How social media affects political action: the effects of digital network structures and motivations on movement participation

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Abstract

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The advent of utilizing social media for political purposes has been a significant change in recent decades. While most agree that social media can propel political change, the mechanisms underlying why social media affects political action remain unclear. This dissertation uses micro and meso-level perspectives to examine such mechanisms. Drawing from cases of the Sunflower Movement in Taiwan and Black Lives Matter Sacramento in the US, the dissertation assembles survey data and digital trace data to unravel the psychological and network processes that underlie the mobilizing power of social media. It consists of three chapters that highlight different conditions by which social media affects political action. The first chapter uses structural equation modeling to delineate how social media activates certain psychological incentives that motivate participation. The second chapter uses social network analysis and demonstrates how the mobilizing power of social media depends on the type of social media networks and the type of political action. The third chapter combines social network analysis and agent-based modeling to show how the structure of social media networks can both enhance and inhibit political mobilization. Overall, the dissertation calls for the need to pay attention to the heterogeneity of political actions mobilized by social media, and the need to distinguish mechanisms by which social media affects political action.

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INTRODUCTION

The decade of 2011-2020 has witnessed a flurry of large-scale social movements, often with unprecedented turnout numbers. Such movements, including the 15-M Movement in Spain, the Sunflower Movement in Taiwan, Black Lives Matter in the United States, and numerous political revolutions in the Middle East, have brought significant political change. The mobilization power appears to cut across political spectrums, as political movements such as the Alternative für Deutschland (AfD) in Germany or right-wing rallies in the United States have also recorded large numbers of participants. The "will of the people" has expressed itself more than ever on the streets.

What led to such change in mobilization power? On one macro level, one can point to the weakening of political and social institutions (Foa and Mounk 2016). Nonetheless, another macro shift observers cannot ignore is the advent of social media such as Facebook, Twitter or Telegram (Bennett and Segerberg 2012; Castells 2015). In normal times, such social media allow users to build friendship relationships with others, often mirroring pre-existing social networks offline such as working relationships or school relationships (Bond et al. 2012). In times of unrest, politicians and citizens use social media to connect, persuade and mobilize, leading to cascades of mobilization (Howard and Hussain 2011). A rosy picture appears as it seems that with the usage of social media, citizens can easily organize collective action and express political will. We are witnessing the rise of "digital activism."

It is obvious in numerous cases that citizens utilized social media for mobilization purposes. However, there are also numerous *failed* cases of social media mobilization. Many political calls on social media fall on deaf ears, receiving little support from others. It is also true that not everyone who uses social media participates in collective action. Why?

Via the pathbreaking work of many, it is now general consensus that there is a positive relationship between social media usage and political participation (Boulianne 2015; Valenzuela, Arriagada, and Scherman 2014). Scholars have also pointed out the functionalities of social media, such as gathering resources, interacting with others, and broadcasting information (Eltantawy and Wiest 2011; Vasi and Suh 2016). What is less understood, however, is the *mechanisms* by which social media translates into political action. By unraveling the mechanisms, one can understand why some movements succeed in recruiting many participants, while others fail to mobilize.

This dissertation aims to explore the mechanisms of the relationship between social media and participation in collective action. However, as I delved into this endeavor, I realized that this topic touches on three fundamental issues. Without resolving these issues, it is difficult to depict the mechanisms.

The first issue is how new are the processes of mobilization on social media? While the field of sociology is still trying to comprehend the incorporation of social media, scholars have established solid grounding in explaining offline collective action. Since the 1960s, scholars have proposed to examine collective action mechanisms such as political opportunity structure, psychological incentives or network relationships (Kim and Pfaff 2012; McAdam 1988; Morris 1984; Opp 2009). On the other hand, numerous new theories have emerged regarding how mobilization on social media occurs, most prominently regarding the "logic of connection action" (Bennett and Segerberg 2012; Bennett, Segerberg, and Walker 2014; Castells 2015; Gerbaudo 2012). Are we witnessing a paradigm shift where conventional theories are less useful in understanding digital activism? Alternatively, how much can we incorporate conventional theories into understanding new forms of political activism?

The second issue is that one cannot assume that "social media" is one thing and has the same relationship with political participation. Instead, one needs to decompose the concept and examine the heterogeneity of social media. I highlight a few aspects that are relevant to this dissertation. For one aspect, different people use social media for different purposes, especially regarding social and political issues. Some use social media to interact and debate political opinions, while others use social media to take in information (Valenzuela, Arriagada, and Scherman 2012). The former resembles a public sphere (Shirky 2011) for the exchange of ideas, while the latter is similar to information consumption on mass media. As another aspect, although social media encourages users to create relationships, there are many types of network relationships that can be formed. One can follow others, mentioned others, reply to their opinions, or reshare/retweet their posts. These are heterogeneous modes of interaction, and one should disentangle how such heterogenous relationships affect mobilization.

The third issue concerns how forms of collective action have changed. Before digital media, going on the streets, often gathering at a few specific locations, was the common repertoire. People needed to travel to a specific location, such as The National Mall in Washington D.C., and occupy it for extended periods to showcase unity in numbers. But with social media, supporters of a movement can express their opinions online in individualized fashion. Users have used hashtags such as #MeToo or #BlackLivesMatter to signify their support for a movement. Users can also fundraise or e-petition online as alternative ways of participation. Still, there are other cases where social media is used to gather people for offline activism at specific locations such as Tahrir Square. Under the umbrella of "digital activism," forms of participation now include online-only activism or online-mobilized offline activism (Earl et al. 2010). Does social media (and its diverse aspects) have similar relationships with participation in different forms of activism?

These are questions that shaped the work of this dissertation. It is beyond the scope of this dissertation to tackle all aspects of all the questions, yet this dissertation will contribute to our understanding of all three issues. I find two perspectives particularly useful – a social-psychological perspective and a structural network perspective.

As Coleman (1994) contended, one should examine the micro-processes that translate macro factors into individual behavior. To understand why social media affects participation or non-participation, it would be fruitful to depict the psychological processes – the emotions and feelings – that arise when people use social media, and how such psychological processes relate to collective action participation. In the field of sociology, the tradition of examining emotions in politics has contributed to understanding why people do not free-ride in collective action (Polletta and Jasper 2001). In explaining participation, scholars have identified a range of psychological factors such as grievances, identification, efficacy, and social incentives (Klandermans 2014; Opp 2009; van Zomeren, Postmes, and Spears 2008). Nonetheless, few studies systematically measure and examine which of these factors are elicited by social media usage. While recent studies hint at the possibility of some of these factors (Kavada 2015; Kharroub and Bas 2016; Moeller et al. 2014), this dissertation goes a step further and surveys a wide range of psychological incentives and builds a macro-micro model that connects the chain of social media—psychological incentives—collective action participation.

The other theoretical pillar of this dissertation is a structural network perspective. The idea that social relationships form the basis of political participation has been around for decades (Kitts 2000; Morris 1984; Pfaff 1996). Formal and informal relationships, such as churchattending relationships, civic groups, or even dormitory-living relationships, can transfer into connections that support mobilization in collective action. Nevertheless, since the late 1990s, developments of how to understand the *structural* properties of network relationships have advanced our understandings of why behavior spreads (Centola 2018; Valente 1996; Watts 1999). The same number of friendship relationships, depending on the topology of the network, can either accelerate or inhibit the spread of collective action. Recent studies on digital activism have started to incorporate a structural network perspective (Bennett et al. 2014; Gonzalez-Bailon, Kaltenbrunner, and Banchs 2010), yet aforementioned issues remain when investigating structural network properties. The conceptual lacunas arise because scholars mix different types of networks and different forms of participation. As mentioned, social media consists of various relationships. Digital activism also consists of heterogeneous forms of political participation. The critical question is thus more complicated than bringing a structural network perspective in understanding new forms of activism. Instead, it is how do we use a structural network perspective to understand various types of networks and behavior related to social media. The other aim of this dissertation is to unravel these intricate processes.

Understanding the mechanisms of how social media affects collective action requires triangulating multiple sources of data, then paired with various types of methods. Frontiers of sociology will move forward towards incorporating the multiplicity of data and methods, and this dissertation is an example. Different theoretical questions call for different data and methods. It is difficult to gauge complex psychological processes using digital traces on social media. However, questionnaires can easily survey a broad range of psychological incentives. On the other hand, mapping out network topologies is a formidable ask for survey data, but easily achieved by scraping public records on social media.

By responding to different theoretical questions, this dissertation draws data from uniquely designed surveys, digital traces on social media, and simulated data from agent-based modeling. Furthermore, disentangling complex mechanisms requires advanced methods beyond standard regression techniques. To understand interlocking causal chains with latent factors, I use structural equation modeling. To gauge the relationship between structural network positions and political participation, I use hurdle autoregressive models. To map out the process of diffusion, I generate counterfactual network topologies and use agent-based modeling. The plurality of data and methods echoes the earlier statement that "social media" comprises complex phenomena and complex mechanisms.

In short, this dissertation is motivated by four broad questions:

(1) Which psychological factors of collective action participation are affected by social media usage?

(2) How do different types of relationships on social media affect digital activism participation?

(3) How does the network structure on social media affect digital activism participation?

(4) How do the above processes differ by different types of digital activism?

The dissertation is divided into three chapters, each surrounding the theme of how social media affects digital activism participation, but through different lenses focusing on different micro-macro levels.

Chapter Two focuses on the micro-level, as it examines the micromechanisms of psychological factors. I examine how social media changed people's psychological incentives of protest in the 2014 Sunflower Movement in Taiwan, the largest student protest ever in Taiwan. I implemented a survey that inquires into a wide range of psychological factors including grievances, identification, individual efficacy, group efficacy, positive social incentives, negative social incentives, and perception of issue relevance. I also designed an index of social media usage, as well as asked about whether they physically participated in the movement. In addition, the survey is designed to sample both participants and non-participants, reduce selection bias and enhance the ability to sort our effect chains. Using structural equation modeling, the chapter shows that interactions with others on social media triggers the psychological incentives of anger, social incentives, identification, and individual efficacy. In particular, individual efficacy was shown to be a direct mediator between social media usage and protest participation, while the other factors might be indirect mediators. The chapter provides the microfoundations of digital activism, and shows that it is because social media enhances the belief of efficacy that led people to show up in the streets. The chapter is also a standalone paper published in *New Media & Society* (Hsiao 2018).

Chapter Two shows how relationships on social media translate into psychological incentives. However, due to its focus on psychological factors, it overlooks the fact that different users are embedded in the networks of social media differently. Some users are in more central positions in the social media network than others. Also, some users have connections that form small groups that can create the social reinforcement for political participation. Chapter Three addresses this concern by examining the structural network positions of users. Focusing on the case of Black Lives Matter Sacramento, I draw data from millions of tweets and map out the structural network positions of isolate status, centrality, and local clustering. Furthermore, I distinguish between *interactional ties* where users have social exchanges, from *informational ties* where users merely consume information, echoing the aforementioned concern that social media consists of different types of relationships. Based on users' tweets, I then also distinguish between online-only activism and online-mobilized offline activism. Network analyses using hurdle network autocorrelation models indicate that those in conducive network positions in social media networks are indeed more likely to participate in digital activism. Yet, the network effects depend on the interaction between structural network characteristics, type of ties, and forms of activism. Interactional ties have much stronger relationships than informational ties, and effects appear to be stronger for online-only activism than online-mobilized offline activism. The study highlights the heterogeneity on social media, and calls for the need to distinguish network types of activism types to understand the mobilizing power of social media.

Chapter Four moves towards a further macro level. While chapter three examines how people's position in networks relate to participation in different types of digital activism, the unit of analysis is still individuals. By reducing social network structures into structural positions of individuals, one cannot examine how the network structure as a whole is conducive or inhibitive of mobilization. Chapter Four takes on this challenge and examines how the topology of social media networks relates to participation in different forms of digital activism. Again using Black Lives Matter Sacramento as the case, I use agent-based modeling to test the mobilization power of the BLM network structure. Specifically, I construct the Twitter following network for BLM, then simulate ideal type networks that are commonly observed in the empirical world. I then simulate diffusion processes for the BLM network and the ideal type networks. I find that the BLM network exhibits a topology that I describe as a "Cluster-Connective network." Results from diffusion simulations further show that paradoxically, this "Cluster-Connective" configuration benefits participation for high-cost behavior, but hinders participation for low-cost behavior. Supplementary analyses also show that the Cluster-Connective configuration is observed in two other social media organizations. The chapter shows that digital networks do not always benefit the diffusion of digital activism. Instead, the magnitude of diffusion depends on the type of digital activism. The chapter is itself also a standalone paper published in *Social Forces* (Hsiao 2020).

Overall, the dissertation draws from two cases in two countries to unpack the mechanisms by which social media affects new forms of collective action. It shows that conventional theories such as psychological models of collective action or network perspectives of protest, have much utility in explaining digital activism. However, the dissertation also shows that such theories need modifications. It needs to take into account that social media consists of multiple types of networks and multiple forms of digital activism. Thus, while the general orientation of psychological and network approaches remains the same, the mechanisms are much more complex. Because of this complexity, the dissertation also shows that some theoretical questions are best answered via new sources of data such as digital traces on Twitter, other questions are more suited for conventional sources such as survey designs, and still others require a combination of both such as combining Twitter data with agent-based modeling. I hope this dissertation can push forward the agenda of combining innovative methods and data to answer complex social science questions.

References

Baldassarri, Delia, and Peter Bearman. 2007. "Dynamics of Political Polarization." *American Sociological Review* 72(5):784–811. doi: 10.1177/000312240707200507.

Bennett, W. Lance. 2012. "The Personalization of Politics: Political Identity, Social Media, and Changing Patterns of Participation." *Ann. Am. Acad. Pol. Soc. Sci.* 644(1):20–39. doi: 10.1177/0002716212451428.

Bennett, W. Lance, and Alexandra Segerberg. 2012. “The Logic of Connective Action: Digital Media and the Personalization of Contentious Politics.” *Inf. Commun. Soc.* 15(5):739–68.

Bennett, W. Lance, Alexandra Segerberg, and Shawn Walker. 2014. “Organization in the Crowd: Peer Production in Large-Scale Networked Protests.” *Inf. Commun. Soc.* 17(2):232–60. doi: 10.1080/1369118X.2013.870379.

Bisbee, James, and Jennifer M. Larson. 2017. “Testing Social Science Network Theories with Online Network Data: An Evaluation of External Validity.” *The American Political Science Review* 111(3):502.

Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam D. I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. 2012. “A 61-Million-Person Experiment in Social Influence and Political Mobilization.” *Nature* 489(7415):295. doi: 10.1038/nature11421.

Boulianne, Shelley. 2015. “Social Media Use and Participation: A Meta-Analysis of Current Research.” *Inf. Commun. Soc.* 18(5):524–38. doi: 10.1080/1369118X.2015.1008542.

Castells, Manuel. 2015. *Networks of Outrage and Hope: Social Movements in the Internet Age*. Cambridge: Polity.

Centola, Damon. 2018. *How Behavior Spreads: The Science of Complex Contagions*. Princeton University Press.

Coleman, James S. 1994. *Foundations of Social Theory*. Harvard university press.

DeLuca, Kevin M., Sean Lawson, and Ye Sun. 2012. “Occupy Wall Street on the Public Screens of Social Media: The Many Framings of the Birth of a Protest Movement.” *Communication, Culture & Critique* 5(4):483–509. doi: 10.1111/j.1753-9137.2012.01141.x.

Earl, Jennifer, Katrina Kimport, Greg Prieto, Carly Rush, and Kimberly Reynoso. 2010. “Changing the World One Webpage at a Time: Conceptualizing and Explaining Internet Activism.” *Mobilization* 15(4):425–46.

Elder-Vass, Dave. 2018. “Lifeworld and Systems in the Digital Economy.” *European Journal of Social Theory* 21(2):227–44.

Eltantawy, Nahed, and Julie B. Wiest. 2011. “The Arab Spring| Social Media in the Egyptian Revolution: Reconsidering Resource Mobilization Theory.” *Int. J. Commun. Syst.* 5(0):18.

Foa, Roberto Stefan, and Yascha Mounk. 2016. “The Danger of Deconsolidation: The Democratic Disconnect.” *Journal of Democracy* 27(3):5–17.

Gerbaudo, Paolo. 2012. *Tweets and the Streets: Social Media and Contemporary Activism*. London: Pluto Press.

Gonzalez-Bailon, Sandra, Andreas Kaltenbrunner, and Rafael E. Banchs. 2010. “The Structure of Political Discussion Networks: A Model for the Analysis of Online Deliberation.” *J. Inf. Technol. Impact* 25(2):230–43. doi: 10.1057/jit.2010.2.

Howard, Philip N., and Muzammil M. Hussain. 2011. “The Role of Digital Media.” *Journal of Democracy* 22(3):35–48. doi: 10.1353/jod.2011.0041.

Hsiao, Yuan. 2018. “Understanding Digital Natives in Contentious Politics: Explaining the Effect of Social Media on Protest Participation through Psychological Incentives.” *New Media & Society* 20(9):3457–78. doi: 10.1177/1461444817749519.

Hsiao, Yuan. 2020. “Evaluating the Mobilization Effect of Online Political Network Structures: A Comparison between the Black Lives Matter Network and Ideal Type Network Configurations.” *Social Forces*.

Kavada, Anastasia. 2015. “Creating the Collective: Social Media, the Occupy Movement and Its Constitution as a Collective Actor.” *Inf. Commun. Soc.* 18(8):872–86. doi: 10.1080/1369118X.2015.1043318.

Kharroub, Tamara, and Ozen Bas. 2016. “Social Media and Protests: An Examination of Twitter Images of the 2011 Egyptian Revolution.” *New Media & Society* 18(9):1973–92.

Kim, Hyojoung, and Steven Pfaff. 2012. “Structure and Dynamics of Religious Insurgency: Students and the Spread of the Reformation.” *Am. Sociol. Rev.* 77(2):188–215. doi: 10.1177/0003122411435905.

Kitts, James. 2000. “Mobilizing in Black Boxes: Social Networks and Participation in Social Movement Organizations.” *Mobilization: An International Quarterly* 5(2):241–57.

Klandermans, Pieter G. 2014. “Identity Politics and Politicized Identities: Identity Processes and the Dynamics of Protest.” *Polit. Psychol.* 35(1):1–22. doi: 10.1111/pops.12167.

Kristofferson, Kirk, Katherine White, and John Peloza. 2014. “The Nature of Slacktivism: How the Social Observability of an Initial Act of Token Support Affects Subsequent Prosocial Action.” *Journal of Consumer Research* 40(6):1149–66.

McAdam, Douglas. 1988. *Freedom Summer*. New York: Oxford University Press.

Moeller, Judith, Claes De Vreese, Frank Esser, and Ruth Kunz. 2014. “Pathway to Political Participation: The Influence of Online and Offline News Media on Internal Efficacy and Turnout of First-Time Voters.” *American Behavioral Scientist* 58(5):689–700.

Morris, Aldon D. 1984. *The Origins of the Civil Rights Movement*. New York: The Free Press.

Opp, Karl-Dieter. 2009. *Theories of Political Protest and Social Movements: A Multidisciplinary Introduction, Critique, and Synthesis*. New York: Routledge.

Paret, Marcel. 2015. "Violence and Democracy in South Africa's Community Protests." *Rev. Afr. Polit. Econ.* 42(143):107–23. doi: 10.1080/03056244.2014.995163.

Pfaff, Steven. 1996. "Collective Identity and Informal Groups in Revolutionary Mobilization: East Germany in 1989." *Social Forces* 75(1):91–117. doi: 10.1093/sf/75.1.91.

Polletta, Francesca, and James M. Jasper. 2001. "Collective Identity and Social Movements." *Annu. Rev. Sociol.* 27(1):283–305. doi: 10.1146/annurev.soc.27.1.283.

Shirky, Clay. 2011. "The Political Power of Social Media: Technology, the Public Sphere, and Political Change." *Foreign Affairs* 28–41.

Tausch, Nicole, Julia C. Becker, Russell Spears, Oliver Christ, Rim Saab, Purnima Singh, and Roomana N. Siddiqui. 2011. "Explaining Radical Group Behavior: Developing Emotion and Efficacy Routes to Normative and Nonnormative Collective Action." *Journal of Personality and Social Psychology* 101(1):129.

Thompson, Robin. 2011. "Radicalization and the Use of Social Media." *Journal of Strategic Security* 4(4):167–90.

Valente, Thomas W. 1996. "Social Network Thresholds in the Diffusion of Innovations." *Soc. Networks* 18(1):69–89. doi: 10.1016/0378-8733(95)00256-1.

Valenzuela, Sebastián, Arturo Arriagada, and Andrés Scherman. 2012. "The Social Media Basis of Youth Protest Behavior: The Case of Chile." *Journal of Communication* 62(2):299–314.

Valenzuela, Sebastián, Arturo Arriagada, and Andrés Scherman. 2014. "Facebook, Twitter, and Youth Engagement: A Quasi-Experimental Study of Social Media Use and Protest Behavior Using Propensity Score Matching." *International Journal of Communication* 8:2046–70.

Vasi, Ion Bogdan, and Chan S. Suh. 2016. "Online Activities, Spatial Proximity, and the Diffusion of the Occupy Wall Street Movement in the United States." *Mobilization* 21(2):139–54.

Watts, Duncan J. 1999. "Networks, Dynamics, and the Small-World Phenomenon." *Am. J. Sociol.* 105(2):493–527.

van Zomeren, Martijn, Tom Postmes, and Russell Spears. 2008. "Toward an Integrative Social Identity Model of Collective Action: A Quantitative Research Synthesis of Three Socio-Psychological Perspectives." *Psychol. Bull.* 134(4):504–35. doi: 10.1037/0033-2909.134.4.504.

EXPLAINING THE EFFECT OF SOCIAL MEDIA ON PROTEST PARTICIPATION THROUGH PSYCHOLOGICAL INCENTIVES

Abstract

Many have observed that a new political generation of digital natives has heavily used social media as means of facilitating street protests. Nevertheless, the mechanisms by which social media affects protest participation are not completely understood due to the shortage of psychological explanations. This study employs a uniquely designed survey on a massive demonstration to address such concerns. Social media activity triggers the psychological incentives of anger, social incentives, identification, and individual efficacy. In particular, individual efficacy directly mediates the relationship between social media activity and protest participation. The findings substantiate new theories of connective action and suggest that social media may be a new mobilization structure via changing the decision-making processes of individuals. Theoretical implications on understanding digital natives and deliberative democracy are discussed.

Introduction

In 2011, the person of the year for TIME magazine was "The Protestor" (Time 2011). From New York to Berlin to Cairo, millions took to the streets calling for political change. Interestingly, "The Protestor" as person of the year followed the 2010 person of the year, Facebook co-founder Mark Zuckerberg (Time, 2010). The two may be linked. Many have argued that social media (SM) is a critical factor in mobilizing large-scale protest, including the Occupy Movement in the US, the Arab Spring revolutions in the Middle East, and the *Indignados* Movement in Spain (Segerberg and Bennett, 2011; Castells, 2015; Tufekci and Wilson 2012). The influence of SM appears strongest among the younger generation. As Milkman (2017) contends, we are observing a younger generation of "digital natives" who are accustomed to the presence of digital media and have transformed the daily usage of digital media into effective tools for political goals.

Why are digital natives so active, and what role does digital media play in mobilizing political involvement? One approach to address the question would be to understand social-psychological process. Past research shows that psychological incentives such as anger, identification, or efficacy are predictors of protest participation (Klandermans and de Weerd, 2000; Opp and Kittel, 2010; Van Zomeran et al., 2008). Not only are psychological incentives important in explaining collective action, but they also serve as mechanisms that connect societal factors, such as organizational resources (Klandermans, 1984) or political change (Opp and Gern, 1993), to mobilization. However, regarding the prevalence of SM as a factor in societal change, it is unclear which psychological incentives it generates, which in turn limits our understanding of the processes by which SM affects social movements.

This study utilizes a uniquely designed web-based survey that investigated the largest student protest in Taiwan to test the effect of SM on participation as well as its psychological mechanisms. The questionnaire included a broad range of social-psychological incentives, such as anger, identification, and sense of efficacy to capture the interrelationships between SM, psychological incentives, and protest participation. Furthermore, by including retrospective and prospective questions, the questionnaire allows us to capture temporal variation in a cross-sectional survey to examine linkages between personal histories and protest behavior, reduce sources of selection bias, and enhance the validity of the findings.

Mobilization and psychological incentives in collective action

The problem of mobilization can at least be traced to Olson's (1965) theory of collective action. For Olson, the marginal effect of each individual's action on the outcome of protest is minuscule that it may seem irrational for individuals to participate rather than "free ride" on the benefits. In response, scholars have investigated a host of factors that facilitate mobilization, such as resource mobilization (McCarthy and Zald, 1977; Jenkins, 1983), social networks (Morris, 1981; McAdam, 1990), political opportunities (McAdam et al., 1996), or framing strategies (Noonan, 1995; Snow et al., 1986).

One line of research views collective action as a decision-making process and investigates psychological factors that incentivize people (Opp, 2009; Van Zomeren et al., 2008; Van Stekelenburg, 2013). Through the lens of the individual, scholars have pinpointed grievances and anger (Opp, 1988), identification (Melucci, 1988; Klandermans and de Weerd, 2000), efficacy (Van Zomeren et al., 2008; Van Stekelenburg, 2013), and social incentives (Opp and Gern, 1993) as important factors that predict movement participation.

The study of grievances has a longstanding tradition. The classical model on grievances draws from relative deprivation theory which argues that those in relatively disadvantaged social positions hold grievances that spark protests (Finkel and Rule, 1986). This view has been challenged by many in showing that structural advantages do not constitute the sufficient condition for movement participation (e.g., McCarthy and Zald, 1977; Jenkins and Perrow, 1977). In response, scholars have shown that grievances, especially immediate grievances that lead to anger, can lead to protest. In Opp's (1988) classical examination of grievances in Chernobyl anti-nuclear protests, immediate grievances had a casual effect on protest participation, while lagged effects of grievances five years ago were not found. Similarly, Van Zomeren et al. (2004) show that group-based anger is an important motivator of protest participation. Finally, Hechter et al. (2016) propose the theoretical distinction between structural grievances and incidental grievances, with the former indicating structural disadvantages and the latter regarding grievances triggered by immediate events. As they show in the case of the Royal Navy, mutiny was more likely under conditions of incidental grievances. Thus, anger as triggered by incidental grievances seems to be the proximate predictor of protest participation.

Identification draws on social identity theory (Tajfel, 1974) on how emotional attachment to a social group is related to collective action. Melucci (1988) argues that through the creation of a collective identity, potential participants connect as a cohesive group which aligns collective action goals with individual meaning. In the case of Dutch farmers, Klandermans and de Weerd (2000) find that identification with the farmers' group predicted intentions to participate in farmers' movements. Furthermore, identification can elicit other conducive psychological factors as well. Van Zomeran and colleagues (Van Zomeran et al., 2004; Van Zomeran et al., 2008) find that identification can lead to the intensification of grievances and enhanced feelings of efficacy, which in turn motivates individuals to resort to protest action.

Efficacy is another factor. Originating from Bandura's (1977) concept as one's perception of confidence in achieving intended results, scholars have extended the notion of efficacy to the realm of collective action. Two types of efficacy have arisen. Group efficacy refers to one's belief that the protest group would be effective in achieving movement goals, while individual efficacy is the belief of personal influence in that one could contribute to the collective action (Finkel and Muller, 1998). The evidence is present that both group efficacy and individual efficacy are important incentives. Utilizing panel data in Germany, Finkel and Muller (1998) show that even when controlling for each other, group efficacy and individual efficacy have independent effects on participation in protest activities. Opp and Kittel (2010) show that perceived influence is a strong predictor of movement participation. Van Stekelenburg (2013) finds that in diaspora protests, those who hold stronger beliefs on group efficacy were more likely to participate.

