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 though a study of Black Lives Matter, utilizing both observational and experimental data. 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 research into the effects of images on issue-framing (Corrigall-Brown and Wilkes 2012; Rohlinger and Klein 2012), political attitudes (Grabe and Bucy 2009; Wright and Citrin 2011; Dahmen 2012), and even on compliance with authoritarian regimes (Bush et al. 2016), little to no prior work has systematically addressed the role of images in mobilizing participation in protests and social movements (though see Kharroub and Bas 2015 for a preliminary attempt). 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 (Corrigall-Brown and Wilkes 2012), or present accounts of how particular images spread awareness of specific issues (see for example Howard and Hussain 2013, 18-22 on the Arab Spring images of Mohamed Boazizi and Khaled Said).

In this paper, we attempt to fill this gap in the literature by presenting and rigorously testing both a comprehensive theory for why images affect social movement mobilization and hypotheses derived from specific mechanism pathways that make some images more effective than others. 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. For our data we turn to the Black Lives Matter (BLM) movement. We track the online spread of general support for BLM and support for a specific BLM protest, ShutdownA14, that occurred on April 14, 2015. We then conduct a survey experiment to see whether images spread online during the ShutdownA14 protest affect signatory rates on a hypothetical online petition in support of BLM.

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 (Raiford 2007). More recently, Occupy Wall Street, the Arab Spring and the Gezi Park protests all became sources of "viral" images. The challenge of 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 outsized historical significance – are the well-known images of prior study 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 (Howard and Hussain 2013; Aday et al 2012.; Bennett and Segerberg 2013; Kharroub and Bas 2015). 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 (Gitlin 1980; Gamson and Modigliani 1989; Oliver and Maney 2000; Smith et al. 2001; Gamson 2003; Andrews and Biggs 2006; Raiford 2007; Amenta et al 2009). 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 (Raiford 2007). 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 (cf Castells 2009; Howard and Hussain 2013; Farinosi and Trere 2014; Webb Williams 2015). Today small or emerging social movements such as BLM can rely on thousands of participants to take pictures "from the trenches" (Payne 1998) 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 (Kharroub and Bas 2015). 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 laid out clear theoretical expectations or tested these theories with 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 (Chadwick 2007). Nevertheless, online participation, such a liking a post or signing an online petition, has also proved to be a pivotal source of social movement support. Instead of helping a movement in spreading the word by talking to friends one-by-one, people can share a message via social media and immediately reach multiple friends at once; or instead of physically going to sign a petition, people can sign it online from home and in a fraction of time. Some scholars are highly sceptical about the political impact of those online activities or 'slacktivism' (e.g. Morozov 2011). However, other scholars such as Gonzalez-Bailon et al. (2011) and Barbera et al. (2015) show that the diffusion of protests online are relevant when explaining the success of on-street mobilizations like the *Indignados* movement in Spain in 2011, the Occupy movement in the United States in 2011, and the Taksim Square protests in 2013. Moreover, there are also numerous online petitions that end up achieving their goals. For example, in response to multiple actions including an online petition,[1] the California legislature passed a bill (SB277) forbidding parents to opt out of immunizing their children for personal beliefs if they go to day care or public and private schools. These online activities come at a low cost to both participants and to organizers and are increasingly used by both traditional social movements and activist upstarts (Kahn and Kellner 2004; Bimber et al. 2005, 2012; Garret 2006; Earl and Kimport 2011; Walgrave et al. 2011; Bennett and Segerberg 2013; Anduiza et al. 2014, Earl 2015, Casas et al. 2016). Given the importance of understanding both online image sharing and online mobilization, especially in the context of Black Lies Matter, and to keep the study to a more manageable scope, this paper thus examines variation in online participation in response to images (see De Choudhury 2016 for a preliminary attempt to link online BLM text to offline BLM action).

The contributions of this paper are therefore 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. We then corroborate our findings with an online survey experiment conducted on Mechanical Turk; the survey had a total of 5,000 respondents. Finally, we add to the available body of knowledge regarding the BLM movement and the means by which the movement has

[1] https://www.change.org/p/california-governor-eliminate-the-personal-belief-vaccine-exemption-that-s-putting-sick-california-kids-at-risk#petition-letter

spread.

2 Theoretical Framework and Expectations

Existing research on images and politics

As a result of improvements in color printing, the emergence of TV, and the rise of the Internet and all kinds of ICTs (online mass media, blogs, social media platforms, etc.), 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 (Grabe and Bucy 2009; Corrigall-Brown 2012). In particular, literature studying the effect of images on political mobilization is almost nonexistent (see Kharroub and Bas 2015 for an exception). The existing literature mostly focuses on the effect that images have on issue-framing and political attitudes.

There is extensive research studying the ability of mass media to set the agenda and frame issues (McCombs and Shaw 1972; Gitlin 1980; Iyengar and Kinder 1987; Baumgartner and Jones 1993; Baumgartner et al. 2008). However, although visuals are a core component of mass media, most of this research uses 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 example, Corrigall-Brown and Wilkes (2012) study newspaper images of a collective action in Canada to conclude that, whereas textual content confirmed the "protest paradigm," – marginalization of protesters and 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. In another study, Rohlinger and Klein (2012) look at how different news sources cover several abortion-related protests to find that visual content is very similar across outlets and events. They conclude that homogeneous journalist practices not only produce similar textual but also visual issue-frames.

Another line of research studies the role of images in shaping political attitudes. For example, Wright and Citrin (2011) test if hypotheses derived from the common in-group identity model still hold in an experimental setting when using images as treatments. They ask the participants about their political attitudes towards immigrant population 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, Dahmen (2012) finds that different images do not have much of an effect on the attitudes that experiment participants hold towards stem cell research. However, using eye-tracking technology, the author observes that respondents pay more attention to visual content than to text.

Some scholars do suggest that images are important in explaining political mobilization. For example, Castells (2012:2) argues that social movements today benefit from "viral diffusion of images and ideas." Bennett and Segerberg (2012:4) argue that the Spanish Indignados "achieved impressive levels of communication with outside publics ... via images and messages spread virally across social networks", and in the context of the Arab Spring, Howard and Hussain (2013:21) 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." However, there is still no clear theoretical and empirical framework in the literature explaining why images should matter for political mobilization. In the next section we build on visual communication and cognitive psychology to advance a theoretical explanation.

Theory: 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 (e.g. Downs 1957; Olson 1965): people need to know about the existence of a mobilization before deciding whether to support it or not; and the more rapidly they can process pro-mobilization information, the more likely they are to join the action. We take this assumption as starting point of our theory. 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 particularly help processing all this information, and that the lower the information-processing costs, the higher the likelihood that individuals would decide to support a movement.

We theorize that 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 deeper learning process (Barry 1997; Gazzaniga 1998; Graber 2009; Grabe and Bucy 2009; Kraidy 2012). For example, human brains do a poor job at processing written information. The picture-superiority effect, the fact that humans recall pictures easier than words and/or verbal messages, is a well established finding in the cognitive psychology literature (Nelson et al. 1976; McBride and Dosher 2002; Whitehouse et al. 2006). Learning processes involving visual communication take place in a deeper part of the brain, the visual cortex. As a result, individuals learn more efficiently and what they learn has a larger effect on their consciousness (Barry 2002; Grabe and Bucy 2009; Kraidy 2012). Grabe and Bucy (2009) argue that "visual experience remains the most dominant form of learning" and Graber (1996) states that "human brains extract valuable information from audiovisuals more quickly and more easily than from purely verbal information." When comparing humans' capacity to learn from words versus learning through visual content, Gazzaniga (1998:6) goes as far as saying that "brains were not build to read. Reading is a recent invention of human culture ... Our brains have no place dedicated to this new invention."

Second, images trigger stronger emotional reactions than written or spoken information (Graber 2008, 2009; Grabe and Bucy 2009; Barry 1997, 2002). An extensive literature argues that individual emotional responses are important to understand social mobilization (Melucci 1996; Jasper 1998; Goodwin et al. 2004; Flam and King 2005; Goodwin and Jasper 2006) and political participation in general (Valentino et al. 2011). Emotions generate moral shocks, and play a key role in attributing blame, and framing political debates (Jasper 1998). For example, Gould (2002, 2009) shows how emotions such as grief, anger, pride, and shamed are important to understand the evolution of street AIDS activism in the 1980s and 1990s; and Polletta (2002) shows how emotions such as apathy and anger motivated African American students to participate in sit-ins in the 1960s. Existing visual communication literature argues that images are "specially powerful in transmitting realism and emotional appeal" (Graber 2009) and that "because visual are processed via emotional pathways in the brain, they are inherently affect laden" (Grabe and Bucy 2009:8). Thus existing literature not only suggest 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. Scholars such as Grabe and Bucy (2009) argue that images provide information to individuals in a very plain and straightforward manner. 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 visual communication and cognitive psychology literature to generate our main expectation:

$\mathbf{H}_1$ (*General Image Effect*) Hypothesis: The more visual content related to a social movement or a protest exists, the more likely the movement is to get attention and diffuse.

