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

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Abstract

Do images affect 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 participation in social movements. We theorize that images are more easily processed than text, lowering the cost of deciding to participate in a social movement. In addition, images might trigger emotional responses, increase expectations of success, and generate collective identity; all leading to greater mobilization. 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 while also teasing out the mechanisms at play in a new media environment.

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 images spread awareness of specific issues.[7]. While those works that study more general political effects of images tend to rely on clear experimental treatments, 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 first presenting a comprehensive theory and a set of hypotheses derived from specific mechanism pathways for why images might affect social movement mobilizations. We theorize that, relative to text, images make information about social movements easier to process. Beyond this main effect, we suggest that the presence of emotional triggers, crowds that raise expectations of success, or symbols that generate collective identities explains 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

[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

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 to new online participants.

The idea that images might matter to social movements like BLM is not new. The 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 – are the well-known images of prior studies the exception or the rule in modern social movement mobilization? 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. Technological developments such as the Internet, cell phones, and social media and their impact on social movement mobilization are a source of scholarly and popular fascination. Many authors have noted the potential of images to have an enhanced impact in this new information communication technology (ICT) landscape.[9] Mainstream media (e.g. newspapers, radio, TV, and mass media companies in general) 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.[10] 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

[8] Raiford 2007

[9] Howard and Hussain 2013; Aday et al. 2012; Bennett and Segerberg 2013; Kharroub and Bas 2015

[10] Gitlin 1980

movement was framed.[11] 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.[12] Today small or emerging social movements such as BLM can rely on thousands of participants to take pictures "from the trenches"[13] and immediately share them. Along these lines, recent academic works point to "online image-sharing" as a specific ICT-enabled activity that may increase the likelihood of protests to diffuse.[14] Images, these authors suggest, could play a particularly important role in social movement organization in the twenty-first century due to the new technologies of image sharing. However, few studies have actually tested these 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.[15] Nevertheless, online participation, such a liking a post or signing an online petition, has also proved to be an increasingly important tool for social movements to increase protest turnout[16] and set the media and political agenda.[17] Given the importance of understanding both online image sharing and online mobilization, especially in the context of Black Lives Matter, 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 movement 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 from April 13 to April 20, 2015.

[11] Raiford 2007
[12] cf Howard and Hussain 2013; Webb Williams 2015
[13] Payne 1998
[14] Kharroub and Bas 2015
[15] Chadwick 2011; Bimber, Flanagin, and Stohl 2012
[16] De Choudhury et al. 2016
[17] Freelon, McIlwain, and Clark 2016; Casas, Davesa, and Congosto 2016

By *diffusion*, we mean the spread of movement 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 develop a theory with testable hypotheses for why images could increase the spread of social movement participation. 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 today are a central part of our lives. However, despite their clear social relevance, political scientists have traditionally paid little attention to how images affect social and political processes.[18] In particular, literature studying the effect of images on social protest mobilization is scarce.[19] The existing literature mostly focuses on the effect that images have on issue-framing, political attitudes, and participation in non-mass protest-related political activities, such as voting.

There is extensive research studying the ability of mass media to set the agenda and frame issues.[20] However, although visuals are a core component of mass media, most of the research on framing uses textual data to

[18]Grabe and Bucy 2009; Corrigall-Brown and Wilkes 2012

[19]See Kharroub and Bas 2015

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

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," – marginalization of protesters and the special salience of government authorities in media coverage of protests – protesters were equally likely to be present in the images and only some government authorities received high visual media coverage.[21] 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.[22] They conclude that homogeneous journalist practices produce not only similar textual frames but also similar visual issue-frames.

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.[23] They ask the participants about their political attitudes towards immigrant populations in the U.S.A. and find some evidence supporting the argument that people are more likely to hold positive views towards immigrants who are holding American flags as opposed to Mexican flags. 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.[24]

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. Rosenberg et al. for example manipulate images of fake political candidates to find that the ones with a favorable appearance are more likely to receive more positive evaluations

[21] Corrigall-Brown and Wilkes 2012
[22] Rohlinger and Klein 2012
[23] Wright and Citirn 2011
[24] Powell et al. 2015

and votes.[25] Todorov et al. 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]

