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

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Paper prepared for the American Political Science Association Annual Meeting,
Philadelphia 1-4 September 2016

Abstract

Do images shared online increase rates of protest mobilization? If so, how? In this paper we study the spread of Twitter support for Black Lives Matter and for Shutdown April 14, a specific Black Lives Matter protest, from April 13 to April 20, 2015. As predicted by the literature on images and social movements, we find using observational data that, all else equal, an increase in the percentage of tweets with images contributes to an increase in subsequent tweets about the movement and to an increase in the number of new users tweeting about the protest. We then examine which types of images contribute most to increases in online social movement support using both observational Twitter data and a survey experiment. This allows us to adjudicate between theories that claim different mechanisms for why new imaging technology should facilitate political mobilization. Beyond providing low cost information, images might a) act as an emotional trigger; b) increase expectations of success; or c) generate collective identity. Our paper thus provides evidence supporting the broad argument that image-sharing increases the likelihood of a protest to spread while also teasing out the narrow mechanisms at play in a new media environment.

1 Introduction

Do images shared online increase rates of protest mobilization? If so, how? Anecdotal evidence from recent protests around the world suggests that the answer to the first question is a resounding "yes": for examples, one need look no farther than the 2013 Gezi Park protests in Turkey, where images of the "woman in red" being sprayed in the face with tear gas were shared online via social media and arguably contributed to an increase in support for the movement. In the United States, images of police actions against both the 2011 Occupy Wall Street (OWS) movement and the journalists who covered OWS galvanized support for the protesters. In Tunisia, images of Mohamed Bouazizi, the fruit vendor who set himself on fire in response to government mistreatment, spread rapidly on social media and have been described as catalyzing the late 2010-2011 Arab Spring uprisings throughout the Middle East. Video clips and still frames of Eric Garner's 2014 arrest and death in New York City expanded the reach of the Black Lives Matter movement.

However, despite compelling narratives along the lines described above, very little research has attempted rigorously test the role of images in the spread of protests online (though some general explorations have begun, see for example Kharroub and Bas 2015). Beyond case selection concerns, researchers must contend with overlap between images and other variables of interest: perhaps the effect of the images in the protest movements above was less about the images themselves and more about the people sharing those images. Addressing both a gap in the literature and these methodological concerns, our paper makes two contributions to the discussion of images and the spread of protests online. First, we show a strong image effect in the expansion of an April 14, 2015 Black Lives Matter protest on Twitter, even after controlling for other factors that might mitigate the image effect, such as the differential influence of various Twitter users. Second, we tease out which types of images were the most impactful in spreading the protest online in order to test specific hypotheses put forward by prior scholars as to why images might matter in online social movement mobilization.

On April 14, 2015 a coalition of activist groups, including the Stop Mass Incarceration Network and Hands Up United, organized a protest against police brutality in the United States. 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 in order to recruit new participants and to spread information about their cause. 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 Black Lives Matter movement active throughout the United States.

In this paper we begin by studying the spread of online Twitter messages related to the protest to see if those messages that contained images played a special role in mobilizing supporters. We divide the general concept of social movement mobilization into two subcategories: attention and diffusion. In short, we are interested in whether and which Twitter images lead to variation in the number of movement-related tweets and the number of new Twitter users for the protest.

First, we consider attention to the movement. We measure this by examining the number of people tweeting about Black Lives Matter 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 the specific April 14 protest to new members. Diffusion here is therefore conceptually equivalent to recruitment into the action. Given the narrow timeframe of our data collection, we are unable to analyse the number of new recruits to Black Lives Matter due to April 14 images, as individuals may have been active online in the movement long before our protest of interest. Therefore we focus our diffusion analysis on the April 14 protest, counting the number of new people tweeting about #ShutdownA14 over the course of the event.

To further strengthen our analysis, we then conduct a survey experiment to see if variation in images leads to differential rates of social movement support, as measured by respondents' willingness to sign an online petition in support of Black Lives Matter. The survey was conducted on Mechanical Turk, with a total of 5,000 respondents randomly assigned into one control and four treatment groups.

Arguing that more scholarship should focus on images in the mobilization of protests online requires us to stake out two broad positions within the literature on social movement activism: first, that online social media activity and diffusion matter for social movements and, second, that images matter within the framework of expanding protests online. We address these literatures in the next section of the paper to develop our primary hypothesis regarding the mobilizing role of images shared via social media. We then turn to our specific mechanisms hypotheses, examining types of images that might be more likely to increase online protest support. Our mechanisms hypotheses are threefold. Images might a) act as emotional triggers (Ansolabere and Iyengar 1995; Brader 2005; Valentino et al. 2011), b) increase expectation of success (e.g. Raiford 2007; Kuran 1997), and/or c) promote inclusive collective identities (e.g. Kharroub and Bas 2015). After discussing both the broad and specific literature of relevance, we then present the April 14 data and our analyses. We conclude with a summary of results and suggestions for future reserach.

Protests in the Twenty-First Century

Individuals today have greater access to information communication technologies (ICTs) than ever before (e.g mobile-phones, tablets, laptops, smart-watches, etc.). Connectivity is increased even more by Internet access. ICTs have transformed the way people perform a large number of tasks and, in particular, the way people protest. If we take a look at some of the most visible protests that had taken place in the last few years, we immediately see that ICTs have played a relevant role in the organization and diffusion of social mobilizations such as the Anti-Iraq War demonstrations, Occupy Wall Street and the Arab Spring (e.g. Bennett et al. 2008; Castells 2009; Howard 2010; Gonzalez-Bailon et al. 2011; Kharroub and Bas 2015). However, how do ICTs, and social media in particular, affect the way people protest?

Scholars studying social movements and the diffusion of protest theorize that new ICTs help facilitate political mobilization as a result of (1) reducing information, coordination and participation costs, (2) decreasing the relevance of strong central organizations, and (3) partially solving the free-rider problem by allowing a more personalized participation (e.g. Bimber 2005; Garret 2006; Earl and Kimport 2011; Walgrave et al. 2011; Bennett and Segerberg 2013).

First, ICTs have decreased coordination, communication, and participation costs associated with social mobilizations (Garret 2006). In the past, coordination between groups with scarce resources was very costly and ineffective. It was difficult for an organization to know what other organizations or individuals 'out there' supported similar causes and it was also hard to coordinate strategies with them all by post-mail or phone. However, the technological innovations of the last decades have facilitated the creation of both transnational and regional advocacy networks (Keck and Sikkink 1998). For example, Bimber (2005) and Bennett and Segerberg (2013) highlight the role that ICTs have played in the organization of multiple anti-globalization protests since the "Battle of Seattle" in 1999; without email, webpages, video calls, or social media, those macro coordinated protests would not had been possible.