Finally, some pay attention to social incentives. The impact of network embeddedness has been explored by many who show that personal ties to supportive others motivate people to participate in collective action (Morris, 1981; McAdam, 1990). Opp and colleagues (Opp and Gern, 1993; Opp, 1998; Opp and Kittel, 2010) connect network embeddedness with the psychological factor of social incentives, defined as the perception of encouragement to protest by others. They demonstrate that in addition to factors such as anger or identification, social incentives have unique effects on protest participation. Similarly, van Stekelenburg (2013) finds that being embedded in a supportive network induces individuals to attend diaspora protests.

Research on psychological incentives is not merely listing a grab-bag of factors. By identifying decision-making processes at the individual-level, psychological incentives shed light on the processes in which structural or contextual factors, such as organizational resources

(Klandermans, 1984) or political change (Opp and Gern, 1993) affect collective action. As Opp (2009) proposes in his "structural-cognitive model," the effect of societal-level or mesolevel factors such as political opportunities or network embeddedness can be explained through micro-level incentives. The perspective is shared by van Zomeran and colleagues (2008: 504) who posit, "A key challenge is to bridge *subjective* (psychological) and *social* (structural) perspectives on when, why, and how people engage in social protest."

New media, psychological incentives, and protest

The ever-increasing interactivity of SM platforms has facilitated a new wave of large-scale social movements, such as the Arab Spring in the Middle East and the Black Lives Matter Movement in the US. Numerous scholars have argued for the importance of interactive SM, such as Facebook or Twitter, in facilitating the new wave of social movements (Castells, 2015; Howard and Hussain, 2011; Segerberg and Bennett, 2011).

As increasing evidence indicates positive relationships between SM activity and social movement participation (e.g., Boulianne, 2015; Valenzuela et al., 2014), scholars have moved to unravel mechanisms. One stream of thought turns to psychological factors. Similar to the concern on how societal factors translate into psychological incentives (Opp, 2009; Van Zomeran et al., 2008), notions of anger, identification, efficacy, and social incentives have been alluded to in research on new media.

SM may be effective in upstirring anger. First, SM allows for easier transmissions of personal stories and experiences (Bennett and Segerberg, 2012), which may allow for SM users to generate awareness of shared grievances. Second, the interface of SM facilitates easy uploading and sharing of video and audio content which instigate emotions such as anger. Third, SM allows activists to bypass mainstream media or government censorship and represent their grievances online. In the cases of upheaval in Tunisia and Egypt, Howard and Hussain (2011) suggest that the spreading of outrageous content on SM creates the awareness of shared grievances that foster collective action. For instance, the video of Mohamed Bouazizi's self-immolation went viral on SM and marked the trigger of the Tunisian revolution. The footage filming of Eric Garner repeatedly saying "I can't breathe" in a police arrest intensified the Black Lives Matter movement and spurred the trending hashtag "#ICantBreathe" on Twitter. At the time of the incident, more than a million tweets were discussing the case of Eric Garner (BBC, 2014). Lim (2012) argues that SM allowed activists to spread grievances that bypassed control of the Egyptian government and to a broader audience in the Egypt uprisings.

SM may also influence identification with protest groups. Consistent with the perspective that being embeddeded in a group with intensive social interaction fosters identification (Klandermans et al., 2008), SM enhances opportunities for activists or supporters to interact with like-minded users through online communities such as the Twitter page of "@BlkLivesMatter" or simply by connecting with friends of friends on SM. In the extreme, terms such as "filter bubbles" or "echo chambers" have been proposed to describe how SM exacerbates one's political preference, although evidence on the degree of such homogeneity effects has been mixed (see Flaxman, Goel, and Rao 2016). As Tremayne (2014) documents in a Twitter analysis on the Occupy Movement, SM allows for frame alignment of multiple "memes", such as hashtags. Through shared memes supporters could connect with other supporters online and create a sense of identification and unity. Similarly, Kavada (2015) traces SM users in the Occupy Movement and points out that as SM users interacted with one another, developments of common practices, codes of conduct, demands and statements and their codification in texts were constantly negotiated, which in turn contributed to the formation of a collective identity.

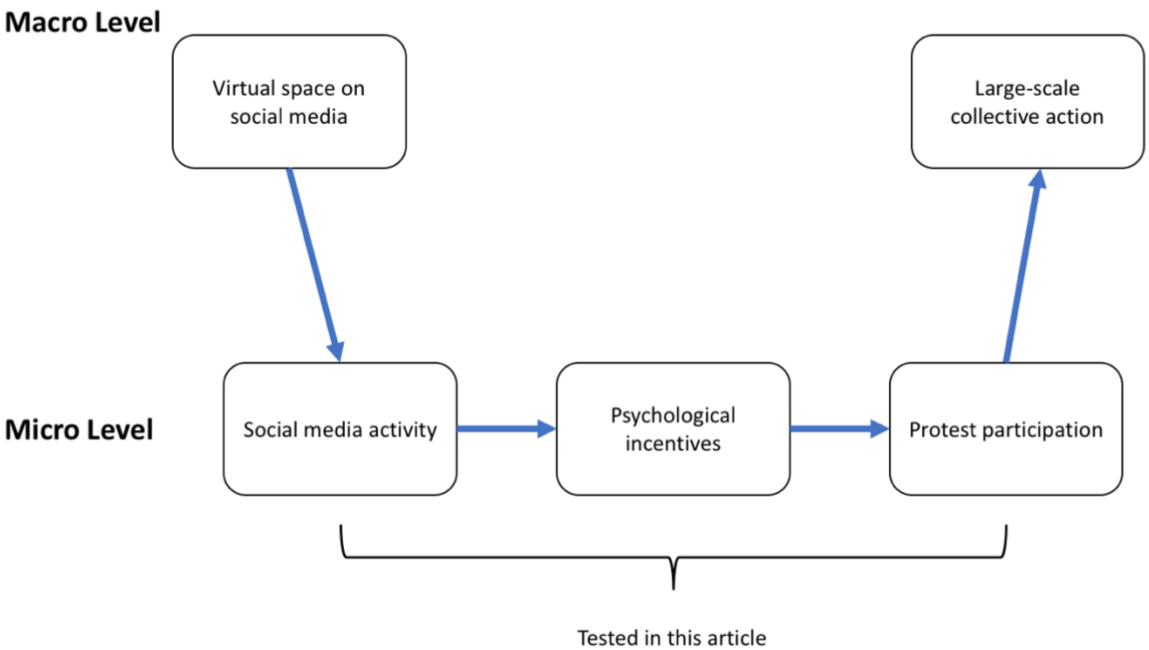
While few studies directly address how SM increases efficacy in collective action, we can draw from theories of political communication. First, as one becomes more knowledgeable about political affairs, one may feel more capable of participating in related behavior (Delli Carpini, 2000; Shah, McLeod, and Lee, 2009). SM usage, if related to political issues, may increase efficacy through enhanced exposure to political knowledge. The second theory draws from deliberative democracy and contends that interpersonal exchanges of political opinions with fellow citizens elevates one's sense of political efficacy (Gutmann and Thompson, 1998). As SM allows for intensive interactions between users, it may increase efficacy via discussions on political issues. Both theories have received some empirical support. Jung et al. (2011) contend that online political messaging has a positive effect on political efficacy, both directly and through an indirect route via political knowledge. Moeller et al. (2014) utilize panel data in the Netherlands and show that civic messaging online has a strong effect on political efficacy. Min (2007) shows through experimental evidence that computer-mediated political discussion leads to higher levels of political efficacy. Nevertheless, research on the relationship between SM and collective action-related efficacy is scant. Kharroub and Bas (2016) depict how efficacy-eliciting images were widely used on SM in the Egyptian revolution, especially during the phase of political conversation after the revolution. Implicitly, their finding supports the deliberative model that political exchanges are associated with higher levels of efficacy.

Finally, SM creates networks supportive of protest that motivate online users to take part in offline action. As the word "social" implies, the interface of SM such as Facebook or Twitter encourage users to connect with others. As evinced in Bennett and Segerberg's (2012) discussion of "connective action," SM allows one to integrate not only strong but also weak ties into resources for social movements. Such a perspective is echoed by scholars on how the connectivity of SM creates linkages between activists and participants and hence mobilization power for social movements (Castells, 2015; Juris, 2012; Kavada, 2015). Accordingly, we would expect supportive networks to generate social incentives for embedded individuals.

Nevertheless, understandings of the psychological foundations of SM is far from complete due to two restrictions. First, most studies focus on one or two factors and do not systematically compare psychological incentives. As evinced by Opp and Kittel (2010), Van Zomeran et al. (2008), and van Stekelenburg (2013), psychological factors are often associated with one another. One would need to survey a broad range of psychological factors to understand the unique impact of each. Second, many studies draw inferences on psychological factors via proxies from SM material. Tremayne (2014) measures collective identity through messages on Twitter. Kharroub and Bas (2016) discuss how efficacy-eliciting images by coding whether the image includes crowds, protest activities, or protest symbols. Direct measures of psychological factors, such as survey data, could be complementary as it allows for better measures on psychological factors but perhaps indirect accounts on SM activity.

This article adopts a structural-cognitive model (Opp, 2009), which connects societal level factors with individual-level variables to explain the process in which the SM environment (i.e., the virtual space where SM users interact) affects protest participation. The elegance of a structural-cognitive model is that while it examines micro-mechanisms, it incorporates societal level factors through their measurements on the individual level. Similar to how Opp and Gern (1993) utilize membership status at the individual-level (micro) to measure the degree citizens are affected by political groups (macro), this article utilizes SM activity at the individual-level (micro) to measure the degree users are affected by the digital environment (macro). Figure 1 represents the diagram of the model.

Figure 1. Diagram of model



As recent research implies that SM influences anger, identification, efficacy and social incentives, and past research suggests that each of the psychological incentives influences protest participation. This research hypothesizes:

H1: SM activity elicits psychological incentives of anger, identification, efficacy and social incentives.

H2: Each of these psychological incentives mediate the relationship between SM activity and protest participation.

Data and methods

Case description

This study draws on the Sunflower Movement in Taiwan as the research case. The Sunflower Movement was driven by a coalition of students and civic groups between March 18 and April 10, 2014, in Taipei, the capital of Taiwan. On March 17, the ruling Kuomintang government announced in the Legislative Yuan (the parliament of Taiwan) the passing of the Cross-Strait Service Trade Agreement between the Taiwanese and Chinese government, which was aimed at liberalizing trade and services. Many perceived the bill invalid as it did not receive clause-by-clause legislative review and as a potential threat to Taiwan's sovereignty. On March 18 via mobilization on Facebook and other SM, protestors broke in and occupied the parliament building for the first time in Taiwanese history. Many more conducted sit-ins surrounding the Legislative Yuan. Shortly after the movement began, thousands of riot police were mobilized across the country to surround the protesters, but the Legislative Speaker Jin-pyng Wang promised not to use force on the protesters. As the ruling government was not willing to drop the Trade Agreement, protestors continued to occupy the Legislative Yuan. On March 23, protestors further attempted to occupy the Executive Yuan but were forcefully evicted by the police, injuring many protestors during the process. Protest activists decided to initiate a large demonstration on March 30 on the streets in front of the Presidential Office, which rallied more than half a million participants[1], marking the largest student movement ever in Taiwan. On April 6, Jin-pyng Wang visited the occupied parliament and promised to postpone review of the trade pact until legislation monitoring all cross-strait agreements has been passed. In response, activists decided on the following day to end the occupation on April 10.

The Sunflower Movement generated considerable discussion on SM. Facebook and other SM were heavily utilized by activists throughout the movement, and especially around the March 30 large demonstration. The official Facebook page of the movement received more than 390,000 likes, signifying the visibility of the movement on SM.

Survey design

The goals of the survey were to allow for the testing of the relationship between SM activity, psychological factors, and protest participation. To prevent overburdening the reader, complete information of the survey is described in detail in APPENDIX A, including pretest procedures, implementation details, validity checks, and measurements of control variables. Also described are various implementations to increase the validity of the survey. Below are highlighted elements of the survey.

Target population

Following Milkman's (2017) perspective on the new generation of digital natives, the study was restricted to people aged 18 to 30 to select a target population that was relatively available regarding time and obligations to participate in the protest in Taiwan. 18 is the average age at which students graduate from high school, and 30 is roughly the average age when people marry (Directorate General of Budget, Accounting and Statistics, 2014). A few respondents (n=37) reported that their age was outside the range. Results do not change if these cases are excluded.

Sampling

The link to the questionnaire was posted on a series of forums on PTT, a BBS (Bulletin Board System) site used extensively by the younger generation. The BBS operated since 1983 in Taiwan (Shen, 1995), which is even before the advent of World Wide Web (McPherson, 2009). Although the DOS format interface has remained much the same since 1983 and is remarkably primitive with very limited interactivity compared to SM (see Figure 2), it is widely used by the younger generation, many of whom are college students[2]. The PTT contains many boards that are differentiated by topic (e.g., political issues, news, movies). Most respondents were recruited from boards that were *unrelated* to politics, as seen in Table 1. Controlling for possible board effects does not change the results.

Figure 2. Interface of PTT.

Table 1. Summary of respondents from PTT boards.

Board Topic	# of Respondents
Politics	23
Public issues	23
Mobile phones	166
Personal funny stories	413
Women topic	135
Questionnaire	91
Other	6
Did not Respond	56

Retrospective design

To reduce causal endogeneity between variables, the questionnaire borrows from life history techniques (Freedman et al., 1988; Berney and Blane, 1997) and includes retrospective questions to differentiate time frames. The questionnaire can be divided into two chronologically sequential periods. The first period includes items that asks about behavior *before the issue of the Trade Agreement emerged*. Variables in this period are control variables regarding previous political behavior or previous SM usage. The second period consists of items about thoughts and behavior after the issue of the Trade Agreement emerged but *before* the respondent participated in the Sunflower Movement (for protestors) or during the Sunflower Movement (for non-protestors). Thoughts and behavior may change after people protest, so it was necessary to identify only thoughts and behavior that occurred before participation. Pretest results suggest that respondents could differentiate their thoughts before and after the protest. For non-protestors, this problem is not relevant, and it was only necessary to ask about their thoughts and behavior during the period. Variables in this period include SM activity and psychological variables. The survey design allowed for the chronologically ordering of factors and reduced problems of endogeneity. In addition, procedures were implemented to reduce recall bias and telescoping backwards (Appendix A).

Measures

Protest

Protest was measured by a binary item: "Did you physically participate in the Sunflower Movement?" (0 = no, 1 = yes).

As a supplementary analysis (results not shown), an ordinal version of protest participation was measured by "How often did you physically participate in the Sunflower Movement?" (0 = did not participate, 5 = everyday). However, since many respondents indicated that they did not know how often they participated (n = 135), the binary item was used for the analysis. Results are similar using either item.

Social media activity

SM activity was measured on a scale with five items (Cronbach's α=0.9): "On your social media, how often did you post comments on the Trade Agreement issue or the Sunflower Movement?", "On your social media, how often did you reply to other people's posts on the Trade Agreement issue or the Sunflower Movement?", "On your social media, how often did you repost or re-share other people's posts on the Trade Agreement issue or the Sunflower Movement?", "On your social media, how often did you "like" other people's posts on the Trade Agreement issue or the Sunflower Movement?", and "On your social media, how often did you did you encourage others to participate physically in the Sunflower Movement?" Respondents indicated their frequency on a five-point scale (1= never, 5= everyday).

Psychological variables

Building on previous work, the measures of psychological factors closely follow Opp and colleagues (see Opp and Gern, 1993; Opp and Kittel, 2010).

(1) Anger

Anger was measured by the item "I felt angry towards the government." Respondents indicated their agreement on 4-point scales (1 = strongly disagree, 4 = strongly agree).

(2) Identification

Identification consisted of two items (correlation γ=0.72): "In general, I felt close to those who physically attended the movement" and "In general, I admired those who physically attended the movement" (1 = strongly disagree, 4 = strongly agree).

(3) Social incentives

Social incentives were measured by the item "In general, my friends wish that I would physically attend the Sunflower Movement" (1 = strongly disagree, 4 = strongly agree).

(4) Individual efficacy

Individual efficacy was measured by the item "I felt that I would have an impact if I attended the Sunflower Movement" (1 = strongly disagree, 4 = strongly agree).

(5) Group efficacy

Group efficacy was measured by the item "I felt that the Sunflower Movement would have an impact on the government" (1 = strongly disagree, 4 = strongly agree).

Analytical strategy

Respondents who indicated that their SM activity was *against* the Sunflower Movement were excluded (n = 78) as we would not expect SM activity that is against the movement to have mobilizing effects. The final sample size for analysis was 880. Including these respondents does not change the results.

Structural equation modeling was used via the statistical software *Mplus 7.3*. Since theoretically the relationship should be "SM Activity → Psychological Incentives → Protest Participation", the Appendices include robustness checks on each of the sequences. Robustness checks on "SM Activity → Psychological Incentives" are shown in Appendix B, and checks on "Psychological Incentives → Protest Participation" in Appendix C. Finally, since protest participation was measured as a binary variable, additional analysis using the ordinal version of protest participation yield similar results (not shown).

Descriptive statistics are shown in Table 2 (see Appendix A for measures on control variables).

Table 2. Descriptive statistics of variables.

Variable	Items		Range	Mean	SD
Dependent Variable	1. Protest		(0,1)	0.39	0.49
Social media Variable	1. Social media activity		(5,25)	12.20	5.58
Psychological Variables	1. Anger		(1,5)	3.48	0.61
	2. Identification		(2,10)	6.60	1.12
	3. Friend social incentive		(1,5)	2.86	0.69
	4. Individual efficacy		(1,5)	2.69	0.74
	5. Group efficacy		(1,5)	3.13	0.66
Control Variables	1. Demographics	Female	(0,1)	0.50	0.50
		Age	(16,39)	23.52	3.80
		Father education	(1,7)	4.30	1.00
		Mother education	(1,7)	4.06	0.97
		College Student	(0,1)	0.51	0.50
	2. Previous political behavior	Discuss politics	(1,5)	2.61	1.23
		Read political news	(1,5)	3.70	1.27
		Attend protest	(0,1)	0.16	0.37
		Attend political rally	(0,1)	0.16	0.37
		Attend community meeting	(0,1)	0.18	0.39
		Work for politician	(0,1)	0.03	0.17
		NGO experience	(0,1)	0.10	0.30
		Solve community problem	(0,1)	0.19	0.39
	3. Previous social media behavior	Posting	(1,5)	1.45	0.86
		Responding	(1,5)	1.51	0.92
		Reposting	(1,5)	1.45	0.85
		Liking	(1,5)	2.04	1.21
		Encouraging others to protest	(1,5)	1.49	0.89

Results

Structural equation modeling was applied to test whether anger, identification, friend social incentives, individual efficacy, and group efficacy mediated the relationship between SM activity and protest. The scales of SM activity and identification were specified as latent variables. Because variables are ordinal (e.g., Strongly Disagree to Strongly Agree), weighted least squares with means and variance adjusted estimation (WLSMV) was used, which performs better for categorical data (Muthén and Asparouhov, 2002; Beauducel and Herzberg, 2006).

Table 3 shows the Confirmatory Factor Analysis for the latent variable "SM activity." All five items had standardized factor loadings from 0.77~0.95. The fit statistics suggest good fit ($\chi 2$ (4) = 17.52, p = .002; CFI = 0.999; TLI = 0.997; RMSEA = 0.063). An error correlation between SM responding and SM reposting was specified due to unexplained negative residual correlation after the latent variable specification. Nevertheless, because the magnitude of errors is relatively small (i.e., error variances less than 0.06 after the latent specification), this is a minor issue.

Table 3. Unstandardized, Standardized, and Significance Levels for Confirmatory Factor Analysis on SM activity (Standard Errors in Parentheses; N = 875)

Parameter Estimate	*Unstandardized*	*Standardized*	*p-value*
Measurement Model			
SM Activity → X_1	1.00	0.85	
SM Activity → X_2	1.76 (0.19)***	0.95	.00
SM Activity → X_3	1.57 (0.15)***	0.93	.00
SM Activity → X_4	0.74 (0.04)***	0.77	.00
SM Activity → X_5	0.90 (0.05)***	0.83	.00
Error X_3 ←→ Error X_4	-0.75 (0.16)***	-0.75	.00

Note: a. $\chi 2$ (4) = 17.52, p = .002; CFI = 0.999; TLI = 0.997; RMSEA = 0.063
b. *p<.05; **p<.01; ****p<.001

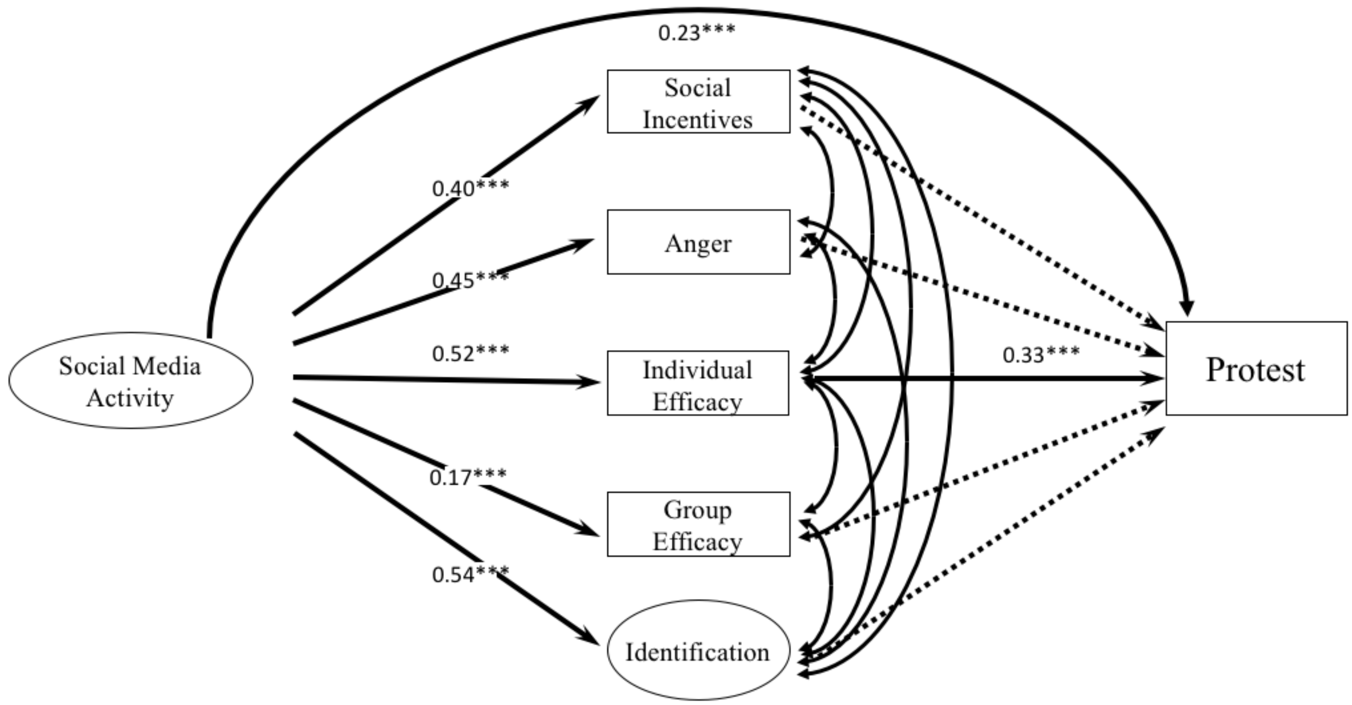
A structural regression model was estimated to investigate whether the psychological factors mediate the relationship between SM activity and protest. Results are shown in Table 4 and Figure 3.

Table 4. Unstandardized, Standardized, and Significance Levels for Model in Figure 3 (Standard Errors in Parentheses; N = 875)

Parameter Estimate	*Unstandardized*	*Standardized*	*p-value*
Measurement Model			
SM Activity → X_1	1.00	0.86	
SM Activity → X_2	1.40 (0.13)***	0.92	.00
SM Activity → X_3	1.33 (0.11)***	0.91	.00
SM Activity → X_4	0.78 (0.05)***	0.80	.00
SM Activity → X_5	0.91 (0.05)***	0.84	.00
Identification → X_6	1.00	0.92	
Identification → X_7	0.69 (0.14)***	0.85	.00
Structural Model			
Path coefficients			
SM Activity → Social Incentives	0.26 (0.03)***	0.40	.00
SM Activity → Anger	0.30 (0.03)***	0.45	.00
SM Activity → Individual Efficacy	0.36 (0.03)***	0.52	.00
SM Activity → Group Efficacy	0.10 (0.03)***	0.17	.00
SM Activity → Identification	0.76 (0.12)***	0.54	.00
SM Activity → Protest	0.16 (0.04)***	0.23	.00
Social Incentives → Protest	0.11 (0.08)	0.10	.14
Anger → Protest	-0.07 (0.10)	-0.07	.48
Individual Efficacy → Protest	0.33 (0.07)***	0.33	.00
Group Efficacy → Protest	-0.11 (0.06)	-0.09	.08
Identification → Protest	0.00 (0.06)	0.01	.94
Covariances			
Social Incentives ←→ Anger	0.12 (0.05)*	0.12	.01
Social Incentives ←→ Individual Efficacy	0.28 (0.04)***	0.28	.00
Social Incentives ←→ Group Efficacy	0.10 (0.05)*	0.10	.04
Social Incentives ←→ Identification	0.77 (0.14)***	0.39	.00
Anger ←→ Individual Efficacy	0.27 (0.05)***	0.27	.00
Anger ←→ Group Efficacy	0.19 (0.05)***	0.19	.00
Anger ←→ Identification	1.22 (0.21)***	0.61	.00
Individual Efficacy ←→ Group Efficacy	0.33 (0.04)***	0.33	.00
Individual Efficacy ←→ Identification	0.84 (0.15)***	0.42	.00
Group Efficacy ←→ Identification	0.44 (0.10)***	0.22	.00
Error X_3 ←→ Error X_4	-0.33 (0.09)***	-0.33	.00
Residual variances for Identification	3.96 (1.23)***	0.71	.00

Note: a. $\chi2$ (37) = 131.759, $p < .001$; CFI = 0.994; TLI = 0.989; RMSEA = 0.054
b. *p<.05; **p<.01; ****p<.001

Figure 3. Structural regression model on relationship between SM activity, psychological factors, and protest participation.



Note: a. Solid lines indicate significant relationships. Dashed lines represent insignificant relationships.
b. Standardized coefficients are reported.
c. Factor loadings are omitted.
d. Coefficients of correlations between psychological factors are omitted.

The fit indices suggest a good fit ($\chi^2(27)= 95.938$, CFI= 0.995, TLI=0.992, RMSEA= 0.056, WRMR= 0.738). Also, none of the residual correlations have an absolute value of 0.1 or higher, the rule of thumb for model fit (Kline, 2015). Standardized coefficients are reported (i.e., in metrics of standard deviations) in Figure 3 because many variables are on a latent scale and the original metrics are not meaningful.

Supporting *H1*, results suggest that SM activity has a positive effect on all psychological incentives, including social incentives, anger, individual efficacy, group efficacy and identification. The relationships between psychological factors are specified as correlated rather than causal, since the variables are measured within the same time frame and do not allow a direct test of causality.

Tests of indirect estimates are presented in Table 5. Partially supporting *H2*, the effect of SM activity → Individual efficacy → Protest participation is statistically significant, while the indirect effects between other psychological factors and protest participation are not significant. There are multiple possibilities for the non-significance. First, these factors do not have any mediating role. Second, since the correlations between these psychological variables are statistically significant[3], previous literature suggests that these may be indirect mediators between SM activity and protest via efficacy (Klandermans 2008; Van Zomeran et al. 2008). Third, as psychological factors are positively correlated with one another (e.g., the correlation between anger and identification is .61), larger sample sizes are needed to separate the collinear effects. However, future research is required to distinguish the possibilities.