Going back to the relationship between images and participation in mass contentious activities, some scholars do suggest that images are important in explaining social protest mobilization. For example, Castells argues that social movements today benefit from "viral diffusion of images and ideas."[27] Bennett and Segerberg argue that the Spanish Indignados "achieved impressive levels of communication with outside publics ... via images and messages spread virally across social networks,"[28] and in the context of the Arab Spring, Howard and Hussain argue that an "image of Khaled [Said]'s bruised face ... passed from one mobile phone to another, until thousands had seen the picture and were actively developing protest strategies online."[29] However, these authors do not present a clear theoretical and empirical framework explaining why images matter for political mobilization. In the next section we build on prior work from the fields of visual communication and cognitive psychology to advance a theoretical explanation and expectations.

2.2 Argument: The General Image Effect

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 not.[30] The more rapidly they can process pro-mobilization information, the more likely they are to join the action. We take this assumption as the starting point of our argu-

[25] Rosenberg et al. 1986
[26] Todorov et al. 2005. Participants only evaluated pairs of candidates for which they did not recognize either of the two candidates.
[27] Castells 2012,2
[28] Bennett and Segerberg 2013, 4
[29] Howard and Hussain 2013, 21
[30] Downs 1957; Olson 1965

ment. Gaining information is important but learning about a protest or a movement has costs attached to it, such as reading news stories, pamphlets, social media posts, the content of petitions, etc. We argue that images provide a cheaper way to process all of this information, and that the lower the information-processing costs, all else equal, the higher the likelihood that individuals will decide to support a movement.

Compared to other forms of communication, visual content such as images lower individual information-processing costs for three main reasons. 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.[31] Learning from visuals takes place in a specialized and developed part of the brain (the visual cortex). However, no such specialized area exists for text processing, making learning from text a much more consuming task.[32] 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;[33] 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.[34] 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."[35] Graber states that "human brains extract valuable information from audiovisuals more quickly and more easily than from purely verbal information."[36] When comparing humans' capacity to learn from words versus learning through visual content, Gazzaniga goes as far as saying that "brains were not build to read. Reading is a recent invention of human

[31]Barry 1997; Gazzaniga 1998; Graber 1996; Grabe and Bucy 2009; Kraidy 2012
[32]Grabe and Bucy 2009
[33]Messaris and Abraham 2001
[34]Grabe and Bucy 2009
[35]Grabe and Bucy 2009, 13
[36]Graber 1996

culture ... Our brains have no place dedicated to this new invention."[37]

Second, images trigger stronger emotional reactions than written or spoken information.[38] An extensive literature argues that individual emotional responses are important to understand social mobilization and political participation in general.[39] Marcus et al. show that when exposed to new information, individuals feel first and think second: emotions preceed and activate rational thinking, and they often motivate information-seeking and participation in political processes such as elections.[40] Social movement scholars also argue that emotions generate moral shocks that become motives for mobilization,[41] and that emotions forge social bonds that bind people in a common cause.[42] Existing visual communication literature argues that images are "especially powerful in transmitting realism and emotional appeal"[43] and that "because visual are processed via emotional pathways in the brain, they are inherently affect laden."[44] 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.

Finally, we also theorize that images reduce information-processing costs and facilitate social mobilization because they do not require high levels of literacy to be processed. News stories related to a protest or social movement often contain complex language, and activists sometimes use technical terms when designing pamphlets or web content. Grabe and Bucy argue that images provide information to individuals in a very plain and straightforward manner.[45] This facilitates emerging movements to get to publics with lower levels of general knowledge or to people who know little about the specific policy at hand. In sum, we build on this extensive

[37] Gazzaniga 1998, 6)

[38] Graber 1996; Grabe and Bucy 2009; Barry 1997

[39] 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

[40] George E. Marcus, Neuman, and MacKuen 2000; Valentino et al. 2011

[41] J. Jasper 1998

[42] Papacharissi 2014

[43] Graber 2009

[44] Grabe and Bucy 2009, 8

[45] Grabe and Bucy 2009

visual communication and cognitive psychology literature to generate our main expectation:

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

2.3 Images and the Mechanisms of Protest Mobilization

Are all images equally likely to foster political mobilization? All images lower information-processing costs but different images provide different types of information. We argue that certain types of information about a protest have a stronger mobilizing effect than others, and so we expect some types of images to play a special mobilizing role. In this section we present the specific mechanism pathways that may make some images more effective than others and lay out the rest of our hypotheses.

