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

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Abstract

Do images affect online political mobilization? If so, how? These questions are of fundamental importance to scholars of social movements, contentious politics, and political behavior generally. However, little prior work has systematically addressed the role of images in mobilizing online participation in social movements. We first confirm that images have a positive mobilizing effect in the context of online protest activity. We then describe and test specific features of images that are hypothesized to drive the mobilization effect. Images might trigger various emotional responses, increase expectations of success, and generate collective identity. We test these theories through a study of Black Lives Matter. We find that both images in general and the proposed key attributes of images contribute to online participation. Our paper thus provides evidence supporting the broad argument that images increase the likelihood of a protest to spread online while also teasing out the mechanisms at play in a new media environment.

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1 Introduction

Do images affect political mobilization? If so, how? People today are bombarded with more images than ever before in human history. However, despite small-N studies and experimental research demonstrating the effects of images on issue-framing,[1] voting preferences,[2] political attitudes,[3] and even on compliance with authoritarian regimes,[4] there is still little work systematically addressing the role of images in mobilizing participation in protests and social movements,[5] nor are there studies that have leveraged large, digitized corpora of real world protest images. Those works that do address images in relation to social movements tend to focus on the framing of images in traditional media outlets, such as newspapers,[6] or present accounts of how particular, individual images spread awareness of specific issues.[7] And those works that study the more general political effects of images tend to rely on clear experimental treatments, while real political images from everyday individuals are messy and often vary on multiple dimensions, making large-N observational studies a must.

In this paper, we attempt to fill these gaps in the literature by presenting and testing a set of hypotheses derived from specific mechanism pathways for why images might affect social movement mobilizations. We first confirm that, as expected from prior research, images increase participation in the context of online mobilization. Beyond this main effect, we suggest that the presence of emotional triggers, of crowds that raise expectations of success, or of symbols that generate collective identities might explain why some images may have a greater mobilization effect than others. We then rigorously test these hypotheses on a large-N dataset. For our data we turn to the Black Lives Matter (BLM) movement. We track the online spread of general support for BLM and for a specific BLM protest, ShutdownA14, that occurred on April 14, 2015. Our focus is on the spread of attention to the movement and on the diffusion of the protest, operationalized by the volume of total retweets and the volume of retweets by new protest participants.

The idea that images might matter to social movements like BLM is not new. The

[1] Corrigall-Brown and Wilkes 2012; Rohlinger and Klein 2012

[2] Rosenberg et al. 1986; Todorov et al. 2005

[3] Grabe and Bucy 2009; Wright and Citirn 2011; Dahmen 2012

[4] Bush et al. 2016

[5] See Kharroub and Bas 2015 for a preliminary attempt. See also Bas and Grabe 2016 for a study of how images affect participation in other types of political behavior, such as making donations and volunteering.

[6] Corrigall-Brown and Wilkes 2012

[7] See for example Howard and Hussain 2013, 18-22 on the Arab Spring images of Mohamed Boazizi and Khaled Said

Civil Rights movement in the United States, for example, became known for its powerful mobilizing images.[8] More recently, Occupy Wall Street, the Arab Spring and the Gezi Park protests all became sources of "viral" images. The issue with studying these cases after the fact, however, is the biasing selection effect of only looking at potentially rare cases where images did have an impact. Our challenge is to examine the effects of images without knowing ex ante whether any of them will come to have out-sized historical significance. Instead of picking a case where there is evidence of a potential effect by looking at the historical record, we chose a case prior to mobilization to see which images, if any, explained subsequent variation in the spread of the given protest and support for its associated social movement.

Our paper also speaks to the urgency of studying images now, in the current new media environment. Mainstream media traditionally has had enormous power in deciding what social movements were worth paying attention to and how those social movements were framed to and by the public.[9] However, when photographic cameras became available to the mass public, social movements increased their capacity to give more salience to the movement and to decide how the movement was framed.[10] And with the rise of mobile phones with cameras, the ability of almost everyone to share images from a protest has become an important consideration for scholars.[11] Today small or emerging social movements such as BLM can rely on thousands of participants to take pictures "from the trenches"[12] and immediately share them. However, few studies have actually tested clear theoretical expectations on large-N, quantitative data.

Responding to the existing literature on contemporary protest mobilization, we focus our efforts here on the effect of online image sharing on online social movement mobilization. We readily acknowledge that the offline arena is equally important; at the very least, it plays a key role in our study as a source of protest images that spread online. Organizations today clearly use hybrid offline and online tactics to achieve their goals.[13] And while some scholars are skeptical of the role of online activism,[14] others find that online participation is an increasingly important tool to increase protest turnout[15] and

[8]Raiford 2007
[9]Gitlin 1980
[10]Raiford 2007
[11]cf Howard and Hussain 2013; Webb Williams 2015
[12]Payne 1998
[13]Chadwick 2011; Bimber, Flanagin, and Stohl 2012
[14]Morozov 2011
[15]De Choudhury et al. 2016

to set the media and political agenda.[16] As noted by Freelon et al., a relatively simple action of movement participation such as a retweet of a protest message can help drive media coverage and political attention. [17] In the case of Black Lives Matter for example, De Choudhuryy et al find that social media activity related to the movement, such as retweets and post volume, is strongly correlated with future offline mobilization.[18] But what drives the initial online activity is not yet well understood. Given the importance of understanding both online image sharing and online mobilization, and to keep the study to a more manageable scope, this paper thus examines variation in online participation in response to images. We consider two specific measures of online mobilization: attention and diffusion. By *attention*, we mean the amount of discussion occurring about a given movement, which we operationalize as the number of retweets of ShutdownA14 and BLM related tweets. By *diffusion*, we mean the spread of online support to new individuals, which we operationalize as the number of ShutdownA14 tweets that were retweeted by individuals who had not tweeted about the protest previously.

The contributions of this paper are fourfold. First, we confirm an image effect in the case of a specific Black Lives Matter protest. Second, we suggest specific mechanisms that might make certain types of images more effective at mobilizing participants. Third, we test these hypotheses using a large-N observational dataset of tweets containing protest keywords and hashtags from April 13 to April 20 2015, along with all of the images included in those tweets. The dataset includes approximately 150,000 tweets and 9,500 manually labeled images, which we expect will serve as an important dataset for future researchers. Finally, we add to the available body of knowledge regarding the BLM movement and the means by which the movement has spread.

2 Theoretical Framework and Expectations

2.1 Existing research on images and politics

Images are a central part of our lives but political scientists have traditionally paid little attention to how they affect social and political processes.[19] In particular, literature

[16] Freelon, McIlwain, and Clark 2016; Casas, Davesa, and Congosto 2016
[17] Freelon, McIlwain, and Clark 2016
[18] De Choudhury et al. 2016
[19] Grabe and Bucy 2009; Corrigall-Brown and Wilkes 2012

studying the effect of images on social protest mobilization is scarce.[20] The existing literature mostly focuses on the effect that images have on issue-framing, political attitudes, and participation in non-protest related political activities, such as voting.

There is extensive research studying the ability of mass media to set the agenda and frame issues,[21] but most studies on framing use textual data to test arguments and draw conclusions. Nevertheless, in the last few years, a growing body of literature has paid more attention to how mass media images play a particular issue-framing role for protests and social movements. For example, Corrigall-Brown and Wilkes study newspaper images of a collective action in Canada to conclude that, whereas textual content confirmed the "protest paradigm," protesters were equally likely than government authorities to receive visual coverage.[22] In another study, Rohlinger and Klein look at how different news sources cover several abortion-related protests to find that visual content is very similar across outlets and events.[23]

Another line of research studies the role of images in shaping political attitudes. For example, Wright and Citrin test if hypotheses derived from the common in-group identity model still hold in an experimental setting when using images as treatments.[24]: participants hold more positive view towards immigrant population holding an American than a Mexican flag. In another study, Powell et al. perform an experiment studying individual-level framing effects and find that images shape people's opinions and behavioral intentions more than similar textual content.[25]

Finally, research also finds that images affect political participation in activities other than social protests. A large body of literature demonstrates how images of political candidates affect viewers' evaluations of those candidates and their voting preferences. Todorov et al. for example ask people to evaluate pairs of real candidates competing for United States House or Senate seats only based on their visual appearance. Candidates that experiment participants believed to be more competent after glancing at candidate photos often matched the candidate that actually won that particular electoral seat.[26]

[20]See Kharroub and Bas 2015

[21]McCombs and Shaw 1972; Gitlin 1980; Iyengar and Kinder 1987; Baumgartner and Jones 1993; Baumgartner, De Boef, and Boydstun 2008

[22]Corrigall-Brown and Wilkes 2012

[23]Rohlinger and Klein 2012

[24]Wright and Citirn 2011

[25]Powell et al. 2015

[26]Todorov et al. 2005 Participants only evaluated pairs of candidates for which they did not recognize either of the two candidates.

