (1 lag)	−0.00000	−0.000	0.00000	−0.000	−0.00000***	−0.00000	
	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.000)	(0.00000)	
BLM tweets (1 lag)	0.001**	0.001***			0.004***		
	(0.001)	(0.0002)			(0.0004)		
BLM tweets (2 lag)	0.00004	0.0001			0.0003		
	(0.0003)	(0.0002)			(0.0003)		
A14 tweets			0.007***	0.001**		0.003**	
			(0.002)	(0.0003)		(0.001)	
A14 new users (1lag)			0.007*	0.001***		0.010***	
			(0.004)	(0.0004)		(0.002)	
Tweets							0.001***
							(0.00002)
Constant	4.500***	4.859***	1.547***	3.564***	3.817***	0.902***	0.032***
	(0.242)	(0.421)	(0.298)	(0.505)	(0.052)	(0.135)	(0.001)
Observations	50	51	50	51	1,000	1,000	15,303
R^2							0.065
Adjusted R^2							0.064
Log Likelihood	−332.490	−356.158	−187.624	−291.828	−5,283.422	−3,380.491	
Akaike Inf. Crit.	678.980	726.317	389.247	597.656	10,580.840	6,774.982	

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 4: Predicting percentage of a user's followers that started messaging about BLM and/or A14 after they tweeted for the first time (OLS)*



**Standardized coefficients (the effect of a variable moving from its mean to 1 standard deviation above)*

F Appendix: Supplemental Survey Experiment Materials

The following appendix contains the four treatment images used in the survey experiment, as well as the survey questions.

(a) Sad treatment image

(b) Fear treatment image

(c) Crowd treatment image

(d) Symbol treatment image

Survey on the #BlackLivesMatter movement

We are academic researchers from the University of Washington who study the #BlackLivesMatter movement. Please respond to the following questions related to the social movement.

Treatment Image

1. How familiar are you with the Black Lives Matter movement? (Select the option that best describes your familiarity with the movement)

- ☐ I don't know what the Black Lives Matter movement is
- ☐ I know about its existence but I don't know or am unsure what its claims are
- ☐ I know about its existence and am aware of some of its claims
- ☐ I am very familiar with the movement and its claims

2. Have you attended a Black Lives Matter event or protest in the past with the intent to support the movement? (If you attended a counter-protest against Black Lives Matter, please select "No")

- ☐ No
- ☐ Yes, once
- ☐ Yes, more than once but less than 6 times
- ☐ Yes, between 6 and 10 times
- ☐ Yes, more than 10 times

3. If there was a Black Lives Matter protest close to where you live and you didn't have any scheduling conflicts, how likely would you be to attend it as a supporter? (Type a number between 0 and 100% describing the likelihood of you attending that protest. If you would attend as a counter-protester against Black Lives Matter, please enter 0).

4.Where would you position the Black Lives Matter movement in an ideological scale (1 being extremely liberal or left-wing; and 10 being extremely conservative or right-wing)?

4b.Where would you position yourself in an ideological scale (1 being extremely liberal or left-wing; and 10 being extremely conservative or right-wing)?

5. Have you ever sent a message on social media (e.g. Twitter, Facebook, Instagram, ...) in support of or neutral towards the Black Lives Matter movement? (If you have posted against the Black Lives Matter movement, please select "No").

☐ No

☐ Yes, once

☐ Yes, more than once but less than 6 times

☐ Yes, between 6 and 10 times

☐ Yes, more than 10 times

6. What is the likelihood that you will support Black Lives Matter in the future by mentioning the movement and/or their claims on social media? (Type a number between 0 and 100% representing such likelihood. If you would post against Black Lives Matter, please enter 0)

7. What is your gender?

☐ Male

☐ Female

☐ Other

8. What is your age?

9. Which of the following best describes your highest achieved education level?

☐ What is your highest level of education?

☐ No formal schooling

☐ Some primary school (elementary school)

☐ Finished primary school

☐ Some high school (secondary school)

☐ Graduated high school or equivalent

☐ Some higher education (college/university)

- ☐ Graduated with an associate's or equivalent degree
- ☐ Graduated with a bachelor's or equivalent degree
- ☐ Some graduate studies (Master's, PhD)
- ☐ Completed Master's degree
- ☐ Completed PhD

10. What is the total annual income of your household?

- ☐ Less than $10,000
- ☐ $10,000 - $29,999
- ☐ $30,000 - $49,999
- ☐ $50,000 - $69,999
- ☐ $70,000 - $89,999
- ☐ $90,000 - $109,999
- ☐ $110,000 - $149,999
- ☐ More than $150,000

11. What is your race/ethnicity?

- ☐ White: Hispanic or Latino
- ☐ White: Non-Hispanic or Latino
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Multiracial or biracial
- ☐ Other

Treatment Image

Thanks for taking the survey. Your job is done!

Please consider signing this **ONLINE PETITION** to President Obama in support of Black Lives Matter before submitting your results.

Click on the highlighted link to sign. It will take only 30 seconds. You will be asked to give your name and zip code. Your information on the petition will in no way be linked to Mechanical Turk.

Submit