ICTs have also decreased the communication costs associated with protests. In order to recruit new participants and spread the message of a protest, social movements need to spend time and resources communicating their messages. In the past, communication tasks were costly, time-consuming, and did not have an immediate impact. The communication strategy of the National Association for the Advancement of Colored People (NAACP) during the first half of the 20th century is a good example of this. The NAACP principally communicated its message through an in-house publication (*The Crisis*) and issue-based pamphlets (Francis 2014). The costs of printing and distribution those publication were extremely high compared to the costs of maintaining the current NAACP website (http://www.naacp.org/). Moreover, it takes longer for printed and manually-distributed material to get to a larger number of people and to achieve the desired impact.

New digital media have also contributed to decrease participation costs: supporting a political cause is less costly today than it was in the past (e.g. Walgrave et al. 2011). 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 such as 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.

Second, social movements today are less dependent of strong formal organizations thanks to new ICTs. According to traditional theories of collective action (Hardin 1968; Olson 1965), resourceful organizations

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

play a key role in solving communication and coordination problems. However, as scholars such as Bimber (2005), Castells (2009), and Bennett and Segerberg (2013) point out, because ICTs have drastically decreased communication and coordination costs, small groups of individuals can coordinate actions by building a "self-organizing network" (Bennett and Segerberg 2013) without the need of a strong central organization such as unions and macro NGOs. The *Indingados* protest in Spain in 2011 is a good example of this phenomenon; a group of about 400 small and recently-created organizations used digital media to coordinate the initial demonstration and occupation of Madrid's main square (*Plaza del Sol*) without the support of any union or political party (Bennett and Segerberg 2013; Anduiza et al. 2014).

Finally, Bimber (2005) also notes that ICTs have changed the notion of free-riding. Traditional theories of collective action (e.g. Olson 1965) pay special attention to the discretionary decision that individuals make about getting involved or not in a collective action. However, as Bimber (2005:372) points out, "individuals can now contribute to information repositories with no or only partially knowledge of contributing to communal information with public goods properties." Webb Williams (2015) similarly notes that the spread of ICTs has enabled the rise of "protest observation" as a distinct and important level of protest involvement – a desire to take and share a picture from a protest might not represent participation in that protest, but posting the image online might still help the movement grow. On the one hand, the change in the free-rider phenomenon is the result of a decrease of participation costs; on the other hand, this also happens because ICTs allow individuals to engage with a social movement in a more personalized and emotional way (Bennett and Segerberg 2013). Individuals can choose to contribute to a social movement's debate with their own words, a picture of a protest taken from the sidelines, or by engaging with a specific frame or sub-debate. Although sometimes social movements sacrifice clarity of discourse and media impact when doing so, this does not have to be the case. For example, Casas et al. (2016) show that the *Indignados* movement in Spain was capable of accurately transmitting its message to the mainstream media despite having a highly fragmented discourse.

Scholars have also debated whether the mechanics of ICT-enabled activism are really all that special, or whether they simply represent an acceleration of processes that are already well understood (e.g. how reduction in costs might increase participation). Are ICTs a newly powerful democratizing force, or business as usual at a slightly faster pace? Right after the emergence of the Internet, some scholars (e.g. Schwarts 1996; Bryan 1998; Dahlgreen 2000) saw such technological innovation as an instrument and opportunity to reverse negative social patterns in Western democracies such as unequal political participation (Verba and Nie 1992), unequal political influence (Verba et al. 1995), a decrease in social capital and civic culture (Putnam 2000), and the marginalization and under-representation of certain target populations (Schneider and Ingram 1993; Cameron et al. 1996; Lerman and Weaver 2010). However, subsequent scholars were more cyber-skeptic (Norris 2000, Morozov 2011). For example, Davis and Owen (1998), Golding (2000) and Norris (2000) argued that the Internet would exacerbate the unequal power that the affluent have in politics because access to Internet was expensive and only those with resources would benefit from having more information available, better ways to connect with others, and new instruments to participate in politics. Others such as Sunstein (2001) also argued that digital media would worsen political polarization and create more "echo-chambers." Finally, some have noted the rise of innovative social media-enabled repression under authoritarian regimes that could swamp any possible ICT democratizing effect (Pearce 2014, 2015).

Debates aside, there are still reasons to believe that ICTs, and online image-sharing in particular, can facilitate participation by a wider swath of individuals than ever before in history. These technologies and behaviors give more power to smaller organizations and social movements so that they might recruit participants, spread their messages and, ultimately, influence the political agenda and the decision-making process. There is evidence today that undermines some of the cyber-skeptical arguments: ICTs are cheaper than ever (e.g. Internet, phones, smart-phones, tables...) and their prices keep decreasing; and some academic works suggests that "previous studies may have overestimated the degree of mass political polarization" in social media (Barbera et al. 2015). Moreover, images and online image-sharing allow social movements to have more control over their own discourse. Mainstream media (e.g. newspapers, radio, TV, and mass media companies in general) traditionally 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; Raiford 2007). 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. For example, Raiford (2007:1131-1132) highlights that photography played a key 'democratizing' role in the 1960s during the Civil Rights Movement:

> "When network television or dominant newspapers did report on movement activities, they tended to provide accounts of events involving white or well-known African American participants [...] In contrast, photography proved a more accessible, contemplative, and democratic medium than television. [...] Cheaper and more readily available, still cameras enabled activists themselves to frame the movement as they shaped and experience it. [...] Photography constituted a democratic practice that strove for the fullest representation possible. Photography offered, literally, what historian Charles Payne has called 'a view from the trenches'."

These words from Raiford perfectly exemplify the potential of images, ICTs, and 'online image-sharing' to enhance social movement mobilization, particularly online. The capacity of taking images and sharing them with others in pamphlets or in-house newspapers (Francis 2014) helped the Civil Rights Movement to frame and give more salience to the cause. With the emergence of ICTs this power has increased exponentially. During the Civil Rights Movement organizations such as the NAACP or SNCC needed semi-professional photographers on the streets in order to capture images they could later include in their publications and share with others. Today small or emerging social movements such as Black Lives Matter can rely on thousands of participants to take pictures "from the trenches" (Payne 1998) and immediately share them. 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). We take these insight as inspiration to focus on the sharing of images via online social media.