Table 5. Unstandardized, Standardized, and Significance Levels for Indirect Estimates.

Parameter Estimate	*Unstandardized*	*Standardized*	*p-value*
SM Activity → Social Incentives → Protest	0.03 (0.02)	0.04	.15
SM Activity → Anger → Protest	-0.02 (0.03)	-0.03	.48
SM Activity → Individual Efficacy → Protest	0.12 (0.03)***	0.17	.00
SM Activity → Group Efficacy → Protest	-0.01 (0.01)	-0.02	.11
SM Activity → Identification → Protest	0.00 (0.04)	0.00	.94

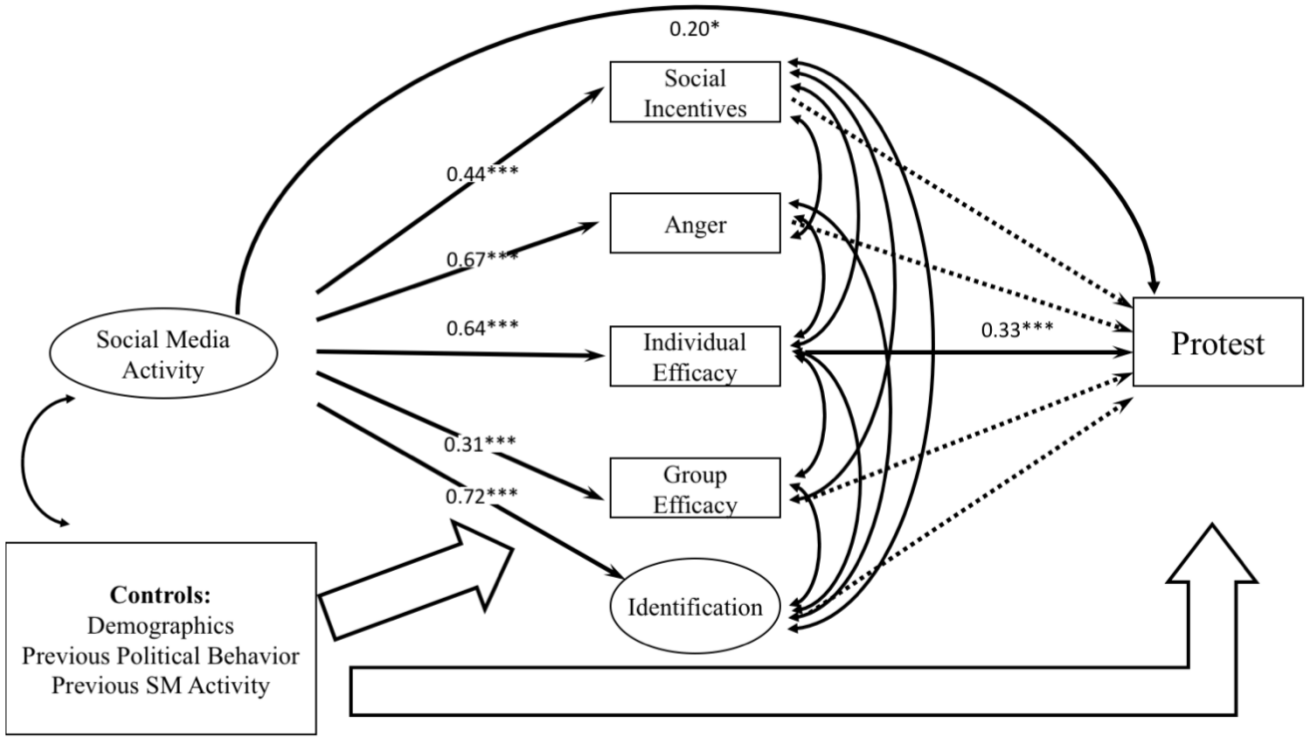
Nevertheless, the simple model above does not account for the possibility that if there are third variables that confound the relationships between SM activity, psychological incentives, and protest participation. Therefore, the following model includes a variety of control variables, including gender, age, father education, mother education, college student status, several previous political behavior, and previous SM activity. Structural equation modeling was used to test the same model above, except that the controls are now added.

Fit indices suggest good fit (χ^2 (212)= 594.05, CFI= 0.983, TLI=0.964, RMSEA= 0.045,). In addition, none of the residual correlations have an absolute value of 0.1 or higher.

Results are presented in Figure 4 and Table 6 below. Figure 4 represents the core coefficients of the model. The large hollow arrows signify that pathways between control variables and psychological variables, and between control variables and protest participation are estimated, although the numbers are omitted. In addition to the core coefficients, Table 6 also presents effects from demographic variables as it reveals insight on how people with different characteristics associate with psychological incentives and protest participation. Whereas coefficients of other control variables may be interesting, they are not presented since they are not the central concern of this article but available upon request.

The relationships between SM activity and psychological incentives, and between psychological factors and protest participation remain significant. The indirect path between *SM activity* → *Individual efficacy* → *Protest* also remains significant (standardized coefficient = 0.21 , $p < .001$).

Figure 4. Structural regression model on relationship between SM activity, psychological factors, and protest participation, including controls of selection bias (N = 880).



Note: a. Solid lines indicate significant relationships. Dashed lines represent insignificant relationships.
b. Standardized coefficients are reported.
c. Factor loadings are omitted.
d. Coefficients of correlations between psychological factors are omitted.

Table 6. Unstandardized, Standardized, and Significance Levels for Model in Figure 4 (Standard Errors in Parentheses; N = 880)

Parameter Estimate	*Unstandardized*	*Standardized*	*p-value*
Measurement Model			
SM Activity → X_1	1.00	0.86	
SM Activity → X_2	1.38 (0.13)***	0.92	.00
SM Activity → X_3	1.31 (0.11)***	0.91	.00
SM Activity → X_4	0.74 (0.05)***	0.79	.00
SM Activity → X_5	0.92 (0.06)***	0.85	.00
Identification → X_6	1.00	0.92	
Identification → X_7	0.67 (0.15)***	0.85	.00
Structural Model			
Core model coefficients			
SM Activity → Social Incentives	0.29 (0.05)***	0.44	.00
SM Activity → Anger	0.47 (0.07)***	0.67	.00
SM Activity → Individual Efficacy	0.45 (0.06)***	0.64	.00
SM Activity → Group Efficacy	0.19 (0.04)***	0.31	.00
SM Activity → Identification	1.02 (0.19)***	0.72	.00
SM Activity → Protest	0.15 (0.07)*	0.20	.03
Social Incentives → Protest	0.04 (0.08)	0.04	.58
Anger → Protest	-0.08 (0.10)	-0.07	.46
Individual Efficacy → Protest	0.35 (0.08)***	0.33	.00
Group Efficacy → Protest	-0.10 (0.07)	-0.08	.14
Identification → Protest	0.02 (0.06)	0.04	.75
Demographic variables coefficients			
Female → Social Incentives	-0.08 (0.10)	-0.04	.42
Age → Social Incentives	0.01 (0.01)	0.02	.62
College student → Social Incentives	0.38 (0.10)***	0.17	.00
Father education → Social Incentives	0.04 (0.06)	0.04	.51
Mother education → Social Incentives	0.02 (0.06)	0.02	.77
Female →Anger	-0.04 (0.10)	-0.02	.72
Age → Anger	-0.02 (0.01)	-0.08	.05
College student → Anger	-0.05 (0.10)	-0.02	.64
Father education → Anger	-0.04 (0.06)	-0.04	.43
Mother education → Anger	-0.11 (0.06)*	-0.09	.05
Female → Individual Efficacy	0.18 (0.10)	0.08	.06
Age → Individual Efficacy	-0.03 (0.01)*	-0.08	.05
College student → Individual Efficacy	0.03 (0.10)	0.01	.75
Father education → Individual Efficacy	-0.03 (0.06)	-0.02	.63
Mother education → Individual Efficacy	-0.02 (0.07)	-0.02	.72
Female → Group Efficacy	-0.11 (0.08)	-0.05	.19
Age → Group Efficacy	-0.03 (0.01)**	-0.11	.01
College student → Group Efficacy	-0.03 (0.09)	-0.01	.77
Father education → Group Efficacy	-0.03 (0.05)	-0.03	.52
Mother education → Group Efficacy	0.08 (0.05)	0.07	.13
Female → Identification	0.04 (0.19)	0.01	.83
Age → Identification	-0.03 (0.03)	-0.05	.16
College student → Identification	0.11 (0.19)	0.02	.58
Father education → Identification	-0.13 (0.12)	-0.06	.29
Mother education → Identification	-0.03 (0.12)	-0.01	.79
Female → Protest	0.14 (0.11)	0.06	.18
Age → Protest	0.03 (0.02)*	0.09	.04
College student → Protest	0.45 (0.11)***	0.18	.00
Father education → Protest	-0.05 (0.06)	-0.04	.48
Mother education → Protest	0.22 (0.07)**	0.16	.00
Covariances			
Social Incentives ←→ Anger	0.12 (0.05)*	0.12	.02
Social Incentives ←→ Individual Efficacy	0.29 (0.04)***	0.29	.00

Social Incentives ←→ Group Efficacy	0.09 (0.05)	0.09	.06
Social Incentives ←→ Identification	0.77 (0.15)***	0.40	.00
Anger ←→ Individual Efficacy	0.25 (0.05)***	0.25	.00
Anger ←→ Group Efficacy	0.17 (0.05)***	0.17	.00
Anger ←→ Identification	1.12 (0.21)***	0.58	.00
Individual Efficacy ←→ Group Efficacy	0.31 (0.04)***	0.31	.00
Individual Efficacy ←→ Identification	0.79 (0.15)***	0.41	.00
Group Efficacy ←→ Identification	0.40 (0.11)***	0.20	.00
Error X_3 ←→ Error X_4	-0.32 (0.04)***	-0.32	.00
Residual variances for Identification			

Note: a. $\chi 2$ (212) = 594.047, p < .001; CFI = 0.983; TLI = 0.964; RMSEA = 0.045
b. *p<.05; **p<.01; ****p<.001

Regarding the robustness checks (Appendices B-C), the effects of SM activity on anger social incentives, identification, and individual efficacy are robust to alternative models. However, the effect of SM activity to group efficacy was not significant in the robustness checks.

In sum, SM activity affects psychological incentives, which in turn influence protest participation. Individual efficacy is a direct mediator of SM activity and protest, while anger, identification, and social incentives are perhaps indirect mediators. The role of group efficacy requires further research the effects do not pass robustness checks.

Discussion and conclusion

This paper utilized a structural-cognitive framework to understand the relationship between SM and collective action via psychological incentives. Results suggest that SM elicits anger, social incentives, identification, and efficacy among younger individuals. In particular, individual efficacy is a direct mediator between SM activity and protest participation, while direct mediation effects were not found for other psychological incentives. We can draw several implications from the findings.

The impact of efficacy has been investigated by both psychologists and sociologists, and has been shown to be a potent predictor of participation (Finkel and Muller, 1998; Opp and Kittel, 2010; Van Stekelenburg, 2013). Nevertheless, very rarely have scholars examined whether SM affects efficacy that is related to collective action, partially due to data difficulties. While it is possible to detect emotions such as anger via text analysis (e.g., via machine learning on emotion classification), it is challenging to know how efficacious people feel based on online texts. Kharroub and Bas (2016) undergo an innovative attempt by studying proxies of *efficacy-eliciting* images, defined as images that include crowds, protest activities, or protest symbols. Still, such measures do not directly address the relationship between SM and efficacy as we have no method of knowing whether receivers of these images indeed perceive efficacy. This study provides the much-needed empirical evidence supporting the claim that SM enhances efficacy in collective action.

As this study provides empirical evidence on the effect SM has on efficacy specific to collective action and that such feelings are transferrable to participatory behavior, it complements studies that study general political efficacy (Min, 2007; Moeller et al., 2014). The distinction is important for two reasons. First, compared to other political behavior such as connecting with politicians, protests bear higher levels of costs and risks (e.g., the Sunflower occupants at the Executive Yuan were forcefully evicted and many were beaten by the riot police). It is critical that participants are armed with the belief that they can contribute in spite of adverse conditions. Second, in collective action there is no guarantee that the protest group would have an impact. While success (partially) depends on collective participation, the contribution of each person is minuscular (Olson, 1965). Individual efficacy is a key condition to over-come the hurdles as it overcomes the belief that one's contribution is negligible. In short, given the nature of high-risk collective action such as protests, the results that SM can increase individual efficacy is particularly encouraging.

The results for efficacy may have implications on deliberative democracy. Following the deliberative democracy tradition that political exchanges increase political efficacy (Gutmann and Thompson, 1998) and evidence on how online political expression raises political efficacy (Min, 2007; Moeller et al., 2014), this study shows that SM activity can promote citizens to engage in alternative types of political involvement through elevated levels of efficacy. As an alternative to representative democracy such as voting or contacting politicians, SM can encourage users to engage in collective action. Through deliberative interactions with other users on SM, those who have lost faith or are excluded from representative democracy may still be interested in political affairs. Empowered with perceived political influence, they may take part in more spontaneous forms of political participation.

While the results suggest that anger, identification, group efficacy and social incentives are not direct mediators between SM activity and protest, the finding that SM elicits each of these incentives may still have implications for future research. Tausch et al. (2011) suggest that group efficacy and anger are predictors of normative actions tendencies as opposed to non-normative protest strategies such as violence. As the Sunflower Movement adopted non-violent strategies throughout (even when the police utilized force), SM could have played a role in producing the supporting psychological factors of group efficacy and anger. Identification is an interesting factor as previous research shows that it not only predicts protest participation (Van Zomeran et al., 2004; Van Zomeran et al., 2008), but also intentions to participate in the future (Klandermans and de Weerd, 2000; Saunders et al., 2012). Collective identity connects to the fundamental meaning of how individuals connect to the social world (Melucci, 1988), making it a long-lasting incentive. Supplementary analysis (Appendix C) indicates that identification significantly mediates the relationship between SM activity and future intentions to attend protests. Compared to one-day demonstrations, the Sunflower Movement lasted for almost a month, and identification may have contributed to its continuity. Although outside of the scope of this study, studying how such psychological incentives affect characteristics of collective action beyond participation, such as normative inclinations or commitment, would be a fruitful line of research.

While each of the psychological factors embodies theoretical implications, one should not overlook the broader picture of the process in which societal changes creates conditions for collective action. Echoing Opp (2009) and Van Zomeran et al.'s (2008) call on the need to bridge psychological and societal factors, this study suggests that the societal change of SM allows more people to express political opinions online, which in turn changes incentives and hence motivates individuals to participate in social movements. Without SM, users are less likely to express grievances, feel more socially isolated, feel emotionally detached to protest groups, and most importantly, think that they cannot do anything to redress their concerns.

The limitations of this study open avenues for future research. As this study uses a mimic-longitudinal design through retrospective questions, it did not examine general psychological incentives (e.g., general efficacy or general grievances) before the issue of protest since people tend to remember behavior much better than attitudes (Smith, 1984). Future research that incorporates longitudinal surveys on SM usage, psychological incentives, and collective action could advance the framework of this study.

In theory, a socio-psychological framework should be robust to societal context as psychological processes should be able to explain decision-making (Opp, 2009; Van Zomeran et al., 2008). Nonetheless, it is possible that the specific psychological incentives activated by SM may change across social context. As the sample is from a democratic country, we would expect results to generalize better to similar states with less media censorship, such as Germany or Australia. In authoritarian states, since the results of this study may not be generalizable, we may need to re-examine the psychological implications of SM.

Understanding different usages of SM may also be another venue of research. Since this study excluded respondents whose SM activity were against the Sunflower Movement, results are only generalizable to SM activity that is supportive or neutral of the protest. While beyond the scope of this study, it would be interesting to consider how oppositional SM activity relates to psychological incentives, and in turn protest participation or even counter-protest participation.

In addition, there are biographical variables that could be incorporated in the analysis, such as work status, marital status, children, or whether one's friends and family invited them to participate or participated in the movement. Although the effect of such background information could partially be captured in previous political behavior (e.g., whether one is biographically available may be reflected in previous participation in protests or NGOs), including such information could depict complex causal chains, such as how biographical availability affects SM activity and in turn psychological incentives and protest participation.

Finally, as the goal is to examine the younger generation of digital natives, the results better generalize to the younger generation and not to those beyond age 30. This study enriches Milkman's observations on the "digital natives" who characterize the core young participants of a new wave of social movements, such as the young undocumented immigrant "Dreamers," the Occupy Wall Street uprising, the campus movement protesting sexual assault, and Black Lives Matter (Milkman, 2017). Results suggest that the reason why digital natives are increasingly politically active may be due to their heavy use of SM, which creates differences in their psychological processes compared to older generations. Through more studies that pay attention to the psychological impact of societal change, we may better understand why a new generation is increasingly bringing force to the political realm.

Notes

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[1] Because there is no actual count, the estimate is derived from density calculations based on aerial photos (see Cool3c.com, 2014). Note that this is a conservative estimate because it only counts participants in the largest rally on March 31.

[2] Given the 100% Internet penetration rate of people between the ages of 18 and 30 in Taiwan (Taiwan Network Information Center, 2014), we need not worry that those who do not use the Internet are different from those who do use it. However, the respondents differ substantially in terms of their frequency of SM use related to politics, providing variation to examine the relationship between SM and protest participation.

[3] Alternative models without the correlations suggest worse model fit.

References

Bandura A (1977) Self-Efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review* 84(2):191–215.

BBC News (2014) Eric Garner: Why #ICantBreathe is trending. Available from: http://www.bbc.co.uk/newsbeat/article/30326891/eric-garner-why-icantbreathe-is-trending (accessed 7 October 2017).

Beauducel A and Herzberg PY (2006) On the Performance of Maximum Likelihood Versus Means and Variance Adjusted Weighted Least Squares Estimation in CFA. *Structural Equation Modeling* 13(2):186–203.

Bennett WL and Segerberg A (2012) The Logic of Connective Action. *Information, Communication and Society* 15(5):739–68.

Berney LR and Blane DB (1997) Collecting Retrospective Data. *Social Science & Medicine* 45(10):1519–25.

Boulianne S (2015) Social Media Use and Participation: A Meta-Analysis of Current Research. *Information, Communication and Society* 18(5):524–38.

Castells M (2015) *Networks of Outrage and Hope*. Cambridge: Polity Press.

Cool3c.com (2014) http://www.cool3c.com/article/78336. (accessed: 28 June 2017).

Delli Carpini MX (2000) Gen.com: Youth, Civic Engagement, and the New Information Environment. *Political Communication* 17(4): 341–349.

Directorate General of Budget, Accounting and Statistics (2014) http://ebook.dgbas.gov.tw/public/Data/452693633T6LW6MTY.pdf. (accessed: 22 October 2015).

Finkel, SE and Muller EN (1998) Rational Choice and the Dynamics of Collective Political Action. *The American Political Science Review* 92(1):37–49.

Finkel SE. and Rule J (1986) Relative Deprivation and Related Psychological Theories of Civil Violence. *Research in Social Movements, Conflicts and Change* 9: 47–69.

Flaxman S, Goel S and Rao JM (2016) Filter Bubbles, Echo Chambers, and Online News Consumption. *Public opinion quarterly* 80: 298–320.

Freedman DA, Thornton D, Camburn DA and Young L (1988) The Life History Calendar: A Technique for Collecting Retrospective Data. *Sociological Methodology* 18:37–68.

Gutmann A and Thompson DF (1998) *Democracy and Disagreement*. Cambridge, Massachusetts: Harvard University Press.

Hechter M, Pfaff S and Underwood P (2016) Grievances and the Genesis of Rebellion. *American Sociological Review* 81(1):165–89.

Howard, PN and Hussain, MM (2011) The role of digital media. *Journal of Democracy* 22(3): 35–48.

Jenkins JC and Perrow C (1977) Insurgency of the Powerless. *American Sociological Review* 42(2):249–68.

Jung, N, Kim Y and de Zúniga HG (2011) The mediating role of knowledge and efficacy in the effects of communication on political participation. *Mass Communication and Society* 14(4): 407–430.

Juris JS (2012) Reflections on #Occupy Everywhere: Social Media, Public Space, and Emerging Logics of Aggregation. *American Ethnologist* 39(2):259–79.

Kavada A (2015) Creating the Collective: Social Media, the Occupy Movement and Its Constitution as a Collective Actor. *Information, Communication and Society* 18(8):872–

86.

Kharroub T and Bas O (2015) Social Media and Protests: An Examination of Twitter Images of the 2011 Egyptian Revolution. *New Media & Society* 18(9):1973–92.

Klandermans B (1984) Mobilization and Participation: Social-Psychological Expansions of Resource Mobilization Theory. *American Sociological Review* 49(5):583–600.

Klandermans B and de Weerd M (2000) Group Identification and Political Protest. In: Sheldon Stryker S, Owens TJ and White RW (eds) *Self, Identity, and Social Movements*. Minneapolis: University of Minnesota Press, pp. 68-90.

Klandermans B, van der Toorn J and van Stekelenburg J (2008) Embeddedness and Identity. *American Sociological Review* 73(6):992–1012.

Kline RB (2015) *Principles and Practice of Structural Equation Modeling*. Guilford Publications.

Lee N-J, Shah DV and McLeod JM (2013) Processes of political socialization: A communication mediation approach to youth civic engagement. *Communication research* 40(5): 669–697.

Lim M (2012) Clicks, Cabs, and Coffee Houses. *The Journal of Communication* 62(2):231–48.

McAdam D (1990) *Freedom Summer*. Oxford: Oxford University Press.

McAdam D, McCarthy JD and Zald MN (1996) *Comparative Perspectives on Social Movements*. Cambridge: Cambridge University Press.

McCarthy JD and Zald MN (1977) Resource Mobilization and Social Movements. *The American Journal of Sociology* 82(6):1212–41.

McPherson SS (2009) *Tim Berners-Lee: Inventor of the World Wide Web*. Twenty-First Century Books.

Melucci A (1988) Getting Involved: Identity and Mobilization in Social Movements. In: Klandermans B, Kriesi H and Tarrow S (eds) *International Social Movement Research, Volume 1*. Greenwich: JAI Press, pp. 329–348

Milkman R (2017) A New Political Generation: Millennials and the Post-2008 Wave of Protest. *American Sociological Review* 82(1):1–31.

Min, SJ (2007) Online vs. face-to-face deliberation. *Journal of Computer-Mediated Communication* 12(4): 1369–1387.

Moeller J, de Vreese C, Esser F and Kunz R (2014) Pathway to political participation: The influence of online and offline news media on internal efficacy and turnout of first-time voters. *American Behavioral Scientist* 58(5): 689–700.

Morris A (1981) Black Southern Student Sit-in Movement. *American Sociological Review* 46(6):744–67.

Muthén B and Asparouhov T (2002) Latent Variable Analysis with Categorical Outcomes. *Mplus Web Notes* 4(5):1–22.

Noonan RK (1995) Women against the State. *Sociological Forum* 10(1):81–111.

Olson M (1965) *The Logic of Collective Action*. Harvard University Press.

Opp KD (1988) Grievances and Participation in Social Movements. *American Sociological Review* 53(6):853–64.

Opp KD (1998) Does Anti-regime Action Under Communist Rule Affect Political Protest After the Fall? *The Sociological Quarterly* 39(2):189–213.

Opp KD (2009) *Theories of Political Protest and Social Movements*. London: Routledge.

Opp KD and Gern C (1993) Dissident Groups, Personal Networks, and Spontaneous Cooperation. *American Sociological Review* 58(5):659–80.

Opp KD and Kittel B (2010) The Dynamics of Political Protest. *European Sociological Review* 26(1):97–109.

Saunders C, Grasso M, Olcese C, Rainsford E and Rootes C (2012) Explaining Differential Protest Participation: Novices, Returners, Repeaters, and Stalwarts. *Mobilization* 17(3):263–80.

Segerberg A and Bennett WL (2011) Social Media and the Organization of Collective Action. *The Communication Review* 14(3):197–215.

Snow DA, Rochford EB, Worden SK, and Benford RD (1986) Frame Alignment Processes, Micromobilization, and Movement Participation. *American Sociological Review* 51(4):464–81.

Shen WC (1995) *The Applications of Internet Skills of Internet/Fidonet*. Taipei: Songgang.

Smith TW (1984) Recalling Attitudes: An Analysis of Retrospective Questions on the 1982 GSS. *Public Opinion Quarterly* 48(3):639–49.

Taiwan Network Information Center (2014) http://www.twnic.net.tw/download/200307/20140820c.pdf. (accessed: 15 December 2015).

Tajfel H (1974) Social Identity and Intergroup Behaviour. *Information* 13(2):65–93.

Tausch N, Becker JC, Spears R, Christ O, Saab R, Singh P and Siddiqui RN (2011) Explaining radical group behavior: Developing emotion and efficacy routes to normative and nonnormative collective action. *Journal of Personality and Social Psychology* 101(1): 129–148.

Time (2010) Person of the year
http://content.time.com/time/person-of-the-year/2010/ (accessed 1 August 2017)

Time (2011). Person of the year.

http://content.time.com/time/person-of-the-year/2011/ (accessed 1 August 2017)

Tremayne M (2014) Anatomy of Protest in the Digital Era. *Social Movement Studies* 13(1):110–26.

Tufekci Z and Wilson C (2012) Social Media and the Decision to Participate in Political Protest. *The Journal of Communication* 62(2):363–79.

Valenzuela S, Arriagada A and Scherman A (2014) Facebook, Twitter, and Youth Engagement. *International Journal of Communication* 8: 2046–2070.

Van Stekelenburg J and Klandermans B (2013) The Social Psychology of Protest. *Current Sociology* 61(5-6):886–905.

Van Zomeren M, Spears R, Fischer AH and Leach CW (2004). Put Your Money Where Your Mouth Is! Explaining Collective Action Tendencies through Group-Based Anger and Group Efficacy. *Journal of Personality and Social Psychology* 87:649–64.

Van Zomeren M, Postmes T and Spears R (2008) Toward an Integrative Social Identity Model of Collective Action. *Psychological Bulletin* 134(4):504–35.

DIGITAL NETWORK TYPES AND ACTIVISM: THE INTERACTION BETWEEN STRUCTURAL NETWORK POSITIONS, NETWORK TYPES, AND ACTIVISM FORMS IN BLACK LIVES MATTER SACRAMENTO

Abstract

This paper investigates how social media networks affect political engagement through the lens of a structural network perspective. Mapping network relationships and participatory activity using 1.9 million tweets from 1215 Twitter users in Black Lives Matter Sacramento, I demonstrate how social media networks relate to activism engagement. However, the network effects depend on the interaction between structural network positions, type of ties, and forms of activism. Interactional ties have much stronger relationships than informational ties, and effects appear to be stronger for online-only activism than online-mobilized offline activism. Furthermore, the effects of structural network positions can be largely explained by network similarity. The study shows that how a structural network perspective can shed light on understanding innovative forms of political movements.

Introduction

In March 2018, British political firm Cambridge Analytica made the headlines by illegally acquiring profiles of millions of Facebook users, potentially influencing major political campaigns such as the 2016 US president elections (Confessore 2018). Shortly after, Facebook CEO Mark Zuckerberg was called to Congress to testify on the data protection procedures of Facebook, and reforms were proposed to supervise social media like Facebook.

The incident raises the broad question of whether networks on social media can influence users to engage in political action, or social action in general. If network effects are present, what kind of social action does it instigate – do social media networks create digital trends purely online, or do they motivate peoples to offline behavior?