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 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 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 (e.g. Valentino et al. 2011) and protests (Melucci 1996; Jasper 1998; Goodwin et al. 2004; Flam and King 2005; Goodwin and Jasper 2006). Questions remain as to which emotions play a role (Valentino et al. 2011). Jasper (1998:405-406) 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. 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 and distinguishing between them when modeling protest mobiliaztion 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 (e.g. Abelson et al 1982; Marcus and MacKuen 1993). However, as Valentino et al. (2011) point out, by aggregating all emotions into two groups, researchers may be missing relevant variation and including into the same category emotions that one can theoretically expect to have an opposing effect (e.g. anger and fear). Hence, in order to model and estimate the role that emotions play in protest diffusion it is necessary to find the right balance between taking into consideration all possible emotions and considering too few.

Valentino et al. (2011) argue that three main emotions have the potential to increase political participation: anger, enthusiasm, and fear; and that, out of the three, anger has the most potential to mobilize. However, as we previously noted, other scholars argue that a larger set of emotions are important to explain political mobilization (e.g. Jasper 1998; Goodwin and Jasper 2006; Gould 2009). For example, recent research studying the spread of BLM tweets shows that messages with sad text have had a strong mobilizing effect (De Choudhury et al. 2016), and other political behavior studies show how disgust influences people's attitudes towards policies such as health (Clifford and Wendell 2016) and homelessness (Clifford and Piston, *forthcoming*). Schmidt and Stock (2009) show how survey respondents are capable of distinguishing how much anger, enthusiasm, fear, sadness and disgust particular images trigger. We build on this literature and code images for these five emotions. We describe the coding protocol in detail in the *Observation Data & Management* section.

Anger "emerges in situations when people are threatened or find obstacles blocking their path to reward" (Brader and Marcus 2013:179) and it motivates individuals to mobilize in order to find a solution to the threat or to remove the existing obstacle (Valentino et al. 2011; Brader and Marcus 2013). 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" (Brader and Marcus 2013:175). Similar to anger, enthusiasm also might boost participation because there is a desire to achieve certain goals. However, Valentino et al. (2011) argue that since in the case of enthusiasm the goals are close to being attained, a free-rider dynamic may emerge and that is why they theorize mobilization to be higher in cases of anger than in situations where enthusiasm is present.

Fear (or anxiety[2]) "is a product of an emotional system that monitors the environment for potential threats and adapts behavior accordingly" (Brader and Marcus 2013:178). The mobilizing effect of fear is less clear than anger or enthusiasm. On the one hand, when we fear something we have the desire to change it in order to end that potential threat;

[2]Although fear and anxiety can be theoretically distinguished, empirical evidence show that they are highly correlated and difficult to distinguish in practice (Marcus et al. 2000; Brader 2005). For this reason in this paper we use Valentino et al.'s (2011) approach and we treat fear and anxiety interchangeably.

on the other hand, individuals may deal with fear or anxiety "indirectly through emotion-focused avoidance behavior rather than attacking the problem at hand" (Valentino et al. 2011:159). Valentino et al. (2011) further argue that the impact of emotions on participation will depend in part on the cost of participation and the resources available to potential participants: people want to do something to end the threats they fear, but only if their actions have no negative repercussions, or if they are not visible or traceable. We study how images that trigger certain emotions affect the diffusion of two different online actions related to BLM: social media mentions of the movement, and an online petition supporting it. We argue that engaging with these two actions have completely different social costs for potential participants: whereas posting a message in social media is highly visible, signing an online petition is usually a relatively private action that most of the time goes completely unseen. Hence we expect fearful images to discourage social media mentions but to increase signing rates for the online petition. In fact, recent research on the role of emotions in the diffusion of BLM shows that fearful text messages are related with lesser attention to the movement in social media (De Chaudhury et al. 2016).

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" (Brader and Marcus 2013:176-77). However, this seems to be the case when individuals feel sad for something that directly happened to them (e.g. losing a family member or not achieving a goal). On the contrary, in cases where someone feels sad for what happened to others (e.g. the death of Eric Garner and Tamir Rice), "sadness is thought to support group social behavior by evoking sympathy and helping responses in others" (Bonanno et al. 2008:799). In this regard, De Choudhury et al. 2016 find that sad messages related to BLM in social media were related to larger on-street protests.

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:

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

$\mathbf{H}_3$ (*Enthusiasm*) Hypothesis: Images that generate enthusiasm and that are associated with a protest will increase the likelihood of that protest to spread; but the diffusion power of enthusiastic images is smaller than the power of anger images.

$\mathbf{H}_{4a}$ (*Fear a*) Hypothesis: Images that generate fear and that are associated with a protest increase the likelihood of that protest to spread when the costs of participating are low.

$\mathbf{H}_{4b}$ (*Fear b*) Hypothesis: Images that generate fear and that are associated with a protest decrease the likelihood of that protest to spread when the costs of participating are high.

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

Mechanisms of Mobilization: Expectations of Success

Existing literature suggests that expectation of success explains in part why individuals participate in political protests. Classic rational-choice models (e.g. Downs 1957; Olson 1965) 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. Some social movements scholars (e.g. Klandermans 1984; Oberschall 1994; Kuran 1997; Finkel and Muller 1998; Kharroub and Bas 2015) 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. 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 or social movement, 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 (2015) show that some of the most tweeted images during the revolts contained crowds of people on the streets. Images during the Civil Rights Movement in the 1960s had similar effects.

Raiford (2007) 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. Once a movement has gained significant momentum and awareness, however, images with large numbers of protesters may have the opposite effect: if potential participants perceive that the movement has already achieved a high degree of success, they might reasonably assume that their participation is not needed – images with large numbers of protesters might reinforce that perception.

We study how images affect variation in support for BLM through two different actions (mentioning the movement in social media and signing an online petition) that took place in two different moments in time: April 2015, when the movement was still in its earlier stages, and August 2016, when the movement finally reached high media and political attention. Following the inverse U-shape relationship between expectation of success and willingness to participate that rational theories predict, we expect images increasing expectations of success to foster mobilization in the first (observational) study but not not in the second (experimental) one.

$\mathbf{H}_{6a}$ (*Success Expectation a*) Hypothesis: Images related to a protest that include large numbers of people will increase the likelihood of that protest to get more attention and diffuse when the protest is at its initial stages.

$\mathbf{H}_{6b}$ (*Success Expectations b*) Hypothesis: Images related to a protest that include large numbers of people will have no effect on the likelihood of that protest to get more attention and diffuse once the protest has already reached a substantial level of attention and support.

Mechanisms of Mobilization: Generate Collective Identity

A collective identity is relevant for a social movement for several reasons (cf Polleta and Jasper 2001) but particularly because it creates motivations for individuals to join the movement. As Melucci (1996) 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" (Melucci 1996:43). 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 (1998) 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. 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 (2015) 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" (Kharroub and Bas 2015:7).

$\mathbf{H}_7$ (*Symbol*) Hypothesis: 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 observational and experimental 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 mobilization in our analysis: attention and diffusion. By attention, we mean the amount of discussion occurring about a given movement. By diffusion, we mean the spread of movement to support to new individuals. First, we consider attention to the movement. We measure this by examining the number of people tweeting about BLM from April 13 to April 20. We care about attention, or the sharing of information about the movement, for reasons both practical and theoretical. On the practical side, gaining attention is often a goal of social movements themselves. Attention is, one might argue, a necessary condition for a movement to exist or to succeed at framing and setting policy agendas (Baumgartner and Jones 1993; Kingdon 1984; Baumgartner et al 2008). On the theoretical side, many studies of social movements within a new media environment stress the importance of social media in changing how information spreads in the absence of traditional media gatekeepers (Castells 2009; Earl and Kimport 2011).

Second, we consider the diffusion of specific BLM actions to new members. Diffusion here is therefore conceptually equivalent to recruitment into the action. Given the narrow timeframe of our observational data collection, we are 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 observational diffusion analysis on the April 14 protest, counting the number of new people tweeting about ShutdownA14 over the course of the event. In the experimental portion of the study, we tracked the diffusion of a hypothetical pro-BLM online petition to new signatories. Here we were much more sure that the new participants were in fact new to the given action, in this case the online petition.

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 (see the Observational Data section below for more detail on image collection and cleaning procedures). We worked with both university undergraduates and Mechanical Turk workers to accurately label the roughly 9,500 images collected over the course of the

ShutdownA14 protest. We address the labeling in more detail below and in the online appendix.