The goal of this paper is not to argue that online activism is the only activism that matters in the 21st century. Black Lives Matter holds on-street protest as well as on-line activities; many of the images analysed in this paper came from offline actions. Organizations today clearly use hybrid offline and online tactics to achieve their goals (Chadwick 2007). Instead, the main aim of this paper is to better understand which types of online activism via image sharing are more likely to be successful in promoting attention to and diffusion of a specific protest activity and a broad social movement. We turn next to these specific elements of online mobilization.

Online Image-Sharing and Mechanisms of Protest Mobilization

There are multiple reasons to believe that ICTs as a whole might facilitate the spread of protests online, but how do specific ICT-enabled activities, such as online image sharing, contribute to this mobilization process? Scholars such as Howard and Hussain (2011), Aday et al. (2012), Bennett and Segerberg (2013) and Kharroub and Bas (2015) argue that visual content such as images and videos played a key role in the spread of revolutions during the Arab Spring and the Occupy movements around the globe. Although there is still little systematic evidence showing such an effect, broader literature suggests that images have great potential as instruments of diffusion because they: can reduce information costs, act as emotional triggers, generate expectations of success, and promote inclusive collective identities. We first address the general image effect hypotheses, then evaluate the specific mechanisms proposed in the literature.

The General Image Effect

Images, regardless of their type images, might increase the likelihood of an online protest to spread because they lower the costs of obtaining information. ICTs in general decrease information costs by making information about protests more available in multiple technological devices in our hands; but images may contribute even more to lowering those costs because they facilitate information-processing. First, images can briefly summarize the key points of a protest by showing the motto of the protest or a set of banners. Second, some neurology scholars (e.g. Gazzaniga 1998) also argue that we learn more efficiently through visual communication because it involves a more passive comprehensive process than reading or engaging in a conversation; and finally, other scholars (e.g. Barry 2002) argue that people do a better job at processing visual information (TV news or images in newspapers) because it is easier for humans to relate to reality the information they perceive visually: humans principally learn about their world and their environment through personal experience and such personal experiences principally involve visual communication. In sum, this set of literature indicates that 'online image-sharing' may increase the mobilization of protests as a result of lowering the information costs for potential participants. This expectation informs our first, most general hypothesis:

$\mathbf{H}_1$ (*General Image Effect*) Hypothesis: As more protest-related images are shared online, the likelihood that that movement will diffuse to new members and attract additional attention will increase.

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 (Jasper 1998). Questions remain as to which emotions play a role (Valentino et al. 2011). Jaspers (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. Jaspers 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. In our analyses, we coded images for anger, enthusiam, fear, sadness, and disgust, based on Valentino et al. (2011) and Schmidt and Stock (2009). *Anger* "emerges in situations when people are threatened or find obstacles blocking their path to reward" (Huddy et al. 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; Huddy et al. 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" (Huddy et al. 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" (Huddy et al. 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; 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. Accordingly, we expect that the impact of fear will depend on the cost of action. In a 2016 paper, De Choudhury et al. categorized Black Lives Matter tweets based on the emotional content of the text; they found that fear was associated with lower rates of protest, while *sadness* was associated with higher rates of involvement; we follow those authors in our expectation for sadness. 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.

[2]Although fear and anxiety can be theoretically distinguished (Ohman and Mineka 2001), 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.

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

Images have an enormous potential to unleash and trigger emotions (e.g. Ansolabehere and Iyengar 1995; Brader 2005) but emotions are subjective, which may complicate studying the specific effect than an image has on different individuals. However, although the same image does not always generate the same emotion to all observers, existing studies show that on average survey respondents do use the same emotion to tag the same image (Schmidt and Stock 2009); we further address this potential concern in our robustness checks below (see Appendices C and E).

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.

$\mathbf{H}_{6a}$ (*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.

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 1995:43). 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.

2 Empirical Framework

We use a two pronged-approach to test the above hypotheses. First, we analyze observational data from the April 14, 2015 Black Lives Matter protest. Second, we implemented a randomized survey experiment using images collected during the protest. This strategy allows us to address potential concerns regarding both internal and external validity. The observational data provides "real-world" evidence of the phenomenon of interest; the experimental data allays many potential alternative explanations for the mobilization effects we find. Moreover, this strategy also allows us to test the different predictions for the images inspiring fear (H_{4a} and H_{4b}) and the images with protesting crowds (H_{6a} and H_{6b}). We theorize that the effect of fearful images depends on the costs associated with taking action, and that the effect of images with crowds depends on whether the movement is in its early stages or not. With the observational data we study the attention to and diffusion of BLM through an action (posting messages in social media) that we argue is more costly than signing an online petition: social media posts are a lot more visible and have relatively higher social costs. Finally, when we collected the observational data the movement was still in its earlier stages, whereas by the time we conducted the survey experiment the movement already reached high national salience.

3 Observational Data & Measurements

To test the general hypothesis that 'online image-sharing' increases the protest mobilization, we first study Twitter messages related to the Black Lives Matter (BLM) movement and to the Shutdown April 14 (A14) protest, a specific BLM action that took place in multiple cities in the United States on April 14, 2015. 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 related to the Protests

A14	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 A14 messages because it allows us to test the effect that images have on two dynamics that are crucial for social activism: 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 A14 action started right before the demonstration took place on April 14, 2015. Thus we use the volume of messages related to both BLM and A14 to study the attention to BLM in social media, and only the messages related to the A14 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 (40,409 sent by 22,950 unique users) were related to the A14 protest, and about 43.2% of the messages had an image.

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-minutes 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-minutes cutoff because we think messages sent at any point in time should particularly have an 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 Appendix E).

The dependent variables of the analysis are the *attention* to the BLM movement and the *diffusion* of the A14 protest. In this social media context, we define and measure *attention* as the number of tweets that mentioned one of the BLM or A14 hashtags sent during each 30-minute period. We measure *diffusion* using the number of new unique users that started using an A14 hashtag in each 30-minutes period. Our key explanatory variable of interest is the percentage of the total messages for each 30-minutes 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-minutes 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 A14 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 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.

To address our specific hypotheses about why images increase the likelihood of a protest to diffuse and get more attention, we need to have 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 had to find a way to identify 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.