One opportunity to understand the effect of social media networks is through the analysis of African-American mobilization in the United States. Large-scale, extensive mobilization had been largely dormant since the Civil Rights Movement even though inequality between racial groups has persisted or worsened in recent decades. However, in the past few years incidents of police brutality against African Americans have drawn much attention, largely due to efforts by the #BlackLivesMatter movement. As the hashtag suggests, although street protests have occurred in numerous locations in connection with police brutality, the movement was born of social media. Following the deaths of Trayvon Martin, Michael Brown, and Eric Garner, the hashtag #BlackLivesMatter became viral on Twitter, instigating protests everywhere (Freelon, McIlwain, and Clark 2016). In 2018, the killing of Stephon Clark in Sacramento has led many to angrily express their grievances in both online and offline forums (Chavez et al. 2018).

How can a movement that seemed dormant for decades suddenly explode to national attention, and how should we understand the role of social media networks in it? If we can disentangle the network mechanisms by which social media affects political behavior, we may also expect similar mechanisms to be at play in economic or communal behavior.

One approach is to understand how network structures affect social action (Granovetter 1983; Martin 2009; Wellman and Berkowitz 1988), and the perspective has been extended to contentious politics. For example, Gould (1991) formally examined network influence on battalion size and death rates in the Parisian insurrection of 1870, which allows for inquiry into network structures that operates on a supra-individual level. The insight that network structures matter in contentious politics (Diani 2003; Fernandez and McAdam 1988) could shed new light on the so-called "digital activisms" such as Occupy Wall Street (Castells 2015), the Arab Spring (Tufekci and Wilson 2012), or even candidate Donald Trump's usage of Twitter in the 2016 US presidential campaign (Ahmadian, Azarshahi, and Paulhus 2017; Ott 2017).

Studies of digital activism do not ignore the role of networks. Quite the opposite is true; scholars argue that at the heart of social media is the linchpin that users exchange information and personal opinions via online networks (Castells 2015; Bennett and Segerberg 2012; Gerbaudo 2012). Nevertheless, the depiction of how social media networks encourage participation appears to be at odds with past research. Studies of conventional movements have demonstrated how network ties embedded in deep social interaction (hereafter *interactional ties*) facilitate collective action (Morris 1984; McAdam 1986; Pfaff 1996; Taylor 1989). However, scholars who examine digital activism have argued that mobilization via media draws from ties of "the online crowd" (Bennett, Segerberg, and Walker 2014) or "online spectators" (Kavada 2015) who have little interaction history. The literature suggests that social media networks create informational channels that connect users (hereafter *informational ties*), which allow information, memes, and personalized frames to transmit freely and in turn activate engagement.

To build the argument that informational ties generate strong mobilization power, one would have conduct three parts of hypothesis testing: (1) test for a network effect, (2) validate that the effect originates from informational ties rather than interactional ties, and (3) show that the effects encourage users to participate in online-only activism (e.g., e-petitions) as well as offline activism (e.g., street protests). However, most studies examine the *symbolic meanings that flow through networks* (e.g., personalized frames transmitting in networks) rather than *the structure of networks* (e.g., how individuals' structural network positions relate to participation). The orientation of current studies is suitable for delineating possible mechanisms rather than hypothesis testing. Certainly, network meanings and network structures are both theoretically significant (Emirbayer 1997; Mische 2003), but the over-reliance on a cultural paradigm can benefit from the contributions of a *structural network perspective* that allows for theory testing.

This study investigates the interrelationship between structural network positions, type of ties (informational vs. interactional), and forms of activism (online-only vs. online-mobilized offline). Utilizing the case of the Sacramento chapter of Black Lives Matter (hereafter BLM), this study draws from Twitter data on 1.9 million tweets from 1215 users to examine three research questions: (1) What are the structural network positions associated with the different forms of activism? (2) Can network similarity explain the effects of structural network positions? (3) Are there differences in the above processes between interactional ties and informational ties?

Results show that network effects differ according to the structural network positions, type of ties, and form of activism. Contrary to the argument that informational ties provide the basis for mobilization, structural network positions in interactional ties have much larger effects than informational ties. Effects of structural network positions can be explained through network similarity, with the similarity effect of interactional ties larger than that of informational ties. Finally, many network effects are in play in online-only activism but not in online-mobilized offline activism, suggesting that while social media networks can easily motivate people to participate online, it may be much harder to motivate them to engage offline.

Networks, participation, and digital activism

The idea that social networks are intertwined with mobilization can at least be traced to Tilly's (1978) adoption of Harrison White's idea of 'catnets' (category-networks) to describe the "groupness" of actors. Formal or informal, relationships between actors constitute the mobilization roots of collective action (Krinsky and Crossley 2014). Ties to participants and supporters increase the likelihood of movement participation, while ties to nonparticipants and opponents often inhibit the success of mobilization (Gould 1991; Kitts 2000; Passy 2003).

Scholars have identified several mechanisms by which social networks contribute to mobilization. From a rational choice perspective, networks give rise to norms conducive to collective action. Coleman (1988) shows how dense networks overcome the free-rider problem through the creation of norms and sanctioning systems. Opp (2001) pinpoints how social networks create protest norms that incentivize individuals to participate. Second, networks nurture collective identities, as network positions help determine the relevant construction of the self-understanding, thus aligning personal experiences with collective meaning (Polletta and Jasper 2001). Pfaff (1996) illustrates that ties within and between informal groups facilitated a collective identity that enabled the 1989 uprisings in East Germany. Van Stekelenburg (2013) provides evidence on how social embeddedness affects identification and, in turn, emotions contributive to protest participation. Third, early participants coalesced through dense networks can give rise to the formation of the critical mass needed for mass mobilization (Marwell and Oliver 1988; Marwell and Oliver 1993). Centola (2013) further elaborates how small networks create local coalitions to solve the start-up problem and achieve the critical mass. Finally, Jasper and Poulsen (1995) point out that networks provided mediums of framing that provide motivations for recruitment.

In addition to initial mobilization, networks also contribute to the continuity of collective action. As McAdam (1989) posits, participating in social movements creates biographical consequences through the formation of new ties that support activists across movements over time. Taylor's (1989) detailed accounts of the women's movement reveal that the existence of 'abeyance structures' allowed small clusters of activists to provide collective memory of and symbolic links to earlier movement activities, which in turn fostered later generations of activists to rekindle movement issues. Barker (2001) shows that small networks of independent labor activists in the 1970s allowed for the formation of a core which new participants could be recruited in the 1980s.

Whether explaining mobilization or movement continuity, conventional accounts underscore the significance of network relations with strong interaction histories. The network origins of collective action participation burgeon not from a few encounters with acquaintances but from trusted relationships that require histories of personal relationships to nurture. This does not necessarily imply that all participants of a movement know each other well, as small clusters of dense networks could provide the movement foundations that further coordinate into larger collective actions. For example, Morris (1984) shows that the National Association for the Advancement of Colored People was a key "mobilizing structure" that underlay the resurgence of militant challenges to Jim Crow. Taylor's (1989) illustrations of abeyance structures relied on clusters of activists who had frequent interactions with one another. In the case of the East Germany, small informal groups of "trusted friends and associates" horizontally coordinated into large-scale uprisings (Opp and Gern 1993; Pfaff 1996).

Considering the mechanisms by which networks contribute to participation, the evidence on the strength of interactional ties makes sense. Norms and social sanctioning (Coleman 1998; Opp 2001) are most effective from significant others such as close friends. Early pioneers willing to bear additional start-up costs are necessary before thresholds of the critical mass is achieved (Centola 2013; Marwell and Oliver 1993), and only relationships that have a history of interaction can motivate the pioneers to devote commitment. The establishment of collective identity is at its best when social categories and social embeddedness coincide. As Klandermans (2014) points out, since each person has multiple social categories, embeddedness is a key to understand which categories are salient in times of unrest.

Connective action: reimagining networks

Recent studies on digitally-enabled activism have challenged the consensus that social interactions are necessary for network effects. Events such as the Arab Spring or the US presidential campaigns by Obama and Trump have fueled interest in how social media might affect citizens' participation in political affairs. In response, researchers have scrambled to document the effects of social media (Bennett and Segerberg's 2012; Castells 2015; Tufekci and Wilson 2012). The bulk of the research concerns mobilization, as many studies have documented a positive relationship between online activity and protest participation (Earl & Kimport 2011; Valenzuela, Arriagada, & Scherman 2014). Fewer studies have considered the topic of participation over time, but suggest that social media can create lasting effects that persist beyond the initial stages of mobilization (Bennett, Segerberg, and Walker 2014; Freelon, McIlwain, and Clark 2016).

Interestingly, compared to the emphasis on interaction ties in past studies, contemporary theories appear to be centered around the strength of informational ties. Often using the analogy of Wikipedia where contributors peer-produce without necessarily knowing one another, scholars have contended that movements can be initiated and sustained via loosely connected individuals (Bennett and Segerberg 2012; Bennett, Segerberg, and Walker 2014; Juris 2012; Kavada 2015). Juris (2012) proposes the term "logic of aggregation" to describe how social media generates a new collective by aggregating individuals who have little direct social relationships. Bennett, Segerberg, and Walker (2014) name social media participants as the "online crowd" to emphasize the peer-production process of digitally-enabled protests that relieves the necessity of pre-existing relationships. Kavada (2015) coins the term "online spectators" to describe large masses on the virtual space who were instrumental for the sustenance and resonance of the Occupy movement. The argument is best illustrated in Bennett and Segerberg's (2012) theory of "connective action." As they propose, the familiar logic of collective action is associated with high levels of coordination based on "rich histories of social transmission," such as organizations, leaders, or coalitions. On the other hand, social media-enabled "connective action" is based on personalized content sharing across media networks that transcend the boundaries of friends and trusted others. These broadly-spanned informational ties expand the reach of personalized frames and memes, resulting in mass-participation in digital activism.

Despite its emphasis on the power of informational ties, scholars contend that connective action achieves the functionalities of traditional networks, such as fostering norms, nurturing collective identity, or reaching the critical mass. DeLuca, Lawson, and Sun (2012) argue that in the Occupy movement, social media fostered an ethic of participation, thus creating a norm of perpetual participation. Kavada (2015) argues that in Occupy a collective identity was established through social media, enabling online spectators to provide emotional support for offline activists. Harlow (2012) points out that the large number of friends per user on Facebook provides easy access to the critical mass in collective action. Finally, Bennett and Segerberg (2012) argue that personal frames transmit rapidly via online networks, providing the necessary basis for connective action.

Social media networks: data and theoretical concerns

The argument that informational ties are critical in participation in digital activism is appealing, as it suggests that mass mobilization can arise in a short time without necessarily developing long histories of social interaction. Nevertheless, the argument must rest on three pillars: (1) an actual test for a network effect, (2) validation that the effect originates from informational ties rather than interactional ties, and (3) demonstration that the mobilization power motivates users to not only participate in online-only activism, but offline activism as well. Accomplishing these goals requires a *structural network perspective*.

Network scholars have studied social ties from two complementary approaches – the individual approach and the structural approach. Many studies edge towards individualistic accounts of network effects, often assessing network factors from the focal respondent, such as questionnaires or interview transcriptions (e.g., Opp and Gern 1993; Snow, Zurcher and Ekland-Olson 1980; Taylor 1989). Proxies of networks (e.g., self-report on friends' behavior) are utilized to capture network effects. The individual approach usually entails the benefit of surveying on a broad range of personal characteristics, which allows for disentangling effects from various social traits (Klandermans and Oegema 1987) or examining intermediate psychological mechanisms (Opp and Gern 1993; Opp and Kittel 2010). Nevertheless, the individualistic approach also bears the constraint of the inability to observe supra-individual network structures. Building on the insights of Harrison White (2008), scholars have discovered that social relations create structures which have unique implications for social action (Martin 2009; Wellman and Berkowitz 1988). The need to engage in structural network analysis is well articulated by Veenstra et al. (2013). First, data originating from the focal respondent may potentially inflate the magnitude of peer effects owing to exaggeration of similarity to friends in behavior (i.e., a false-consensus bias). Second, unique relationships between network positions and behavior that are not obvious to the individual. For instance, understanding how central the individual is in the network may capture dynamics that are neglected from ego-centric data.

Many studies in contentious politics have followed such a structural network tradition (Diani 2003; Fernandez and McAdam 1988; Rosenthal et al. 1985), but recent evidence on the strength of informational ties is heavily imbalanced towards individualistic data. Juris's (2012) theory draws from observations on activists in Boston. Kavada (2015) relies on interviews to trace processes of network influence. Gil de Zúñiga and Valenzuela (2010) utilize self-report survey data on one's friends' behavior to infer how network ties impact civic engagement. Fortunately, a burgeoning body of work has started to adopt a structural approach. A few studies have noticed that social media networks appear to be of larger size and lower density than face-to-face interactions (Bennett, Segerberg, and Walker 2014; Tang and Lee 2013; Tremayne 2014). Other research has mapped network relationships and examined the narrative and discourse diffusion that arise from such network relationships (Conover et al. 2013; Jackson and Foucault Welles

2016). Building on this approach, the present study not only maps the network relationships, but investigates the correspondence between network structures and participation.

Second, social media may consist of both interactional ties where users have interactional histories, and informational ties where users primarily exchange information. Social circles consist of multiple network types with multiple effects (Granovetter 1983; Gould 1991), but as the term "connective action" can be used to signify both interactional or informational ties, it is difficult to distinguish effects of different network types. This is not to say that interactional ties and informational ties are essentially contradictory (e.g., interactional ties can also transmit information), but distinguishing the two is theoretically important to address the central question of whether loose ties with little interactions can facilitate political participation.

Finally, current theories sow confusion concerning the type of activism being explained. As Earl et al. (2010) contend, the impact of internet media depends on the form of activism being studied. It is important to separate at least two forms – *online-only activism* and *online-mobilized offline activism*. The arena of contention for online-only activism (e.g., raising consciousness online, e-petitions, email campaigns) is in the virtual space of social media. On the other hand, physical participation is often required in events such as March for Science or Occupy, where the goal of online activity is to facilitate offline actions. In McAdam's (1986) words, online-only activism that merely requires one to open his/her smartphone entails much lower risks/costs compared to offline activism which requires participants to take to the streets or confront the police. While the costs are often not as extreme as Freedom Summer or the Arab Spring, the theoretical differentiation of costs/risks remains important and useful to understand the scope conditions of social media effects.

The present study: a structural network perspective

The present study adopts a structural network perspective to understand the relationships between network structures, type of ties, and form of activism.

First, drawing from the perspective of multiple networks (Granovetter 1983; Gould 1991), I differentiate *interactional ties* and *informational ties*.

Second, I distinguish *online-only activism* from *online-mobilized offline activism* (Earl et al. 2010), as the former may conceptually be mapped to low-risk activism while the latter typically requires higher costs/risks.

Third, I draw from the tradition that considers network structures as the basis of social action (Martin 2009; Wellman and Berkowitz 1988). Three types of structural network positions are examined. *Isolates* indicate that the actor has no ties to other. *Centrality* refers to the degree of connectedness of the actor. *Local Clustering* refers to the extent to which the actor's alters are connected to one another. I further examine whether *network similarity* explains the effect of structural network positions, which refers to the process on how the decision to participate is affected by how many tied alters are participating.

Broadly, the approach draws from the Granovetter's (1985) conceptualization that social action is embedded in social relations. Specifically, the literature on networks and political action has extensively discussed the three network positions. *Isolates* distinguish the threshold of having absolutely no ties to others from having at least one tie. Past studies have pointed out that a major barrier for recruitment is the lack of invitations from people with deep interaction history such as friends or relatives, and even one contact can be beneficial for participation (McAdam 1986; Snow, Zurcher and Ekland-Olson 1980).

Centrality, in contrast, measures not the threshold but the degree of connectedness to others[4]. Connectedness to multiple supporters increases participation, while connectedness to non-supporters decreases participation (Kitts 2000; McAdam 1986; Passy 2003; Kim and Pfaff 2012). There may be multiple explanations. Similar to *isolates*, connectedness provides channels of information on recruitment or at least some social support. Second, drawing from social learning theory (Bandura 1977), through observation on the behavior of many supporters one may also be more prone to participate. Third, having a group of friends or relatives of supporters may create social incentives because others expect the actor to participate (Opp and Gern 1993; Opp and Kittel 2010). Finally, connectedness may give rise to identification by creating the social circles that emotionally attach the actor to the group (Klandermans 2014; Pfaff 1996).

Finally, *local clustering* measures the degree in which one's alters are connected to one another and essentially a "clique" effect. Although seldom directly tested, various research suggests that local clustering in interactional ties is an important factor for movement participation. Local clustering may facilitate collective action through the creation and enforcement of norms by generating social restraint and potential sanctioning (Burt 2001; Burt 2009; Coleman 1988). Second, as interactional ties signify relationships that are important for actors, if a small group of actors share common ideas and grievances frequently with one another, it could give rise to collective identity that may be conducive for movement participation (Pfaff 1996; Taylor's 1989).

One mechanism may explain why the three structural network positions relate to participation – the tendency to be behaviorally similar to people one is tied to, or network similarity. Network similarity is often a reinforcing process, as people tend to form ties with people with similar characteristics, and tend to be influenced by tied others. Recent literature has described network similarity in online networks as “filter bubbles” or “echo-chambers” where like-minded users frequently connect to one another (Flaxman 2016; Pariser 2011), but the argument can be traced in the literature. People tend to develop network connections with others who have similar characteristics (McPherson et al. 2001; Lewis et al. 2012), which creates clusters of homophily. Furthermore, mathematical models on social influence show that each individual’s decision to participate is a function of how many ties one has, and whether the tied others participate (Friedkin 2006; Leenders 2002), which further intensifies the process of network similarity. The parsimonious but elegant model has been applied to the social movement literature (Gould 1991) and reveals aspects by which structural network positions may influence participation, such as social incentives (Opp and Kittel 2010), collective identity (Pfaff 1996), or frame transmission (Jasper and Poulsen 1995). The central assumption is that actors draw references from tied alters, which is consistent with the literature on how interactional ties influence opinions, attitudes, and behavior (Kandel 1978; Zimbardo and Leippe 1991). It is plausible that the people who are not isolates, more central in the network, and have a supportive clique are more likely to develop network similarity. These three structural network positions may relate to participation through the process of network similarity.

Data, scope conditions, and methods

Research case: Black Lives Matter Sacramento on Twitter

While the central concern of this study is theoretically broad and could apply to other movements, I choose the BLM movement for the prominent role of social media, especially Twitter, in its mobilization.

The BLM movement began in 2013 following the acquittal of the suspect who shot Trayvon Martin to death, as the hashtag "#BlackLivesMatter" appeared and trended on Twitter. The movement received nationwide attention in 2014 when Michael Brown and Eric Garner were killed by police officers, resulting in protests in Ferguson and other cities across the USA. As more African-American deaths were revealed in the subsequent years, a robust movement to achieve racial justice emerged to worldwide activism (for a detailed historical account, see Freelon et al. 2016a or Lowery 2016). In the process, social media, especially Twitter, created online hubs of the movement and allowed activists to connect with one another. Trending hashtags such as "#BlackLivesMatter", "#ICantBreathe" or "#MichaelBrown" were used to communicate with one another. For instance, at the time of the incident of Eric Garner, more than a million Tweets were recorded using the hashtag "#ICantBreathe" (BBC 2014). Furthermore, BLM founded chapters to connect with issues in different locations. The chapters not only had social media accounts but often organized offline events to increase grassroots support, such as Black history week or public demonstrations.

I choose the Sacramento chapter of BLM for three reasons. First, BLM is a well-known movement that coordinates between online and offline activism, which provides a suitable case to study the impact of online networks. Second, the chapter regularly hosts events in Sacramento (at least two events per month), and information on the events are available on Twitter. Although other chapters may also host local events, the information was not publicly accessible. Thus, the Sacramento chapter allows for a unique opportunity to compare online-only activism with online-mobilized offline activism. Third, incidentally (and unfortunately) after the initial data collection of this study, the killing of Stephon Clark in Sacramento ignited widespread protests, allowing for an exogenous event for a robustness check on the results (see S6 in Supplementary).

Data collection

The time of data collection was June 27-July 2, 2017[5]. The subjects consisted of all 1397 Twitter users who follow @BLMSacramento, the official Twitter account for the chapter. In short, the data consists of a population who are aware of and probably interested in @BLMSacramento, but vary in their degree in formulating online connections and participatory behavior.

I choose Twitter over other social media for the case of BLM due to its significant role in the rise of the movement. I queried the Twitter API to sample all the followers of @BLMSacramento. 1215 users (87%) had at least one publicly available tweet and are included in the analysis. Since the first tweet on @BLMSacramento was posted on November 4, 2015, the analysis only included tweets from November 4, 2015 to June 27, 2017, with a total of 1,935,535 tweets.

Scope conditions

It would be useful to define the scope conditions and targets of inference of this paper. First, this is *not* a paper to explain the rise of BLM Sacramento. Rather, it examines the relationship between social media networks and activism in BLM Sacramento. Although I would discuss some implications on BLM in the discussion, the paper focuses on using the case of BLM Sacramento to understand the general impact of social media networks. Second, the target of inference is *not* all supporters of BLM but the group of people who follow @BLM_Sacramento, which theoretically corresponds to a group of sympathizers to a movement. The paper explains the networks and participation in activism *within this group of sympathizers*. Although networks formed outside this group may be relevant, it is not of primary interest. This is similar to many studies on complete networks that necessitate the drawing of inference boundaries (e.g., studies on classroom networks can only examine networks within classrooms but not cross-classroom friendships).

Third, the strength of this study is the observation of *online network positions* and *online participation*, with limited information on offline actions (although some inferences can be drawn). The issue touches on the data dilemma facing scholars. The optimal method to measure social media networks is through social media data, but it is then difficult to know what users do offline. On the other hand, from survey or interview data it is difficult to map social media relationships between respondents. A better measurement on the dependent variable (e.g., offline participation) is linked to a worse measurement on the independent variable (i.e., social media networks). As mentioned, since most studies utilize survey or interview data (e.g., Juris 2012; Kavada 2015), this study should be viewed as complementary by providing the much lacking structural measure of online networks.

Measures

From the data I operationalize measures of activism and network relationships. To understand the social meaning of Twitter relationships, pretest interviews with 9 Twitter users were recruited through personal networks. The measures below referenced the responses from the pretests. Also see S8 in Supplementary for the pseudo-code on variable operationalization.

Activism

For online-only activism, *BLM Expression* is measured by the number of hashtags (the "#" symbol) on BLM used (#BlackLivesMatter, #blacklivesmatter, #BLM,

#blacklivesmattersacramento). Theoretically, *BLM Expression* corresponds to online activism since there these are general expressions with no conspicuous reference to any offline event.

For online-mobilized offline activism, *BLMSacramento Events* are references to regular offline events hosted by the Sacramento chapter. As mentioned, the Sacramento chapter hosts regular events monthly (e.g., protests, summer activities, parties) that create group support. The events are mobilized through social media, including Facebook and Twitter. Since each event has a Facebook event URL, *BLMSacramento Events* is measured by counting if the user includes these URLs in his/her tweets.

These mentions are proxies rather than direct measures of offline participation. However, a vast amount of studies has demonstrated that online mentioning of an offline event is often correlated with (though not necessary causal of) offline participation (see Boulianne 2015 for a meta-analysis). Although whether the relationship is causal is less clear, the fact that online mentioning of an offline event correlates with offline participation serves the purpose of this study as a proxy instrument, and has been utilized by other studies (e.g., González-Bailón et al. [2010] use Twitter mentions of a protest as indicative of street participation). From another angle, online participation at least measures the intentions to participate in the offline events, and intentions are a good predictor of behavior (Ajzen 1985). Finally, S5 in Supplementary investigates online mentions of Sacramento protests in general (i.e., not restricted to BLM) for auxiliary confidence on results regarding online-mobilized offline activism.

As a side note, this measurement of offline activism is a *favorable* measurement since not all users who tweet about the offline events will necessarily physically participate. However, as seen later in the results, even in such a favorable condition we do not observe many network effects compared to online-only activism. The results provide even more theoretical leverage to understand how the cost of activism affect the relationship between networks and activism.

Network ties

I measure *Informational ties* as following relationships. On Twitter users can follow other users, which indicates that the focal user would then regularly see the tweets of the followed users. A tie is constructed if user *i* follows user *j*. Thus, the relationship indicates that user *i* would receive additional information disseminated from user *j*. However, this does not necessary indicate that the two users have social interaction of any sort.

Following Bond et al. (2012), I measure *interactional ties* as mentioning relationships (the "@" symbol). A tie is constructed if user *i* mentions user *j*, either through direct mentioning or retweeting (examples in Table 1). The relationship indicates that user *i* initiates social interaction with user *j* and signifies a deeper connection between the two users than following. Note that this is a broad definition of interactional ties, since it does not distinguish the frequencies in which users interact (i.e., a weighted network). Results from a weighted network are similar (see S4 in Supplementary).

Conceptually, informational ties and interactional ties are mutually exclusive as they indicate different levels of interaction. Thus, if user *i* follows user *j* but also mentions user *j*, the relationship is operationalized as an interactional tie.

One can test the distinctive validity of network operationalization by examining global structural characteristics. First, compared to informational ties, interactional ties require investment of energy, which limits the number of maintainable ties (Granovetter 1983; Martin 2009). Thus, one would expect the average number of interactional ties to be smaller than informational ties. Second, the transitivity of interactional ties would be higher since interactions lead to social bonding, and friends tend to be friends of friends (Granovetter 1983; Martin 2009). Both expectations are confirmed (see Table 3 later). The average number of interactional ties (4.8) is lower than informational ties (7.2), but the transitivity is higher for interactional ties (0.24) than informational ties (0.14).

Table 1. Examples of user mentioning.

Text	User(s) mentioned
@SenPatRoberts How many tries did it take to make that basket?	SenPatRoberts
@wilw had a nice weekend in San Francisco	wilw
RT @mattdpearce: Look what happened when Politifact tracked down the guy who claimed he found 3 million people who voted illegally	mattdpearce

This study made other data decisions, including using directed interactional ties[6] and dichotomizing the network for comparison purposes[7]. See the corresponding notes for explanations.

One thing to mention is that the analyses include potential Twitter accounts of organizations, such as Black advocacy groups. The main analyses retain such organization-users because they have frequent social contact with some users but not others, and receive information from some but not others. Thus, they still play the role of disseminating participatory information and fostering interactional ties, and removing such entities would miss certain network dynamics. S7 in Supplementary excludes such users, and the results are somewhat different and discussed. In brief, the supplementary results show that such users play a significant role in mobilization, especially on how we perceive the effects of structural network positions, and removing organizations misses important structural network mechanisms.

Structural network positions

For each user, I calculate structural network positions for both interactional ties and informational ties.

Isolates are defined as having no ties.

I measure *Centrality* by eigenvector centrality, which weighs the relational strengths by considering the prominence of who the user is connected to (Bonacich 1987). Simply put, if a user is connected to a well-connected user, the user will be more central compared to a user who is connected with a less-connected user. As explained by Fernandez and McAdam (1988), being connected to individuals who are more centrally located is more important than being connected to people who are in the periphery the former type is linked to many people and are more likely to experience social influence (p. 365).

I measure *Local Clustering* by calculating the local clustering coefficient (Watts and Strogatz 1998), which measures the connectedness of those who have ties with the user. Clustering captures whether the local network of the user is dense. If the user's neighbors have ties with one another, the clustering coefficient is high.

Network similarity

I measure network similarity by the product of the network matrix and activism (i.e., autocorrelation). It captures how one's behavior is associated with the behavior of others which one is tied to.

Number of tweets

The models include the number of tweets for each user to control for more active users. The covariate is logged to account for the extreme skewness.

Analytical strategy

The dataset is aggregated from November 4, 2015 (the first post of @BLMSacramento) to June 27, 2017, and hence resembles cross-sectional rather than longitudinal data. The reason is to trade the ability to sort out temporal sequences to make comparisons between interactional ties and informational ties. While one could identify which user mentioned which users over time, the Twitter API only allows for following relationship information at the time of data collection and not for backtracking. As this article is concerned with both interactional and informational ties, exploring temporal sequences would be a limitation for the main analysis. However, S6 in Supplementary uses another wave of data from July 2, 2017 to March 28, 2018, which also covers the incident of the killing of Stephon Clark on March 18, 2018 and the subsequent protests. Results are similar to the main analysis.