Regarding the relationship between images and participation in mass contentious activities, although authors such as Castells, Bennett and Segerberg and Howard and Huusain suggest that images are important in explaining social protest mobilizations, they do not advance clear theoretical expectations nor empirical tests. In the next section we build on prior work from the fields of visual communication and cognitive psychology to explain the theoretical underpinnings of a positive image effect expectation in the context of online protest mobilization.

2.2 The General Image Effect

The logic of a general image effect on attitudes and behaviors is well established in the existing literature. First, individuals principally learn about the reality surrounding them through experience, and images act as quasi-experiences that trigger a faster and more efficient learning process.[27] Learning from visuals takes place in a specialized part of the brain (the visual cortex) whereas no such specialized area exists for text processing, making learning from text a much more consuming task.[28] Moreover, people are more capable of structuring information learned from visuals and what they learn is more likely to affect their consciousness. Messaris and Abraham point out that because images have an 'analogical' quality (they resemble real life), it is easier for people to 'index' and later access visually-learned information;[29] and Grabe and Bucy point out that since the visual cortex is in the part of the brain where thinking takes place, the neocortex, visually-learned information has a significant impact on social cognition.[30] This brings Grabe and Bucy to argue that "visual experience remains the most dominant form of learning... visual processing is central to building synaptic connections and ultimately forms the basis of extended awareness,"[31] and Graber to state that "human brains extract valuable information from audiovisuals more quickly and more easily than from purely verbal information."[32]

A large collective action literature portrays information costs as playing a key role in determining the failure or success of mobilizing efforts: people need to know about the existence, costs, and benefits of a mobilization before deciding whether to support it or

[27]Barry 1997; Gazzaniga 1998; Graber 1996; Grabe and Bucy 2009; Kraidy 2012
[28]Grabe and Bucy 2009
[29]Messaris and Abraham 2001
[30]Grabe and Bucy 2009
[31]Grabe and Bucy 2009, 13
[32]Graber 1996

not.[33] The more rapidly they can process pro-mobilization information, the more likely they are to join the action, underscoring the potential importance of images in the context of protest mobilization.

Second, images trigger stronger emotional reactions than written or spoken information.[34] An extensive literature argues that individual emotional responses are important to understand social mobilization and political participation in general.[35] Marcus et al. show that when exposed to new information, individuals feel first and think second: emotions motivate information-seeking and participation in political processes such as elections.[36] Social movement scholars also argue that emotions generate moral shocks that become motives for mobilization,[37] and that emotions forge social bonds that bind people in a common cause.[38] Existing visual communication literature argues that images are "especially powerful in transmitting realism and emotional appeal"[39] and that "because visual are processed via emotional pathways in the brain, they are inherently affect laden."[40] Thus, the existing literature not only suggests that emotions are important for social mobilization but that images play a key role in generating strong emotional reactions.

Although there is a clear expectation of a positive effect based on the cognitive findings described above, to our knowledge the general image effect has not been studied in the context of online protest participation. Our initial empirical hypothesis is therefore a basic test of the image effect in this context:

$\mathbf{H}_1$ (*General Image Effect*): Compared to protest messages without images, messages with images will attract more online attention and recruit more new online participants.

2.3 Images and the Mechanisms of Online Protest Participation

A key contribution of this paper is to go beyond the general image effect hypothesized above. We wish to better understand what features of images are more likely to foster

[33]Downs 1957; Olson 1965
[34]Graber 1996; Grabe and Bucy 2009; Barry 1997
[35]Melucci 1996; J. Jasper 1998; George E. Marcus, Neuman, and MacKuen 2000; Goodwin, J. M. Jasper, and Polletta 2004; Flam and King 2005; Goodwin and J. M. Jasper 2006; Valentino et al. 2011; Papacharissi 2014
[36]George E. Marcus, Neuman, and MacKuen 2000; Valentino et al. 2011
[37]J. Jasper 1998
[38]Papacharissi 2014
[39]Graber 2009
[40]Grabe and Bucy 2009, 8

online political participation. Relative to text, all images lower information-processing costs and are potentially more emotionally-triggering, but what information and which emotions matter most? We argue that certain types of information about a protest should have a stronger mobilizing effect than others, and so we expect images conveying that information to play an enhanced mobilizing role. Similarly, some specific emotions triggered by images might have a mobilizing effect, while others might be demobilizing. In this section we present the specific theoretical mechanism pathways that may make some images more effective than others and then set out our testable hypotheses.

Mechanisms of Mobilization: Emotional Trigger

Political psychologists studying political participation argue that a wide range of emotions explain different levels of participation in collective political processes such as elections[41] and protests.[42] Questions remain as to which emotions play a role.[43] Jasper argues that a large set of affective and reactive emotions "help lead people into social movements, keep them there, and drive them away,"[44] but he is not very clear about under which conditions we should expect these emotions to encourage or discourage social mobilization, and some of the emotions he proposes are closely related. For example, emotions such as enthusiasm and hope are highly correlated and distinguishing between them when modeling protest mobilization may be impossible in practice. Because of this high correlation between emotions, in the past scholars have often aggregated different emotions into only two categories: positive and negative.[45] However, as Valentino et al. point out, by aggregating all emotions into two groups, researchers may be missing relevant variation by including in the same category emotions that one might theoretically expect to have an opposite effects (e.g. anger and fear).[46] Hence, in order to model and estimate the role that emotions play in online protest participation it is necessary to find the right balance between taking into consideration all possible emotions and considering too few.

Valentino et al. argue that three main emotions have the potential to increase political participation: anger, enthusiasm, and fear.[47] However, as previously noted, other scholars

[41] e.g. Valentino et al. 2011

[42] Melucci 1996; J. Jasper 1998; Goodwin, J. M. Jasper, and Polletta 2004; Flam and King 2005; Goodwin and J. M. Jasper 2006

[43] Valentino et al. 2011

[44] J. Jasper 1998, 405-406

[45] Abelson et al. 1982; George E Marcus and Mackuen 1993

[46] Valentino et al. 2011

[47] Valentino et al. 2011

argue that a larger set of emotions are important to explain political mobilization.[48] For example, recent research studying the spread of BLM tweets shows that messages with sad text have had mobilizing effects,[49] and other studies show how disgust influences people's attitudes towards policies such as health[50] and homelessness.[51] We build on this literature and code images for five emotions: anger, enthusiasm, fear, disgust, and sadness.[52]

Anger "emerges in situations when people are threatened or find obstacles blocking their path to reward"[53] and it motivates individuals to act in order to find a solution to the threat or to remove the existing obstacle.[54] Individuals experience *enthusiasm* "when the system receives positive feedback about a pursuit, namely when rewards appear within reach, are getting closer, or have been attained."[55] Similar to anger, enthusiasm also might boost participation because there is a desire to achieve certain goals. *Fear* (or anxiety[56]) "is a product of an emotional system that monitors the environment for potential threats and adapts behavior accordingly."[57] Marcus et al. argue that fear triggers a reflective process and has the potential to mobilize new audiences; it increases the likelihood that people will reconsider their believes, seek further information, and mobilize on new issues.[58] When the costs of addressing fear are high, people may act "indirectly through emotion focused avoidance behavior rather than attacking the problem at hand."[59] However, we see online participation in democratic regimes as a low-cost activity and we expect images triggering fear to have a mobilizing effect.

While these emotions are mostly related to action, existing literature often argues that *sadness* is "related to the reverse: failure and loss... [it] motivates withdrawal and more effortful processing of information, encouraging individuals to accept the loss, reflect on their situation, and change goals and plans accordingly."[60] In recent study De Choudhury et al. find that sad messages related to BLM in social media were related to larger on-

[48] J. Jasper 1998; Goodwin and J. M. Jasper 2006; Gould 2009
[49] De Choudhury et al. 2016
[50] Clifford and Wendell 2016
[51] Clifford and Piston 2016
[52] We describe the coding protocol in detail in the Observational Data & Measurement section.
[53] Brader and George E Marcus 2013, 179
[54] Valentino et al. 2011; Brader and George E Marcus 2013
[55] Brader and George E Marcus 2013, 175
[56] Although fear and anxiety can be theoretically distinguished, empirical evidence show that they are highly correlated and difficult to distinguish in practice (George E. Marcus, Neuman, and MacKuen 2000; Brader 2005. For this reason in this paper we use the Valentino et al. (2011) approach and we treat fear and anxiety interchangeably.
[57] Brader and George E Marcus 2013, 178
[58] George E. Marcus, Neuman, and MacKuen 2000
[59] Valentino et al. 2011, p.159
[60] Brader and George E Marcus 2013, 176-177

street protests.[61] However, this finding is in contrast to the expectations of prior political psychology literature.