Mechanisms of Mobilization: Emotional Trigger

Political psychologists working on political participation argue that a wide range of emotions explain different levels of participation in collective political processes such as elections[46] and protests.[47] Questions remain as to which emotions play a role.[48] Jasper argues that a large set of affective and reactive emotions "help lead people into social movements, keep them there, and drive them away": hate, love, solidarity, suspicion, trust, anger, grief, outrage, shame, sympathy, cynicism, defiance, enthusiasm, resentment, fear, hope, and resignation.[49] Jasper is not very clear about under which condition we should expect these emotions to encourage or discourage social mobilization, and some of these emotions are closely related. For example, emotions such as enthusiasm and hope are highly correlated

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

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

[48] Valentino et al. 2011

[49] J. Jasper 1998, 405-406

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.[50] 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 a opposite effects (e.g. anger and fear).[51] Hence, in order to model and estimate the role that emotions play in protest mobilization 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.[52] However, as previously noted, other scholars argue that a larger set of emotions are important to explain political mobilization.[53] For example, recent research studying the spread of BLM tweets shows that messages with sad text have had some mobilizing effect,[54] and other studies show how disgust influences people's attitudes towards policies such as health[55] and homelessness.[56] We build on this literature and code images for five emotions: anger, enthusiasm, fear, disgust, and sadness.[57]

Anger "emerges in situations when people are threatened or find obstacles blocking their path to reward"[58] and it motivates individuals to mobilize in order to find a solution to the threat or to remove the existing obstacle.[59] 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."[60] Similar to anger, enthusiasm also might boost participation because there is a desire to achieve

[50]Abelson et al. 1982; George E Marcus and Mackuen 1993
[51]Valentino et al. 2011
[52]Valentino et al. 2011
[53]J. Jasper 1998; Goodwin and J. M. Jasper 2006; Gould 2009
[54]De Choudhury et al. 2016
[55]Clifford and Wendell 2016
[56]Clifford and Piston 2016
[57]We describe the coding protocol in detail in the Observational Data & Measurement section.
[58]Brader and George E Marcus 2013, 179
[59]Valentino et al. 2011; Brader and George E Marcus 2013
[60]Brader and George E Marcus 2013, 175

certain goals. *Fear* (or anxiety[61]) "is a product of an emotional system that monitors the environment for potential threats and adapts behavior accordingly."[62] 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.[63] When the costs of addressing fear are high, people may act "indirectly through emotion focused avoidance behavior rather than attacking the problem at hand."[64] 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."[65] In recent study De Choudhury et al. find that sad messages related to BLM in social media were related to larger on-street protests.[66] 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:[67]

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

[61] 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.

[62] Brader and George E Marcus 2013, 178

[63] George E. Marcus, Neuman, and MacKuen 2000

[64] Valentino et al. 2011, p.159

[65] Brader and George E Marcus 2013, 176-177

[66] De Choudhury et al. 2016

[67] 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.

$\mathbf{H}_3$ (*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.[68] 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.[69] 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. However, if at a certain point the movement ends up achieving mass participation, it becomes irrational again to join the protest because of a free-rider problem. In sum, these approaches predict an inverse U-shape relation between expectation of success and willingness to participate. In the early stages of a 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 recent study of the 2011 Egyptian revolution Kharroub and Bas show that some of the most tweeted images during the revolts contained crowds of people on the streets.[70] Images during the Civil Rights Movement in the 1960s had similar effects. Raiford describes how a

[68]e.g Downs 1957; Olson 1965

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

[70]Kharroub and Bas 2015

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.[71] We therefore have the following expectation:

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 participants, especially when the protest is at its initial stages.