Finally, we recognized the difficulty of making causal claims through our hypotheses and analyses. With our observational data, we leveraged the rich, time-series nature of the data to rule out many potential alternate explanations for the associations we found. We then turned to the experiment to bolster these claims. Whenever possible in the experiment we emulated real-life processes to strengthen external validity. For example, we used real images shared about BLM in the experimental treatments. Having made the case for the strength of our empirical research strategies, we now turn to presenting the details of the observational and experimental data, measurements, analyses and findings.

4 Observational Data & Measurements

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 first 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. The inability to collect Twitter messages sent a long time ago means that we are 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 a protest in Twitter. 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 had an image.

Main Variables

To model the data and test our hypotheses we divide the messages into periods of 30 minutes and then use the information from the messages in each of these 30-minute breaks to build a set of variables. In order to leverage our time-series data we need to split the data set into time periods. We chose a 30-minute cutoff because we think messages sent at any point in time should have their greatest effect in the following 30 minutes. However, to make sure the results of our analysis do not depend on this particular cutoff, we include lags of the key explanatory variable in our models and we also replicate the main models using a 10-minute cutoff (see online appendix E).

The dependent variables of the analysis are the *attention* to the BLM movement and the *diffusion* of the ShutdownA14 protest. In this social media context, we define and measure *attention* as the number of tweets that mentioned one of the BLM or ShutdownA14 hashtags sent during each 30-minute period. We measure *diffusion* using the number of new unique users that started using a ShutdownA14 hashtag in each 30-minute period. Our key explanatory variable of interest is the percentage of the total messages for each 30-minute period that had an image (*Percent Images*). Then we also control for other plausible explanations. Previous research shows that users with larger number of followers are more influential than others and these could also explain an increase on attention and a faster diffusion (Gonzalez-Bailon et al. 2011). To control for that, we measure the sum of the number of followers of the unique users tweeting in each 30-minute period (*Followers*), and also a lag of this same variable (*Followers (1 lag)*). Since the number of people talking about the BLM movement or joining the ShutdownA14 action in any given time period depends in part on the people who talked about the movement and joined the action in the recent past, we need to control as well for lags of the two dependent variables. Partial autocorrelation functions (PACF) indicate that the dependent variable *attention* is correlated with its own two previous values and the dependent variable *diffusion* with one (see online appendix B). For this reason we control for two lags of the dependent variable in models predicting attention and one lag for models predicting diffusion.

Mechanisms Variables: Images-As-Data

To address our mechanisms hypotheses, we needed more information about each particular image. The Twitter Streaming API provides a link to the tweeted images, so the week after the protest, having collected the tweets, we wrote a computer program to gather all the images that were present in the messages. Some tweets had the same image under a different link, so before studying them we first identified which images were the same. We did that in three different steps. First we looked for which messages shared an image stored in the same URL. Second we wrote a computer program to identify what images were very similar.[3] 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 identify the presence of the hypothesized mechanisms in each of the 9,458 images. To get to the hypotheses on emotions ($H_{2,3,4,5}$), enumerators indicated on a ten point scale to what extent the picture incited anger, fear, disgust, sadness, and enthusiasm. For the *expectation of success* mechanism (H_6), annotators indicated the number of people they saw present in the image, and also whether or not the image was from a street protest. To test the *symbol* hypothesis (H_7), they checked if a symbol such as a flag or a logo was in the image. Labelers also coded for the *race* of individuals seen in the images; we include this as a control variable, as prior research suggests that who is in the image might affect in-group identity (Wright and

[3]A computer program written in `python` that uses some functions of the `Python Imaging Library` module to compare to what extent two images are the same. The program will be made available with the replication material of the paper.

Citrin 2011). For more detail on the labeling scheme, along with two sample images with their assigned labels, see online appendix A.

We had two main concerns during this labeling process. First, we wanted to make sure that the labels for the top 1,000 images (949 after removing duplicates) were reliable since these would strongly influence the analysis: the distribution of the images was right skewed, with only few images being highly tweeted and the rest being only tweeted few times or once. We were particularly concerned about having a reliable measure of how many people were in the image. 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 can trigger different emotions to different people. Hence 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 emotionally similar to these images. We mitigated these concerns as follows: first, two research assistants labeled the top 1,000 images, producing two sets of emotional labels for each image. Then we used Amazon's Mechanical Turk service to obtain three extra sets of labels from three different people. As a result, for each of the unique top images, the value indicating the number of people present in the picture and the emotional score for each emotion was the mean of the values given by all annotators. We also employed Mechanical Turk workers to label, only once, the remaining unique images (n = 8,509).[4].

Once the annotators finished the labeling, we matched each unique image to all the messages containing that picture and we constructed our variables of interest. To build these variables we also aggregated information from messages within each 30-minute period. The variables *Anger, Fear, Disgust, Sadness*, and *Enthusiasm* are the average score for each emotion for images sent in that period. *People protesting* represents the average number of people in images that were sent in each 30-minute period – we restricted this variable to only include a people count from images that were clearly taken at a street protest, in order to ensure that we were capturing the expectation of success mechanism. The variable *Symbol* is the percentage of all the images sent in each time period that contain a symbol. Finally, the variables *Black, White, Latino, Asian,* and *Native* are the percentage of all the images sent in each time period that have a person from that race or

[4]In online appendix C we provide further socio-demographic information for the Mechanical Turk workers that participated in the labeling process; we also show how on average different people used very similar emotion scores for the same image.

ethnicity. Since the percentage of the total messages with images is not the same across time periods, we weight these variables for the percentage of the total messages sent in each time period that contain an image. We present a brief description of each variable in Table 2.

Table 2: Brief description of the variables of the Observational study

Variable	**Description** (Unit of Analysis = periods of 30 minutes)
	Outcome Variables
BLM tweets (attention)	# of tweets mentioning any hashtags/keywords in Table 1
A14 new users (diffusion)	# of users that mention A14 hashtags/keywords for the first time
	Explanatory Variables
Percent Images	% total messages that have an image
Symbol*	% total messages that have an image with at least 1 symbol
People protesting*	Average # of people present in images in each period
Fear*	Average of the fear scores for images in each period
Enthusiasm*	Average of the enthusiasm scores for images in each period
Anger*	Average of the anger scores for images in each period
Disgust*	Average of the disgust scores for images in each period
Sadness*	Average of the sadness scores for images in each period
	Control Variables
BLM tweets (1 lag)	1 lag of the outcome variable *BLM tweets*
BLM tweets (2 lag)	2 lags of the outcome variable *BLM tweets*
A14 tweets	# of tweets mentioning A14 hasthags/keywords
Followers	Av number of followers of users messaging in each time period
Followers (1 lag)	1 lag of the variable *Followers*
Percent Images (1 lag)	1 lag of the variable *Percent Images*
White*	% total messages that have an image with at least 1 white person
Asian*	% total messages that have an image with at least 1 Asian person
Black*	% total messages that have an image with at least 1 Black person
Latino*	% total messages that have an image with at least 1 Latino person
Native*	% total messages that have an image with at least 1 Native person

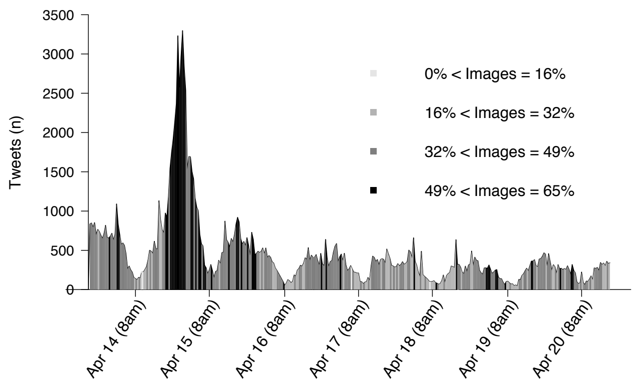
**We weight these variables for the % of the total messages that have an image in that time period*

5 Observational Results

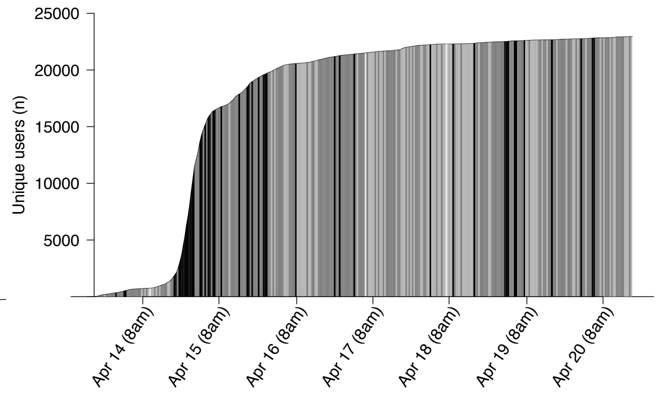
A first glance to the bivariate relationship between the two dependent variables (*attention* and *diffusion*) and the independent variable of interest, percentage of the total tweets that have an image (*Percent Images*), indicate a potential strong relationship. Darker colors in Figure 1 represent moments where a larger percentage of the total messages had an image. Lighter colors indicate the opposite. We observe that the *attention* to the BLM movement (numbers of messages) and the *diffusion* of the ShutdownA14 action (cumulative unique users, where the slope shows the rate of recruitment of new users) particularly increased when people shared images in a larger percentage of their tweets. Attention appears to decrease when a smaller percentage of the messages had an image.