Building on this existing literature on political psychology and participation, we have the following expectations about the effect that different type of images shared online will have on the spread of a protest:[62]

$\mathbf{H}_2$ (*Anger*): Images that generate anger and that are associated with a protest will increase the likelihood of that protest to spread.

$\mathbf{H}_3$ (*Enthusiasm*): Images that generate enthusiasm and that are associated with a protest will increase the likelihood of that protest to spread.

$\mathbf{H}_4$ (*Fear*): Images that generate fear and that are associated with a protest increase the likelihood of that protest to spread.

$\mathbf{H}_5$ (*Sadness*): Images that generate sadness and that are associated with a protest decrease the likelihood of that protest to spread.

Mechanisms of Mobilization: Expectations of Success

Existing literature suggests that an expectation of success explains in part why individuals participate in political protests. Classic rational-choice models predict that people with a material interest in joining a collective action are more likely do so if their action is needed and worth it.[63] Some social movements scholars apply this logic to argue that joining a small social movement may not be rational when the movement is perceived as having only a small likelihood of success.[64] As the number of participants increases past some threshold, all else equal, individuals have a larger incentive to join the protest because the likelihood of success increases and the participation of one extra person represents a relevant contribution to the movement. Particularly in the early stages of a movement and/or protest, images showing large numbers of protesters on the streets may help social movements to increase people's perception of the movement's potential for success and to recruit more participants. For example, in a study of the 2011 Egyptian revolution

[61] De Choudhury et al. 2016

[62] We do not have a clear prior expectation about the effect of disgust on social movement mobilization. Research on how disgust affects political behavior and attitudes is still in its early stages (see Clifford and Wendell 2016 Clifford and Piston 2016 for an example), so we include disgust in our models in order to add to the preliminary literature on this emotional response.

[63] e.g Downs 1957; Olson 1965

[64] Klandermans 1984; Oberschall 1994; Kuran 1997; Finkel and Muller 1998; Kharroub and Bas 2015

Kharroub and Bas show that some of the most tweeted images during the revolts contained crowds of people on the streets.[65] Images during the Civil Rights Movement in the 1960s had similar effects. Raiford describes how a picture with a line of African American demonstrators waiting to get into a segregated swimming pool encouraged others to join the movement because they saw others already involved.[66] We therefore have the following expectation:

$\mathbf{H}_6$ (*Success Expectation*): Images related to a social mobilization that are of street protests will increase the likelihood of that mobilization to get more attention and diffuse to more participant.

Mechanisms of Mobilization: Generate Social Collective Identity

A collective identity is relevant for a social movement for several reasons,[67] but in particular because it creates motivations for individuals to join collective actions.[68] As Melucci points out, collective action is in part an expression of a set of purposes: "a purposive orientation constructed by means of social relationships within a system of opportunities and constraints."[69] In constructing and connecting purposes, and thus in building motives for others to join the movement, symbols may play a very important role. Images, because of their strong emotional and symbolic component, are capable of building common meaning between people with similar but different purposes; bringing them together. Kharroub and Bas argue that images of symbols such as the Egyptian flag and religious symbols (e.g. the Muslim Crescent and the Christian Cross) facilitated the 2011 revolts "by making salient the collective inclusive identity and hence increase identification with the movement and efficacy beliefs, where efficacy increases the likelihood to participate in the movement."[70] We therefore have the following expectation:

$\mathbf{H}_7$ (*Symbol*): Images related to a protest that include symbols of collective identity (such as flags or group logos) increase the likelihood of that protest to diffuse.

[65] Kharroub and Bas 2015
[66] Raiford 2007
[67] cf Polletta and J. M. Jasper 2001; Tajfel 1981; and Tajfel 1982
[68] Zomeren, Spears, and Leach 2008
[69] Melucci 1996, 43
[70] Kharroub and Bas 2015, 7

3 Research Design

In setting out to test the above hypotheses, we faced four fundamental research design challenges: 1) case selection; 2) measuring online social movement mobilization; 3) treating images as data; and 4) making valid causal claims. In the following section we address each of these challenges before presenting our analysis.

To assuage case selection concerns, we chose our case in advance of the protest event. In the spring of 2015, we learned of an upcoming BLM action against police brutality, called ShutdownA14, which would be held on April 14, 2015. We decided to track this case on Twitter without knowing in advance if any images would be spread online during our established protest window of April 13-20, 2015. ShutdownA14 was organized by a coalition of activist groups, including the Stop Mass Incarceration Network and Hands Up United. Actions took place on the national level with demonstrations in numerous cities. The demonstrations were a reaction to a set of episodes where police officers acted violently towards, and in some cases killed, African American citizens. The organizing groups not only called for a mobilization on the streets but also coordinated an online social media campaign. To promote the movement, organizing materials asked people to share messages about the protest and its goals by using specific hashtags and keywords such as #shutdownA14, #policebrutality, and #murderbypolice. In addition, organizing materials and tweets about the protest often included #blacklivesmatter, highlighting the crossover between the April 14 protest and the broader BLM movement active throughout the United States.

As previously mentioned, we use two operationalizations of online participation in our analysis: attention (number of retweets of ShutdownA14 and BLM related tweets) and diffusion (number of ShutdownA14 messages retweeted by new ShutdownA14 users). We care about attention because it is a necessary condition for a movement to exist or to succeed at setting policy agendas.[71] We study diffusion because it is key for social movements in order to achieve larger support and be more likely to set media and political agendas.[72] Diffusion here is therefore conceptually equivalent to online recruitment into the action. Given the narrow time frame of our observational data collection, we were unable to analyze the number of new recruits to BLM due to April 14 images, as individuals

[71] Baumgartner and Jones 1993; Kingdon 1984; Baumgartner, De Boef, and Boydstun 2008; Casas, Davesa, and Congosto 2016

[72] Barberá et al. 2015; De Choudhury et al. 2016; Freelon, McIlwain, and Clark 2016

may have been active online in the movement long before ShutdownA14. This is why we focus our diffusion analysis on the April 14 protest.

Our next challenge was in treating images as data. While computer programs have become more adept at categorizing images, the level of detail and emotional response data that we required from the collected ShutdownA14 images necessitated human coding. We worked with both university undergraduates and Mechanical Turk workers to label the roughly 9,500 unique images collected over the course of the ShutdownA14 protest. Each image was manually labeled on each of the hypothesized mechanisms, so that we could analyze each mechanism in isolation by controlling for the remaining mechanisms.

Finally, we recognize the difficulty of making causal claims for our hypotheses and analyses. One contribution of this paper is our attempt to describe important patterns in human behavior using messy, real-world data and events, which necessarily poses a challenge for causal research. We attempt to rule out alternative explanations by controlling for other relevant message-level covariates when testing our hypotheses. Having made the case for the strength of our empirical research strategies, we now turn to presenting the details of the data, measurements, analyses, and findings.

4 Data & Measurement

To test our theoretical claims we study Twitter messages related to the BLM movement and to the ShutdownA14 protest. We use the hashtags promoted by the groups organizing the demonstrations and a similar set of keywords to identify which messages were about the protest. We collected the hashtags and keywords by observing the websites of the main organizing groups, Stop Mass Incarceration Network and Hand Up United, in the weeks prior to the protest. Then, from April 13 to April 20, we collected all Twitter messages containing the hashtags and keywords in Table 1 using the Twitter Streaming API.

Table 1: List of Hashtags and Keywords Used to Collect the Tweets

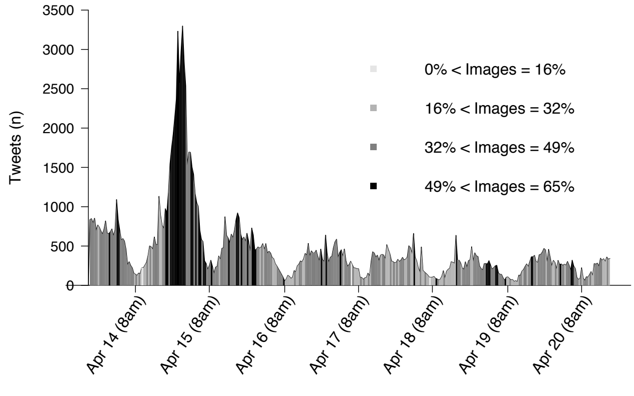
ShutdownA14	BLM	
#shutdownA14	murder by police	mass incarceration
shutdownA14	killer cops	police murder
	stop business as usual	stolenlives
	massincarceration	stolen lives
	#policebrutality	#stolenlives
	#blacklivesmatter	black lives

We look at this particular case and both BLM and ShutdownA14 messages because, as mentioned, it allows us to test the effect that images have on both attention and diffusion. As a result of the data collection process we obtained a data set with 150,324 tweets sent by 67,484 unique users; 26.8% of the messages were related to the ShutdownA14 protest, and about 43.2% of all messages contained an image.