The analytical strategy is as follows. First are network graphics for a first assessment, followed by examining correlations between variables.

The third section tests the core model of how structural network positions are related to activism, and whether network similarity explains the associations. The latter uses extensions of the network autocorrelation model (see Leenders 2002)[8].

As the dependent variables (i.e., tweets that include hashtags or event URLs) are count variables and the number of zeros is large (see Table 2 later), I use a hurdle model (Cragg 1971)[9]. The assumption of a hurdle model is that going from 0 to 1 is a qualitatively different decision from getting from 1 to further positive counts, which is theoretically significant given the literature on thresholds for participation (Granovetter 1978; Marwell and Oliver 1993). Hurdle models estimate two processes: how covariates relate to the decision to participate (i.e., the binomial coefficients), and how covariates associate with the decision to participate more once the individual has participated (i.e., the count coefficients). As this article is concerned with explaining the decision to participate, to prevent overburdening the reader with many tables I present and discuss the count model coefficients in S2 in Supplementary. Also, since online-mobilized offline activism is a rare event (see descriptive statistics later in Table 2), the statistical power to test count model coefficients is limited.

Results

Descriptive statistics

Table 2 presents descriptive statistics. The variables on network similarity are the product of the network matrix and the user behavior. As seen in the high standard deviations of *BLM Expression* and *BLMSacramento Events* compared to their means, there is considerable variability in these activism forms. Also, the percentages of *BLM Expression* and *BLMSacramento Events* that is non-zero are 57% and 4% respectively, indicating that online activism is a relatively common event while online-mobilized offline activism is a rare event. Thus, even for sympathizers of BLM Sacramento, there is considerable variation in activism, structural network positions, and network similarity.

Table 2. Descriptive statistics of variables

Variable	Min	Max	Mean	SD
Activism				
BLM expression	0	566	10.75	37.45
BLMSacramento events	0	50	.15	1.94
Structural network positions				
Interactional Ties				
Isolates	0	1	.28	.45
Eigenvector centrality	0	.19	.02	.09
Local clustering	0	1	.22	.30
Informational Ties				
Isolates	0	1	.09	.29
Eigenvector centrality	0	1	.05	.13
Clustering	0	1	.14	.18
Network Similarity				
Interactional Ties				
BLM expression	0	2896	232.67	413.07
BLMSacramento events	0	98	5.25	10.95
Informational Ties				
BLM expression	0	5859	518.16	684.32
BLMSacramento events	0	118	9.33	15.28
Number of observations: 1215				

Table 3 presents network summary statistics. The densities of the networks are very low, and there are many of isolates, especially for interactional ties. As seen later, isolates play a special role in explaining different forms of activism.

Table 3. Summary of Networks.

	Interactional Ties	Informational ties
Number of actors	1215	1215
Density	.004	.006
Reciprocity	.148	.143
Transitivity	.235	.143
Hierarchy	.691	.531
Connectedness	.509	.811
Mean Indegree	4.857	7.236
(standard deviation)	(19.389)	(21.773)
Mean Outdegree	4.857	7.236
(standard deviation)	(7.061)	(9.667)
Number of isolates	340	114

Visualizing network structures

Figure 1 graphs the network for interactional ties. Red nodes indicate that the user has a non-zero value in *BLM Expression*, purple nodes indicate a non-zero value in *BLM Sacramento Events*, blue nodes indicate that the user participated in both, and grey nodes indicate participation in neither. arrows indicate ties between users.

First, there is only one purple node and much more blue nodes, indicating that if the user participated in *BLMSacramento Events*, the user is also likely to participate in the online-only activism of *BLM Expression*.

Second, there are lots of red nodes but much fewer blue or purple nodes, suggesting that a lot of users participated in online-only activism but not offline events, and consistent with Lichbach's (1998) discussion of the "five percent rule" in that in most movements most supporters do not physically participate.

Third, there are many isolates, and one particularly dense cluster in the bottom of the graph. Furthermore, only one isolate is blue, suggesting that being an isolate has a strong negative association with offline activism. On the other hand, although red nodes seem to be more frequent in the clusters, there are still some red nodes in the isolates.

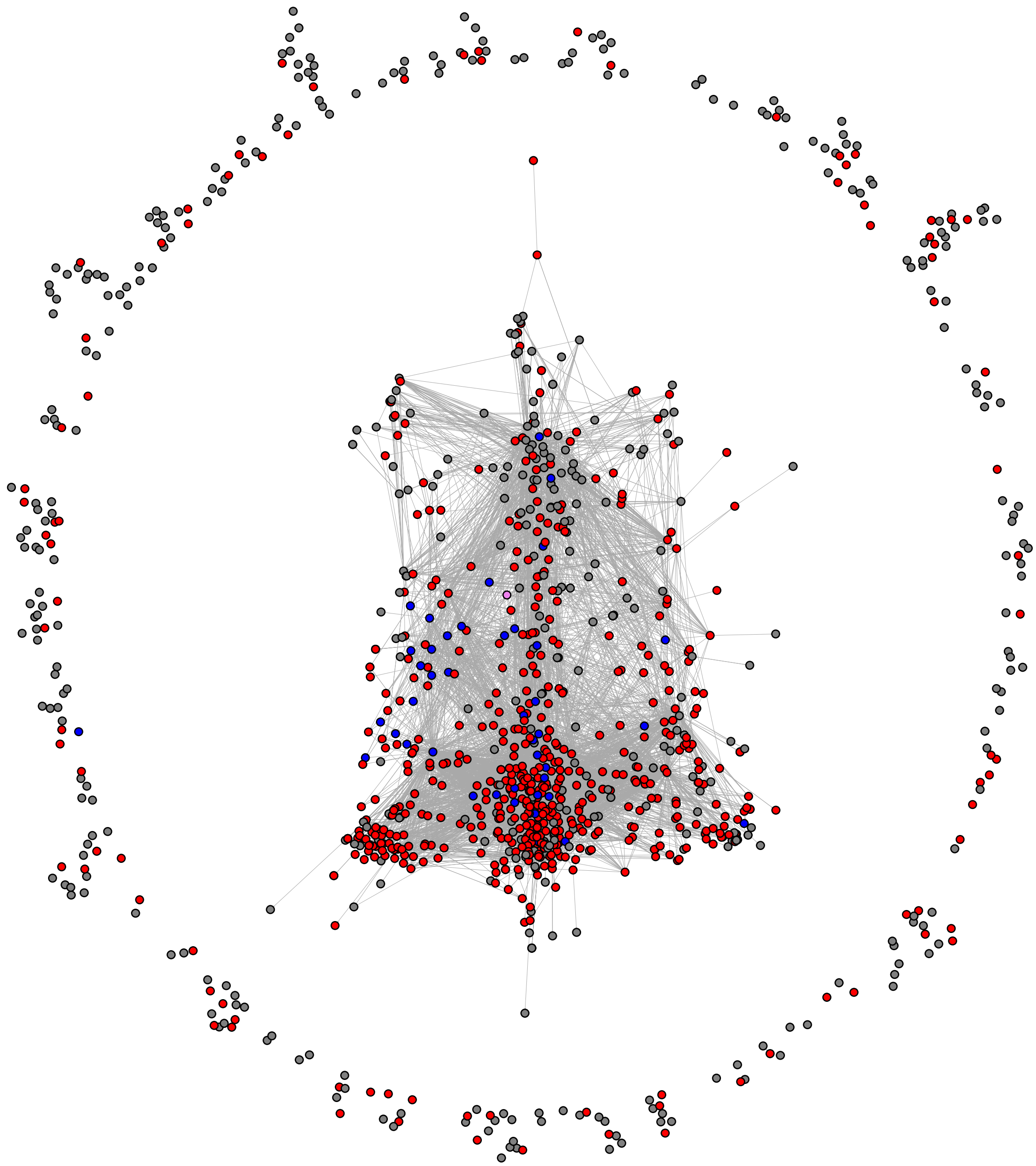

Figure 1. Graph of interactional ties

Figure 2 plots the network for informational ties. One can notice that the number of isolates is much fewer compared to interactional ties. Again, blue and red nodes tend to not be isolates. However, it appears that the proportion of red nodes within isolates is higher compared to interactional ties.

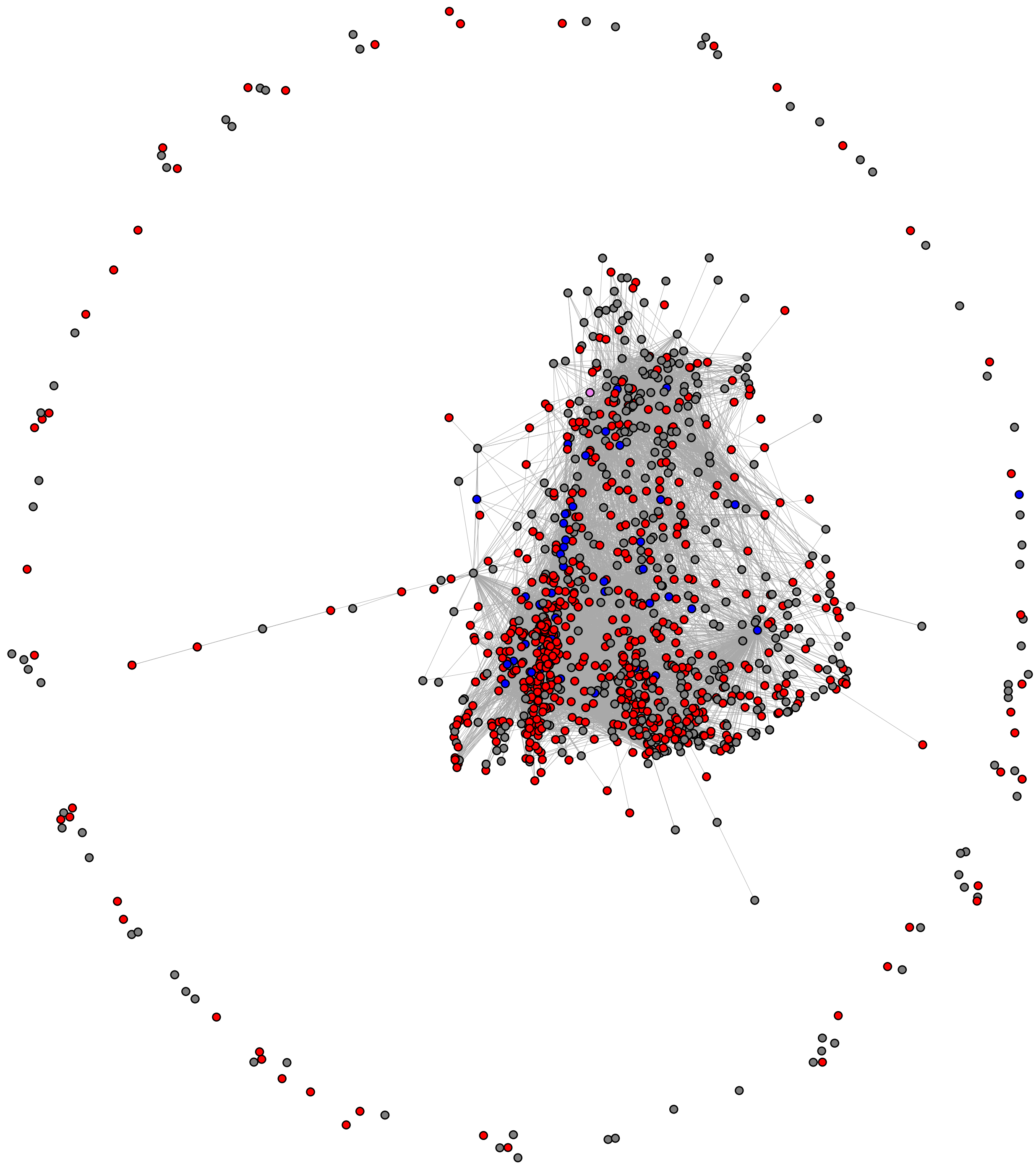

Figure 2. Graph of informational ties.

Correlational analysis

I then assess the strength of association between variables. Since the main concern is to explain participate/not participate in activism, I dichotomize the dependent variables to calculate tetrachoric, biserial, and Pearson correlations (Drasgow 1988) and presented in Table 4. I present Pearson correlations in S1 in Supplementary. The implications are similar although the magnitudes differ.

Regarding the dependent variables, the correlation between *BLM Expression* and *BLMSacramento Events* is .65, which is consistent with the above graphical analysis in that the two types of activism often co-occur.

Regarding independent variables. *BLM Expression* is positively associated with both interactional tie centrality and informational tie centrality, while negatively associated with interactional tie isolate status. However, network similarity from interactional ties appears to be the strongest covariate ($\rho = .52$). *BLMSacramento Events* is positively associated with interactional tie centrality and informational tie centrality, and network similarity from interactional ties also appears to be the strongest predictor ($\rho = .89$). Such results preliminarily suggest that network similarity from interactional ties creates larger incentives for activism regardless of the activism form.

For interactional ties, consistent with the framework that network structures affect network similarity, isolates, centrality, and clustering all have a moderate association with network similarity. For informational ties, we still observe such associations, but the associations are smaller.

Table 4. Tetrachoric, biserial, and Pearson correlations.

	1	2	3	4	5	6	7	8	9	10	11	12
1 BLM Expression	1.00											
2 BLMSacramento Events	.65	1.00										
3 Isolate (Interactional tie)	-.62	-.54	1.00									
4 Centrality (Interactional ties)	.22	.31	-.21	1.00								
5 Clustering (Interactional ties)	.41	.12	-.62	-.04	1.00							
6 Isolate (Informational ties)	-.21	-.29	.17	-.13	-.12	1.00						
7 Centrality (Informational ties)	.29	.23	-.31	.74	.02	-.23	1.00					
8 Clustering (Informational ties)	.01	-.03	.05	-.06	.07	-.45	-.03	1.00				
9 Network similarity: BLM Expression (Interactional ties)	.52	.66	-.47	0.52	.29	-.21	.59	.00	1.00			
10 Network similarity: BLM Expression (Informational ties)	.26	.11	-.08	.24	.06	-.39	.44	.16	.26	1.00		
11 Network similarity: BLMSacramento Events (Interactional ties)	.42	.89	-.40	.25	.26	-.09	.30	-.04	.65	.09	1.00	
12 Network similarity: BLMSacramento Events (Informational ties)	.11	.31	.01	.08	-.03	-.34	.11	.10	.02	.39	-.01	1.00

The core model: Network positions, network similarity, and participation

I next test how structural network positions and network similarity affect different forms of activism. Again, as the primary concern is to explain participation rather than degree of participation after one participates, the binomial model coefficients are reported (see SXX in Supplementary for count model coefficients).

Since the ranges of the variables differ dramatically, covariates are scaled and X-standardized coefficients are presented (i.e., the change in log-odds for one standard deviation increase in the covariate). The standardization allows for comparisons between variables.

I add log of the number of tweets of the Twitter account to control for user activeness. Controlling for the age of the Twitter account yields similar results (not shown but available).

S4 in Supplementary presents robustness checks using a weighted network that considers degrees of interaction. Results are similar.

Network positions and network similarity in BLM Expression

Table 5 presents the results using *BLM Expression* as the dependent variable.

(1) Structural Network Positions

Models 1-3 examine network positions. First we see the role of *isolates* regarding interactional ties. Having no interactional ties has a strong negative effect even when controlling for other characteristics (Models 1 & 3). In contrast, having no informational ties has no statistically significant effect (Models 2 & 3). The results support the framework that being an isolate has a qualitative different threshold effect from connectedness.

Centrality is also associated with online-only activism. As seen in Models 1 & 2, the coefficients for both interactional tie centrality and informational tie centrality are statistically significant, and are marginally significant when controlling for one another (Model 3). Connectedness to a sympathetic group through both interactional and informational ties appears to enhance online-only activism.

Regarding *local clustering*, interactional tie clustering is positively associated with online-only activism (Models 1 & 3), while for informational tie clustering it is not significant and the point estimates are very close to zero (Models 2 & 3). The effect of dense networks appears only in interactional ties.

(2) Explaining network positions through network similarity

Model 4 & Model 5 estimate whether network similarity can explain the structural network positions.

As seen in Model 4, significant network similarity effects were found for both interactional ties and informational ties. However, it appears that similarity effects from interactional ties (β = 2.44) are much larger than informational ties (β = .38). Consistent with the correlation analysis, interactional tie similarity is much more strongly associated with online-only activism.

Model 5 investigates whether network similarity explains the structural tendencies in Models 1-3. The similarity effects of interactional ties and informational ties remain statistically significant, while the effects of almost all the structural network positions are insignificant, except for the negative effect of being an interactional tie isolate. Isolates are unique as it represents a threshold of being connected to the support group that cannot be explained through network similarity.

Table 5. Hurdle autoregressive model on BLM Expression (binomial coefficients).

	Network positions: Interactional Ties	Network positions : Informational Ties	Network positions	Network similarity	Network positions & Network similarity
	Model 1	Model 2	Model 3	Model 4	Model 5
Network Position					
Interactional Ties					
Isolates	-.28***		-.28***		-.21*
	(.08)		(.08)		(.08)
Centrality	.69**		.41+		.05
	(.21)		(.24)		(.27)
Local clustering	.51***		.50***		.13
	(.08)		(.08)		(.09)
Informational Ties					
Isolates		-.07	-.06		-.01
		(.06)	(.07)		(.07)
Centrality		.57***	.26+		-.39*
		(.14)	(.16)		(.18)
Local clustering		.06	.04		-.03
		(.06)	(.07)		(.07)
Network Similarity					
Interactional Ties				2.44***	2.07***
				(.26)	(.28)
Informational Ties				.38***	.50***
				(.09)	(.10)
log(Number tweets)	.39***	.50**	.38**	.41***	.38***
	(.05)	(.04)	(.05)	(.05)	(.05)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Network positions and network similarity in BLMSacramento Events

Table 6 presents the results using *BLMSacramento Events* as the dependent variable. Although the dependent variable is a rare event, S3 in the Supplementary show that the results are robust to influential points.

(1) Structural Network Positions

Models 6-8 examine structural network positions. First is the role of *isolates*. Being an interactional tie isolate has a strong negative effect even when controlling for other network positions (Models 6 & 8). In contrast, being an informational tie isolate has a no statistically significant effect (Models 7 & 8).

Centrality is also associated with *BLMSacramento Events*. Interactional tie centrality has a significant positive effect even when controlling for other interactional tie network positions (Model 6), and a borderline significant effect when controlling for informational tie network positions (Model 8, $p = .05$). However, informational tie centrality has no significant effect once interactional tie network positions are considered (Model 8). Results suggest that only interactional tie centrality is conducive for mobilization for online-mobilized offline activism.

In contrast, neither interactional ties nor informational ties *local clustering* is statistically significantly related to online-mobilized offline activism. The results suggest that the effect of dense local networks does not seem to appear in online-mobilized offline activism.

(2) Explaining structural network positions through network similarity

Models 9 & 10 examine the effects of network similarity and how they explain the structural network positions.

As seen in Model 9, significant network similarity effects were found for both interactional ties and informational ties. However, it again appears that interactional tie similarity effects ($\beta = .70$) are larger than informational tie similarity effects ($\beta = .44$).

Model 10 investigates whether network similarity explains the structural network positions. Similar to results regarding *BLM Expression*, the similarity effects remain statistically significant, while the effects of almost all the structural network positions are insignificant, except the marginal effects of interactional tie isolates and centrality.

Since one may be concerned with the issue of rare events, another robustness check was conducted examining mentions of protests in Sacramento (S5 in Supplementary), which has much more cases of non-zeros. Although such protests may not necessary relate to the issue of BLM, they correspond also to offline activism. Results are similar to Model 10.

Table 6. Hurdle autoregressive model on BLMSacramento Events (binomial coefficients).

	Network positions: Interactional Ties	Network positions : Informational Ties	Network positions	Network similarity	Network positions & Network similarity
	Model 6	Model 7	Model 8	Model 9	Model 10
Network Position					
Interactional Ties					
Isolates	-1.15*		-1.15*		-.91+
	(.47)		(.48)		(.49)
Centrality	.22**		.25+		.23+
	(.08)		(.13)		(.14)
Local clustering	.06		.06		-.01
	(.15)		(.16)		(.19)
Informational Ties					
Isolates		-.41	-.41		-.24
		(.30)	(.30)		(.31)
Centrality		.18+	-.06		-.26
		(.10)	(.17)		(.20)
Local clustering		-.12	-.11		-.01
		(.19)	(.20)		(.23)
Network Similarity					
Interactional Ties				.70***	.66***
				(.09)	(.09)
Informational Ties				.44***	.41***
				(.10)	(.10)
log(Number tweets)	.10	.27*	.08	.22+	-.07
	(.12)	(.11)	(.13)	(.12)	(.14)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Discussion

The case of BLM Sacramento shows that the relationship between social media networks and engagement (whether online or offline) can best be understood through the interrelationship between structural network positions, network similarity, type of ties, and forms of activism. The results have implications in a variety of areas.

Network structures: complementing the individualistic approach

A primary motivation for this paper is to complement current studies through a structural network perspective. Interpersonal relationships create network structures that affect social action (Martin 2009; Wellman and Berkowitz 1988; White 2008), and examining networks through individual recall neglects the structural effects in which isolates, centrality, and clustering affect participation. The results reveal that structural network positions, and the degree of network similarity, matter for explaining both online-only or online-mobilized offline activism.

Being in the position of an interactional tie isolate is a significant barrier to participation, whether it be online-only activism or online-mobilized offline activism. In contrast, no effect was found for informational tie isolates. Results imply that the social meaning embodied by interactional ties identified in previous literature, such as norms (Coleman 1988), social incentives (Opp and Gern 1993) or identification (van Stekelenburg 2013) may still be the primary linkage that translates the network structure into why people participate in social action.

Connectedness as indicated by centrality is another important network position. People with a higher interactional tie centrality are more prone to participate in both online-only activism and online-mobilized offline activism. Consistent with previous research on how connectedness in interactional ties enhances movement participation (Kitts 2000; Morris 1984; Passy 2003), centrality creates a structural condition that motivates individuals to participate, as evinced in Fernandez and McAdam's (1988) theorization on how centrality indicates the "structural availability" of individuals. Thus, not being an isolate creates a first impact on engagement and being more central in the network creates another layer of impact, but such complexities cannot be revealed by examining individualistic data.

In addition to interactional tie centrality, informational tie centrality had a moderate effect on online-only activism but no effect on online-mobilized offline activism. There are individuals at the center of information flow who are more likely to participate, but the effect only appears for online-only activism. One possible explanation is that these are vocal online users that serve as information hubs. A growing literature suggests that a new type of "connective leaders" that operates purely online, such as Facebook administers of movements, is emerging (Della Ratta and Valeriani 2014; Gerbaudo 2012). As the main goal of connective leaders is to recreate, remix, and organize online information, we would find their participation highest in online-only activism and less so in offline activism. Still, qualitative analysis on such information hubs is required in future studies to fully determine the possibility.

Drawing on theories on how dense social networks catalyze norms and collective identity (Coleman 1988; Pfaff 1996), I hypothesized that local clustering creates a third layer of impact (beyond isolates and centrality) on mobilization. The effect was only found in online-only activism but not online-mobilized offline activism. To explain such an incongruence, one may have to consider both the social meaning of ties and the type of activism. Previous literature on how dense interactional ties give rise to collective identity or protest norms assumed face-to-face interactions (Polletta and Jasper 2001; Pfaff 1996; Taylor 1989), but the assumption is removed in digital forms of interaction. From the sociological tradition on how collective meaning is generated through interaction ritual chains (Collins 2014), it is difficult to conceive how virtual interactions could generate comparable emotional power compared to physical exchanges. Diani (2000) explicitly questioned whether digital media can create emotional elements such as collective identity and trust. It is probable that the incentives created by clustering are present but not very strong. Thus, it may generate enough incentives for the low-cost online-only activism, such as expressing emotions of outrage or disgust, but cannot cross the threshold for online-mobilized offline activism.

Effects of structural network positions on participation can be explained by network similarity. The effects of centrality and clustering on activism are diminished once network similarity is considered. Supporting theories of social influence (Friedkin 2006; Leenders 2002), behaviors of tied others appear to be the proximate motivator for activism while network structures may be more distant factors. Furthermore, interactional ties have a much larger similarity effect compared to informational ties, and suggest the primary source of similarity is from interactional ties.

While this paper argues that people embedded in certain network structures are more likely to participate, since the data is cross-sectional a concern would be that network structures form after participation rather than vice versa. Incidentally, seven months after the data was collected, the Sacramento police killed Stephon Clark in Sacramento on March 18, 2018, creating large-scale expression of grievances in Sacramento. S6 in Supplementary uses a second wave of data to better examine temporal sequences, and the results are substantively the same.

Rethinking social media networks: the role of interactional ties versus informational ties

One result that is consistent across models is that interactional ties have larger effects than informational ties. Network effects in informational ties (e.g., centrality on online-only activism) are always present in interactional ties. In contrast, significant interactional tie effects are either insignificant in informational ties (e.g., isolates on online-mobilized offline activism), or the magnitude is much larger (e.g., network similarity on online-only activism). Results are consistent with the perspective that interactional ties embody both social incentives and information while informational ties carry information (Burt 2001; Granovetter 1973), and also with those who argue that networks of social interaction form the basis of engagement (Opp 2001; Pfaff 1996; Taylor 1989).

Such results may be difficult to reconcile with the growing literature on how loosely connected individuals co-produce "connective action" online (Bennett, Segerberg, and Walker 2014; Juris 2012; Kavada 2015). Does this imply that the observations are inaccurate? Notice that the results only test for *direct effects*. It is possible that informational ties affect participation *through interactional ties*. For instance, informational may create one's issue awareness, and through the discussion of critical issues with one's interactional ties does one then decide to participate. However, such complex causal chains require future studies to disentangle.

Moreover, theories on connective action could be further refined by reconsidering what the word "looseness" signifies. One could bring in the perspective of meso-level networks (Hedström et al. 2000), as it is possible that social media enables organizations rather than individuals to be better connected. Perhaps the "looseness" of networks operates at the organizational level, and within organizations pockets of dense interactional ties create the conditions for collective action.

It is also possible that informational ties create unique bridges that are useful for diffusion. As shown by Siegel (2009), the effectiveness of mobilization power depends on a trade-off between network size, density of ties and presence of elites. The "looseness" may refer to critical ties that allow movements to effectively spread between clusters.

The "looseness" could also refer to brokerage ties that enhance innovation (Burt 2001; Burt 2009). As recent studies document various cases where memes, strategies, and cultural framings are constantly negotiated online (Bennett and Segerberg 2012; Castells 2015), perhaps brokerage contributes to the creativity of connective action.

Finally, S2 in Supplementary analyses suggests that informational ties have substantial effects on degree of participation in online-only activism once one has decided to participate. Perhaps interactional ties create conditions to cross the threshold of participation, but informational ties catalyze the degree of participation after the threshold is crossed.

Thinking about forms of digital activism: a cost-threshold perspective

Echoing Earl et al. (2000), the effects of network structures and network similarity depend on the type of activism.