Mechanisms of Mobilization: Generate Social Collective Identity

A collective identity is relevant for a social movement for several reasons,[72] but in particular because it creates motivations for individuals to join the movement. 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."[73] In constructing and connecting purposes, and thus in building motives for others to join the movement, symbols may play a very important role. For example, Eyerman and Jamison argue that music has played a key role in the formation of collective identities of social movements and in bringing together individuals with similar but still too distinct purposes.[74] 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. For example, 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."[75] We therefore have the

[71] Raiford 2007
[72] cf Polletta and J. M. Jasper 2001; Tajfel 1981; and Tajfel 1982
[73] Melucci 1996, 43
[74] Eyerman and Jamison 1998
[75] Kharroub and Bas 2015, 7

following expectation:

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

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 numerous demonstrations in cities such as New York, Los Angeles, Seattle, Baltimore, Oakland, and Ferguson. The demonstrations were a reaction to a set of episodes where police officers acted violently towards, and in some cases killed, African Americans. Some of the most salient cases were the deaths of Trayvon Martin (February 26, 2012), Eric Garner (July 17, 2014), Michael Brown (August 9, 2014), Tamir Rice (November 23, 2014), Walter Scott (April 4, 2015), and Freddie Gray (April 12, 2015). As a part of the protest, 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, #A14, #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.

We use two operationalizations of online mobilization in our analysis: 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 from April 13 to April 20, 2015. By *diffusion*, we mean the spread of movement 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. We study attention, or the sharing of information about the movement, because it is a necessary condition for a movement to exist or to succeed at setting policy agendas.[76] 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.[77] Diffusion here is therefore conceptually equivalent to online recruitment into the action. Given the narrow timeframe of our observational data collection, we were unable to analyse the number of new recruits to BLM due to April 14 images, as individuals may have been active online in the movement long before ShutdownA14. Therefore 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 accurately label the roughly 9,500 unique images collected over the course of the ShutdownA14 protest. Each image was labeled on each of the hypothesized mechanisms, so that we could analyze each mechanism in isolation by controlling for the remaining mechanisms. We address the labeling in more detail below and in Online Appendix A.

[76]Baumgartner and Jones 1993; Kingdon 1984; Baumgartner, De Boef, and Boydstun 2008
[77]Barberá et al. 2015; De Choudhury et al. 2016; Freelon, McIlwain, and Clark 2016

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 the main theoretical claim that images reduce information-processing costs and increase the likelihood of a movement to get more attention and diffuse, 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
#A14	stop business as usual	stolenlives
	massincarceration	stolen lives
	#policebrutality	#stolenlives
	#blacklivesmatter	black lives

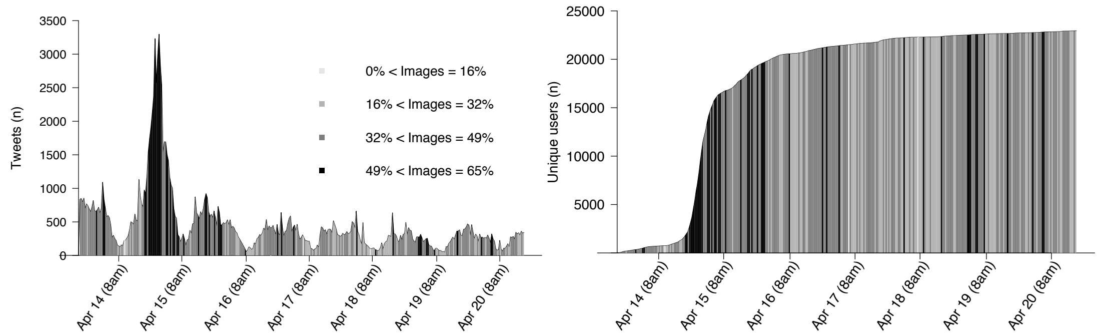
We look at this particular case and both BLM and ShutdownA14 messages because it allows us to test the effect that images have on both attention and diffusion. Social movements aiming to set the media and political agenda need to recruit as many new first-time supporters as possible (diffuse the movement) but they also need to keep their supporters engaged and talking about the movement's claims (attention). The Twitter activity related to the overall BLM movement began in 2012 and particularly after Tamir Rice's death on November 23, 2014, before our data collection began. We were therefore not able to tell which of the users who tweeted during the period of analysis were messaging about BLM for the first time. This means that we cannot study diffusion patterns by simply looking at BLM messages. However, social media activity related to the ShutdownA14 action started right before the demonstration took place on April 14, 2015. Thus we use the volume of messages related to both BLM and ShutdownA14 to study the attention to BLM in social media, and only the messages related to the ShutdownA14 action to study the diffusion of this specific protest on Twitter. As a result of the data collection process we obtained a data set with 150,324 tweets sent by 67,484n 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 with a high concentration of images at the same time that as there is an increase in protest- and movement-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