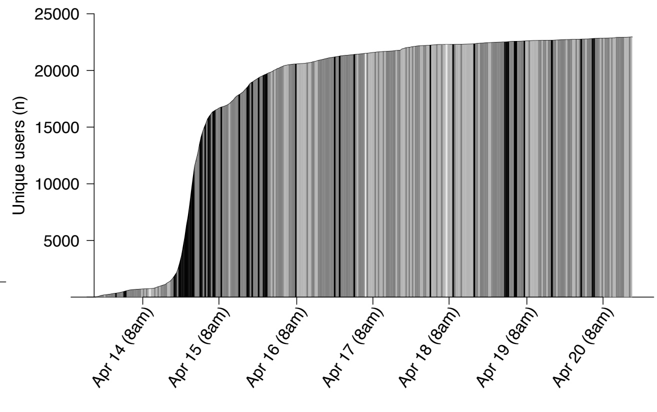
Figure 1 displays a general summary of our data over time by dividing the tweets into periods of 30 minutes. The first panel shows the percent of BLM and ShutdownA14 tweets in a given time period with an image and the total number of tweets for that period. We see a general trend, in that there seems to be a congruence between high concentration of messages with images and larger numbers of protest-related tweets. The second panel shows the percent of ShutdownA14 tweets in a given time period with an image and the number of new tweeters for that period (displayed as cumulative unique users, where the slope shows the rate of recruitment of new users). Again, we see a general trend where a high concentration of images appears to track with a spike in the number of new tweeters.

Figure 1: Bivariate relationship over the study period between the % of messages with images and two summary measures: number of tweets and number of new tweeters.

(a) % of tweets with image and number of tweets



(b) % of tweets with images and number of new tweeters



One concern with modeling attention and diffusion using the aggregated, 30-minute time-break data as shown in Figure 1 is that we cannot be sure that posters are responding to having seen images shared by friends on Twitter. Individuals might be messaging about the movement and the particular action after having a conversation about BLM with a peer or after reading the newspapers instead. Our analysis strategy reduces this concern about overlapping processes and measurement by focusing on retweets as the basis for our dependent variables. The following section describes this strategy in more detail.

4.1 Main Variables

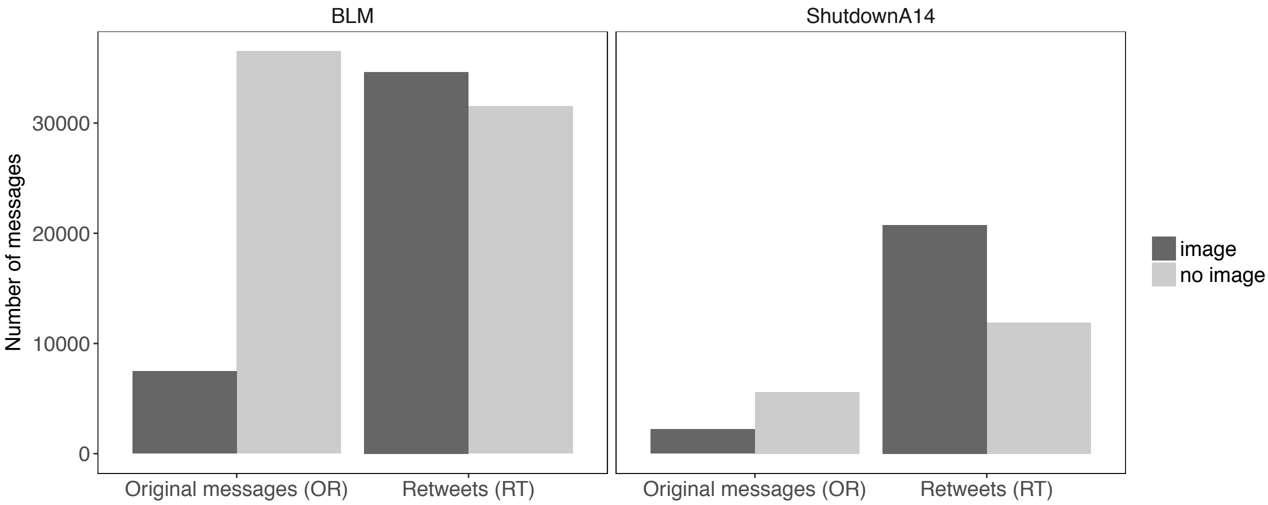
To model the data and build our dependent variables, we split the messages into original tweets and retweets. We then link retweets to their original tweet in order to count how many times an original tweet was subsequently retweeted. The count of retweets is our measure of movement *attention*, where the original tweets could include either BLM or ShutdownA14 hashtags and keywords. To measure movement *diffusion*, we consider only the ShutdownA14 tweets, for the reasons described above. We check which retweeters of a given original message had never before tweeted about the ShutdownA14 protest. If their first tweet in regards to the protest was a retweet, we count them as an individual to whom the original tweet diffused the protest.

Our first key explanatory variable of interest is whether or not an original tweet contained an image (*image*). This is a binary variable derived from the Twitter data available for each original tweet collected. We also control for other plausible explanations for why a tweet might be more likely to be retweeted. Users with more followers are more likely to be retweeted,[73] given that they are exposing their message to a larger audience. To control for that, we include in our models the number of followers of each original message poster (*number of followers*). As people who are more aware of what is trending on Twitter might also be more likely to have their posts retweeted, we also control for the number of friends of the original poster (friends being people that the original poster follows) (*number of friends*). In addition, for each message we control for the number of previous tweets that the original poster sent about BLM or ShutdownA14 (*number of previous tweets*). Finally, the time of day that a tweet is posted can also affect its likelihood of being retweeted. We therefore include a time control (*time*), a 6-class categorical variable where each class is a 4 hour break.

[73]Gonzalez-Bailon et al. 2011

Figure 2 provides an overview of the data we use in the analysis. The plot on the left provides information about messages in our dataset that contain at least one of the BLM hashtags from Table 1 while the plot on the right provides information for messages containing only ShutdownA14 hashtags. Both plots show similar trends: as expected, the number of original messages is smaller than the number of retweets. In addition, a majority of the original messages do not include an image, but most of the retweets are of original messages that do include an image.

Figure 2: Number of tweets about the overall BLM movement and number of tweets only about the ShutdownA14 protest. Each panel shows original messages *versus* retweets, split based on whether the message contained an image.



4.2 Mechanism Variables: Images As Data

To address our mechanisms hypotheses, we needed information about each particular image, not simply the number of individual tweets with images. A week after the protest, we wrote a computer program to collect all of the images that were present in the tweets, using the image links provided by the Twitter Streaming API. Some tweets had the same image under a different link, so we first identified which images were the same, following a three-step procedure. First we looked for which messages shared an image stored in the same URL. Second we wrote a computer program to identify images that were very similar. As a result we obtained a list of images that were the same but also a list of images that were potentially the same. In the third step two annotators manually revised the second group and indicated which were exactly the same. During this last step we found some images that were pictures of the same scene but from different angles or from slightly different times. We decided to code those as unique images. After collecting all the pictures and matching the ones that were the same, we ended up with a dataset of 9,458 unique images.

The next step was to manually label each of the 9,458 images for the presence of our hypothesized mechanisms. We needed to know how much anger, disgust, sadness, and enthusiasm each imaged evoked (*emotional trigger* mechanism), and whether a protest (*expectation of success* mechanism) and/or a symbol (*social collective identity* mechanism) were present in the image. We had two main concerns during this labeling process. First, we wanted to make sure that the labels for the top 1,000 most-tweeted images (949 after removing duplicates) were reliable since these would strongly influence the analysis: the distribution of the images was right skewed, with a few images being highly tweeted and the rest being tweeted only a couple times or once. We were particularly concerned about having a reliable measure of the presences of a protest and/or symbols in the images.

Second, for modeling purposes we needed to give to each unique image one score per emotion. However, emotions are subjective and the same image might trigger different emotions in different people. We wanted to make sure that the emotion scores for the most influential images were the result of multiple emotional reactions, and that on average different people reacted with similar emotional intensity to these images.

We mitigated these concerns by having 5 people label the top 1,000 images (two undergraduate research assistants and three Mechanical Turk workers) and by limiting to 100 the number of images a single Mechanical Turk annotator could label. This meant that a large and diverse pool of people participated in the labeling process (a total of 1,259 Mechanical Turk annotators). The remaining images (n = 8,509) were labeled only once by individuals from the large Mechanical Turk pool.