Figure 1: Bivariate relationship between the key variable of interest (% of messages with images) and the two dependent variables: *attention* and *diffusion*

(a) Relation: % of tweets w. images and *attention*

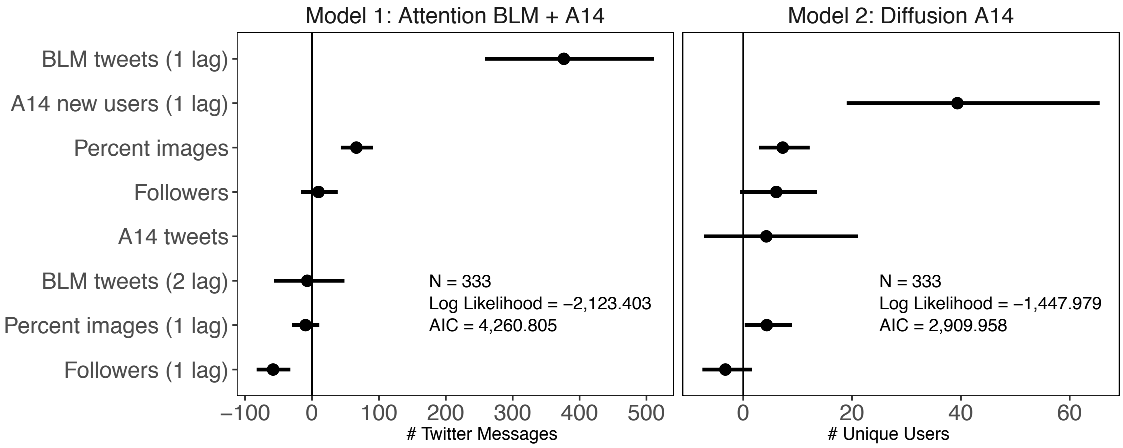


(b) Relation: % of tweets w. images and *diffusion*



Do these initial results persist after controlling for other factors? To assess that we test two multivariate models, with additional robustness checks presented in online appendix E. These are negative binomial models predicting the Twitter *attention* to the overall BLM movement (Model 1) and the *diffusion* of the ShutdownA14 action (Model 2). In both models the independent variable of interest is the percentage of the total messages that contain an image (*Percent Images*). In Model 1 we control for two lags of the dependent variable, so for the number of tweets sent in the two previous 30-minute breaks (*BLM tweets (1 lag)* and *BLM tweets (2 lag)*), for a lag of the explanatory variable of interest (*Percent Images (1 lag)*), and for the average number of followers of the users tweeting during that and the previous time period (*Followers* and *Followers (1 lag)*). In Model 2 we also control for the variables *Followers*, *Followers (1 lag)*, and *Percent Images (1 lag)*. However, since in this case we are predicting the diffusion of the ShutdownA14 protest only (and not the diffusion of the overall BLM movement), in Model 2 we do not control for *BLM tweets (1 lag)* or *BLM tweets (2 lag)*. Nevertheless, we add a control for this second model: the number of tweets containing an ShutdownA14 hashtag in each period of time (*A14 new users (1 lag)*).

Figure 2: Predicting Twitter attention to the BLM movement and the diffusion of the ShutdownA14 action (Negative Binomial Models)*



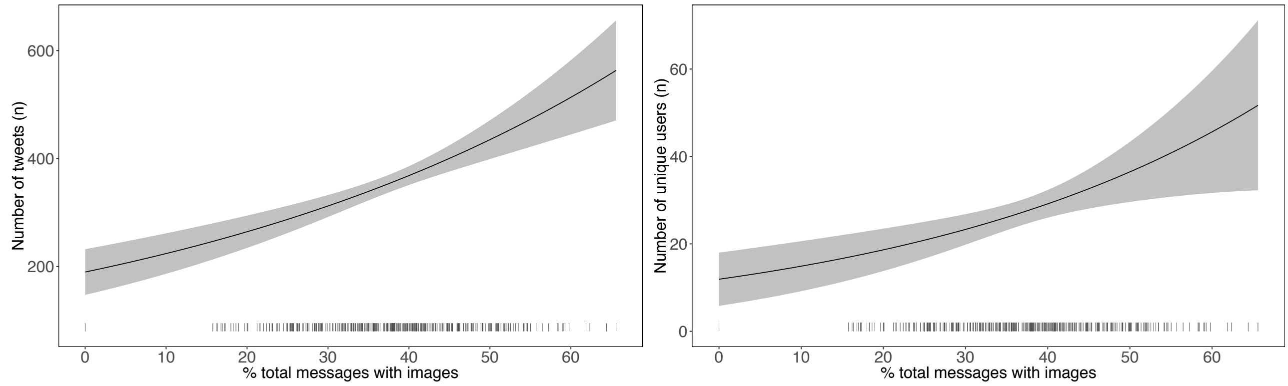
**Standardized coefficients (the effect of a variable moving from its mean to 1 standard deviation above)*

The models' coefficients in Figure 2 show that the first lag of the dependent variables (*BLM tweets (1 lag)* and *A14 new users (1 lag)*) are the strongest predictors of increasing *attention* and *diffusion*.[5] This means that the likelihood of a protest to get more attention and diffuse increases as the number of messages and unique users talking about the protest also increases. In both cases the second most relevant variable in terms of effect size is our variable of interest: the percentage of messages that contain an image (*Percent Images*). It is hard to interpret the substantive effect of this variable by only looking at the coefficients in Figure 2. In Figure 3 we use the coefficients of Models 1 and 2 to plot predicted values of the dependent variables: we keep all the covariates at their mean and only change the key variable of interest. Figure 3a shows that, on average, for the period of analysis when none of the tweets had an image, the expected number of tweets for that time period was around 200. However, if for example 40% of the messages had an image (the mean value of *Percent Images* in our dataset is around 38%), then the expected number of tweets for that time period was around 365; which represents a 82.5% increase. Similarly, in an average 30-minute period we would expect only around 12 unique users to start using ShutdownA14 hashtags for the first time if 0% of the messages had an image, but we would predict the number to raise up to 29 if 40% of the tweets had a picture (a 41.3% increase in the number of users).

[5] See online appendix D for the full regression table.

Figure 3: Predicting values of attention to the BLM movement and diffusion of the ShutdownA14 action using the coefficients of Models 1 and 2.

(a) Predicted values of attention to BLM (b) Predicted values of diffusion of the A14 action

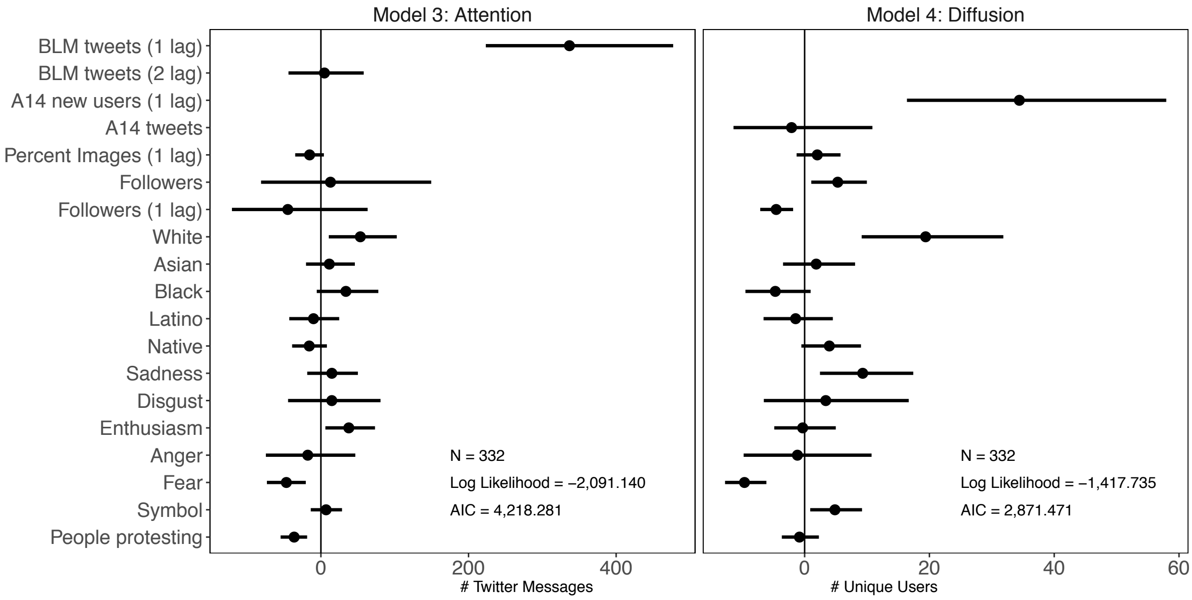


The results of the bivariate (Figure 1) and multivaraite analyses (Models 1 and 2 in 2) are consistent with our *General Image Effect* hypothesis (H_1): the likelihood of a protest to diffuse online and get more attention increases as a larger percentage of the messages related to the protest contain images. The next step is then to test to what extent the mechanisms we presented in the previous sections may actually explain why images related to a protest increase its likelihood to get more attention and diffuse.