Table 2: Data description

all messages 150,324		
no image 85,389 (56.8%)	image 64,935 (43.2%)	
	↓ 9,747	(unqiue URLs)
	↓ 9,458	(after removing duplicates)

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. For more detail on the labeling scheme, along with two sample images with their assigned labels, see 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

[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.

and the rest being only tweeted few times or once. 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 labels for each image. Then we used Amazon's Mechanical Turk service to obtain three extra sets of labels from three different people for each image. We also employed Mechanical Turker workers to label, only once, the remaining the 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. The variables *Anger, Fear, Disgust, Sadness*, and *Enthusiasm* are the average score {0-10} of all images in messages sent in each time period, where ten indicates that the image most strongly incited the given emotion. *People protesting* represents the average number of people in images that were sent in each 30-minutes 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 the expectation of success would come from the A14 event. 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 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. In other words, we weight these variables with our general variable of interest (*Percent Images*).

4 Observational Results

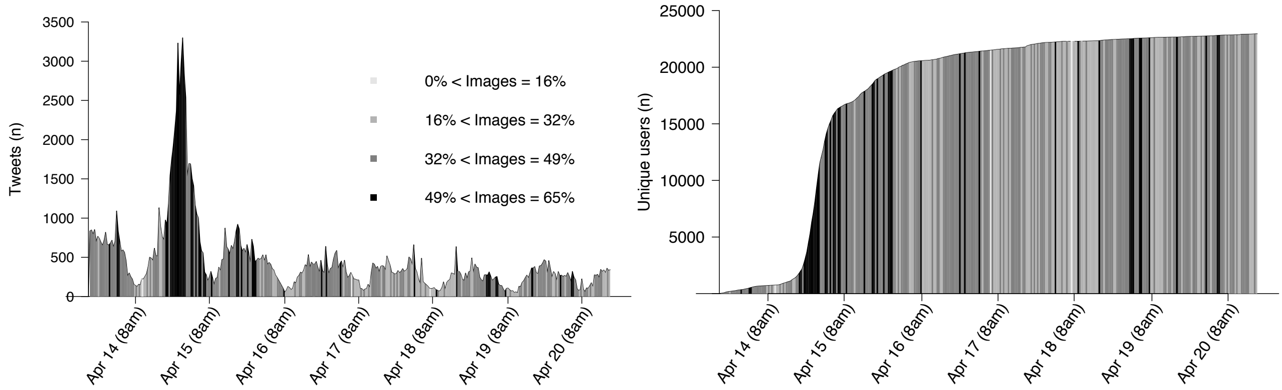
A first glance to the bivariate relationship between the two dependent variables (*attention* and *diffusion*) and the independent variable of interest, percentage of the total tweets that have an image (*Percent Images*), indicate a potential strong relationship. Darker colors in Figure 1 represent 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 A14 action (cumulative unique 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.

[4]In 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.

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

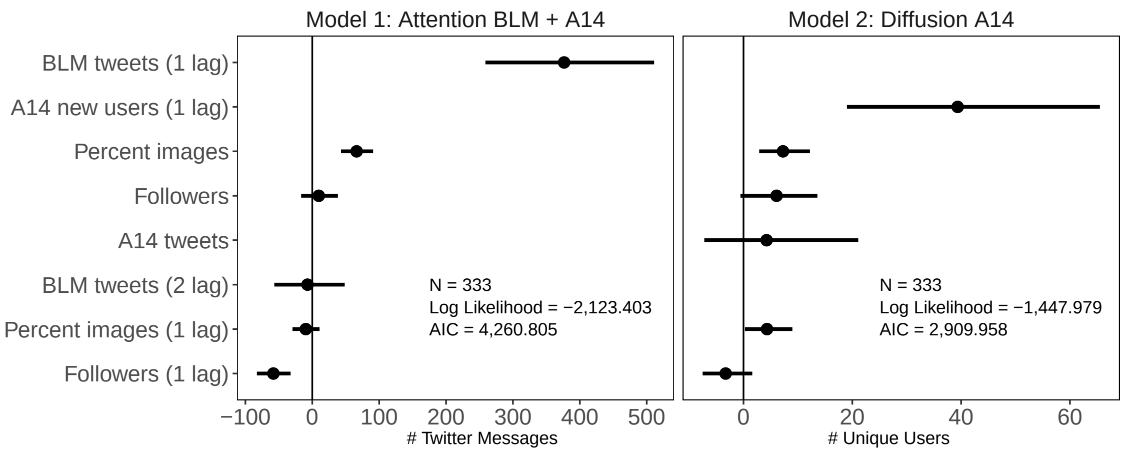
(a) Relation: % of tweets w. images and *attention*

(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 Appendix E. These are negative binomial models predicting the Twitter *attention* to the overall BLM movement (Model 1) and the *diffusion* of the A14 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-minutes 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 A14 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 A14 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 Shutdown A14 action (Negative Binomial Models)*

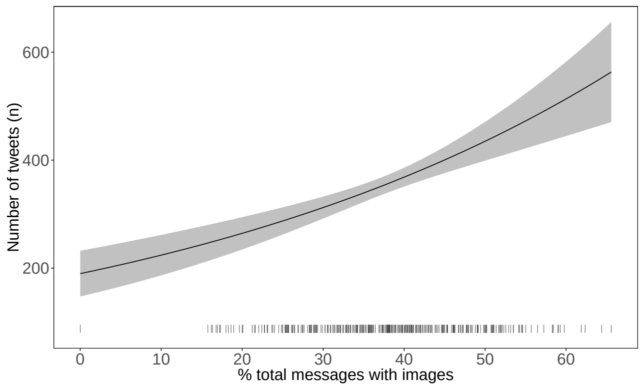


**Standardized coefficients (the effect of a variable moving from its mean to 1 standard deviation above)*

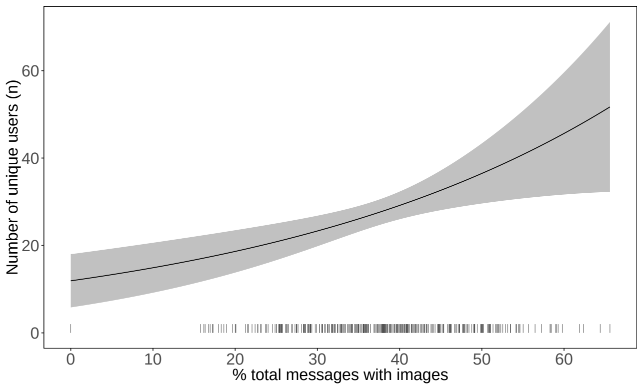
The models' coefficients in Figure 2 show that the first lag of the dependent variables (*BLM tweets (1 lag)* and *A14 new users (1 lag)*) are the strongest predictors of increasing *attention* and *diffusion*.[5] This means that the likelihood of a protest to get more attention and diffuse increases 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-minutes period we would expect only around 12 unique users to start using A14 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).