Annotators indicated whether each image had a protest (a binary indicator), a symbol (a binary indicator), and the extent to which an image evoked in them each of the five emotions (this generated five 0-10 scores per image). Then we used this information to build seven image-level mechanism variables. *Anger*, *Enthusiasm*, *Fear*, *Sadness*, and *Disgust* are each continuous variables ranging from 0 to 10 addressing the *emotional trigger* mechanisms ($H_{2,3,4,5}$). *Protest* is a binary variable addressing the *expectation of success* mechanism (H_6), and *Symbol* is a binary variable addressing the *collective identity* mechanism (H_7). For the top 1,000 images, we considered an image as having a protest or a symbol if at least one of the five annotators indicated the presence of these elements. The emotional score for each emotion on each image is the average of the values given by all five annotators.

A copy of the labeling protocol form, two examples of labeled images, and a summary table for these seven mechanism variable plus the controls can be found in Online Appendix A. Online Appendix B contains inter-rater reliability measures for the two undergraduate research assistants, showing that on average they coded the same images as evoking similar emotional intensities. This appendix also includes the demographics of the Mechanical Turk workers, who had to answer a socio-demographic survey prior to working on any task.

Finally, after completing this image labeling process we matched each unique image to all original messages containing that picture. Table 2 provides a brief description of all of the study variables. The final output is a dataset with rich information about each original BLM and ShutdownA14 message that we use to model the hypothesized image effects.

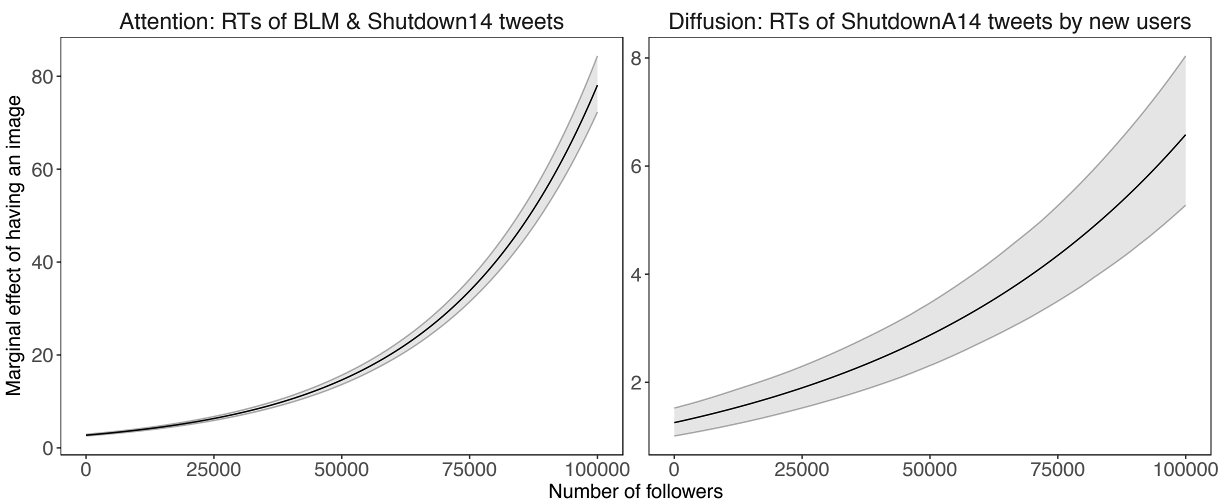
Table 2: Study variable descriptions

Variable	**Description** (Unit of Analysis = Original Tweet)
	Outcome Variables
BLM and A14 tweets (attention)	Number of retweets for tweets mentioning any of BLM hashtags/keywords from Table 1
A14 new users (diffusion)	Number of retweets from users mentioning the A14 hashtags/keywords for the first time
	Explanatory Variables
Image	Whether or not the tweet contains an image
Symbol	Whether or not the image contains a symbol
Protest	Whether or not the image is of a street protest
Fear	Average fear score evoked by the image (0-10)
Enthusiasm	Average enthusiasm score evoked by the image (0-10)
Anger	Average anger score evoked by the image (0-10)
Disgust	Average disgust score evoked by the image (0-10)
Sadness	Average sadness score evoked by the image (0-10)
	Control Variables
Number of followers	Number of followers of original tweeter
Number of friends	Number of friends of original tweeter
Number of previous tweets	Number of previous tweets by the original tweeter in the dataset
Time	6-class categorical variable (each class is a 4-hour break)

5 Modeling and Results

We use negative binomial models to predict how our factors of interest affect the number of times an original tweet is retweeted.[74] We first model the *attention* to the overall BLM movement (Model 1, with 49,345 original messages) and the *diffusion* of the ShutdownA14 action (Model 2, with 7,502 original messages). In both of these basic models the independent variable of interest is whether or not an original tweet contained an image. We then control for the number of followers, number of friends, number of previous tweets, and time. The regression table with the results for these models can be found in Online Appendix C. Our interpretation focuses on the marginal effects of our hypothesized explanatory variables.

Figure 3: Marginal effect of an original tweet having an image versus not having an image on the number of retweets (on the left) and number of retweets by new users (on the right). Marginal effect shown over a selected range of number of followers.



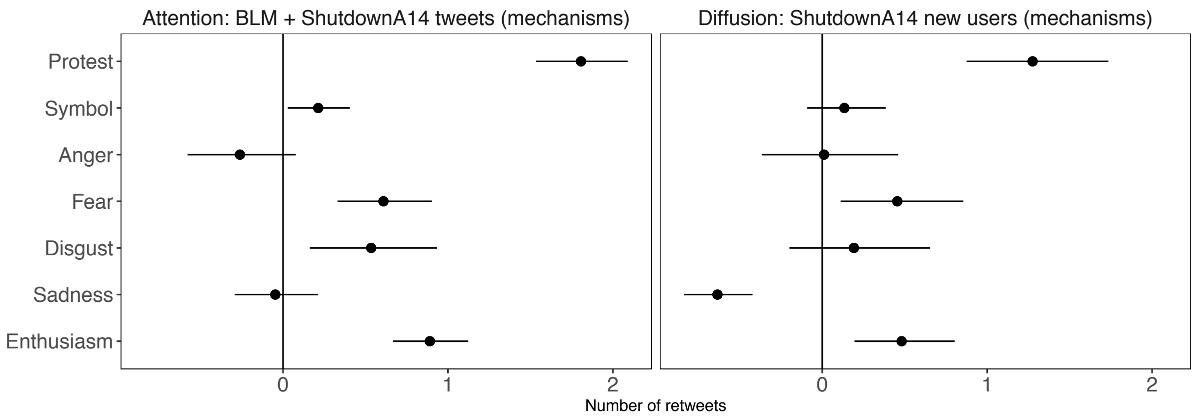
The results of the two basic multivariate analyses shown in Figure 3 are consistent the well established *General Image Effect* hypothesis (H_1): the likelihood of a protest tweet to diffuse to new recruits and to get more attention increases if the tweet contains an image. Using the general BLM data, we find that for users with very few followers (e.g. 1,000), including an image with an original message means getting approximately three more retweets than they would have if they had not included an image (holding all else constant at the mean). Using the specific ShutdownA14 tweets, and again considering an original tweeter with 1,000 followers, we find that tweets with images on average recruit one more new retweeter than tweets without images. The marginal effect is even higher for

[74]Our modeling choice reflects the structure of our dependent variables, which are both counts.

users with a larger number of followers. For example, a BLM message with an image from a hypothetical user with 75,000 followers would get about 35 more retweets compared to a tweet without an image. Original ShutdownA14 messages from the same user would get 4 more retweets from people messaging about the protest for the first time if the tweet has an image.

The next step is to test to what extent the mechanisms we presented in the previous sections explain why images related to a protest increase the likelihood of that protest to get more attention and diffuse. We estimate two new negative binomial models (Models 3 and 4) only using information from original messages that had an image (8,706 original tweets in Model 3 and 2,078 original tweets in Model 4). In this case we include all of the mechanism variables (Protest, Symbol, Anger, Fear, Sadness, Disgust, Enthusiasm) while keeping the same controls (Number of Followers, Number of Friends, Number of Previous Tweets, and Time).[75] The structure of the model and data therefore allows us to examine the effect of each mechanism while controlling for the effects of the other mechanisms.