We estimate two new negative binomial models. In them we substitute out the independent variable of interest *Percent Images* for all the mechanism variables while still keeping *Percent Images (1 lag)* in the models. The results (Figure 4) are supportive of some of the hypothesized mechanisms.[6] First, we find some evidence supporting our hypotheses regarding the role of emotions. In particular, we observe as expected that when a larger percentage of the messages contained images that inspired *enthusiasm* the attention to the BLM movement increased, while in moments where a larger percentage of the tweets had images that inspired *fear* the attention decreased (in line with H_{4b}). Both effects are statistically significant at the .05 level although the negative effect of images inspiring *fear* is of larger magnitude. When looking at the results for the *diffusion* model, *fear* still has a negative effect and the magnitude of the effect is even larger than in the *attention* model. Although in this case *enthusiasm* does not seem to play a relevant role, images inspiring *sadness* do have a positive and statistically significant effect. We do not find images inspiring other emotions such as *anger*, and *disgust* to be related to variation in attention and diffusion.

[6] See online appendix D for the regression tables.

Figure 4: Predicting attention and diffusion using the Image Mechanisms (Negative Binomial Models)*

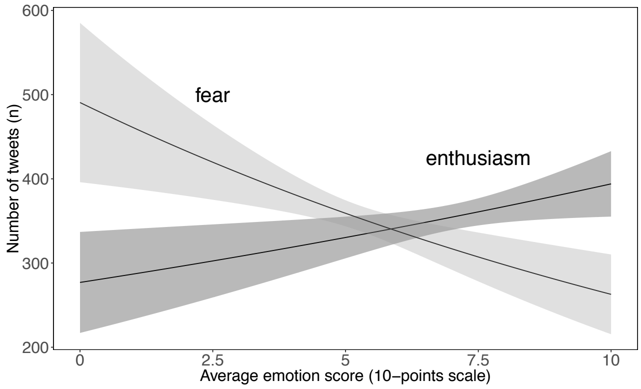


**Standardized coefficients (the effect of a variable moving from its mean to 1 standard deviation above)*

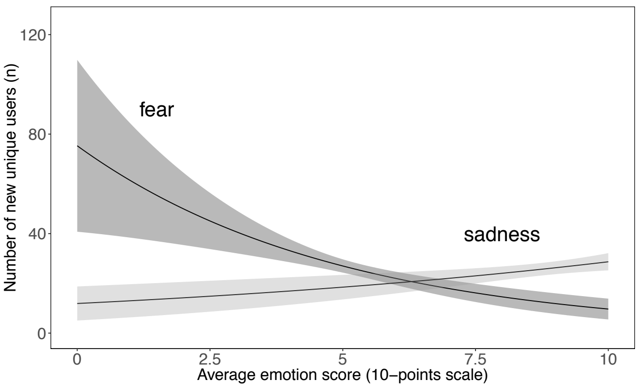
Second, the results of the models in Figure 4 are not supportive of the *Success Expectation* hypothesis (H_6). When users tweeted images of protests that had more people in them, the BLM movement received less social media attention and the ShutdownA14 action did not diffuse faster. For the *attention* model the negative effect is statistically significant at the .001 level although its magnitude is small relative to the effect of other variables. For the *diffusion* model the negative effect is not statistically significant. Third, we find evidence supporting the *symbol* hypothesis (H_7). When a larger percentage of the messages with images had a symbol such as a flag or a logo in them, a larger number of new users started messaging online about the ShutdownA14 action. Finally, as expected lags of the outcome variables explain a significant part of the variation and the variables indicating the race of people in the pictures also seem to matter. Since in this case we do not know the race of the people messaging about the protest, we cannot test hypotheses related to group belongingness. However, the results indicate that the ethnicity of the people in the images plays a role in understanding why images may increase or decrease rates of protest diffusion online. Future work should play closer attention to these hypotheses.

Figure 5: Predicting attention to BLM and diffusion of the ShutdownA14 action using Models 3 and 4.

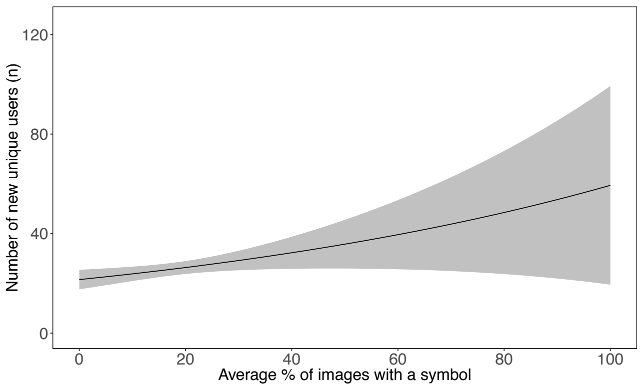
(a) Effects of emotions on *attention*



(b) Effects of emotions on *diffusion*



(c) Effects of images with symbols on *diffusion*



In Figure 5 we present the substantive effect of the covariates that are statistically significant in Models 3 and 4. We report predicted values of *attention* and *diffusion* given different average levels of *fear*, *enthusiasm* and *sadness*, and different average number of images containing a *symbol*. To calculate the predicted values we kept all the other variable at their mean and we simulated a 30-minute time period in which 10% of the messages had images. Figure 5a shows that for this scenario, if the messages with images incite an average *fear* score of 2 in a 10 points scale, we would predict around 430 messages about BLM. However, if the average *fear* is 8, we would predict about 300 messages (30% less). On the contrary, we would expect about 23% more messages when going from an average *enthusiasm* score of 2 to 8 (from 300 to 370 messages). We also observe that for this scenario the same change in the average *fear* has an even larger effect on the diffusion of the ShutdownA14 action: around a 70% decrease of the number of new unique users (from 50 to 15). However, a change from 2 to 8 in the average *sadness* increases the number of new users by about 65% (from 15 to 25). Finally, we see how an increase in the percentage of images that have a symbol has an average positive effect on the diffusion rate. For example, we would expect on average 25% more new users (25 instead of 20) if 20% of the images had a symbol instead of 0%. However, we are much less confident about the effect that images with symbols had of the diffusion rate of the ShutdownA14 action as the confidence intervals of Figure 5c indicate.

6 Experimental Data & Measurements

Despite our care in analyzing the observational data above, this type of analysis suffers from some well-established weaknesses. We are unable, for example, to fully rule out all potential alternative explanations or omitted variable that might explain the associations we found. We therefore turn our attention to an experimental survey research design to further test our hypotheses. The experiment and design are closely linked to the observational data, maintaining the conceptual link to both BLM and online social movement participation.

We recruited 5,000 participants from Amazon's Mechanical Turk service (MT). We announced the survey on MT using the title *"Short Survey"* and the subtitle *"Complete the survey only once. Takes about 1 minute."* We did not mention the topic of the survey to reduce self-selection issues, although MT workers could take a preliminary look at the survey before deciding whether to answer it or not. Respondents answered a battery of socio-demographic and political activity questions (e.g. *"How familiar are you with the Black Lives Matter movement?"* and *"Where would you position yourself in an ideological scale?"*). At the end of the survey, respondents were told that their job was completed but that they could follow an optional link to sign a petition in support of BLM. Respondents were told that going to the outside petition was not a requirement to be paid for the task. If they decided to click on the link, then they were redirected to one of five treatment-specific Google forms with the following text at the top (see Figure 6). In order to increase the external validity of the experiment, we used as a reference text two existing pro-BLM petitions that were posted on https://petitions.whitehouse.gov/. Our dependent variable of interest is the proportion of respondents from each experiment group that signed (entered their first and last name, and zip code) the online petition. For privacy reasons we are unable to link the names on the petition to surveys completed on the MT platform.