Figure 3: Predicting values of attention to the BLM movement and diffusion of the Shutdown A14 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



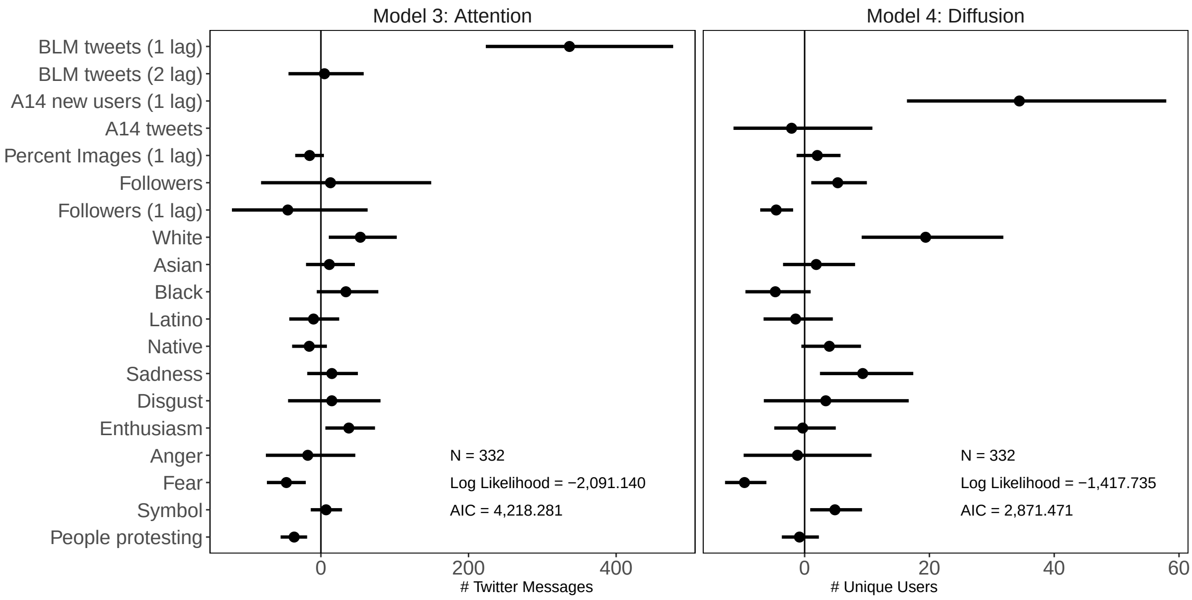
The results of the bivariate (Figure 1) and multivaraite analyses (Models 1 and 2 in 2) are consistent with our *General Image Effect* hypothesis (H_1): the likelihood of a protest to diffuse online and get more attention increases as a larger percentage of the messages related to the protest contain images. However, this evidence still says little about the reasons why this is the case. 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 theories about why images are important for social mobilization.[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 per-

[5]See Appendix D for the full regression table.
[6]See Appendix D for the regression tables.

centage 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 variations in attention and diffusion.

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

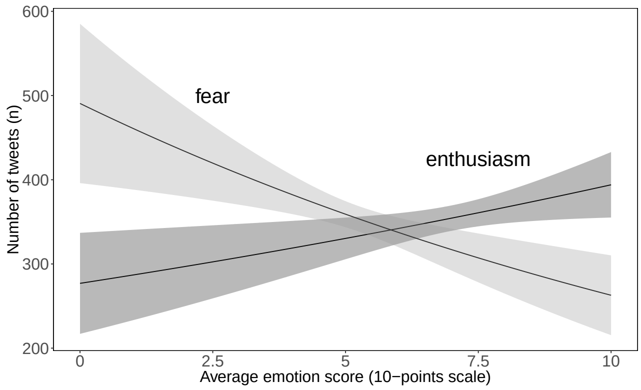


**Standardized coefficients (the effect of a variable moving from its mean to 1 standard deviation above)*

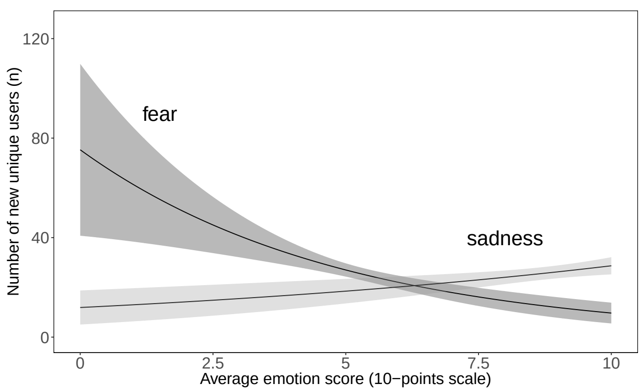
Second, the results of the models in Figure 4 are not supportive of the *Success Expectation* hypothesis (H_6). When users tweeted images of protests that had more people in them, the BLM movement received less social media attention and the ShutdownA14 action did not diffuse faster. For the *attention* 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 A14 action using Models 3 and 4.

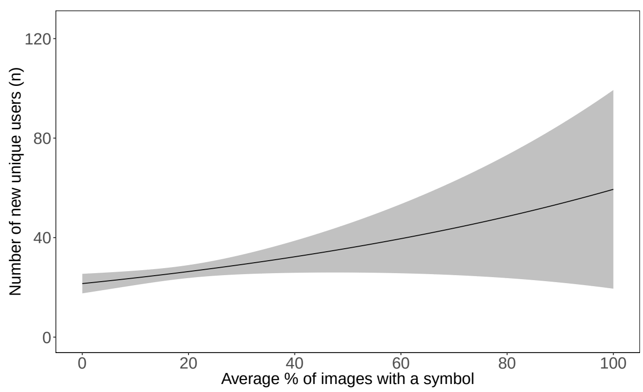
(a) Effects of emotions on *attention*



(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-minutes 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 A14 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 A14 action as the confidence intervals of Figure 5c indicate.

5 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 Black Lives Matter and online social movement participation.