Many significant network effects were found in online-only activism but not in online-mobilized offline activism (e.g., informational tie isolates), or the point estimates are smaller (e.g., network similarity). Note again that these results are under a *favorable measure* of online-mobilized offline activism, which speaks more to how network effects depend on the cost of activism. Drawing from the sociological perspective that engagement depends on costs and critical thresholds (Granovetter 1978; Marwell and Oliver 1993; McAdam 1986), the threshold for participation may be higher for offline forms of activism, as seen in the much larger number of non-participants in *BLMSacramento Events* compared to *BLM Expression*. Furthermore, it may also be fruitful to understand digital activism in the light of biographical availability (McAdam 1986; Wiltfang and McAdam 1991). Digital media allows users to transcend geographical limitations and participate in their free time, which reduces the biographical constraints of activism. However, such advantages are greatly reduced in online-mobilized offline activism. Even though one can receive social influence and information online, to participate one would need to be physically present at the specific time of the event. In contrast, for online-only activism one can comment and spread information on BLM basically at will. Thus, when stating the influential power of social media networks, one should be cautious on defining the type of social action. Whereas online networks may be powerful in online-only forms of activism, the impact may be much smaller in offline forms of activism. The results may also explain why a younger generation of "digital natives" are more prone to be influenced by social media rather than older generations (Milkman 2017), as their biographical availability may be relatively higher due to fewer family or workplace restrictions.

This perspective allows us to better comprehend the mobilization process of BLM. BLM astutely recognized the importance of interactional ties, and the higher threshold for offline activism. Even though BLM already had considerable attention on Twitter, the movement still established local chapters which hosted physical-offline events. As organizational affiliation generates interactional ties (Morris 1984; Opp and Gern 1993), such local chapters strengthened network effects for mobilization, which may be particularly useful in times where street demonstrations with higher costs are needed, such as the protests after the Clark killing. Furthermore, since people who participate online are easier to mobilize offline (Tufekci and Wilson 2012; Valenzuela, Arriagada and Scherman 2014), local chapters create the social conditions for such a sympathetic population to transform into participants. For instance, the BLM Sacramento chapter quickly mobilized protestors in the wake of the Stephon Clark shooting that stirred massive grievances. Echoing research on how multi-networks create additional mobilization power (Gould 1991; McAdam 1986), layering online networks with offline networks may be the best strategy to support offline activism.

Limitations

This study encountered limitations that may be addressed in future research. One obvious limitation is that this study opts for a structural network approach, and therefore does not examine the frames, memes, and symbolic meanings that flow through the networks. Understanding how cultural meanings interact with structural network positions would be an invaluable step for future research.

Also, the choice of better measurements on networks is intricately linked to indirect measurements on offline activism. While there are reasons to believe in the proxies, future studies that utilize survey data and trace social media accounts, even for small groups, would be more complete than the present study.

Regarding the generalizability of this study, since Twitter users tend to be younger (Duggan and Brenner 2013), the results may be particularly relevant for other movements that involve the younger "digital natives" (Milkman 2017), such as the Dreamers immigration movement or Occupy, and less true of more conventional interest-group mobilization drawing older participants.

Although this study examined some temporal processes with a second wave of data in S6 in Supplementary, to tease out long-term dynamics more time periods would be needed. From only two waves of data limited ability is available to rigorously test causal effects.

Conclusion

This paper started with the general question about how to understand social media networks in both online and offline engagement, which has applications in political support, organizational recruitment, or economic behavior. While the specific statistics of this study would not be generalizable, a structural network approach sheds lights on broader areas in at least three ways.

First, social media networks consist of multiple types that cannot be lumped into the general terminology of “online networks”. Following the tradition of how multiple networks perform distinctive functions (Granovetter 1983; Gould 1991), this study shows how interactional ties and informational ties each have distinctive effects. One could hypothesize that multiple social media networks would not only be at play in digital activism but digitally-enabled social action in general.

Second, to understand social media network effects one would need to differentiate structural network positions. Isolates, centrality, and clustering each have distinctive effects. Saying that networks matter is uninformative compared to pinpointing which network structures generate effects on social action. Understanding the role of social media networks in contemporary social action may require scholars to decompose network structures, which demonstrates how a tradition of network studies (Martin 2009; Wellman and Berkowitz 1988) may be particularly useful.

Third, the cost-threshold perspective in this study is also useful in understanding other types of digitally-enabled social action, as it shows the limits of social media networks. Social media networks may be extremely powerful in facilitating low-cost online action (e.g., editing on Wikipedia), but much less so in motivating high-cost offline action (e.g., volunteering at an NGO). Social media networks create the exposure, but offline networks, social sanctions or other social contexts may be needed for individuals to engage in actions of higher cost.

Social media networks create new opportunities for social action. However, it may be the interaction between structural network positions, network types, and action thresholds that influence whether social media networks can be politically powerful.

References

Ahmadian, Sara, Sara Azarshahi, and Delroy Paulhus. 2017. “Explaining Donald Trump via Communication Style.” *Personality and Individual Differences* 107:49–53.

Ajzen, Icek. 1985. “From Intentions to Actions: A Theory of Planned Behavior.” Pp. 11–39 in *Action Control*. Berlin: Springer.

BBC News. 2014. “Eric Garner: Why #ICantBreathe Is Trending.” Retrieved October 7, 2017 (http://www.bbc.co.uk/newsbeat/article/30326891/eric-garner-why-icantbreathe-is-trending).

Bandura, Albert. 1977. *Social Learning Theory*. Englewood Cliffs, NJ: Prentice-Hall.

Barker, Colin. 2001. “Fear, Laughter, and Collective Power.” Pp. 175–94 in *Passionate politics: Emotions and social movements*, edited by J. Goodwin, J. J. M., and F. Polletta. Chicago: University of Chicago Press.

Bennett, W. Lance and Alexandra Segerberg. 2012. “The Logic of Connective Action.” *Information, Communication and Society* 15(5):739–68.

Bennett, W. Lance, Alexandra Segerberg, and Shawn Walker. 2014. “Organization in the Crowd: Peer Production in Large-Scale Networked Protests.” *Information, Communication and Society* 17(2):232–60.

Bonacich, Phillip. 1987. “Power and Centrality: A Family of Measures.” *The American Journal of Sociology* 92(5):1170–1882.

Bond, Robert M., Christopher J. Fariss, Jason Jones, Adam Kramer, Cameron Marlow, Jaime Settle, James Fowler. 2012. "A 61-Million-Person Experiment in Social Influence and Political Mobilization." *Nature* 489(7415): 295.

Boulianne, Shelley. 2015. "Social Media Use and Participation: A Meta-Analysis of Current Research." *Information, Communication and Society* 18(5):524–38.

Burt, Ronald S. 2001. "Structural Holes versus Network Closure as Social Capital." Pp. 31–56 in *Social Capital*, edited by N. Lin and K. S. Cook. New Brunswick, NJ: Transaction Publishers.

Burt, Ronald S. 2009. *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Castells, Manuel. 2015. *Networks of Outrage and Hope*. Cambridge: Polity.

Centola, Damon. 2013. "Homophily, Networks, and Critical Mass." *Rationality And Society* 25(1):3–40.

Chavez, Nashelly, Tony Bizjak, Cathy Locke, Ryan Lillis and Hudson Sangree. 2018 "Protesters of police shooting shut down I-5 and block entry to Sacramento Kings game." *The Sacramento Bee March 22, 2018*. Retrieved from:
https://www.sacbee.com/news/local/crime/article206473869.html

Coleman, James. 1988. "Social Capital in the Creation of Human Capital." *American Journal of Sociology* 94: S95–120.

Collins, Randall. 2014. *Interaction Ritual Chains*. Princeton: Princeton University Press.

Confessore, Nicholas. 2018. "Cambridge Analytica and Facebook." *The New York Times April 4, 2018*. Accessed:
https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html

Conover, Michael D, Clayton Davis, Emilio Ferrara, Karissa McKelvey, Filippo Menczer, and Alessandro Flammini. 2013. "The Geospatial Characteristics of a Social Movement Communication Network." *PloS One* 8(3):e55957.

Cragg, John G. 1971. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." *Econometrica* 39(5):829–44.

Della Ratta, Donatella and Augusto Valeriani. 2014. "Remixing the Spring! Connective Leadership and Read-Write Practices in the 2011 Arab Uprisings." Pp. 288–304 in *Communication Rights and Social Justice*. London: Palgrave Macmillan.

DeLuca, Kevin M., Sean Lawson, and Ye Sun. 2012. "Occupy Wall Street on the Public Screens of Social Media." *Communication, Culture & Critique* 5(4):483–509.

Diani, Mario. 2000. "Social Movement Networks Virtual and Real." *Information, Communication and Society* 3(3):386–401.

Diani, Mario and Doug McAdam. 2003. *Social Movements and Networks*. Oxford: Oxford University Press.

Drasgow, Fritz. 1988. "Polychoric and Polyserial Correlations." *Encyclopedia of Statistical Sciences*.

Duggan, Maeve and Joanna Brenner. 2013. *The Demographics of Social Media Users, 2012*. Pew Research Center's Internet & American Life Project Washington, DC.

Earl, Jennifer and Katrina Kimport. 2011. *Digitally Enabled Social Change*. Cambridge, MA: MIT Press.

Earl, Jennifer, Katrina Kimport, Greg Prieto, Carly Rush, and Kimberly Reynoso. 2010. "Changing the World One Webpage at a Time." *Mobilization* 15(4):425–46.

Emirbayer, Mustafa. 1997. "Manifesto for a Relational Sociology." *American Journal of Sociology* 103(2):281–317.

Fernandez, Roberto M. and Doug McAdam. 1988. "Social Networks and Social Movements: Multiorganizational Fields and Recruitment to Mississippi Freedom Summer." *Sociological Forum* 3(3):357.

Flaxman, Seth, Sharad Goel, and Justin M. Rao. 2016. "Filter Bubbles, Echo Chambers, and Online News Consumption." *Public Opinion Quarterly* 80(S1):298–320.

Freelon, Deen, Charlton D. McIlwain and Meredith Clark. 2016. "Beyond the Hashtags: #Ferguson, #Blacklivesmatter, and the Online Struggle for Offline Justice." Center for Media & Social Impact, American University. Available at SSRN: https://ssrn.com/abstract=2747066 or http://dx.doi.org/10.2139/ssrn.2747066

Friedkin, Noah E. 2006. *A Structural Theory of Social Influence*. New York: Cambridge University Press.

Gerbaudo, Paolo. 2012. *Tweets and the Streets*. London: Pluto Press.

Gil de Zúñiga, Homero and Sebastián Valenzuela. 2010. "The Mediating Path to a Stronger Citizenship." *Communication Research* 38(3):397–421.

González-Bailón, Sandra, Javier Borge-Holthoefer, Alejandro Rivero, and Yamir Moreno. 2011. "The Dynamics of Protest Recruitment through an Online Network." *Scientific Reports* 197.

Gould, Roger V. 1991. “Multiple Networks and Mobilization in the Paris Commune, 1871.” *American Sociological Review* 56(6):716–29.

Graham, Timothy, Robert Ackland, and Chung-Hong Chan. 2017. “SocialMediaLab: Tools for Collecting Social Media Data and Generating Networks for Analysis.”

Granovetter, Mark S. 1973. “The Strength of Weak Ties.” *American Journal of Sociology* 78(6):1360–80.

Granovetter, Mark. 1983. “The Strength of Weak Ties: A Network Theory Revisited.” *Sociological Theory* 1: 201–33.

Granovetter, M., 1985. “Economic Action and Social Structure.” *American Journal of Sociology* 91: 481–510.

Harlow, Summer. 2012. “Social Media and Social Movements.” *New Media & Society* 14(2): 225–43.

Hedström, Peter, Rickard Sandell, and Charlotta Stern. 2000. “Mesolevel Networks and the Diffusion of Social Movements.” *American Journal of Sociology* 106(1):145–72.

Jackson, Sarah J. and Brooke Foucault Welles. 2016. “# Ferguson Is Everywhere: Initiators in Emerging Counterpublic Networks.” *Information, Communication and Society* 19(3): 397–418.

Jasper, James M. and Jane D. Poulsen. 1995. “Recruiting Strangers and Friends: Moral Shocks and Social Networks in Animal Rights and Anti-Nuclear Protests.” *Social Problems* 42(4):493–512.

Juris, Jeffrey S. 2012. “Reflections on #Occupy Everywhere.” *American Ethnologist* 39(2):259–79.

Kandel, Denise B. 1978. “Homophily, Selection, and Socialization in Adolescent Friendships.” *American Journal of Sociology* 84(2):427–36.

Kavada, Anastasia. 2015. “Creating the Collective.” *Information, Communication and Society* 18(8):872–86.

Kim, Hyojoung and Steven Pfaff. 2012. “Structure and Dynamics of Religious Insurgency: Students and the Spread of the Reformation.” *American Sociological Review* 77(2):188–215.

Kitts, James. 2000. “Mobilizing in Black Boxes.” *Mobilization* 5(2):241–57.

Klandermans, Bert and Dirk Oegema. 1987. “Potentials, Networks, Motivations, and Barriers: Steps Towards Participation in Social Movements.” *American Sociological Review* 52(4):519–31.

Klandermans, Pieter G. 2014. “Identity Politics and Politicized Identities.” *Political Psychology* 35(1):1–22.

Krinsky, John and Nick Crossley. 2014. “Social Movements and Social Networks.” *Social Movement Studies* 13(1):1–21.

Leenders, Roger T. A. J. 2002. “Modeling Social Influence through Network Autocorrelation.” *Social Networks* 24(1):21–47.

Lewis, Kevin, Marco Gonzalez, and Jason Kaufman. 2012. “Social Selection and Peer Influence in an Online Social Network.” *Proceedings of the National Academy of Sciences* 109(1): 68–72.

Lowery, Wesley. 2016. *They Can’t Kill Us All: Ferguson, Baltimore, and a New Era in America's Racial Justice Movement*. New York: Little, Brown and Company.

Martin, John Levi. 2009. *Social Structures*. Princeton: Princeton University Press.

Marwell, Gerald and Pamela Oliver. 1993. *The Critical Mass in Collective Action*. New York: Cambridge University Press.

Marwell, Gerald, Pamela E. Oliver, and Ralph Prahl. 1988. “Social Networks and Collective Action: A Theory of the Critical Mass. III.” *American Journal of Sociology* 94(3):502–34.

McAdam, Doug. 1986. “Recruitment to High-Risk Activism: The Case of Freedom Summer.” *American Journal of Sociology* 92(1):64–90.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. “Birds of a Feather: Homophily in Social Networks.” *Annual Review of Sociology* 27(1):415–44.

Milkman, Ruth. 2017. “A New Political Generation: Millennials and the Post-2008 Wave of Protest.” *American Sociological Review* 82(1):1–31.

Mische, Ann. 2003. “Cross-Talk in Movements: Reconceiving the Culture-Network Link.” Pp. 258–80 in *Social Movements and Networks,* edited by M. Diani and D. McAdam. New York: Oxford University Press.

Morris, Aldon D. 1984. *The Origins of the Civil Rights Movement*. New York: The Free Press.

Opp, Karl-Dieter. 2001. “Social Networks and the Emergence of Protest Norms.” Pp. 234–73 in *Social norms,* edited by M. Hechter and K.-D. Opp. New York: Russell Sage Foundation.

Opp, Karl-Dieter and Christiane Gern. 1993. “Dissident Groups, Personal Networks, and Spontaneous Cooperation.” *American Sociological Review* 58(5):659–80.

Opp, Karl-Dieter and Bernhard Kittel. 2010. “The Dynamics of Political Protest.” *European Sociological Review* 26(1):97–109.

Ott, Brian L. 2017. “The Age of Twitter: Donald J. Trump and the Politics of Debasement.” *Critical Studies in Media Communication* 34(1):59–68.

Passy, Florence. 2003. “Social Networks Matter. But How.” Pp. 21–48 in *Social movements and networks: Relational approaches to collective action*, edited by M. Diani and D. McAdam. Oxford: University Press Oxford.

Pfaff, Steven. 1996. “Collective Identity and Informal Groups in Revolutionary Mobilization: East Germany in 1989.” *Social Forces* 75(1):91–117.

Polletta, Francesca and James M. Jasper. 2001. “Collective Identity and Social Movements.” *Annual Review of Sociology* 27(1):283–305.

Rosenthal, Naomi, Meryl Fingrutd, Michele Ethier, Roberta Karant, and David McDonald. 1985. “Social Movements and Network Analysis.” *American Journal of Sociology* 90(5):1022–54.

Siegel, David A. 2009. “Social Networks and Collective Action.” *American Journal of Political Science* 53(1):122–38.

Snow, David A., Louis A. Zurcher, and Sheldon Ekland-Olson. 1980. “Social Networks and Social Movements: A Microstructural Approach to Differential Recruitment.” *American Sociological Review* 45(5):787–801.

Tang, Gary and Francis L. F. Lee. 2013. “Facebook Use and Political Participation.” *Social Science Computer Review* 31(6):763–73.

Taylor, Verta. 1989. “Social Movement Continuity: The Women’s Movement in Abeyance.” *American Sociological Review* 54(5):761–75.

Tremayne, Mark. 2014. “Anatomy of Protest in the Digital Era.” *Social Movement Studies* 13(1):110–26.

Tufekci, Zeynep and Christopher Wilson. 2012. “Social Media and the Decision to Participate in Political Protest: Observations From Tahrir Square.” *Journal of Communication* 62(2):363–79.

Valenzuela, Sebastián, Arturo Arriagada, and Andrés Scherman. 2014. “Facebook, Twitter, and Youth Engagement.” *International Journal of Communication* 8:2046–70.

Van Stekelenburg, Jacquelien. 2013. “The Political Psychology of Protest.” *European Psychologist* 18(4):224.

Veenstra, René, Jan Kornelis Dijkstra, Christian Steglich, and Maarten H. W. Van Zalk. 2013. “Network–Behavior Dynamics.” *Journal of Research on Adolescence* 23(3):399–412.

Watts, D. J. and S. H. Strogatz. 1998. “Collective Dynamics of ‘Small-World’ Networks.”

Nature 393(6684):440–42.

Wellman, Barry and S. D. Berkowitz. 1988. *Social Structures*. Cambridge, MA: Cambridge University Press.

White, Harrison C. 2008. *Identity and Control*. Princeton: Princeton University Press.

Wiltfang, Gregory L. and Doug McAdam. 1991. “The Costs and Risks of Social Activism.” *Social Forces* 69(4):987–1010.

Zeileis, Achim, Christian Kleiber, and Simon Jackman. 2008. “Regression Models for Count Data in R.” *Journal of Statistical Software* 27(8):1–25.

Zimbardo, Philip G. and Michael R. Leippe. 1991. *The Psychology of Attitude Change and Social Influence*. New York: Mcgraw-Hill Book Company.

Notes

[4] As the concern of this paper is participation rather than brokerage, I follow Fernandez and McAdam (1988) and use eigenvector centrality rather than betweenness centrality.

[5] I used *R* package *SocialMediaLab* (Graham et al. 2017) for data collection.

[6] One may wonder whether only users that mention or follow one another are considered relationships (i.e., reciprocal mentioning/following, or undirected ties). This study decided to use directed ties rather than undirected ties for two reasons. Pretest results suggest that certain friendships reflect as asymmetrical mentioning relationships online because some do not have the habit of mentioning others. For example, if a group of friends go hiking together and share the experience on Twitter, often a few users would post and mention others, while others may or may not mention back. Excluding such relationships may bias estimates of network structures, especially local clustering. Second, from the perspective of social influence, if one user frequently mentions another, the user spends a certain amount of time/energy on the mentioned user and is prone to be influenced.

[7] Since informational ties here are binary networks (follow/not follow), to facilitate comparisons on network characteristics between interactional and informational ties (e.g., global density, global transitivity, local clustering, etc.), the interactional tie network is also categorized as a binary network (mention/not mention). However, one might anticipate that people may draw stronger influence from those whom they interact more with. S4 in the Supplementary presents models that use such a weighted network for influence. Results are similar, but fit statistics suggest that the current model has a better fit.

[8] The model parameterizes $g(Y) = \rho WY + \beta X + \gamma * \log(\text{NTweets}) + \epsilon$

$g(Y)$ is the dependent variable via a link function.

ρ is the autocorrelation parameter that indicates network similarity.

β are the regression coefficients for the structural network characteristics X.

γ is the coefficient for the log of the number of tweets.

ϵ represents the residuals.

The model estimates an effect from structural network characteristics (X) and an effect resulting from network autocorrelation (WY). The intuition is that since WY is the product of the network matrix and the dependent variable, it captures how one's behavior (Y) is related to behavior of all the tied others (WY) and essentially network dependency.

[9] *R* package *pscl* (Zeileis et al. 2008).

EVALUATING THE MOBILIZATION EFFECT OF ONLINE POLITICAL NETWORK STRUCTURES: A COMPARISON BETWEEN THE BLACK LIVES MATTER NETWORK AND IDEAL TYPE NETWORK CONFIGURATIONS

Abstract

Do online networks encourage political participation? Much research has theorized on how digital networks transmit mobilizing content, fewer studies examine the structure of online networks, and even fewer test how the structure of online networks affects participation for political behaviors with differing costs. From a structural network perspective, I highlight the puzzle: If according to recent literature, digital networks are loose with many weak ties, how can such a network configuration facilitate high-cost political behavior that requires multiple social reinforcements?

I map the following relationships among 655 Twitter users who follow the Black Lives Matter Sacramento chapter, and compare the structure of the digital network to three commonly-observed ideal type networks. The results show that the digital network is structurally distinct from the ideal types, as it is characterized by an extremely dense cluster but also with many loosely connected components, which I describe as a "Cluster-Connective network." Results from computer experiments further show that paradoxically, this "Cluster-Connective" configuration benefits participation for high-cost behavior, but hinders participation for low-cost behavior. The results illustrate how a structural network perspective helps scholars move from the question of whether digital networks facilitate participation to the conditions under which digital networks encourage participation.

Introduction

In 2011, protestors occupied Zuccotti Park to call on the government to listen to "the 99 percent." In the same year, Egyptians rallied in Tahrir Square to demand the overthrow of the Mubarak government. The growth of the #MeToo movement online raised public awareness of gender inequality. Despite each movement's differing goals, one can see the frequent use of social-networking platforms such as Facebook, Twitter, or Instagram (Castells 2015; Tufekci and Wilson 2012).

Despite initial skepticism (Gladwell 2010), scholars generally agree that social-networking sites played a major role in mobilizing participation (Hsiao 2018; Valenzuela, Arriagada and Scherman 2014; Vasi and Suh 2016), and theories have been proposed to explain the effects (for an excellent review, see Poell and van Dijck 2018). Further scrutiny reveals that these theories draw heavily on the concept of social networks. Bennett and Segerberg (2012: 748) encapsulate these arguments: "the emerging alternative model that we call the logic of connective action applies increasingly to life in late modern societies in which formal organizations are losing their grip on individuals, and group ties are being replaced by *large-scale, fluid social networks*."

More generally, the issue of how social-networking sites affect movement mobilization is a case of how online networks affect behavioral participation, especially political behaviors with different costs. The presence of online networks has been observed not only in protests, but also in community building (Kavanaugh and Patterson 2001), presidential campaigns (Ott 2017), or even jihadist groups (Klausen 2015). Given its broad relevance, many are interested in the question of *whether online networks always benefit participation*. If there are limitations to the mobilizing power, *what are the limiting conditions*?

Current theories commonly view social media networks as a medium for other processes such as transmission of information (Tufekci and Wilson 2012), interchange of personalized frames (Bennett and Segerberg 2012), or collective identity production (Kavada 2015). These theories closely mirror sociological research of how informational provision (McAdam 1986), framing (Snow et al. 1986), and collective identity (Pfaff 1996) benefit mobilization.

While such theories mostly focus on the content transmitted via online networks and the elucidation of cultural meanings that flow through them (echoing Emirbayer 1997; Mische 2003), an equally important issue is investigating how network configuration—network structure—influences network effects. In particular, networks can have favorable or detrimental effects for participation, depending on their configuration (Bearman and Everett 1993; Centola and Macy 2007; Marwell, Oliver and Prahl 1988). Incorporating that knowledge in studies of online networks shifts the question from *whether* online networks facilitate mobilization to *the conditions* under which such networks facilitate mobilization.

Burgeoning research has described patterns that arise from observed online network structures (Aral and Walker 2012; Goel et al. 2012; González-Bailón et al. 2013). However, a looming difficulty in establishing structural network effects is the lack of comparison groups. In a clinical experiment, one can assign subjects to a treatment group and a comparison group and establish the treatment effect. However, when the network structure is the treatment, it is nearly impossible to find the control group since we cannot artificially force humans to alter their relationships. The present study concurs with the perspective that online network structures are important, but differs from previous research by not describing patterns but *generating comparisons*. To be specific, I compare the structure of an empirical online network with *simulated networks* that have been commonly observed in the empirical world. These simulated networks serve as the comparison groups that facilitate the inquiry into whether the structure of the online network facilitates participation. Furthermore, since online networks can be used to mobilize many political behaviors, I experiment with behaviors of different costs and investigate for which behaviors would the observed online network structure facilitate diffusion.

The study of online networks can also contribute to the literature on simulated experiments as well. As most derive general propositions from simulations of hypothetical scenarios (Heckathorn 1993; Kim and Bearman 1997; Marwell, Oliver and Prahl 1988), it is useful to complement these exercises with empirical data. One of the opportunities afforded by the emergence of social-networking sites is the access to individual-level network data that have proved difficult to collect in past studies. Data from online networks facilitates understanding of the network structure. Simulations enable testing of a variety of scenarios and identify when network structures are conducive to participation. Combined together, one can test the conditions under which the online network structure benefits participation.

The value of data-informed simulations is evident when investigating the puzzle of *loose networks with strong mobilization power*. If, as some suggest, social media networks are loose with many weak ties (Bennett, Segerberg, and Walker 2014; Juris 2012; Kavada 2015), how can such configurations facilitate high-cost participatory behavior that requires dense ties and multiple social reinforcements (Centola and Macy 2007; Granovetter 1978; Kim and Pfaff 2012; Kitts 2000)?

The present study investigates the relationship between digital network configuration and political participation in the case of Twitter use by the Sacramento chapter of the Black Lives Matter Movement (hereafter BLM). I use BLM as my focal case because BLM is a significant social issue on racial justice, and because it is a prominent movement that heavily utilizes

Twitter (Freelon, McIlwain, and Clark 2016). Furthermore, it is a movement that encompasses behaviors of different costs, such as online hashtag movements, letters to senators, or political rallies. These characteristics make BLM a case that can generate implications for the effect of online networks on different types of political behavior.

The study draws on data from 655 Twitter users who follow the Sacramento chapter and analyzes their following network. The overarching goal is straightforward—if we reorganized the structure of the BLM network, would the participatory outcome be different? Specifically, the study inquires the following questions. (1) What does a digital network's configuration look like? (2) Might the digital network mobilize more participation if the network were reorganized into other configurations, and for which types of behavior?

To answer the first question, I first constructed the BLM network from Twitter data. Then following Siegel (2009; 2011), I simulate three ideal type networks of size and density comparable to the BLM Sacramento network—the "small world network," the "village network," and the "opinion leader network." In brief, the "small world network" represents a structure where there is some degree of social closure, but it is easy to reach anyone. The "village network" represents a structure where clusters of social circles are far away from one another. The "opinion leader network" represents a structure where many followers are connected to a few leaders, but these followers are relatively unconnected to each other. As Siegel illustrates, these ideal types depict structures that have been commonly observed in the offline networks, which creates comparison groups in reference to the BLM network. The three types to do not exhaust the range of possible network configurations which can be theoretically or empirically derived; however, they do represent three commonly observed forms in offline collective action. Via these comparisons one can see how the configuration of online networks may be similar/different to many typical types of offline networks. I then use summary statistics to compare similarities/differences between the BLM and ideal type networks, which allows us to assess the relative structural characteristics of the BLM network.

To address the second question, I use simulated experiments regarding different behavior types that may be mobilized. I experiment with two parameters: (1) the baseline probability that individuals would participate and (2) the extent to which each individual is influenced by her tied others. These are two general parameters that capture a spectrum of the "cost" of the behavior (Earl et al. 2010; McAdam 1986). For behaviors of higher cost, such as blocking a highway, we would expect the baseline probability of participation to be low, and the ability for individuals to influence others to be also low. For low-cost behaviors, such as signing an online petition, we would expect people to be more generally inclined to participate, and it would be easier to persuade others. Thus, the hypothetical scenarios are not tied to one type of behavior, but encompass a range of behaviors with different costs.