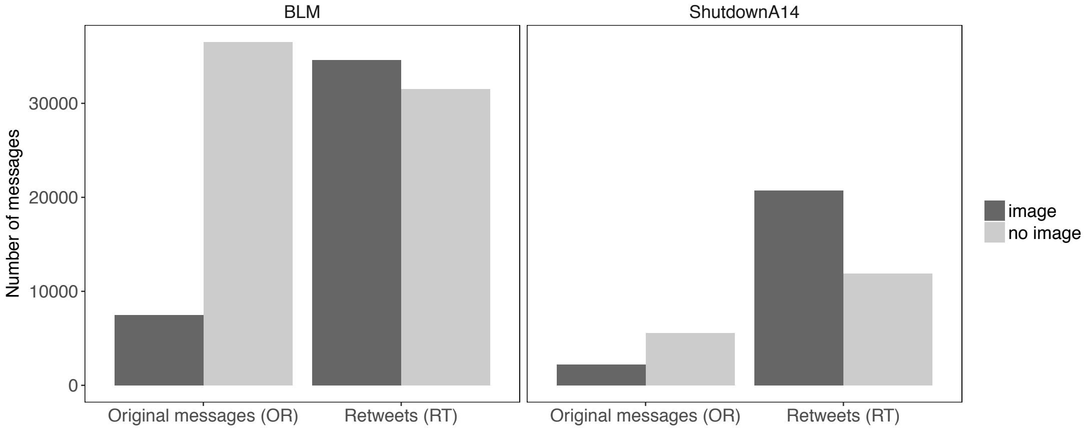
To model the data and build our dependent variables, we split the messages into original tweets and retweets. We then link retweets to their original tweet in order to count how many times an original tweet was subsequently retweeted. The count of retweets is our measure of movement *attention*, where 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 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 collected tweet. 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,[78] 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.

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.

[78] Gonzalez-Bailon et al. 2011

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.

We elaborated a coding protocol to manually label each of the 9,458 images according to each of our hypothesized mechanisms.[79] Note that this

[79]For more detail on the labeling scheme, along with two sample images with their assigned labels of each of the mechanisms, see Online Appendix A.

means that each image contains a score on all of the hypothesized mechanisms. 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 (anger, fear, disgust, sadness, and enthusiasm). 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 as follows: first, two research assistants labeled the top 1,000 images, producing two sets of labels for each image (binary indicators for the *protest* and *symbol* variables; continuous ratings of 0-10 for each of the emotions). Then we used Amazon's Mechanical Turk service to obtain three extra sets of labels from three different people. Each labeler completed a socio-demographic survey prior to labeling images. Online Appendix B contains annotator-agreement measures for the two undergraduate annotators plus demographic summaries for the Manual Turk workers.[80] For each of the top images, we considered an image to have a protest or a symbol if at least one annotator indicated the presence of a protest or symbol. The emotional score for each emotion on each image is the mean of the values given by all annotators. For the remaining unique images (n = 8,509), we employed Mechanical Turk workers to label each image once.

Once the annotators finished the labeling, we matched each unique image to all the messages containing that picture. The variables *Anger, Fear, Disgust, Sadness*, and *Enthusiasm* are the average score for each

[80]Online Appendix B also demonstrates that on average different people used very similar emotion scores for the same image.

emotion across all of the annotators ($H_{2,3,4,5}$). *Protest* is a binary variable indicating whether or not a street protest is in the image, addressing the *expectation of success* mechanism (H_6). The variable *Symbol* is a binary variable indicating whether or not a collective symbol is in the image (H_7). Table 2 provides a brief description of all of the study variables. Summary statistics for these variables can be found in Online Appendix A.