We recruited survey experiment participants from Amazon's Mechanical Turk service (MT). At the time of writing, a total of 4,222 Mechanical Turk employees had completed the survey. 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 then 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 Black Lives Matter. Respondents were told that going to the the outside petition was not a requirement to be paid for the task. Our dependent variable of interest is the rate of clicks to the external (fictional) petition. We were unable to track how many participants would have actually signed such a petition; we assume, however, that clicking on the link served as a better measure of actual support for Black Lives Matter than stated willingnes to support the movement, as it imposed a voluntary time cost on participation.

5,000 respondents were randomly assigned to one of five groups (1,000 per group). Each respondent saw the same survey (see 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. 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 slides/screens so that the workers' activity was similar to what a social media user would do when checking their timeline/wall/newsfeed.

The four treatment images were selected from the compiled Shutdown A14 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 Appendix F. We started conducting the survey on August 1^{st} 2016 and at the time of writing the number of respondents in each group was as follows: control, 839; *sadness*, 861; *fear*, 850; *crowd*, 857; *symbol*, 824.

6 Experimental Results

The preliminary results of the experiment (Table 3) support our main expectation that images related to a social movement contribute to increase the attention to that social movement online (H_1). 5.36% of the respondents in the control group (n = 839), who were not exposed to an image, clicked on the link to sign the online petition. However, about 7.05% of the MT workers that were in one of the treatment group (n = 3,392) clicked on the link. This means that the click rate for the people who saw an image was 1.69 percentage points higher than for those people who did not see an image; the proportion of treatment petition clickers is about 32% higher the the proportion of control petition clickers. This difference is statistically significant at the .1 level.

Table 3: Experiment Results

Group	Sample	Clicked Petition (n)	Click Rate (%)	Percentage Point Difference from the Control Group
No image (control)	839	45	5.36%	–
Image (all treatments)	3,392	239	7.05%	+ 1.69*
(fear)	850	72	8.47%	+ 3.11**
(sadness)	861	64	7.43%	+ 2.07*
(crowd)	857	54	6.30%	+ 0.94
(symbol)	824	49	5.95%	+ 0.59

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 groups is even larger for some of the specific treatment groups. We again see emotions such as fear and sadness playing a key role. The respondents exposed to images triggering these two emotions when completing the survey were the most likely to click on the link to the BLM petition. The click rate for the people who saw the image triggering fear was 7.43%, more than three percentage points higher than the control group, for a percent change of 59%; the difference in proportions is statistically significant at the .05 level. For the group exposed to the sad image, the click rate was 7.43%, more than two percentage points higher, for a percent change of 39%; this result is statistically significant at the .1 level. Two summary points stand out: first, these results support our argument that images can play an important role in online mobilization 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. Finally, these results also corroborate our expectation (H_5) and De Choudlhury et al's (2016) recent findings that content triggering sadness helps increasing online support to BLM.

The results for the group exposed to an image with a crowd supports our expectation that images with larger number of people protesting should increase a movement's online attention 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 click rate for this group was higher than the control, the difference is smaller than 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. This may mean 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 symbol image do not support our hypothesis that images with symbols such as an American flag should contribute to bring people together, bridge cultural gaps between potential participants, and increase online attention and diffusion (H_7). The click rate for this group was only a half percentage point higher than the control group and the difference in proportion was also far from being statistically significant.

7 Discussion and Conclusion

Existing literature claims that online image-sharing 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 2011; Kharroub and Bas 2015). In this paper we contribute to this literature by laying out a set of theoretical mechanisms and conditions under which online image-sharing should increase the likelihood of a protest to receive more attention online, while providing empirical tests using observational data (Twitter messages) from a Black Lives Matter protest that took place in April 2015, and experimental data from a survey experiment about the same social movement conducted in Mechanical Turk in August 2016.

We build on the literature to argue that images should increase rates of online protest diffusion because they lower information costs, act as emotional trigger, increase expectations of success, and generate collective identities. In line with the theoretical predictions, we find that all else equal, in the context of a Black Lives Matter protest, Shutdown A14 (April 14, 2105) promoted on Twitter, a larger percentage of messages with images increased the likelihood of the movement to receive more attention on Twitter and the likelihood of the specific A14 protest to diffuse to new participants on the same social media platform. Images triggering enthusiasm increased the attention to the overall Black Lives Matter movement while images inspiring fear achieved the opposite goal. Images triggering sadness and images with symbols such as flags or logos increased the diffusion rate of the A14 action while images inspiring fear had again the opposite effect.

The preliminary results of the survey experiment also support most of our theoretical expectations. Contrary to the observational findings and in line with existing theory suggesting that the differences in costs between posting on social media and signing an online petition may mitigate the impact of fear (Valentino et al. 2011), we find that fearful images increase the likelihood of signing an online petition in support of Black Lives Matter. We also corroborate the observational findings indicating that images inspiring sadness increase rates of online mobilization. Finally we support the hypothesis that images with protesting crowds do not increase online attention to the movement once this is already 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 empirically test the online image-sharing argument, we decided to focus on the effects of images in the context of a single social movement: Black Lives Matter. We decided to do so because we wanted to focus on clear tests of existing theory and to study a relevant and current social movement. However, as numerous scholars of social movements and agenda setting have pointed out (Walgrave and Van Aelst 2006; Vliegenthart and Walgrave 2011; Baumgartner and Jones 1993; Kingdon 1984; Cobb and Elder 1971), the agenda setting 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 should be revised 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 suggest that online image sharing is an important component in the mobilization of protests in a new media environment. Protest- and social movement- related images boost both attention paid to the movement and diffusion of a specific action to new participants. We also offer insights into which types of online images have the most impact in mobilizing social movement participation: images that incite emotion, particularly sadness, have a strong effect on participation. Images that inspire expectations of protest success, based on the number of protest participants visible, have a nuanced impact, depending on the preexisting salience of the protest and movement. And images that promote a collective identity via commonly-recognized group symbols such as flags have only a slight positive impact on mobilization. These findings open up many potential avenues for future research into the role of online image sharing in social movement participation.