Figure 4: Predicting attention and diffusion by image mechanisms (Negative Binomial Models)*



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

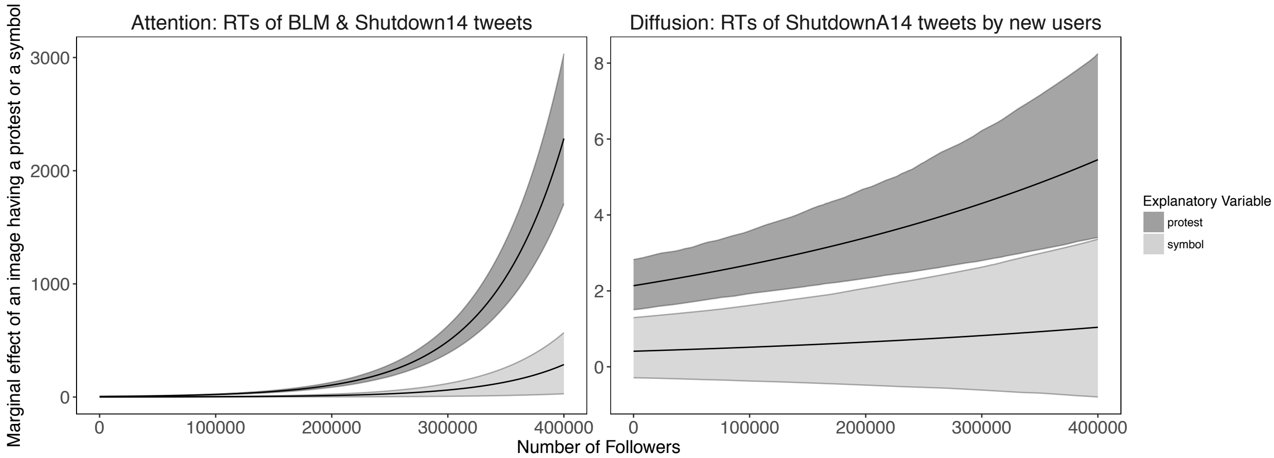
The results, shown in Figure 4, are supportive of some of the hypothesized mechanisms.[76] First, we find evidence supporting both the *expectation of success* (H_6) and *symbol* (H_7) mechanisms. Holding all other image features and original tweeter characteristics constant, images of street protest increase both movement attention and protest diffusion ($p<0.05$). Similarly, but with a smaller substantive magnitude, images with

[75]To assuage concerns that the text of the tweets are driving results, we also run robustness checks for Model 3 that control for message topics; see Online Appendix D. Coefficients do not change in a way that would alter our interpretation of the results.

[76]See Online Appendix C for the regression tables.

collective symbols appear to increase attention ($p<0.05$); the positive effect is not statistically significant for diffusion. Figure 5 shows the marginal effect on attention and diffusion of an original message image containing either a protest or a collective symbol. For a BLM message from a user with 1,000 followers (holding all else at their means), having a protest in the accompanying image would lead to approximately 5 more retweets compared to an image without a protest. A ShutdownA14 message with a protest image from the same user would lead to approximately 2 more retweets from new users. For users with more followers, the effect is more pronounced. Considering a user with 300,000 followers, including a protest image leads to 495 more BLM retweets, and 4.5 new ShutdownA14 retweets. As Figure 5 demonstrates, the marginal effect of an image with a collective symbol is smaller, but still varies over the range of followers. If, for example, a user has 300,000 followers, a symbol image leads to 60 more BLM retweets and has no notable diffusion effect.

Figure 5: Marginal effect of an original message image having a protest or a symbol on the number of retweets (on the left) and number of retweets by new users (on the right). Marginal effect shown over a selected range of number of followers.



Second, we find some evidence supporting our hypotheses regarding the role of emotions. The coefficient for *anger* (H_2) is negative in the attention model, contradicting our initial hypothesis, but in neither model are the coefficients statistically significant. We observe as expected that, all else equal, an increase in the amount of *fear* (H_4) an image evokes will increase both attention and diffusion.[77] *Disgust* (no clear hypothesized expectation) has a statistically significantly positive effect on attention, while for diffusion

[77]Interestingly, this finding contradicts that of De Choudhury et al. (2016), who find based on a text analysis for BLM tweets that fear is demobilizing

the effect is also positive but not statistically significant. Images inspiring *sadness* (H_5) have a negative and statistically significant effect on diffusion, and a negative but not significant effect on attention. Images evoking *enthusiasm* (H_3) also appear to increase attention and diffusion.

Figures 6 and 7 highlight the differential effects of the emotions evoked by images. In Figure 6, for example, we see that as the amount of fear increases, attention increases. Holding all of the other variables at their means, increasing the anger evoked by an image from 0 to 10 increases the predicted number of retweets by about 3. A similar change in enthusiasm has an effect with similar magnitude on retweets. Disgust also increases attention, but with a smaller effect size (roughly 1.5 more predicted rewteets). Increasing the amount of anger in an image decreases the attention a tweet receives, though the size of the effect is slight. For sadness, there is no substantial or significant effect over the range of evoked emotion.

Similar trends appear in Figure 7. Increasing anger seems to have essentially no effect on the diffusion of the movement, while increasing disgust has a very slight positive effect (less than a one new user retweet increase over the range of disgust). Increasing the amount of enthusiasm or fear evoked also increases diffusion. An increase in enthusiasm from 0 to 10, holding all else at the mean, increases the predicted number of new user retweets by approximately 2, while an increase in fear from 0 to 10 increases the predicted number of new user retweets by approximately 3. Increasing sadness decreases the diffusion to new protest tweeters, with an decrease of about 1 new user retweet over the range of sadness. These findings demonstrate the varied effects of images on mobilization based on the content of and emotional responses to a given image.

Figure 6: Predicting attention to BLM over range of evoked emotions

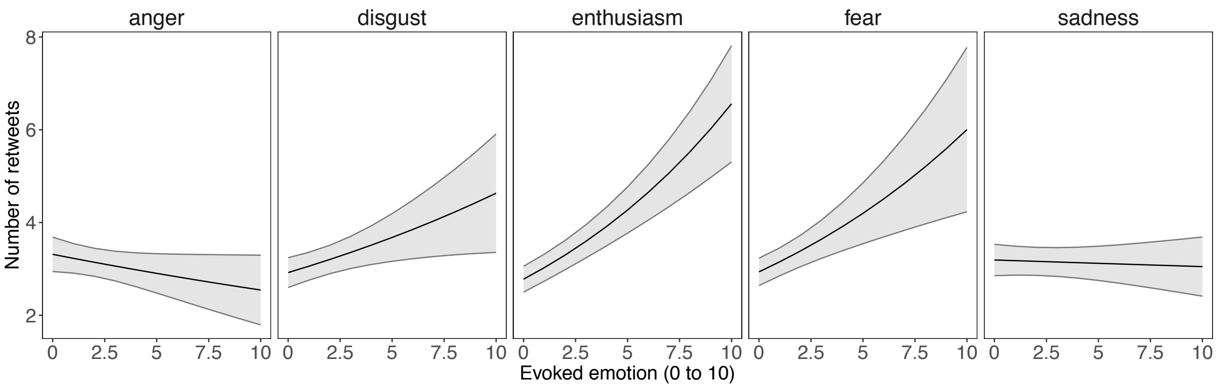
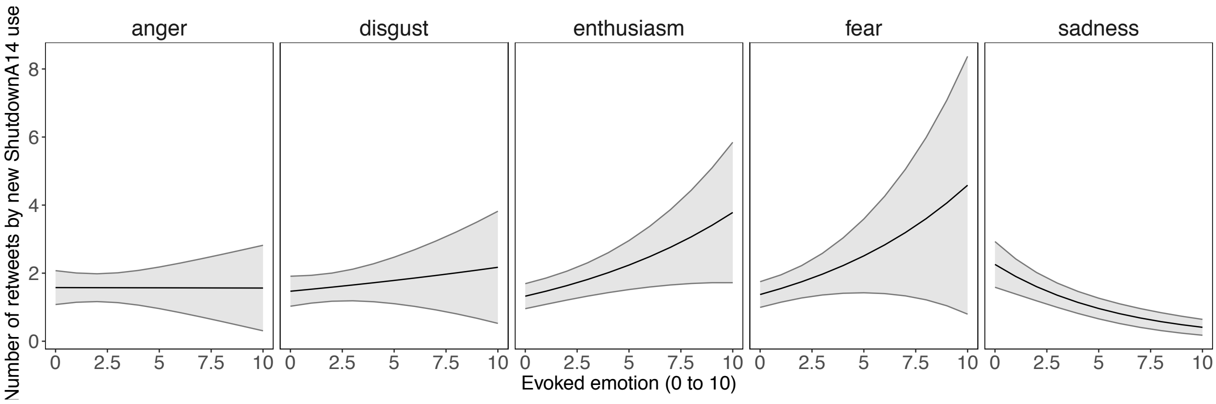


Figure 7: Predicting diffusion of ShutdownA14 over range of evoked emotions



6 Disussion and Conclusion

Despite the prevalence of images in modern life and the prior literature on the importance of images in swaying political opinions and behavior, very little research has leveraged large quantities of observational data to test the role of images in mobilizing political activism. The literature that does exist claims that images played a key role in the success of recent protests such as Occupy Wall Street, the Arab Spring uprisings, and the Gezi Park protests.[78] However, prior studies have generally been limited to small-scale or experimental research. Prior literature provides a theoretical framework for why images should matter during these real world events, but the hypotheses for why images might mobilize support for social movements has not been systematically analyzed on a large scale.