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 tweet 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)

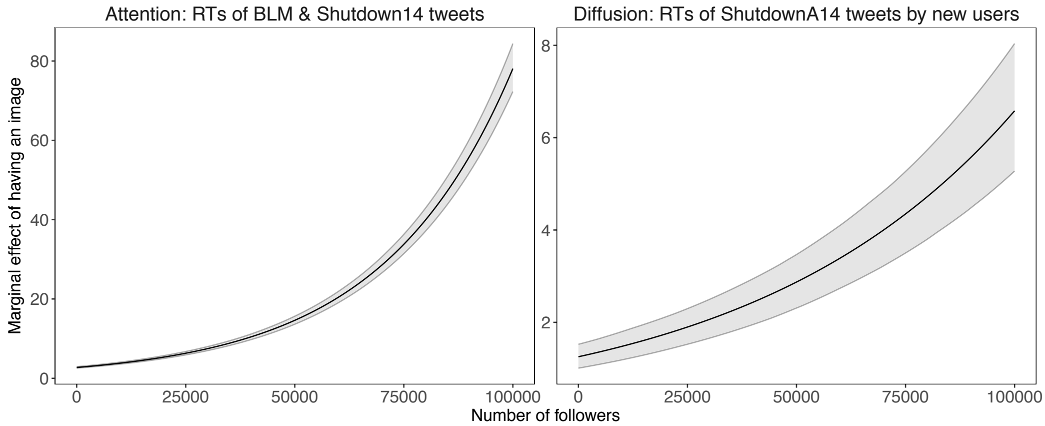
5 Modeling and Results

We use negative binomial models to predict how our factors of interest affect the number of times an original tweet is retweeted.[81] 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 3, 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 follower, number of friends, number of previous tweets, and time. The regression table with the results for these

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

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.

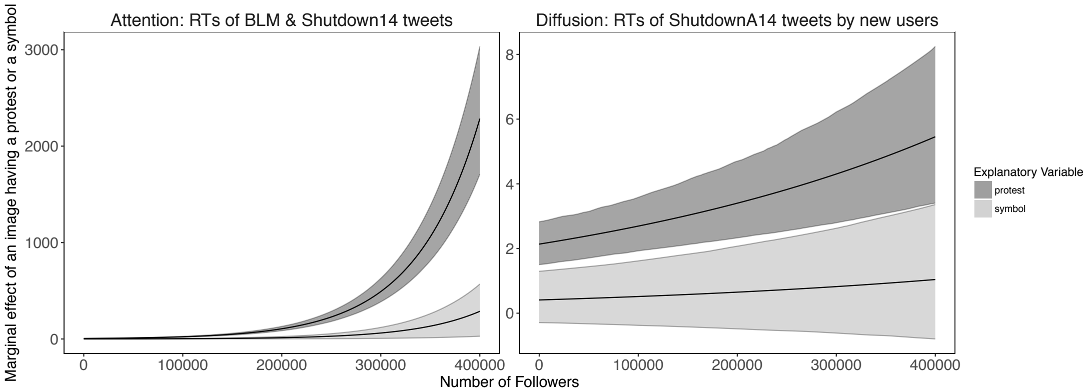


The results of the two basic multivariate analyses shown in Figure 3 are consistent with our *General Image Effect* hypothesis (H_1): the likelihood of a protest tweet to diffuse to new recruits and to get more attention increases if the tweet contains an image. Using the general BLM data, we find that 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 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 2 and 4) only using information from original messages that had an image (8,706 original tweets in Model 2; 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). 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. The results, shown in Figure 5, are supportive of some of the hypothesized mechanisms.[82] 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 collective symbols appear to increase attention ($p<0.05$); the positive effect is not statistically significant for diffusion. Figure 4 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 4 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.

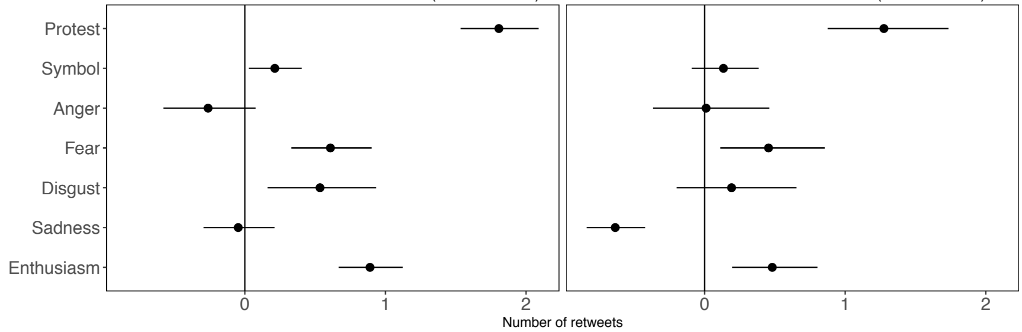
[82]See Online Appendix C for the regression tables.