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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

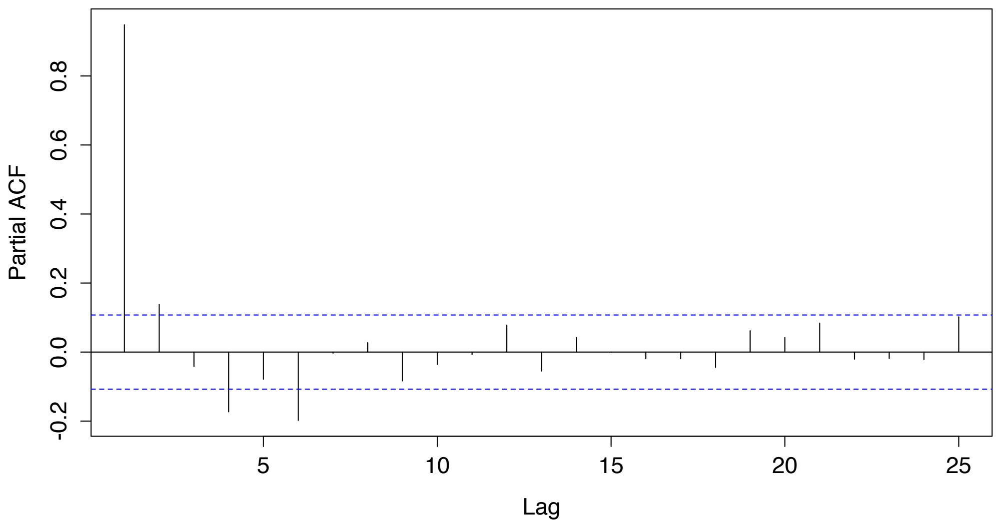
Research staff labeled this image as having 7 people (on average), no signs or slogans, and no symbols. On the emotions, the average scores were: anger: 2, fear: 1, disgust: 2, sadness: 3, enthusiasm: 1. Races/ethnicities identified were Black and White (non-Hispanic)

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

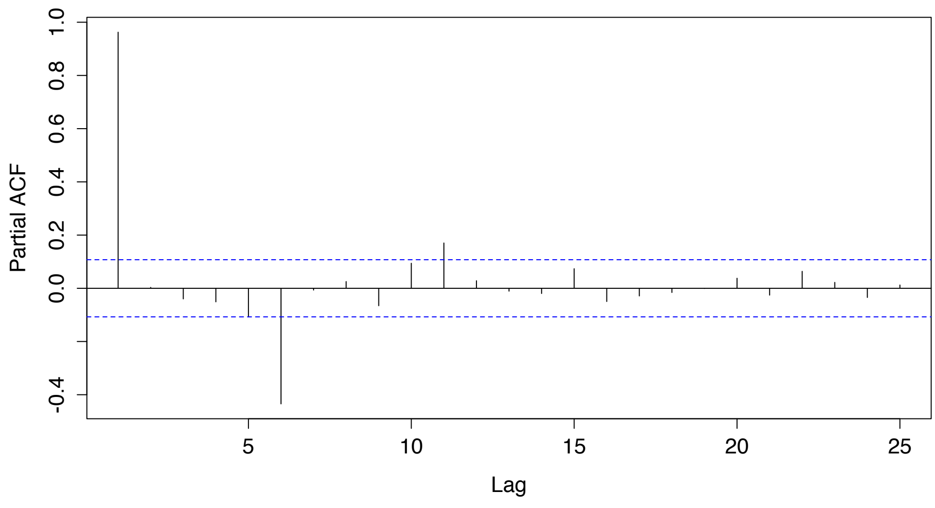
Research staff labeled this image as having 45 people (on average) and protest signs, but no slogans or symbols. On the emotions, the average scores were: anger: 2, fear: 1.5, disgust: 1, sadness: 1, enthusiasm: 2.5. Races/ethnicities identified were Black, White (non-Hispanic) and White (Hispanic).

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)



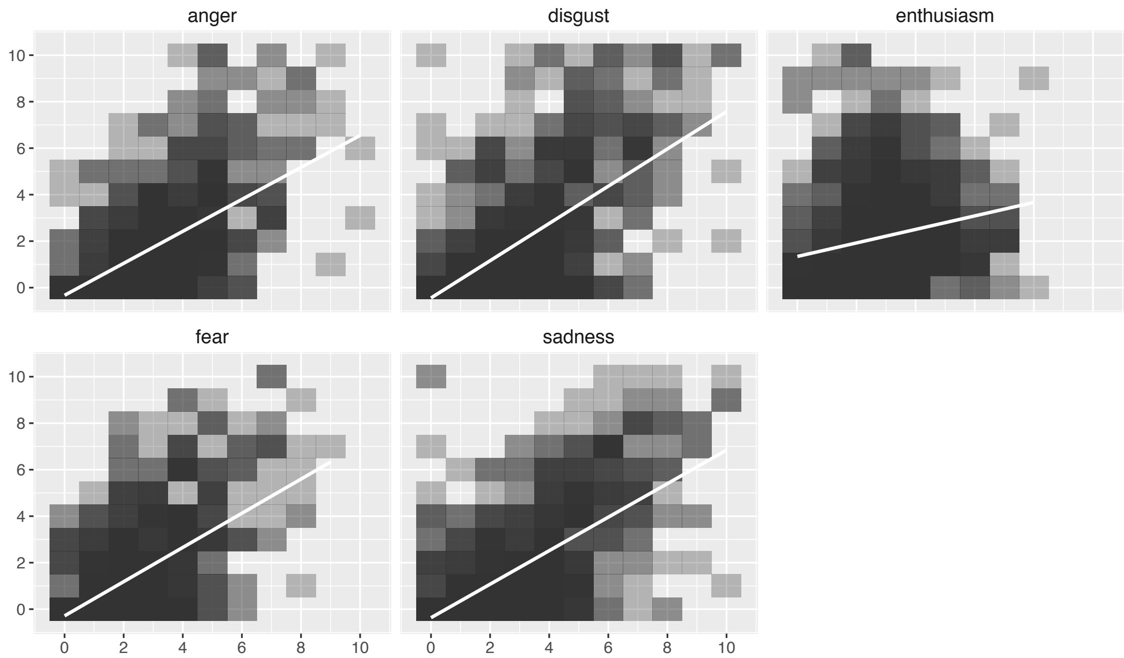
(b) Partial Autocorrelation Function plot for the dependent variable *Diffusion* (Number of new unique users tweeting about a particular BLM protest: Shutdown A14)