The goal is to compare the participation rates for different types of behaviors between the BLM network and the ideal type networks. Such comparisons inform us of the conditions when the BLM network favors participation. For instance, one might find that the participation rates for high-cost behaviors were higher in the BLM network than in the ideal type networks, or participation rates for low-cost behaviors were lower in the BLM network than in the ideal type networks. In short, both the simulated networks and hypothetical scenarios are partly theoretical and partly data-based, generating middle-range results that are less broad than pure theoretical simulations but cover more theoretical possibilities than studies based solely on empirical data.

The results suggest that unlike all three ideal type networks, the BLM network constitutes a configuration that can be characterized as a "cluster-connective" network. This network exhibits a high-density structure involving a few clusters, along with many relatively isolated nodes and fragmented components. The results further indicate, paradoxically, that this cluster-connective configuration can mobilize more participants than all three ideal type networks when general conditions are unfavorable (e.g., high-cost behavior) but mobilize fewer participants when general conditions are favorable (e.g., low-cost behavior). Depending on the type of behavior, the network structure of the BLM network can either help or inhibit participation. Additional data in the Supplementary further suggest that the cluster-connective configuration is observed not only in this one case of BLM Sacramento, but two other online political groups—BLM Philadelphia and JusticeForImmigrants —as well. The combination of structural network theory and digital data yields results that reveal the conditions in which social media networks are likely to facilitate participation of different types.

The puzzle of loose online networks and strong mobilization power

Social-networking sites have fueled mobilization of the Occupy Movement in the US, the Arab Spring revolutions in the Middle East, and the *Indignados* Movement in Spain (Segerberg and Bennett, 2011; Castells, 2015; Tufekci and Wilson 2012). Each case utilizes social-networking sites in a different way. In the case of the Egyptian revolution, Facebook pages, such as the Kullena Khaled Said page, were critical in upstirring the grievances and providing information about focal points of protests (Poell et al. 2016). For the #MeToo movement, sweeping online activism aimed at altering public opinion was the primary mode of mobilization (Mendes, Ringrose and Keller 2018). During the Hong Kong Anti-Extradition Bill demonstrations, the LIHKG forum was used as means to “upvote” and “downvote” which collective action to employ, providing a platform for strategic coordination (Purbrick 2019).

While one should respect the diversity of the usage of social-networking sites, scholarly attempts have been made to consider the common grounds of digital media. In the "connective action literature" (as it commonly references Bennett and Segerberg's (2012) theory of connective action), many have investigated the mechanisms by which social-networking sites affect political action, whether online or offline. The literature frequently refers to network concepts, linking two major arguments. First, networks are understood as media for transmitting information, frames, or emotions. Bennett and Segerberg (2012) argued that, in connective action, personal action frames become transmission units across loosely coordinated social media networks. Castells (2015) contended that users of social media networks can achieve "self-communication" through mutual sharing of emotions and information.

Second, social media networks are characterized by loosely connected weak ties that broaden the reach of information. For instance, Juris (2012) argued that social networking ties create a new collective by connecting individuals who may have little direct social relationship. Bennett, Segerberg, and Walker (2014) coined the term "online crowd" to describe how social networking sites reach a wide audience with few pre-existing ties.

However, while it is appealing to assume that contact creates action and broadening contact reach broadens mobilizing power, this is not necessarily true. The success of network diffusion also depends on the type of behavior. All things equal, network looseness implies that many actors are only connected to few other actors in the network. For behaviors that require some investment of cost, risk or energy, encouragement from a single contact is often insufficient, and many sources of reinforcement is often required (Centola and Macy 2007; Kitts 2000; Schelling 1978; Valente 1996).

This gives rise to the puzzle of loose networks and effective mobilization: *If the structure of social media networks is characterized by loose and weak ties, how can such a configuration facilitate the diffusion of high-cost behavior (e.g., Egyptian Revolution)*?

Network structures and participation

The tradition of studying networks provides some guidance. Formal or informal, relationships between actors are the roots of political behavior (Krinsky and Crossley 2014; Kim and Pfaff 2012; Wellman et al. 2001).

One line of research highlights how *network structures* affect participation (Heckathorn 1993; Macy 1991; Marwell and Oliver 1993). Computer simulations are frequently utilized to test these models because they allow the researcher to experiment a wide range of possibilities. For instance, by varying the cost of participation, the simulations are not specific to one form of political participation, such as protest, but incorporate a broad range of behaviors. Scholars have shown factors such as the network density and heterogeneity (Marwell, Oliver and Prahl 1988), prevalence of weak ties that connect distant groups (Macy 1991), relationship between network centrality and resources (Kim and Bearman 1997) create differential implications for political participation (see reviews by Oliver 1993; Strang and Soule 1998). However, many simulations are based on hypothetical scenarios, leading to questions on external validity regarding how well the results generalize to empirical settings.

The theory of complex contagions (Centola 2010; Centola 2018; Centola and Macy 2007) provides excellent explanations on how network structures can either facilitate or inhibit diffusion depending on the type of diffusion process. Processes of "simple contagion," where one single contact is sufficient to activate adoption, benefit from network structures with many ties between clusters but few overlapping ties between neighbors. In contrast, processes of "complex contagion," where multiple sources of contact are needed for adoption, require network structures that have many overlapping ties between neighbors, or "wide bridges," to spread. Wide bridges create the necessary social reinforcement that allows for the spread of complex contagions. Nevertheless, given the same number of ties, too many wide bridges indicate that many overlapping ties reduce the reach of the network, which hinders the spread of simple contagion. Thus, the same network structure can benefit the spread of one type of diffusion but diminish the spread of another type. Empirical work has also supported the concept of complex contagions in the spread of behaviors such as health-promoting behavior (Centola 2010), online activism regarding same-sex marriage (State and Adamic 2015), mobilization efforts during the Arab Spring (Steinert-Threlkeld 2017), or even the adoption of styles of pottery making (Manzo et al. 2018), showing the importance of multiple reinforcement for the diffusion of behavior.

Recognizing the importance of network structures, scholars have described the characteristics of online networks (Aral and Walker 2012; Goel et al. 2012; González-Bailón et al. 2010; González-Bailón et al. 2013). Aral and Walker (2012) identified clusters in networks that produce stronger influential power. González-Bailón et al. (2013) showed that online networks can be very centralized, generating a few influential actors that generate chains of diffusion. This line contributes to our understanding of the structural network characteristics and their associations with participation. On the other hand, it is difficult to examine the effect of the whole network structure due to the lack of comparison groups. Centola's (2010; 2011) research demonstrates the effect of network structure on diffusion via web experiments, but the networks were artificially designed rather than based on observed groups.

This study agrees with the structural network perspective but inquires a different question—*does the online network structure contribute to the diffusion of participation?* To test this, Siegel's work (2009; 2011) on the relationship between network typologies and political participation is especially relevant. Extending Strogatz's (2001) network typologies, Siegel differentiated ideal types—including the small world network, the village network, and the opinion leader network— that are typically observed. Siegel's approach is informative because the ideal types are abstractions of networks that are regularly observed in the empirical world, and can serve as references to how the online network structure compares to common network structures.

In Siegel's (2009) description, a small world network (Watts 1999) describes a network structure where actors can easily connect with one another through intermediate nodes, based on what is colloquially known as "six degrees of separation." Actors' networks exhibit substantial overlap, resulting in some clustering, but they also have long ties that connect with alters other than those in the clusters. Figure 1 illustrates a small world network with 50 actors.

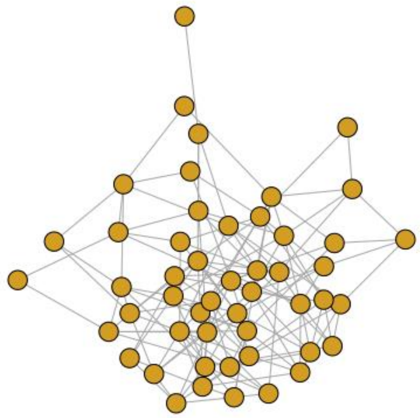

Figure 1. Example of a small world network.

In a village network, there is high density within clusters but very few cross-cluster ties. Siegel (2009) contended that village networks are often observed in small towns and villages where everyone knows everyone else within the cluster, while a small number of actors serve as bridges between clusters. Figure 2 illustrates a village network with 50 actors.

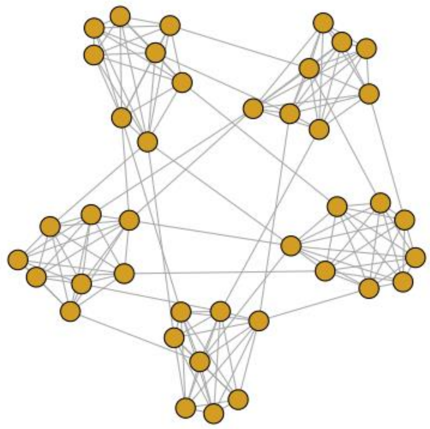

Figure 2. Example of a village network.

In opinion leader networks (formally "scale-free networks"), most actors have few ties while a few (opinion leaders) have many (Siegel 2009; see also Burt 2005). The key network characteristic is that actors exhibit preferential attachment to those who have more ties (Barabási 2016). This is common where there are informal leaders and people exhibit a preference to connect to leaders. Figure 3 illustrates an opinion leader network with 50 nodes.

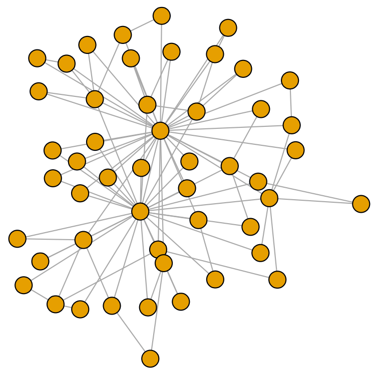

Figure 3. Example of an opinion leader network.

In many settings, it is not possible to collect data on all network relationships and calculate network statistics such as density or transitivity. However, with such typologies it is possible to make general assessments of what the network structure looks like, and its implications for diffusion. Furthermore, from the theory of complex contagions (Centola 2010; Centola 2018; Centola and Macy 2007), such typologies can succinctly summarize common patterns of bridge width. A village network is a structure where there are a lot of wide bridges inside a village, but very “narrow” bridges between villages, which facilitates the spread of complex contagions within but not between villages. An opinion leader network is one where there are a lot of bridges to the leader, and these bridges can become wide bridges if the leaders are connected. A small world network is one where there is medium bridge width, allowing for complex contagions with lower thresholds to spread, but may inhibit the spread of behaviors with very high cost (McAdam 1986). In sum, the theory of complex contagions outlines the mechanisms by which behavior spreads, while the network typologies help us evaluate which mechanisms are more likely to take place.

Study design, data, and model

The present study utilizes data-informed computer simulation to examine the conditions in which online networks may be effective for participation. This synthesis of empirical data and computer simulation has been adopted because, as well as reflecting the real world, it allows for experimentation with hypothetical scenarios (Centola 2018; Janssen and Ostrom 2006). Such a synthesis can provide insights into the puzzle of how loose online networks can influence mobilization. This would be approached in two steps. First, online network configurations would be compared to the ideal type networks to investigate whether social media networks are indeed loose and low-density. Second, computer simulations would be used to test the mobilizing power of online networks as compared to ideal type networks under behavioral conditions, pinpointing those contexts in which mobilization is more likely to succeed.

Figure 4 shows the study design. First, Twitter data was used to generate the empirical network of the BLM Sacramento chapter's followers. From that empirical network, simulated networks were created based on Siegel's typologies (Siegel 2009; 2011), similar in size and density but with very different structures.

The first section compares network statistics for the empirical and simulated networks to establish whether the BLM network is closer to one of the ideal types, so addressing the first research question (about online network configurations). In the second part, both the empirical and simulated networks were used as inputs for the simulations. The simulation results answer the second research question (conditions in which networks might facilitate behavioral diffusion). The model experimented with (1) the baseline probability that each actor would participate and (2) the extent to which actors are influenced by their tied alters. These motivation parameters represent a spectrum of the cost of the behavior. Scenarios with parameters of high motivation correspond to low-cost behaviors (Earl et al. 2010; McAdam 1986), as ceteris paribus individuals are more likely to participate. On the other hand, scenarios with parameters of low motivation indicate high-cost action.

Finally, because the parameters were purely hypothetical, as an auxiliary analysis I utilized the Twitter data to estimate the parameters in two empirical situations: (1) the BLM hashtag movement—which, according to the data, has a very high participation rate—and (2) offline events organized by BLM Sacramento, which are very rare in the given data. The estimates indicate how the hypothetical scenarios reflect the empirical world.

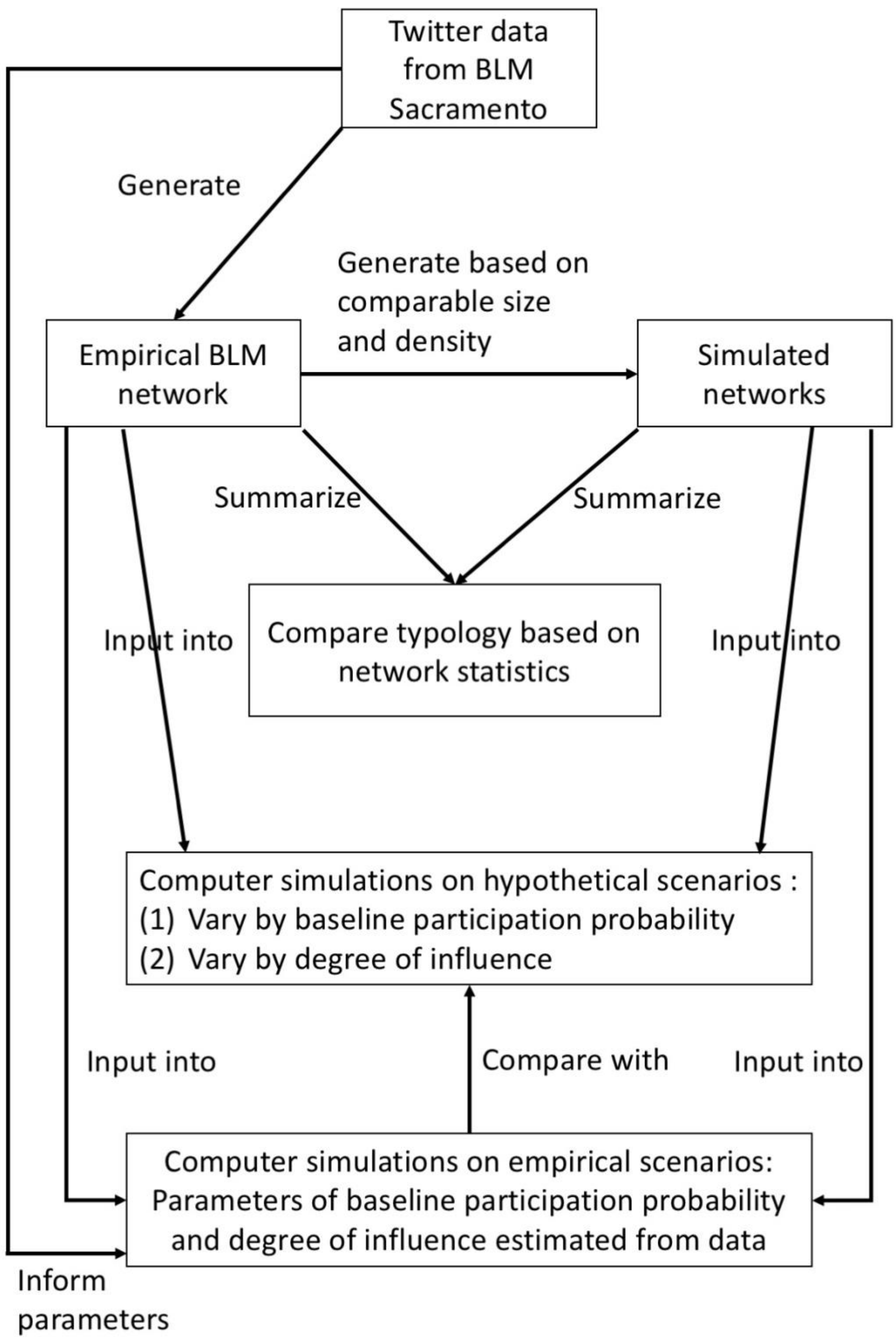

Figure 4. Study design.

The empirical data

The data were drawn from followers[10] of the Black Lives Matter Sacramento chapter's Twitter account (@BLMSacramento). The BLM movement came to prominence following a series of deaths of African Americans in 2013–2014. The hashtag "#BlackLivesMatter" emerged on Twitter after the suspect who shot Trayvon Martin to death was acquitted in 2013, and the BLM movement gained national attention when Michael Brown and Eric Garner were killed by the police in 2014. Protestors rallied on the streets of Ferguson and across other states to raise awareness of racial injustice. Further controversial African-American deaths were subsequently reported, and BLM has become a nationwide movement, calling for institutional and ideological change (for a history of BLM, see Freelon, McIlwain, and Clark 2016; Lowery 2016).

Twitter and other social-networking sites have played a major role in the BLM movement. As incidents occurred, correspondent hashtags such as "#BlackLivesMatter," "#ICantBreathe" or "#MichaelBrown" appeared on Twitter, enabling sympathizers to express their solidarity with the cause. For instance, when the news of Eric Garner's death was reported, the hashtag "#ICantBreathe" appeared in more than a million Twitter posts (BBC 2014). To deepen grassroots support, BLM chapters were founded in cities such as New York, Chicago, Austin, and Sacramento. As well as establishing accounts to connect sympathizers (e.g., "@BLMNYC" or "@BLMPhilly"), these chapters organized offline events such as public demonstrations or communal gatherings.

BLM Sacramento was selected for two reasons. First, as the BLM movement relies heavily on Twitter, it provides a suitable context in which to examine the relationship between social media networks and activism. Second, information about offline events hosted by the Sacramento chapter is publicly available; in contrast, other chapters do not post this information.

As participation in these offline events is relatively rare (only 6.4% of all actors mentioned such events), the Sacramento case provides valuable data for comparing networks' effectiveness for rare and common types of activism (e.g., use of the hashtag "#BlackLivesMatter").

The data were collected from June 27–July 2, 2017. All 1215 Twitter users who followed BLM Sacramento's Twitter account ("@BLMSacramento") and had publicly available following relationships were queried. The data therefore represent users who follow @BLMSacramento, can follow each other online, but vary in terms of their participation in the BLM movement.

The empirical BLM network

From the 1215 users, those suspected to be organizations or bots were removed. A tie was constructed between users who *mutually followed one another*, resulting in an undirected network with mutual acknowledgement. Although Twitter allows users to follow other users unilaterally, only mutual following relationships were considered for three reasons. First, compared to unilateral following, mutual following signifies that both users are aware of one another, often signifying that the two have underlying social relationships, such as friendship or common identities (Cheng et al. 2011; Semertzidis et al. 2013). Such relationships constitute the basis of social influence, which is critical for the current purpose of studying behavioral diffusion. Second, this approach follows research (Kim and Bearman 1997; Marwell, Oliver and Prahl 1988; Siegel 2009) that examined undirected networks, so allowing the present study to dialogue with previous studies. Finally, the development of mathematical properties for ideal types of directed networks is still in progress and is beyond the scope of this paper, making it impossible to find the appropriate counterfactual networks and hindering the validity of this study.

As simulations aimed to examine interdependencies between actors, all isolates (i.e., actors with no ties to others) were removed, as they cannot influence others and cannot be influenced. Because they are never part of the diffusion process, the isolates do not contribute to our understanding of how network structures matter. Including isolates does not change any of the implications.[11]

The resulting network comprised 655 actors. Table 1 presents summary statistics for the BLM Sacramento network (hereafter, *BLM network*). One can see that overall network density is very low, and the standard deviation in distribution of ties is very large.

Table 1. Summary of BLM network

Measure	Value
Number of nodes	655
Number of ties	2335
Density	0.011
Transitivity	0.198
Mean degree	7.130
SD degree	9.195
Diameter	10

The simulated networks

Three ideal type networks were simulated: [12] *small world*, *village*, and *opinion leader*.[13] Because these are general types, each includes a range of possible structures that can vary by density, size, or other characteristics. As the main purpose was to compare with the BLM network, the simulated networks were comparable in size and density to that BLM network.[14] This provides a means of asking "What would be the diffusion outcome if the structure of the BLM network was altered?"

The computer simulation model

The model

Computer simulations were used to investigate scenarios in which the BLM network would be favorable for participation as compared to other networks. As the outcome of the simulations depended on decisions by multiple actors, which were in turn dependent on previous choices, the interdependencies would be too complex to be captured by conventional statistical analysis.

I use the widely-utilized network autocorrelation model to capture the decision-making interdependencies (Leenders 2002; Friedkin 2006). The outcome (Y) was binary: to participate or not to participate. Let $P(Y = 1)$ denote the probability that the individual would participate in the next iteration; then:

$$log\left(\frac{P(Y = 1)}{1 - P(Y = 1)}\right) = \boldsymbol{\alpha} + \boldsymbol{\rho} WY$$

$\boldsymbol{\alpha}$ indicates the ***baseline probability*** that any individual would participate (analogous to internal motivation). This component is independent of other actors' decisions. W is the network adjacency matrix, and Y is the vector of those participating. Together, the WY product specifies how many alters participate, and $\boldsymbol{\rho}$ is the ***network influence*** parameter, signifying how strongly participation relates to whether tied neighbors participate.[15]

Scenario parameters

The two parameters are $\boldsymbol{\alpha}$ and $\boldsymbol{\rho}$**,** or level of baseline probability of participation and network influence power. The simulations experimented with low, medium, and high levels of baseline probability, as well as low, medium, and high levels of network influence, resulting in $3 \times 3 = 9$ scenarios. Together, these reflect a range of costs for behaviors.

1. Baseline probabilities:

(1) Low: baseline probability of .05 ($\boldsymbol{\alpha}$ = -2.94, very rare event)

(2) Medium: baseline probability of .10 ($\boldsymbol{\alpha}$ = -2.20, rare event)

(3) High: baseline probability of .20 ($\boldsymbol{\alpha}$ = -1.39, common event)

2. Network influence:

(1) Low: adding one participating friend increases the participation odds by 20% ($\boldsymbol{\rho}$ = 0.18).[16]

(2) Medium: adding one participating friend increases the participation odds by 50% ($\boldsymbol{\rho}$ = 0.41).

(3) High: one participating friend increases the participation odds by 100% ($\boldsymbol{\rho}$ = 0.69).

Model flow

Because the major goal was to compare the BLM network with simulated networks, the described model is relatively parsimonious. Although previous research has shown the importance of other factors such as the production function of collective goods, resources, or sanction (Heckathorn 1993; Kim and Bearman 1997; Marwell and Oliver 1993), it was unfeasible to incorporate these for two reasons. The outcomes were already dependent on a three-factor interaction of network type, baseline probability, and network influence (or a four-factor interaction after the robustness checks in Supplementary), adding further factors would overcomplicate the results. Additionally, the empirical data in the auxiliary analysis do not provide estimates for such factors.

To initiate the model, all actors participate only according to the baseline probability. For subsequent iterations, the probability that the focal actor would participate was determined by the model.[17] This depends on how many connected alters are participating and therefore depends on the network configuration. The model was run for 50 iterations, and the proportion of participation was calculated.[18]

Results

Comparison of networks

It is interesting to first compare the BLM network to the other ideal types. Table 2 compares the BLM network to the average of 500 simulated networks for each ideal type. As the number of nodes and densities are comparable, the lower rows are of most interest. Transitivity indicates the "clusterness" in the network; standard deviation in degree indicates the variation in how many ties each node has; and diameter indicates the maximum path length between actors.

The BLM network appears to be distinct from any of the ideal type configurations. Transitivity is relatively close to the small world network, but standard deviation in degree is much higher and closer to the opinion leader network, and diameter is very large and closer to the village network. While there is only moderate level of clustering in the BLM network, actors vary significantly in terms of how many ties they have, and there are hard-to-reach actors who have very few ties.

Table 2. Comparison of network statistics.

	BLM	Small World	Village	Opinion Leader
Number of nodes	655	655	648	655
Number of ties	2335	2620	2430	2610
Density	0.011	0.012	0.012	0.012
Transitivity	0.198	0.237	0.863	0.035
SD degree	9.195	1.49	0.706	7.562
Diameter	10	6.030	13.94	5.002

To make sense of these unusual statistics, Figure 5 plots the BLM network. Although the density is very low, those ties appear to be concentrated in a large component comprising two clusters. On the other hand, there are also many hard-to-reach actors that lie at the outer of the components or are unconnected to the large component. Within clusters, actors have high degrees, but degrees are very low among outer actors, resulting in the very large standard deviation in degree distribution and the high diameter.

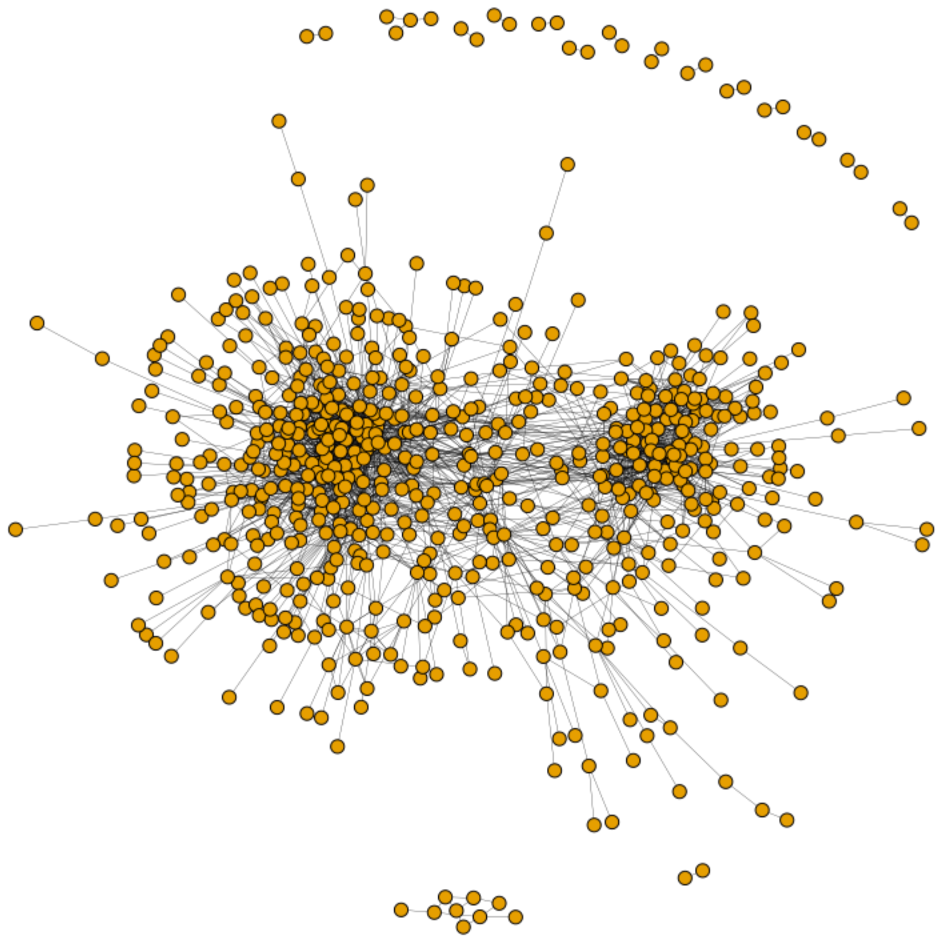

Figure 5. The BLM network.