In this paper we test the general image effect theory in the context of a Black Lives Matter protest. We then specify and test specific mechanisms explaining why images might increase the likelihood of an online protest to receive more attention and to diffuse to new participants. We test these hypotheses using observational data, including roughly 150,000 tweets and 9,500 unique images from a Black Lives Matter (BLM) protest that took place in April 2015.

We argue that particular images might have a larger mobilizing effect because they act as emotional triggers; increase expectations of success; and generate collective identities. In line with the theoretical predictions, we find that in the context of the ShutdownA14 BLM protest promoted on Twitter, messages with images were more likely to be retweeted and were more likely to receive retweets from individuals who had not previously tweeted

[78]e.g. Howard and Hussain 2013; Kharroub and Bas 2015

about the ShutdownA14 protest. Images of street protests and images with collective symbols also increased movement attention and protest diffusion, all else equal. The effects of images that evoked emotions differed based on which emotion was triggered. Images evoking enthusiasm increased attention and diffusion, as did images evoking fear. Images triggering sadness appear to depress attention and diffusion, while the effects of anger and disgust were imprecise. These results held while controlling for various other features of the original tweet, such as the time of the tweet and the number of followers/friends that the original tweet poster had.

These results will be strengthened by further research, especially work that includes a larger variety of protest movements and protest incidents. Image features that mobilize Black Lives Matter supporters may differ from features that mobilize other groups. In addition, while a strength of this work is its leveraging of a large corpus of real world images and responses to those images, our causal conclusions rest on our ability to control for alternative explanations. We find our results to be in line with prior work that uses experimental research designs, but we would encourage future research in a variety of settings on the effects of these messy images, which often vary on multiple dimensions and so make clean experimental tests difficult.

Our study contributes to broad and increasingly relevant discussions of collective action in the age of social media. The ability to send and receive images via social media is a transformative force in social organizing, allowing groups and individuals to circumvent traditional mass media channels. Online image sharing in particular likely contributes to new dynamics of organizing, which tend to emphasize connective identity and personal narratives.[79] Crucially, images have historically helped marginalized populations put their interests on the public agenda, and the explosion of images via social media may serve to amplify these voices.[80] Our study of Black Lives Matter thus illuminates some of the important intersections of organizing, social media, and the mobilizing power of images.

[79] Bennett and Segerberg 2013; Bimber, Flanagin, and Stohl 2012
[80] Freelon, McIlwain, and Clark 2016

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

A Appendix: Image Labeling Procedures and Summary Statistics Table

This appendix presents the questions used to manually label images (Table 1), two sample images with their labeling scores (Figures 1 and 2), and a summary statistics table for the key model covariates (Table 2). For our top 1,000 images, two research assistants tagged images as being of a street protest or not. For the remaining images, we labeled an image of being as a street protest if an annotator indicated that there were more than ten people present in the image and at least one protest sign or slogan.

Table 1: Labeling Form for Images

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 a 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 fear does the image incite in you? If none, select 0.	(0, 1, ..., 10)
disgust	How much 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)
enthusi-asm	How much enthusiasm does the image incite in you? If none, select 0.	(0, 1, ..., 10)

Figure 1: The Most Tweeted Image During the April 14 Protest

Research staff labeled this image as not being a protest, and having no symbols. On the emotions, the average scores were: anger: 2, fear: 1, disgust: 2, sadness: 3, enthusiasm: 1.

Figure 2: The Fifth Most Tweeted Image During the April 14 Protest

Research staff labeled this image as being a protest, but not having any symbols. On the emotions, the average scores were: anger: 2, fear: 1.5, disgust: 1, sadness: 1, enthusiasm: 2.5.

Table 2: Key Variable Summary Statistics

Variable	Minimum	Maximum	Mean	SD
Image	0	1	0.19	0.40
Protest*	0	1	0.03	0.18
Symbol*	0	1	0.02	0.14
Anger*	0	10	1.75	2.70
Disgust*	0	10	1.74	2.79
Enthusiasm*	0	10	1.51	2.41
Fear*	0	10	1.05	2.04
Sadness*	0	10	1.93	2.84
Number of Followers	0	5540545	4692.23	59339.65
Number of Friends	0	350644	1425.84	5198.41
Previous Tweets	0	1815	54.29	179.21

*For these variables we provide summary statistics for the messages that have an image. The statistics for the other variables are based on the whole sample of original messages.

B Appendix: Interrater Reliability, Evidence of Stable Emotions Labeling, and Turker Demographics

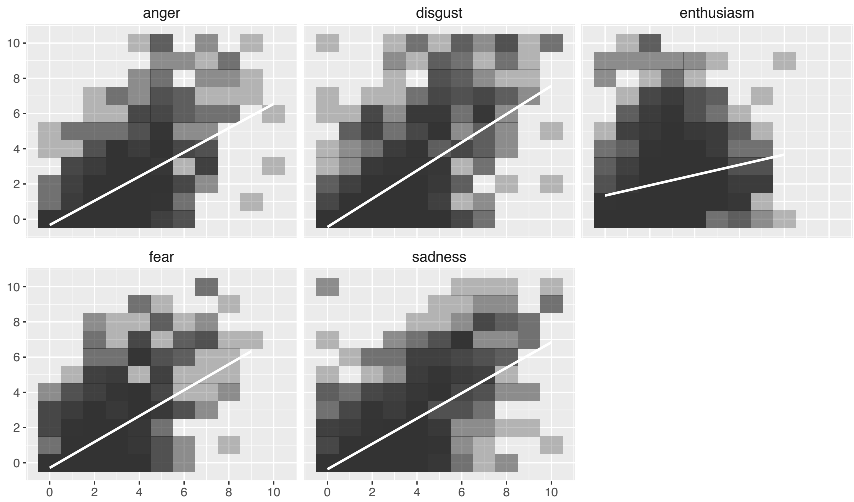
In this appendix we address interrater reliability concerns. Table 3 presents Cohen's Kappa or one-way intraclass correlation coefficients for each of the seven independent variables of interest. These values were generated based on the ratings generated by our two undergraduate coders on the top 1000 most-tweeted images. The raters had generally good agreement, with the lowest agreement for the symbol and enthusiasm labels.

Table 3: Interrater Reliability Measures

Variable	Interrater Reliability	Cohen's Kappa or one-way intraclass correlation coefficient (ICC)
Symbol	0.23	Kappa
Protest	0.78	Kappa
Anger	0.46	ICC
Fear	0.48	ICC
Disgust	0.55	ICC
Sadness	0.54	ICC
Enthusiasm	0.19	ICC

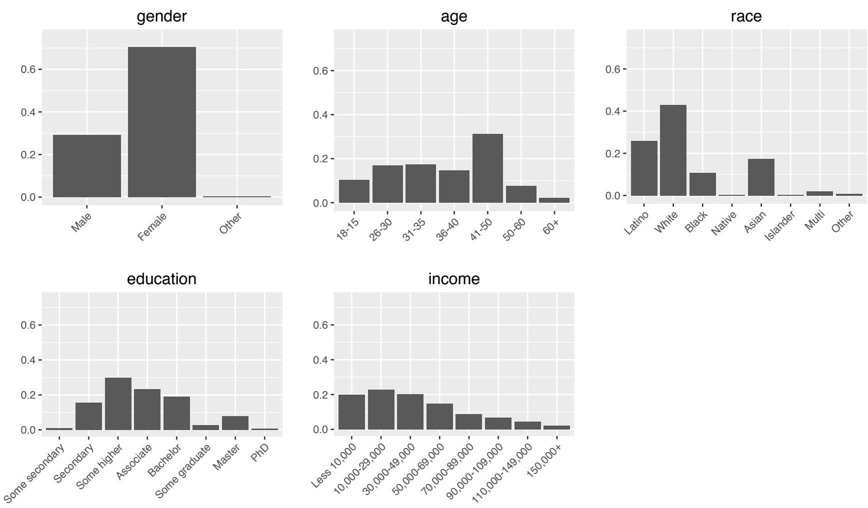
The emotions portion of labeling is particularly important for our purposes. Although emotions are subjective, and we expected a wide range of emotional responses, on average the top 1,000 images (which account for more than 50% of the messages with images) triggered very similar emotions to different people. When modeling the data we give each unique image a single score per emotion (on a 0-10 point 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 3 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 3: Correlation between the emotion scores given by 2 research assistants to the same images (top 1,000 images)