C Appendix: Evidence of Stable Emotions Labeling

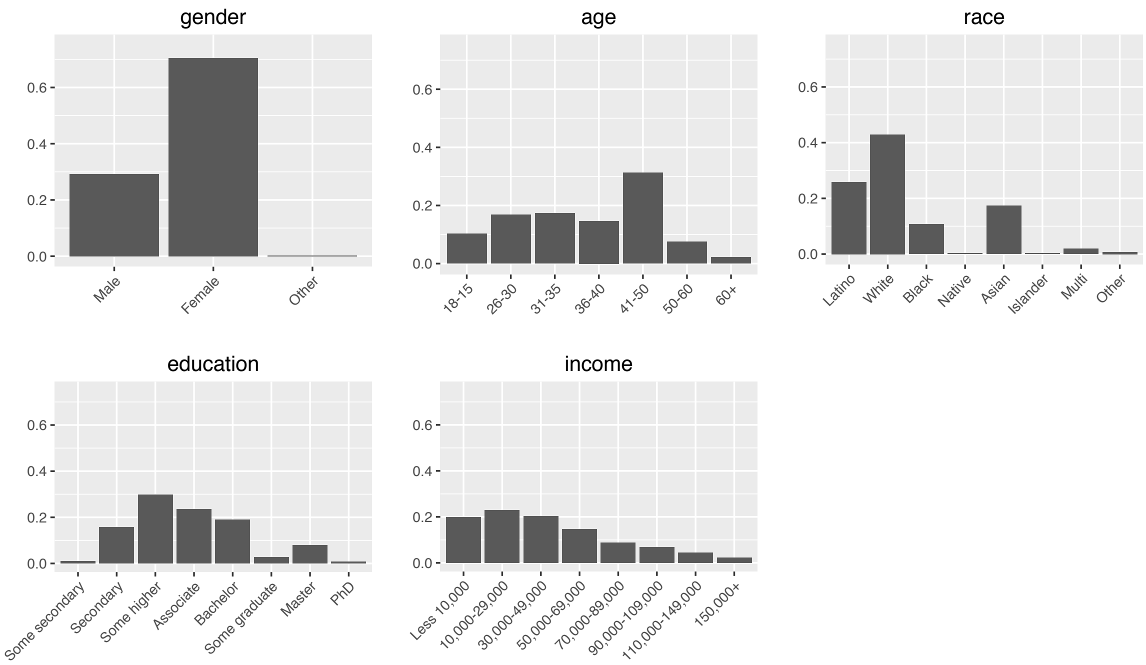
In this Appendix we provide extra information showing that although emotions are subjective, on average the top 1,000 images (which account for more than 50% of the messages with images) triggered very similar emotions to different people. This is important because when modeling the data we give to each 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 6 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 6: Correlation between the emotion scores given by 2 research assistants to the same images (top 1,000)



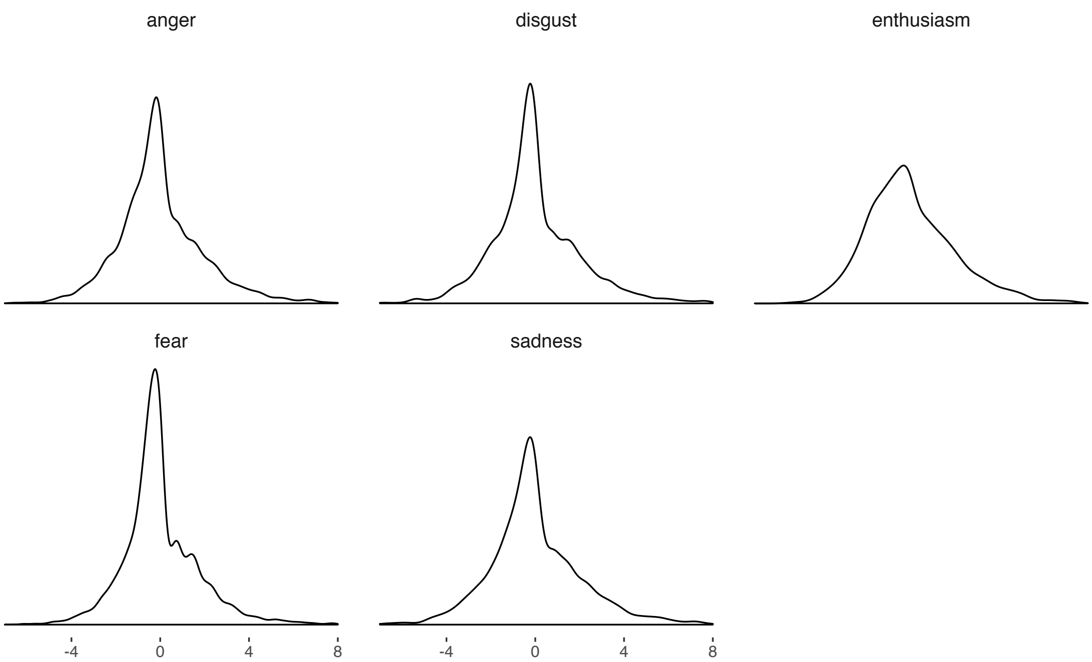
In a second iteration we used Mechanical Turk (MT) to label three more times the top 1,000 images. We decided to do so not only to have more emotion labels per image but also to get scores from people with different backgrounds, since our two research assistants were both undergraduate students, male, 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 7 presents summary statistics for the MT workers that participated to the labeling process. The figure shows how workers had a very diverse background.

Figure 7: 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 8 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 8: 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 2) 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 4 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 9 and Table 4 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.

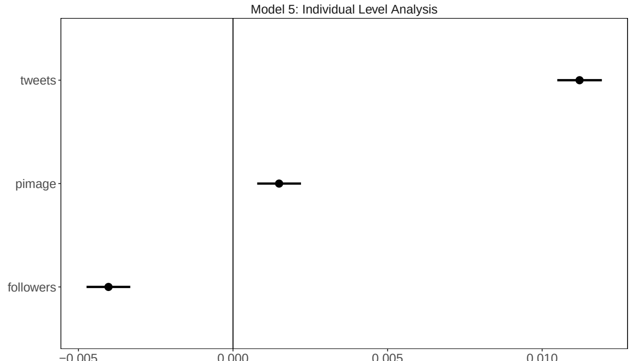
Table 4 Description: The following table presents the coefficients and standard errors in parentheses for the models we use to check the robustness of the findings (Models 1a, 1b, 1c, 2a, 2b, 2c, and 5). All models but the last one are Negative Binomials. Model 5 is a Linear Model (OLS). The dependent 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 4: 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 (1 lag)	−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 (1 lag)			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 9: 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