Figure 6: Text of the online petition

ePetition President Obama in Support of Black Lives Matter

Add your name to the petition! Currently there are 3,852 signatures.

Dear President Obama,
We ask that you officially recognize Black Lives Matter as an important movement that is about bringing change to America through nonviolent protests and demanding that our judicial system work for everyone. We petition the White House to formally support the cause of the Black Lives Matter movement by issuing a statement affirming that the United States of America pledges from this day forward to grant full and equal protection, value, dignity, liberty and justice to Black people and their descendants, as it does to all citizens of America.

Your first name: _______________

Your last name: _______________

Your zip code: ________________

5,000 respondents were randomly assigned to one of five groups (1,000 per group). Each respondent saw the same survey (see online appendix F for a copy of the survey), with the exception of a possible image treatment. In the control group, respondents saw the survey alone. In each of the four treatment groups, respondents saw an image in addition to the survey. One treatment image per survey was placed at the head of the survey; the same image was repeated at the bottom of the survey, just prior to the petition link. Then respondents from each group that clicked on the link were directed to five different copies of the same exact petition so that we could track the number of people who actually signed it by group. The length of the survey was longer than a regular computer screen, about three times the size. This means that MT workers had to scroll down the screen as they were answering the survey, and that they were exposed to the treatment image only for a short period of time. We intentionally chose this online survey layout instead of a survey parsed into multiple screens in order to add even more external validity to the experiment: workers' activity was similar to what a social media user would do when checking their timeline/wall/newsfeed, which is how numerous people today learn about an ongoing online petition.

The four treatment images were selected from the compiled ShutdownA14 tweets. Based on the labels applied to each image, we selected the following treatment images:

one that scored high on *sadness* (and low on the remaining emotions), one that scored high on *fear* (and low on the remaining emotions), an image of a large *crowd* participating in the April 14 protest, and an image that included a prominent *symbol.* The four images are also included in online appendix F. We conducted the survey from August 1st to September 8th 2016.

7 Experimental Results

The results of the experiment (Table 3) support our main claim that images foster political mobilization (H_1). In particular, we observe how images increase the diffusion rate of a BLM online petition. 4.2% of the respondents in the control group (n = 1,000), who were not exposed to an image, signed the online petition. However, about 6.1% of the MT workers that were in one of the treatment group (n = 4,000) signed it. This means that the sign rate for the people who saw an image was 1.9 percentage points higher than for those people who did not see an image; the proportion of treatment respondents who signed the petition is about 45% higher than the control. This difference is statistically significant at the .01 level.

Table 3: Experiment Results

Group	Sample	Signed Petition (n)	Sign Rate (%)	Percentage Point Difference from the Control Group
No image (control)	1,000	42	4.2%	–
Image (all treatments)	4,000	244	6.1%	+ 1.9***
(fear)	1,000	73	7.3%	+ 3.1**
(symbol)	1,000	66	6.6%	+ 2.4*
(sadness)	1,000	53	5.3%	+ 1.1
(crowd)	1,000	52	5.2%	+ 1.0

Note: Statistical significance for 2-sample t-test for equality of proportions
*p<0.1; **p<0.05; ***p<0.01

The difference with the control group is even larger for some of the specific treatment groups. We again see fear playing a key role. The respondents exposed to images triggering this emotion when completing the survey were the most likely to sign the BLM petition. The sign rate for the people who saw the image triggering fear was 7.3%, more than three percentage points higher than the control group, for a percent change of almost 75%; the difference in proportions is statistically significant at the .05 level. Two summary points stand out: first, these results support our argument that images can play an important role mobilizing role because they act as emotional triggers. Second, these results support our hypothesis (H_{4a}) that fearful images can increase rates of online mobilization when the costs of activity are very small: whereas the visibility of one's comments in social media may have a relatively high social cost (posts can be seen by one's followers, followers of followers, etc.), friends and family are often unaware that their friend has signed a potentially controversial online petition. The differential costs of posting to social media versus signing an online petition help explain the change in the effect of *fear* between the observational data and the experiment.

The results for the group exposed to an image with a symbol supports our argument that images with symbols in it appeal to and build a collective identity and foster political mobilization (H_7). In this case, the particular image had a coffin completely covered with the American flag. We chose that image because we believe it is clearly serving the theorized purpose: sending a clear message that BLM is an issue for all Americans and not only the African American community, bridging the gap between different citizen groups. 6.6% of the survey respondents exposed to that image signed the BLM petition, almost 2.5 percentage points more than the control group, for a percent change of about 57%. The results for the group exposed to the image with a protesting crowd on it also supports our expectation that such images should increase a movement's diffusion rate when the social movement is in its early stages but not when the movement has already reached high visibility and substantive support (H_{6b}). Although the sign rate for this group was higher than the control, the difference is only about one percentage point and far from being statistically significant. We conducted the survey experiment right after the 2016 presidential primaries, during the Hillary Clinton and Donald Trump campaigns, and following significant violence in Minnesota and Texas. At that time the BLM movement had already achieved high national salience and was at the center of the political debate. We argue this means that BLM images with protesting crowds had diminishing returns as compared to April 14,2015 and so did not increase the likelihood of participation at the time we conducted the experiment. Finally, the results for the group of respondents exposed to the sadness image do not support our hypothesis that sad images should foster political mobilization (H_5). The sign rate for this group is also higher than the control but the difference is not very substantive and is not statistically significant.

8 Discussion and Conclusion

Despite the prevalence of images in modern life, very little research has addressed 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 (e.g. Howard and Hussain 2013; Kharroub and Bas 2015). However, the literature does not provide a clear theoretical framework for why images should matter, nor has it systematically tested the role of images in mobilizing support for social movements. In this paper we put forward a general theory and lay out a set of specific mechanisms and conditions under which images should increase the likelihood of a protest to receive more attention and diffuse to new participants. We then test our theory and mechanisms by studying the spread of a social movement online. We analyze observational data (Twitter messages) from a Black Lives Matter (BLM) protest that took place in April 2015 and experimental data from a survey experiment about the same social movement conducted on Mechanical Turk in August 2016.

We argue that in general images should increase rates of social movement diffusion 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 collective identities. In line with the theoretical predictions, we find that in the context of a BLM protest promoted on Twitter (ShutdownA14) a larger percentage of messages with images increased the likelihood of the movement to receive more attention and the likelihood of the specific protest to diffuse to new participants. Images triggering enthusiasm increased the attention to the overall BLM movement while images inspiring fear had the opposite effect. Images triggering sadness and images with symbols such as flags or logos increased the diffusion rate of the ShutdownA14 action while images inspiring fear again slowed the spread of mobilization. Contrary to our expectation of success hypothesis, the number of protesters present in images appears to decrease attention to the movement in the early stages of mobilization.

The results of the survey experiment also support our theoretical expectations. In line with existing theory suggesting that the differences in costs may mitigate the impact of fear (Valentino et al. 2011), we find that fearful images increase the likelihood of taking a less personally identifiable action like signing an online petition in support of BLM. The survey results corroborate the observational finding that images with collective-identity generating symbols increase the likelihood of participation. Finally, we find evidence that crowd size does not affect mobilization once the movement has already become widely salient.

However, all studies have their limitations and this one is no exception. In particular, we would like to point out to two limitations that future research should address. First, in our attempt to test the effect of images on mobilization, we decided to focus on a single social movement: Black Lives Matter. We decided to do so because we wanted to focus on clear tests and to study a relevant and current social movement. However, as numerous scholars of social movements and agenda setting have pointed out (Vliegenthart and Walgrave 2011; Baumgartner and Jones 1993; Kingdon 1984), the dynamics and capacity of a social movement may change depending on the issue at stake. Future studies should address to what extent the expectations presented here hold for movements dealing with different political issues. Second, we note the potential for measurement error in our study. Further research will be required to evaluate whether our labeling and analyses are robust to different operationalizations of emotion, street protest size, and symbols.

Despite these limitations, the present study offers numerous theoretical and empirical contributions. We theorize that images are an important component in the mobilization of social movements, especially in a new media environment. We find that protest- and social movement- related images boost both online attention paid to the movement and diffusion of a specific action to new participants. We also offer insights into which types of images have the most impact in mobilizing social movement participation. Images that incite emotion have a strong effect on participation. Images that inspire expectations of protest success, based on the number of protest participants visible, have a negative impact when the movement has low salience and no influence when the movement has high salience. And images that promote a collective identity via commonly-recognized group symbols such as flags have a positive impact on mobilization. These findings open up many potential avenues for future research into the role of images in social and political processes.