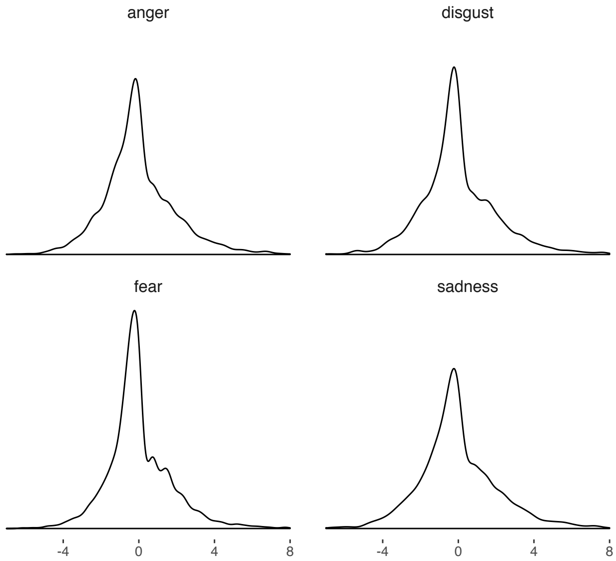
In a second iteration we used Mechanical Turk (MT) to label the top 1,000 images three more times. We decided to do so not only to have more emotion labels per image but also to get scores from people with different backgrounds, since our two research assistants were both undergraduate students, male, 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 4 presents summary statistics for the 1,259 MT workers that participated in the labeling process. The figure shows how workers had a very diverse background.

Figure 4: 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 average score. Figure 5 shows again that the same images triggered very similar emotions in different people, with most individual scores being around 1 or 2 points from the five-scores average. *Enthusiasm* is again the emotion that presents the most variation.

Figure 5: Distribution of the difference between emotions scores for the same top 1,000 images



C Appendix: Regression Analysis Results Table

	Attention: BLM + ShutdownA14 (Number of Retweets)		Diffusion: ShutdownA14 (Retweets by New A14 Users)	
	Basic (1)	Mechanisms (3)	Basic (2)	Mechanisms (4)
Image	1.690***		1.513***	
	(0.032)		(0.097)	
Protest		0.996***		1.123***
		(0.062)		(0.139)
Symbol		0.165**		0.217
		(0.072)		(0.193)
Anger		−0.026		−0.001
		(0.017)		(0.048)
Fear		0.072***		0.121***
		(0.016)		(0.045)
Disgust		0.046***		0.039
		(0.016)		(0.044)
Sadness		−0.005		−0.171***
		(0.012)		(0.033)
Enthusiasm		0.086***		0.105***
		(0.010)		(0.030)
Number of Followers	0.00003***	0.00002***	0.00002***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Previous Tweets	−0.001***	−0.001***	−0.003***	−0.006***
	(0.0001)	(0.0002)	(0.001)	(0.001)
Number of Friends	0.00004***	0.00004***	0.0001***	0.00002
	(0.00000)	(0.00001)	(0.00001)	(0.00003)
Time(t2)	−0.377***	−0.871***	−0.998***	−1.558***
	(0.053)	(0.099)	(0.214)	(0.362)
Time(t3)	−0.411***	−0.723***	1.102***	−0.796*
	(0.061)	(0.116)	(0.242)	(0.442)
Time(t4)	−0.293***	−0.593***	−0.263	−0.500
	(0.043)	(0.083)	(0.195)	(0.328)
Time(t5)	−0.272***	−0.565***	0.329**	0.108
	(0.040)	(0.071)	(0.141)	(0.211)
Time(t6)	0.106***	−0.328***	1.161***	0.485**
	(0.038)	(0.068)	(0.121)	(0.192)
Constant	−0.319***	1.234***	−1.346***	0.069
	(0.030)	(0.058)	(0.105)	(0.184)
Original Tweets (n)	49,345	8,706	7,502	2,078
Log Likelihood	−56,591.870	−18,147.520	−6,393.248	−2,814.994
Akaike Inf. Crit.	113,203.700	36,327.040	12,806.500	5,661.988
Note:				*p<0.1; **p<0.05; ***p<0.01

D Appendix: Robustness Check, controlling for the text of the messages

Are the results reported in the paper a mere function of the tweets' text instead of image effects? We do not believe this is the case for two main reasons.

First, the protest was about a very specific issue, police brutality against African American citizens in the United States, and so we expect most messages to be related to a narrow set of claims and their text to be very similar; and second, after exploring a large number of messages, we observed that most texts were very short (e.g. they only contained a hashtag such as #blacklivesmatter), corroborating our low textual variation expectation.

Nevertheless, to rule out this potential concern, in this Appendix we add different textual controls to Model 3 as follows.[1] First we pre-process the text of the messages by removing urls, mentions to users, punctuation, numbers, stopwords, and by stemming all remaining words. Then we fit 3 Latent Dirichlet Allocation models with a varying number of topics: $k = \{5, 10, 20\}$. Our goal is not to perfectly capture specific topics and/or frames of interest, but to group messages that contain very similar words. This is why instead of choosing a specific number of topics, we check whether our findings hold when controlling for the semantic content of the message, and for different number of topics.

To do so, after estimating each topic model, we re-run Model 3 by including message-level covariates indicating the probability of a message to belong to each of the $k - 1$ topics. For example, the first time we include 4 new message-level variables to the model, the probability that a given messages belongs to topic 1, 2, 3, and 4 of a 5-topic model (we exclude one topic probability to avoid perfect colinearity issues). The second time we include 14 variables, and so on.

[1] We manually checked all messages used to estimate Model 4 and the textual variation was extremely low. For this reason we do not replicate it using these textual controls. A very large percentage for example only had the hashtag #shutdownA14.

Figure 6: Key coefficients of interest when controlling for the textual content of the message, and for a different number of potential textual topics

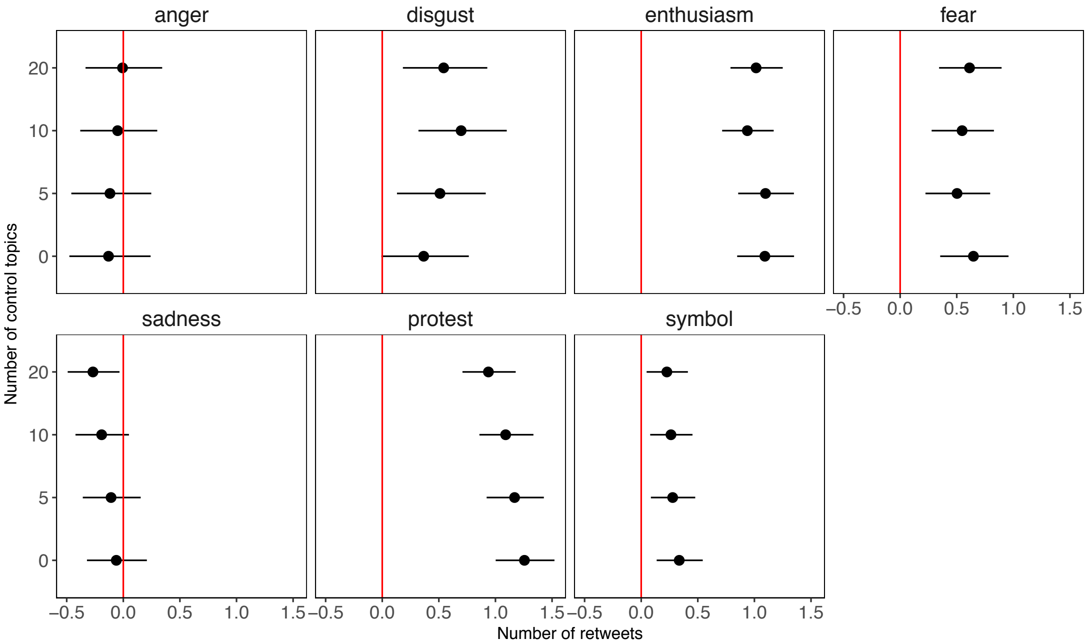


Figure 6 shows the key coefficients of interest across these different versions of Model 3. For each variable we can see the original coefficient at the bottom (number of topics = 0) and the coefficient when controlling for 20 topics at the top. We see that the findings are robust to all textual controls, with the single exception of the sadness coefficient, which goes from not having a statistically significant effect to have a significant negative effect on attention when controlling for 20 topics. If this were to be the true sadness effect, it would corroborate our hypothesis.