Figure 4: 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.[83] *Disgust* (no clear hypothesized expectation) has a statistically significantly positive effect on attention, while for diffusion 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.

Figure 5: Predicting attention and diffusion by image mechanisms (Negative Binomial Models)*



[83]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

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

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

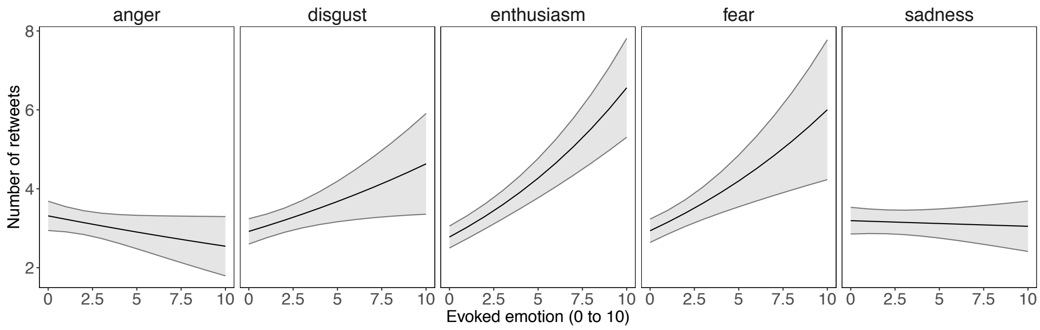
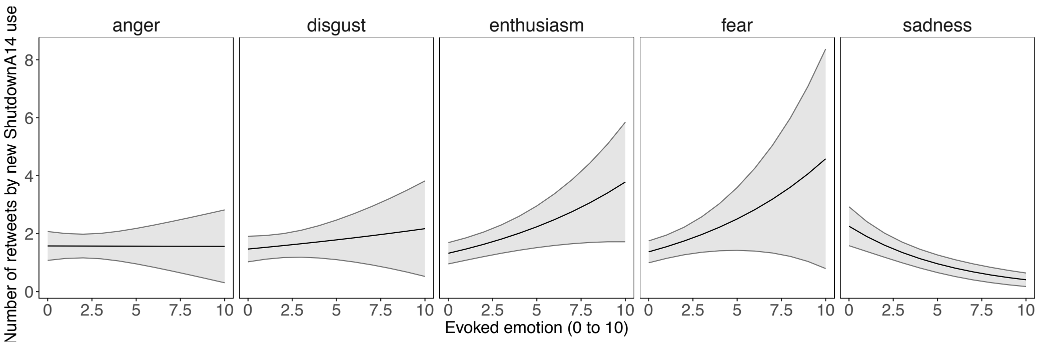


Figure 7: Predicting diffusion of ShutdownA14 Over Range of Emotions



6 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.[84] 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 specify a general theory and specific mechanisms explaining why images might increase the likelihood of an online protest to receive more attention and to diffuse to new participants. We then test our theory and mechanisms by studying the spread of a social movement during a specific offline event. We analyze 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 in general images should increase rates of social movement spreading because they lower information processing costs. In addition, particular images might have a larger mobilizing effect because they act as emotional triggers; increase expectations of success; and generate

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

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 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.

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.[85] 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.[86] Our study of Black Lives Matter thus illuminates some of the important intersections of organizing, social media, and the mobilizing power of images.

[85] Bennett and Segerberg 2013; Bimber, Flanagin, and Stohl 2012

[86] 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 1000 images, two undergraduate labelers 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 persons 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 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)
enthusi-asm	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)