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Online Appendix:

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

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A Appendix: Image Labeling Procedures

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

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

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

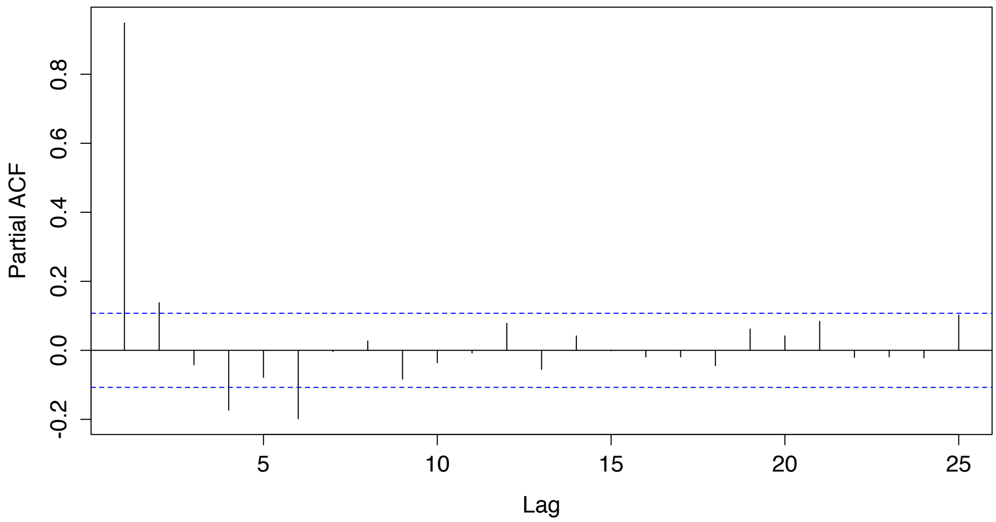
Research staff labeled this image as having 7 people (on average), no signs or slogans, and no symbols. On the emotions, the average scores were: anger: 2, fear: 1, disgust: 2, sadness: 3, enthusiasm: 1. Races/ethnicities identified were Black and White (non-Hispanic)

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

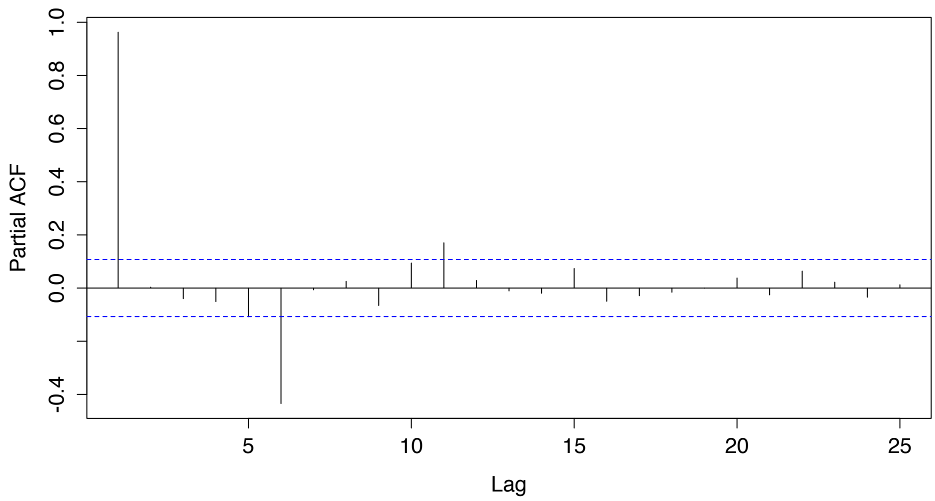
Research staff labeled this image as having 45 people (on average) and protest signs, but no slogans or symbols. On the emotions, the average scores were: anger: 2, fear: 1.5, disgust: 1, sadness: 1, enthusiasm: 2.5. Races/ethnicities identified were Black, White (non-Hispanic) and White (Hispanic).

B Appendix: Observational Dependent Variable PACFs

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



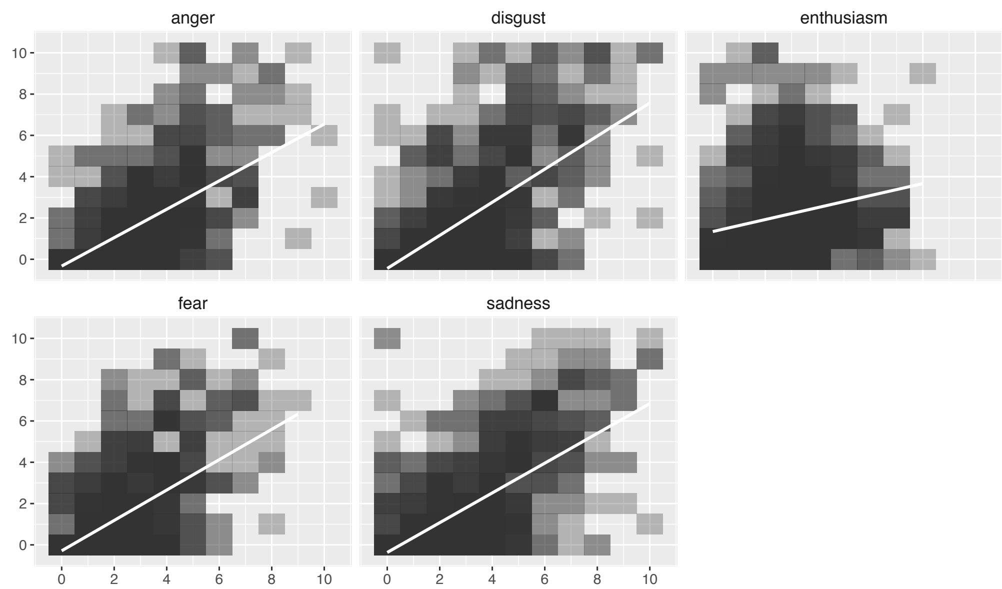
(b) Partial Autocorrelation Function plot for the dependent variable *Diffusion* (Number of new unique users tweeting about a particular BLM protest: Shutdown A14)



C Appendix: Evidence of Stable Emotions Labeling

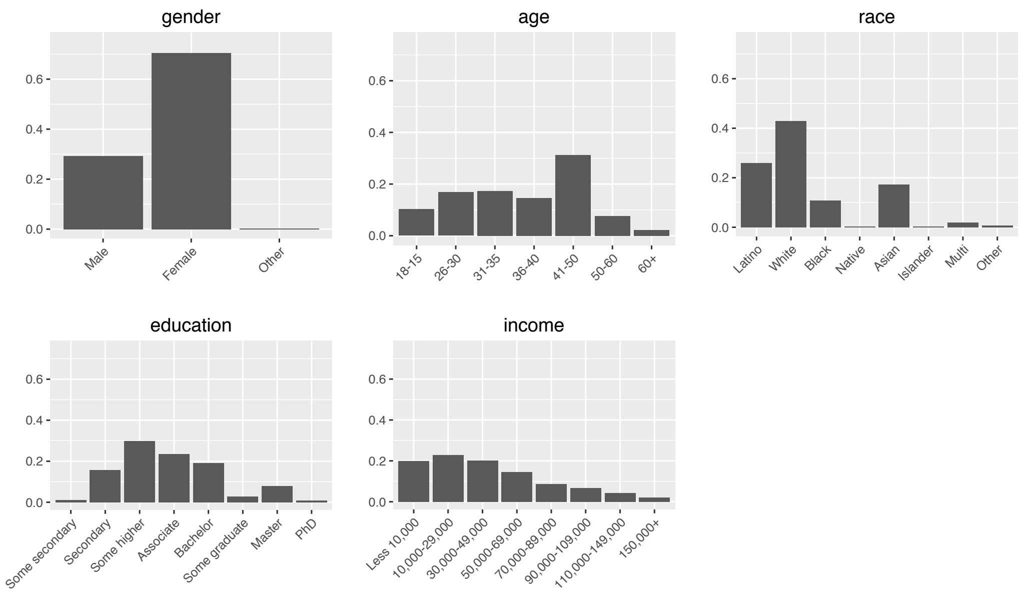
In this Appendix we provide extra information showing that although emotions are subjective, on average the top 1,000 images (which account for more than 50% of the messages with images) triggered very similar emotions to different people. This is important because when modeling the data we give to each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