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

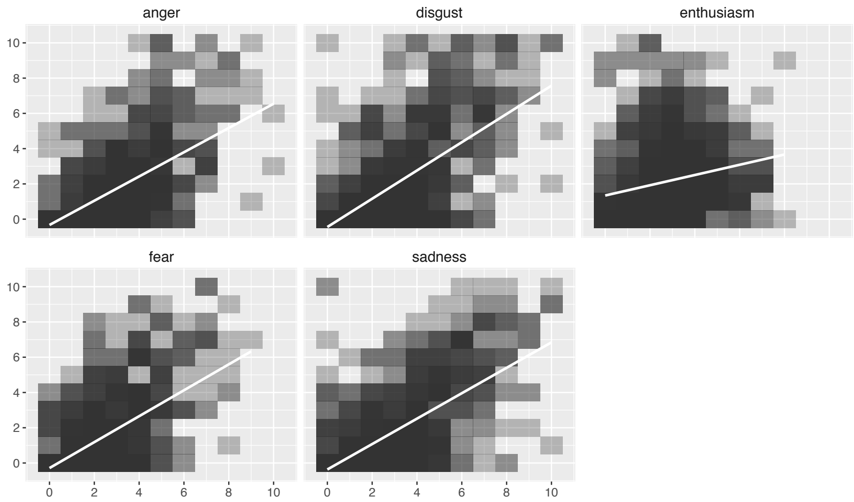
In this appendix we address interrater reliability concerns. Table 3 presents Cohen's Kappa or one-way intraclass correlation coefficients for each of the seven independent variables of interest. These values were generated based on the ratings generated by our two undergraduate coders on the top 1000 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

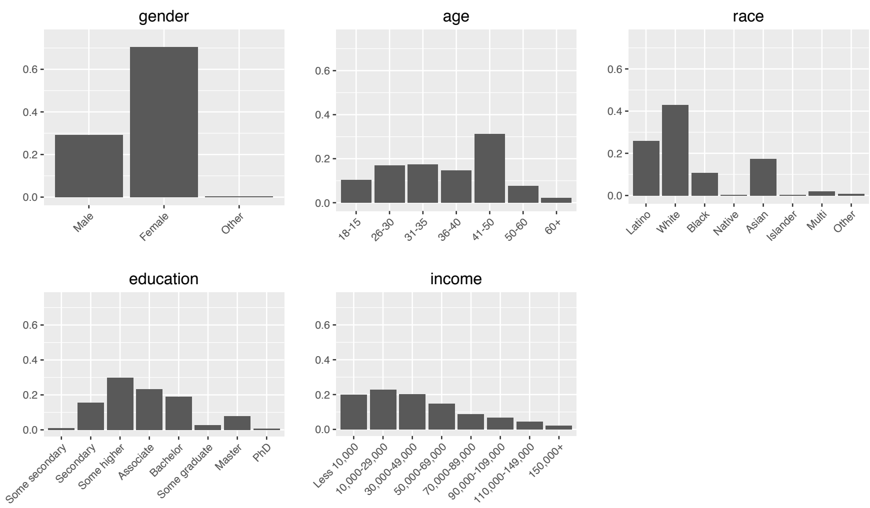
The emotions portion of labeling is particularly important for our purposes. Although emotions are subjective, and we expected a wide range of emotional responses, on average the top 1,000 images (which account for more than 50% of the messages with images) triggered very similar emotions to different 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)



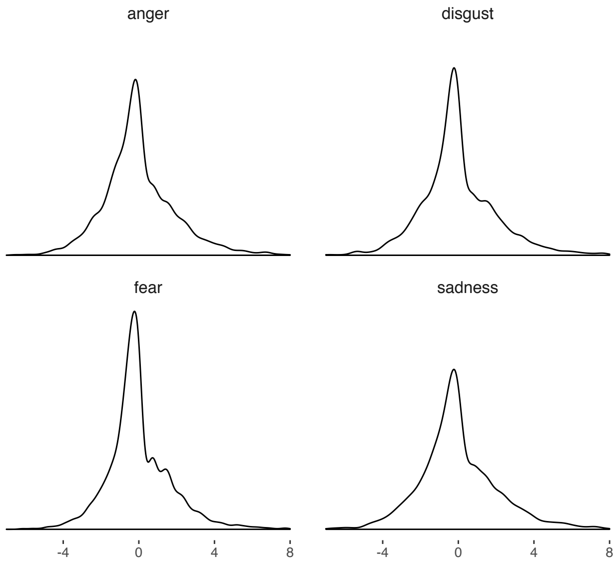
In a second iteration we used Mechanical Turk (MT) to label the top 1,000 images three more times. We decided to do so not only to have more emotion labels per image but also to get scores from people with different backgrounds, since our two research assistants were both undergraduate students, male, 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 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 mean 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 mean. *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