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



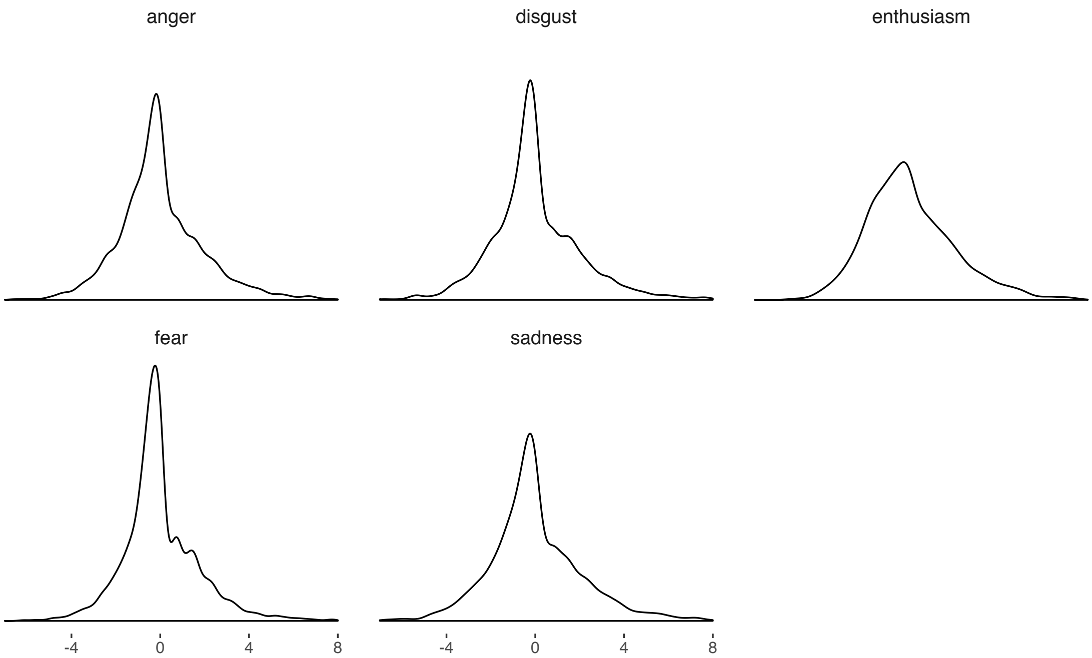
In a second iteration we used Mechanical Turk (MT) to label three more times the top 1,000 images. We decided to do so not only to have more emotion labels per image but also to get scores from people with different backgrounds, since our two research assistants were both undergraduate students, male,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

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



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

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



D Appendix: Observational Data Analysis Regression Table

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

	Model1 (Attention)	Model2 (Diffusion)	Model3 (Attention)	Model4 (Diffuison)
Percent Images	1.659^{***}	2.238^{***}		
	(0.287)	(0.656)		
Percent Images (1 lag)	-0.270	1.363^{**}	-0.418	0.692
	(0.288)	(0.645)	(0.273)	(0.612)
Followers	0.000	0.00000^{*}	0.000	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)
Followers (1 lag)	-0.00000^{***}	-0.00000	-0.00000^{***}	-0.00000^{**}
	(0.000)	(0.00000)	(0.000)	(0.00000)
BLM tweets (1 lag)	0.002^{***}		0.001^{***}	
	(0.0002)		(0.0002)	
BLM tweets (2 lag)	-0.00005		0.00002	
	(0.0002)		(0.0002)	
A14 tweets		0.0003		-0.0003
		(0.001)		(0.001)
A14 new users (1 lag)		0.005^{***}		0.005^{***}
		(0.001)		(0.001)
Black			1.419^{*}	-3.260^{*}
			(0.842)	(1.978)
White			2.279^{**}	9.143^{***}
			(0.923)	(2.154)
Latino			-1.022	-2.231
			(1.686)	(3.890)
Asian			2.156	4.562
			(3.221)	(7.470)
Native			-7.203	21.617^{*}
			(5.416)	(12.728)
People protesting			-0.013^{***}	-0.004
			(0.003)	(0.008)
Symbol			1.161	10.155^{**}
			(1.782)	(4.094)
Anger			-0.170	-0.208
			(0.278)	(0.642)
Fear			-0.624^{***}	-2.052^{***}
			(0.182)	(0.435)
Disgust			0.107	0.298
			(0.244)	(0.570)
Sadness			0.116	0.879^{***}
			(0.137)	(0.318)
Enthusiasm			0.352^{**}	-0.066
			(0.151)	(0.346)
Constant	4.753^{***}	1.552^{***}	5.195^{***}	2.319^{***}
	(0.104)	(0.245)	(0.098)	(0.231)
Observations	333	333	332	332
Log Likelihood	$-2,123.403$	$-1,447.979$	$-2,091.140$	$-1,417.735$
Akaike Inf. Crit.	4,260.805	2,909.958	4,218.281	2,871.471
Note:				*p<0.1; **p<0.05; ***p<0.01

E Appendix: Observational Data Analysis Robustness Checks

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

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

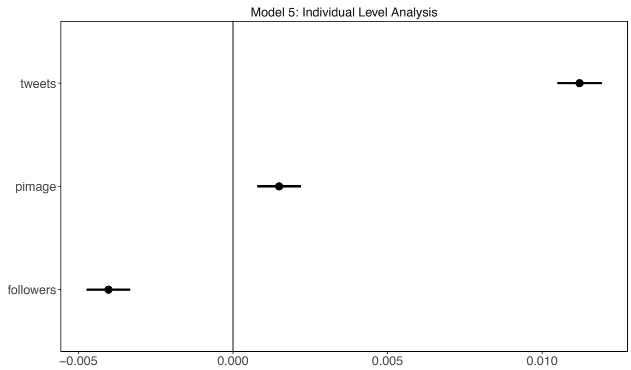
Models 1a, 1b, 2a, and 2c in Table 1 show the results for the first robustness check. We observe very similar results despite using samples from different time periods to estimate the effect that images have on increasing attention to and diffusion of protests online: no matter whether we use observations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

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

Table 1: Robustness Checks Models

	Dependent variable:						
	Model1a (Att.) (NB)	Model1b (Att.) (NB)	Model2a (Diff.) (NB)	Model2b (Diff.) (NB)	Model1c (Att.) (NB)	Model2c (Diff.) (NB)	Model5 (OLS)
Percent Images	2.106***	2.512***	2.046**	3.285***	0.757***	1.389***	0.004***
	(0.782)	(0.871)	(0.873)	(0.942)	(0.135)	(0.339)	(0.001)
Percent Images (1lag)	−0.286	−0.271	0.414	−1.090	0.166	1.260***	
	(0.687)	(0.934)	(0.722)	(1.016)	(0.136)	(0.338)	
Followers	0.00000***	0.000	0.00000	0.000	−0.000	0.00000	−0.00000***
	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.000)	(0.00000)	(0.00000)
Followers (1 lag)	−0.00000	−0.000	0.00000	−0.000	−0.00000***	−0.00000	
	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.000)	(0.00000)	
BLM tweets (1 lag)	0.001**	0.001***			0.004***		
	(0.001)	(0.0002)			(0.0004)		
BLM tweets (2 lag)	0.00004	0.0001			0.0003		
	(0.0003)	(0.0002)			(0.0003)		
A14 tweets			0.007***	0.001**		0.003**	
			(0.002)	(0.0003)		(0.001)	
A14 new users (1lag)			0.007*	0.001***		0.010***	
			(0.004)	(0.0004)		(0.002)	
Tweets							0.001***
							(0.00002)
Constant	4.500***	4.859***	1.547***	3.564***	3.817***	0.902***	0.032***
	(0.242)	(0.421)	(0.298)	(0.505)	(0.052)	(0.135)	(0.001)
Observations	50	51	50	51	1,000	1,000	15,303
R^2							0.065
Adjusted R^2							0.064
Log Likelihood	−332.490	−356.158	−187.624	−291.828	−5,283.422	−3,380.491	
Akaike Inf. Crit.	678.980	726.317	389.247	597.656	10,580.840	6,774.982	
Note:							*p<0.1; **p<0.05; ***p<0.01

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



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

F Appendix: Supplemental Survey Experiment Materials

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

(a) Sad treatment image

(b) Fear treatment image

(c) Crowd treatment image

(d) Symbol treatment image

Survey on the #BlackLivesMatter movement

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

Treatment Image

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

☐ I don't know what the Black Lives Matter movement is

☐ I know about its existence but I don't know or am unsure what its claims are

☐ I know about its existence and am aware of some of its claims

☐ I am very familiar with the movement and its claims

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

☐ No

☐ Yes, once

☐ Yes, more than once but less than 6 times

☐ Yes, between 6 and 10 times

☐ Yes, more than 10 times

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

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

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

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

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

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

7. What is your gender?

- ☐ Male
- ☐ Female
- ☐ Other

8. What is your age?

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

- ☐ What is your highest level of education?
- ☐ No formal schooling
- ☐ Some primary school (elementary school)
- ☐ Finished primary school
- ☐ Some high school (secondary school)
- ☐ Graduated high school or equivalent
- ☐ Some higher education (college/university)

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

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

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

11. What is your race/ethnicity?

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

Treatment Image

Thanks for taking the survey. Your job is done!

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

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

Submit