The structure of the BLM network differs significantly from any ideal type abstracted from the empirical world. Previous research has often assumed a fully connected network (e.g., Centola and Macy 2007; Kim and Bearman 1997; Macy 1991), but the BLM network appears segmented with dyads, triads, or small components unconnected to the large component. This segmented network configuration has also been observed in qualitative accounts of networks in connective action (Hsiao 2017; Juris 2012). Second, some clusters of tightly connected individuals appear to exhibit high local transitivity, but there are also many relatively isolated actors at the periphery. This core-periphery structure distinguishes this configuration from any of the ideal types. Although the opinion leader structure also exhibits an uneven distribution of ties, the core often comprises a few leaders rather than a large cluster.

I describe this network configuration as "cluster-connective" because, while the actors are generally connected, that connectedness occurs only within the clusters and does not apply to the hard-to-reach actors at the periphery. As the cluster-connective network appears to be a different category, it is not immediately clear from past research how effective the structure is for diffusion. I thus turn to the simulations.

Simulation results for hypothetical scenarios

Figure 6 summarizes the results on different scenarios varying by baseline probability and influence power. The x-axis indicates the iteration number, and the y-axis is the proportion that participates. Each dot with different colors and shapes indicate results from different network structures. The points are averages across 1,000 experiments. Additionally, as the plot only shows means of participation proportions, S4 in Supplementary displays the variation for the final participation proportions. However, since the degree of the variation is relatively small compared to the mean, I show only the means here.

The results reveal interesting patterns regarding the BLM network's mobilization capacity (red/circle dots). Depending on the scenario, the BLM network can be either the *best* or the *worst* mobilizing network. Looking at the top row, left column, and center plots, the BLM network clearly exhibits the best rate of higher participation. The opinion leader network (green/triangle dots) is also somewhat effective, but participation rates for the small world network (square/blue dots) and the village network (cross/pink dots) remain near the baseline, indicating that a critical mass has not emerged to create a cascading participation effect. In sum, when the baseline participation probability is low, or network influences are weak, the BLM network can still mobilize a moderate proportion of participants. That is, for high-cost behavior the BLM network appears to be relatively beneficial for diffusion.

The situation is completely reversed when the baseline probability is high or network influence is strong (e.g., bottom-right plot). In these scenarios, the small world, village, and opinion leader networks have much higher participation rates than the BLM network. In short, for low-cost behaviors the BLM network is the worst in mobilizing participants. A robustness check that analyzes only the largest component yields similar results (see S5 in Supplementary).

Taken together, these results may seem perplexing—how can a network configuration that is so effective when conditions are unfavorable for mobilization become relatively ineffective when conditions are favorable? To answer, let us first understand why the simulated networks yield the results using the theory of complex contagions (Centola 2018; Centola and Macy 2007).

Scenarios that are unfavorable for participation, such as when baseline participation is low or influence is weak, are analogous to situations of complex contagions with high thresholds. In such cases, having enough wide bridges between initial participants in the network becomes critical for mobilization. For the small world network, the general bridge width is not wide enough to facilitate diffusion, leading to very low participation rates. For the village network, although the bridge width is wide within the village, due to the low number of initial participants it is unlikely that the initial participants are within the same village, preventing the further spread of the movement. Even if one village were activated, due to narrow bridges across villages it would be difficult to influence another village, leading to low overall participation rates. The opinion leader network can still muster some participants since most people are connected to the leaders, and leaders themselves are likely to be connected. Thus, it is possible to form a group of local coalitions amongst leaders that lead to further diffusion (see Centola 2013). In other words, the opinion leader network is the most likely to satisfy the conditions that the initial participants are connected, and there is enough bridge width for further diffusion.

Now, the “cluster-connective” configuration is different. Compared to the opinion leader network, not only are leaders connected, but all almost all users in the cluster form very wide bridges amongst themselves. It is almost guaranteed that any initial participant in the cluster would be connected to other initial participants, then due to the many wide bridges in the cluster a certain proportion would participate, leading to the superior mobilization outcome compared to the other networks.

On the other hand, scenarios that are favorable for mobilization are analogous to processes of simple contagion or complex contagions with low thresholds. In such scenarios, ties that span across the network and increase reachability become important for diffusion. The small world network facilitates mobilization due to the reachability of the network (reminiscent of the phrase “six degrees of separation”) and the medium bridge width. The village network also helps mobilization due to connectedness within villages and the many bridges across villages. The opinion leader performs somewhat worse, as people who are not directly connected to the leaders require many intermediate steps to activate, and the ties to them are often narrow bridges, which make such users very difficult to activate. Finally, the “cluster-connective” configuration exacerbates the disadvantages of the opinion leader networks. Those who are not closely connected to the cluster(s) are very peripheral in the network, with very narrow bridges (often requiring a sequence of connections of a single tie to reach). Consequently, such users are almost guaranteed to be outside of the influence circle of the clusters, and even if the whole cluster is activated, such users remain uninfluenced, which makes the cluster-connective configuration fare the worst in terms of participation rates.

In layman words, the “cluster-connective” configuration generates unique implications for mobilization. Because the ties are heavily interwoven within the large clusters, the dense clusters may be able to form a critical mass through mutual influence, even when conditions are unfavorable. However, precisely because ties are predominantly distributed within the large clusters, the peripheral, segmented, or relatively isolated nodes are very difficult to mobilize, resulting in a ceiling effect on mobilization, even when conditions are favorable for diffusion. Additional diagnoses (available but not shown) support the speculation. The mobilized actors in unfavorable conditions come predominantly from dense clusters while those nonmobilized in favorable conditions come predominantly from among the peripheral, segmented, or relatively isolated actors. This strong mobilizing effect coupled with a strong ceiling effect is not seen in the ideal types, lending further weight to the argument that the cluster-connective structure is different.

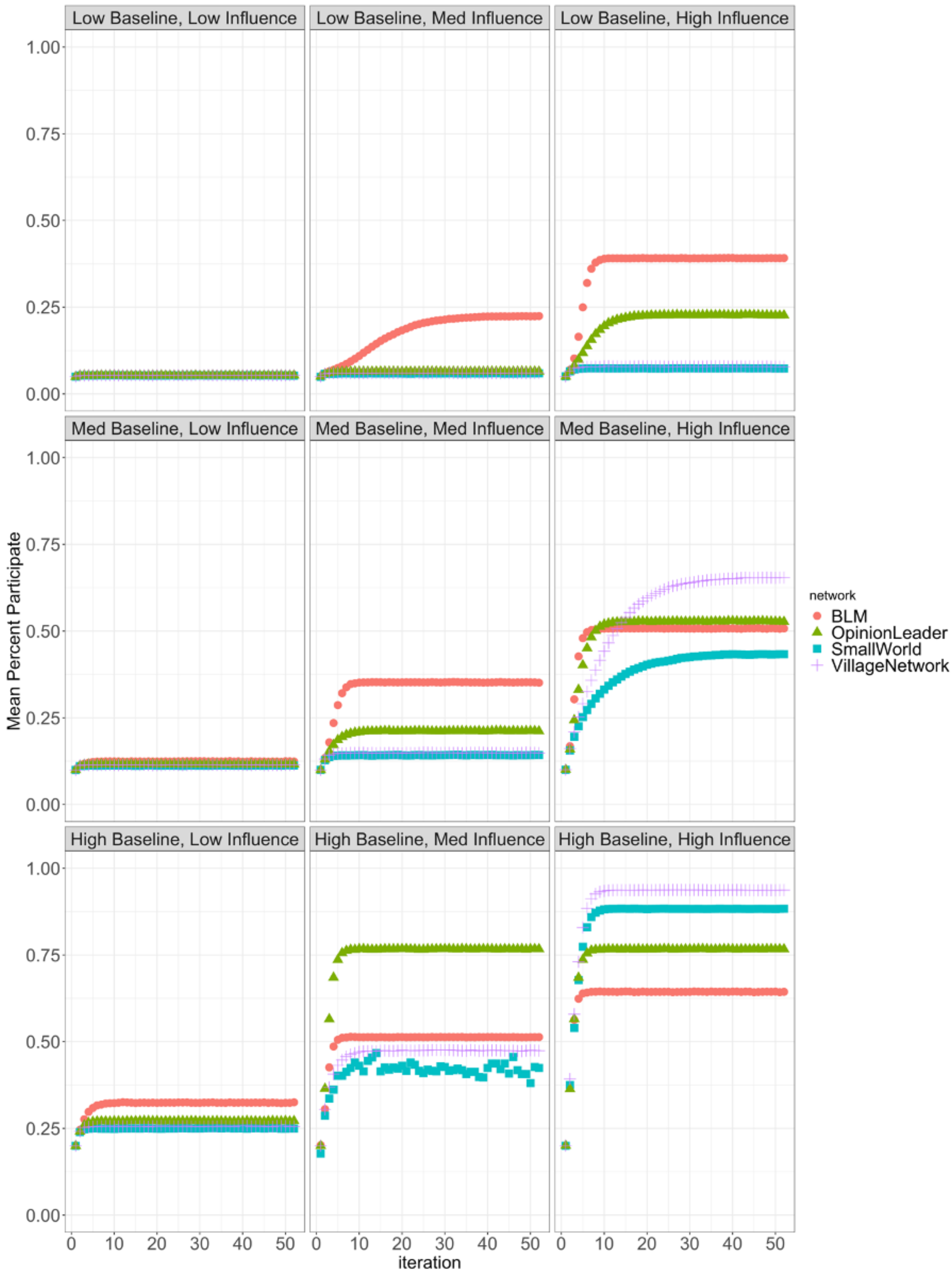

Figure 6. Simulation results for hypothetical scenarios.

Auxiliary analysis: data-informed scenarios

The scenarios above cover a wide range of potential collective action situations. However, because of their hypothetical nature, it was important to seek additional evidence of their realism in empirical settings.

Two movement scenarios were operationalized—one corresponding to mobilization for online-only activism and the other for online-mobilized offline movements. Note that the cost of behavior is a spectrum rather than categories, and the goal of this study is not to determine whether mobilization for a hashtag or an offline event should be categorized as high-cost or low-cost behavior. The central point is similar to State and Adamic's (2015) analysis of the spread of online support for same-sex marriage, online actions may require different degrees of involvement, and in the current case it is rarer to mobilize an offline event than use a hashtag online.

The *BLM hashtag movement* was measured by counting hashtags ("#") related to BLM (#BlackLivesMatter, #BLM, #blacklivesmattersacramento). Theoretically, the hashtag movement corresponds to online activism, as there are obvious references to any offline event. This was very common, as 68% used the hashtag at least once.

In contrast, *BLMSacramento offline events* mapped to an online-mobilized offline movement. The Sacramento chapter hosts regular monthly events that create support within the group. These events include protests, meetings, and movies about Black history. Each event has an event URL, which was posted by the Sacramento chapter as mobilization advertisements for the event. Inclusion of these URLs in user tweets was counted. This was rare, as only 6% of users ever included a tweet about these offline events. Furthermore, even among the users who ever included the URLs, 90% had less than 10 tweets which included the URL, showing the rareness of such actions.

Operationalization involved a binary coding indicating whether a user ever mentioned offline events or used the BLM hashtags. The same autocorrelation model was estimated.

I describe this as an "auxiliary analysis" because rather than a formal statistical analysis because the estimates should be treated qualitatively to assess the empirical plausibility (i.e., rough matching) of hypothetical scenarios. This estimation aims to indicate which of the nine theoretical scenarios were more reasonable rather than determine the parameter values. The aim is to triangulate data with results in the previous section to allow readers to better imagine the empirical settings that map to the hypothetical scenarios. Additionally, 55% of the hashtags and 97% of the URLs were retweets from the Sacramento chapter or another user, leading some credence that the information of these mobilization efforts embodied a network process.

The estimates for each behavior type are:

BLM hashtag: $\boldsymbol{\alpha} = 0.33$, $\boldsymbol{\rho} = 0.10$. Here, $\boldsymbol{\alpha}$ indicates an extremely common event while $\boldsymbol{\rho}$ indicates that the degree of influence is very low.

BLMSacramento offline events: $\boldsymbol{\alpha} = -2.93$, $\boldsymbol{\rho} = 0.33$. $\boldsymbol{\alpha}$ indicates an extremely rare event while $\boldsymbol{\rho}$ indicates that the degree of influence is medium.

Using the parameter estimates, the simulation model was run again (Figure 7). The difference of network configuration is small for the *BLM hashtag movement*, as these are common events with low network influence. However, again the BLM network configuration appears suboptimal, indicating the limitations of the cluster-connective structure. In contrast, the BLM network significantly outperforms all the network counterfactuals for *BLMSacramento offline events*, indicating the strength of the cluster-connective structure. The ability to mobilize a certain fraction of supporters may be especially important in the diffusion of behaviors when many sympathizers are unwilling to help to mobilize.

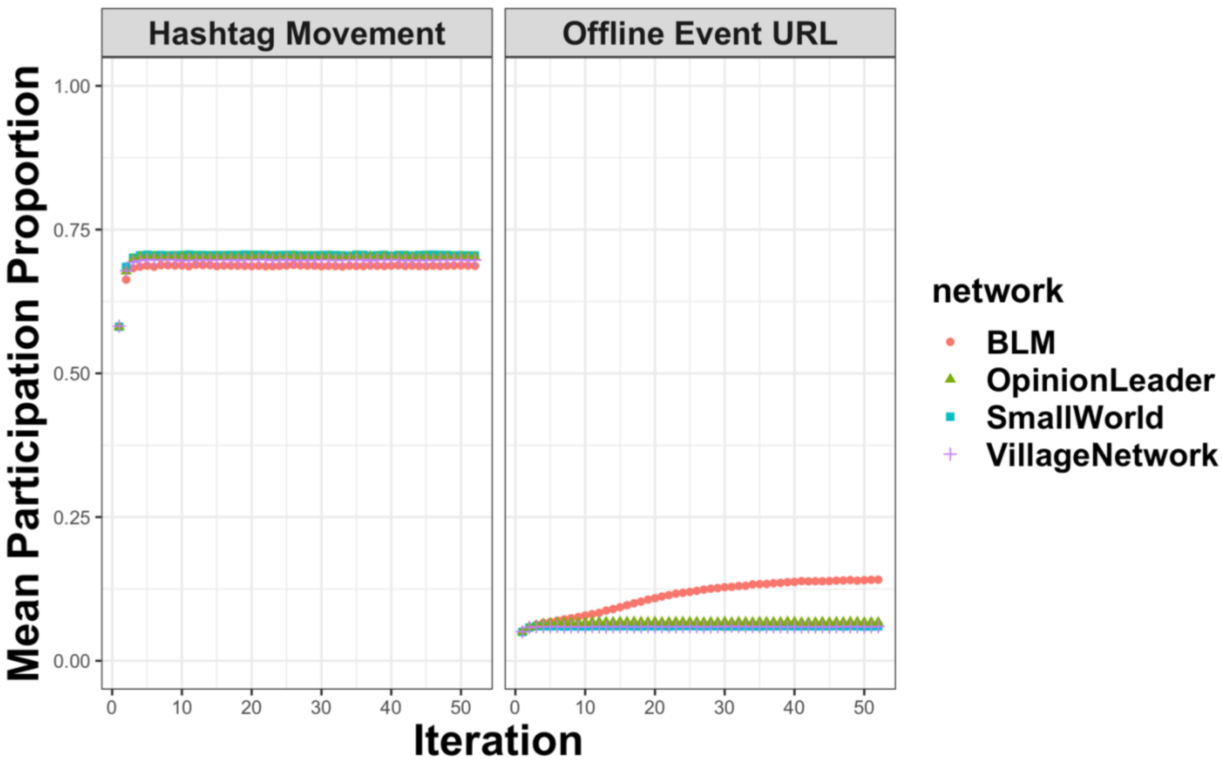

Figure 7. Results from the empirically informed scenarios.

Discussion and conclusion

The cross-fertilization of network simulations and online data identifies the conditions under which online network structures facilitate political diffusion. As a motivating problem, I highlighted the puzzle: how can loose networks generate mobilization power in connective action?

The BLM network had a unique configuration which I described as "cluster-connective," signifying its connectedness within large clusters, accompanied by weak reachability among isolated, segmented, and peripheral actors. Simulations suggested that for high-cost behavior, this cluster-connective configuration can still facilitate the mobilization of a higher proportion of sympathizers than other network structures. However, for low-cost behaviors, the cluster-connective configuration may hinder mobilization because of its fragmented, segmented network, with many hard-to-reach actors. In such scenarios, the cluster-connective structure generates a ceiling effect and exhibits a lower participation rate than alternative configurations.

This study contributes to several areas. Returning first to the puzzle of how loose networks generate strong mobilization, this study explores the configuration of online networks and their corresponding strengths and limitations. The results suggest that social media networks are less loose than previously assumed, with tightly-knit clusters rather than loosely-linked actors at the core of the network. Scholars have correctly observed that there are many loosely-linked actors at the periphery of the cluster-connective configuration, but in the clusters there are many "wide bridges" (Centola 2018) that link users into cohesive groups. Furthermore, because of the wide bridges that facilitate complex contagions (Centola and Macy 2007), it is the connected clusters at the center rather than the periphery that creates the critical mass for the diffusion of high-cost behavior (Centola 2013; Marwell and Oliver 1993). This study moves from the question of *whether* online networks facilitate mobilization to *the conditions under which* online networks facilitate mobilization. Depending on the cost of the behavior, the cluster-connective configuration of social media networks can be advantageous or a hindrance to mobilization.

Most theories on connective action investigate the content that flows through networks (Bennett and Segerberg 2012; Kavada 2015; Tufekci and Wilson 2012), echoing a research paradigm that stresses network meaning (Emirbayer 1997; Mische 2003). The present study complements this line of research by invoking a tradition that examines network configurations in social movements (Centola and Macy 2007; Oliver 1993; Strang and Soule 1998). In particular, I extend the argument that online network structures are significant (Aral and Walker 2012; Goel et al. 2012; González-Bailón et al. 2013) by showing that we can not only examine patterns of online network structures, but also test the types of behavior under which these structures are useful for mobilization. The same political network can effectively mobilize high-cost behaviors such as street rallies or strikes, but at the same time be ineffective in mustering low-cost behaviors like mustering online petitions or spreading political memes. This result echoes González-Bailón et al.'s (2013) finding that the structure of online networks renders many diffusion attempts unsuccessful. Instead, it is the sheer number of participants, rather than the network structure, that successfully sparks large-scale movements. When the baseline willingness to participate is high, the structure of online networks is trivial for mobilization.

This study also sheds light on the structural network paradigm by providing a framework of synthesizing empirical data with theoretical development. Research on network structures has often assumed a fully connected network (Kim and Bearman 1997; Marwell, Oliver and Prahl 1988; Siegel 2009), but the results demonstrate that online networks are often fragmented and segmented (Hsiao 2017; Juris 2012). Developing models that account for segmented networks may be a worthwhile extension. As the cluster-connective configuration does not align with any ideal type, should it be considered a new type, or is it a hybrid? Since the goal was to examine the conditions of participation, I did not delve into the development of a graph model to capture the cluster-connective structure. Additionally, while Siegel (2009) maps common configurations, it does not exhaust all possible types (see Barabási 2016; Leskovec et al. 2005). Interested researchers can experiment with how the "cluster-connective configuration" corresponds to existing graph formulations or hybrid networks.

This study also has implications for activists. Online media can create "echo-chambers" or "filter bubbles," as users tend to connect with like-minded others (Flaxman 2016; Pariser 2011). Viewing the clusters as the "bubble," this study shows that while those in the bubble are easy to mobilize, peripheral segments are very difficult to mobilize. It might prove strategically useful to target these peripheral actors. Although isolates might be harder to reach, dyads, triads, and small components may be viable targets. As Twitter data is currently publicly available, those who see the value of this method could map and target their follower networks.

Furthermore, the results may help us better understand the case of BLM Sacramento or dynamics of movements. As Taylor (1989) mentioned, critical to the survival of movements is the ability to form supportive networks in the face of adversity. The cluster-connective configuration is exactly suited to facilitate such support when conditions are unfavorable. Consider the longevity of the Sacramento chapter. It was established in 2015, but has consistently posted BLM information and regularly hosted offline events even up to now (year 2020). This is an admirable degree of commitment that is very costly to maintain. Certainly the hard work by the organizers was the necessary condition for this commitment, but the cluster-connective structure may have aided the positive feedback to support such efforts. Such a stable mobilization basis proved to be valuable in times of discontent. In March 2018, half a year after the data collection, Stephon Clark, a 23-year-old African-American man, was fatally shot by the Sacramento police, leading to widespread dismay. The Sacramento chapter reacted promptly, organizing protests and advertising on Facebook and Twitter, drawing more than three thousand interested respondents on the event page. The resulting demonstrations blocked the highway and delayed the NBA game of the Sacramento Kings (Lillis et al. 2018).

The study's limitations also suggest future directions. First, it is unclear whether the cluster-connective configuration identified in the Sacramento network is commonplace among online networks. To address this question, S3 in the Supplementary provides additional data from *BLM Philadelphia* and *JusticeForImmigrants*. I selected these networks because *BLM Philadelphia* enables comparison with other BLM networks, and *JusticeForImmigrants* enables comparison with other political networks. Both networks exhibit a cluster-connective configuration with moderate transitivity, high heterogeneity in degree, and a large diameter. There are also numerous isolates and unconnected components, echoing the study's findings.

Second, the advantage of the approach of data-informed simulations is also its limitation. While better empirically grounded than purely hypothetical simulations, this study could not (and was not aimed to) comprehensively survey all the contextual factors that contributed to the mobilization processes of BLM. Fortunately, as the case of BLM has been extensively documented by other scholars (Freelon et al. 2016; Lowery 2016), this study can focus on the network dynamics and complement their findings.

As data on online networks are much more available, this study demonstrates how a synthesis between network theories and online data can help us test the general conditions of political participation.

References

Aral, Sinan, and Dylan Walker. 2012. "Identifying Influential and Susceptible Members of Social Networks." *Science* 337 (6092): 337–41.

Barabási, Albert-László. 2016. *Network Science*. Cambridge University Press.

BBC News. "Eric Garner: Why #ICantBreathe Is Trending." Retrieved October 7, 2017 (http://www.bbc.co.uk/newsbeat/article/30326891/eric-garner-why-icantbreathe-is-trending).

Bearman, Peter, and Kevin Everett. 1993. "The Structure of Social Protest, 1961–1983." *Social Networks* 15 (2): 171–200.

Bennett, Lance and Alexandra Segerberg. 2012. "The Logic of Connective Action: Digital Media and the Personalization of Contentious Politics." *Information, Communication and Society* 15(5):739–68.

Bennett, Lance, Alexandra Segerberg, and Shawn Walker. 2014. "Organization in the Crowd: Peer Production in Large-Scale Networked Protests." *Information, Communication and Society* 17(2):232–60.

Burt, Ronald S. 2005. *Brokerage and Closure: An Introduction to Social Capital*. New York: Oxford University Press.

Castells, Manuel. 2015. *Networks of Outrage and Hope*. Cambridge: Polity.

Centola, Damon. 2010. "The Spread of Behavior in an Online Social Network Experiment." *Science* 329(5996):1194–97.

Centola, Damon. 2011. "An Experimental Study of Homophily in the Adoption of Health Behavior." Science 334(6060):1269–72.

Centola, Damon 2013. "Homophily, Networks, and Critical Mass." *Rationality and Society* 25(1):3–40.

Centola, Damon. 2018. *How Behavior Spreads: The Science of Complex Contagions*. Princeton University Press.

Centola, Damon and Michael Macy. 2007. "Complex Contagions and the Weakness of Long Ties." *American Journal of Sociology* 113(3):702–34.

Cheng, Justin, Daniel Romero, Brendan Meeder and Jon Kleinberg. 2011. "Predicting Reciprocity in Social Networks." Pp. 49–56 in *IEEE International Conference on Social Computing*.

Csardi, Gabor and Tamas Nepusz. 2006. "The Igraph Software Package for Complex Network Research." *Complex Systems* 1695(5):1–9.

Earl, Jennifer, Katrina Kimport, Greg Prieto, Carly Rush, and Kimberly Reynoso. 2010. "Changing the World One Webpage at a Time." *Mobilization* 15(4):425–46.

Emirbayer, Mustafa. 1997. "Manifesto for a Relational Sociology." *American Journal of Sociology* 103(2):281–317.

Flaxman, Seth, Sharad Goel, and Justin Rao. 2016. "Filter Bubbles, Echo Chambers, and Online News Consumption." *Public Opinion Quarterly* 80(S1): 298–320.

Freelon, Deen, Charlton McIlwain, and Meredith Clark. 2016. "Beyond the Hashtags: #Ferguson, #Blacklivesmatter, and the Online Struggle for Offline Justice."

Friedkin, Noah 2006. *A Structural Theory of Social Influence*. New York: Cambridge University Press.

Gladwell, Malcolm. 2010. "Small Change." *New Yorker* 4(2010):42–49.

Goel, Sharad, Duncan Watts, and Daniel Goldstein. 2012. "The Structure of Online Diffusion Networks." In *Proceedings of the ACM Conference on Electronic Commerce*. New York, NY, USA.

González-Bailón, Sandra, Javier Borge-Holthoefer, and Yamir Moreno. 2013. “Broadcasters and Hidden Influentials in Online Protest Diffusion.” *American Behavioral Scientist* 57(7):943–65.

Granovetter, Mark. 1978. “Threshold Models of Collective Behavior.” *American Journal of Sociology* 83(6):1420–43.

Heckathorn, Douglas D. 1993. “Collective Action and Group Heterogeneity.” *American Sociological Review* 58(3):329–50.

Hsiao, Yuan. 2017. “Virtual Ecologies, Mobilization, and Democratic Groups without Leaders.” Pp. 34–53 in *Taiwan’s Social Movements Under Ma Ying-jeou: From the Wild Strawberries to the Sunflowers,* edited by Dafydd Fell. Taylor & Francis.

Hsiao, Yuan. 2018. “Understanding Digital Natives in Contentious Politics: Explaining the Effect of Social Media on Protest Participation through Psychological Incentives.” *New Media & Society* 20(9): 3457–3478.

Janssen, Marco and Elinor Ostrom. 2006. “Empirically Based, Agent-Based Models.” *Ecology and Society* 11(2): 37.

Juris, Jeffrey. 2012. “Reflections on #Occupy Everywhere: Social Media, Public Space, and Emerging Logics of Aggregation.” *American Ethnologist* 39(2):259–79.

Kavada, Anastasia. 2015. “Creating the Collective: Social Media, the Occupy Movement and Its Constitution as a Collective Actor.” *Information, Communication and Society* 18(8):872–86.

Kavanaugh, Andrea, and Scott Patterson. 2001. “The Impact of Community Computer Networks on Social Capital and Community Involvement.” *American Behavioral Scientist* 45 (3): 496–509.

Kim, Hyojoung and Peter Bearman. 1997. "The Structure and Dynamics of Movement Participation." *American Sociological Review* 62(1):70–93.

Kim, Hyojoung and Steven Pfaff. 2012. "Structure and Dynamics of Religious Insurgency: Students and the Spread of the Reformation." *American Sociological Review* 77(2):188–215.

Kitts, James. 2000. "Mobilizing in Black Boxes: Social Networks and Participation in Social Movement Organizations." *Mobilization: An International Quarterly* 5(2):241–57.

Klausen, Jytte. 2015. "Tweeting the Jihad: Social Media Networks of Western Foreign Fighters in Syria and Iraq." *Studies in Conflict and Terrorism* 38 (1): 1–22.

Krinsky, John and Nick Crossley. 2014. "Social Movements and Social Networks." *Social Movement Studies* 13(1):1–21.

Leenders, Roger. 2002. "Modeling Social Influence through Network Autocorrelation." *Social Networks* 24(1):21–47.

Leskovec, Jure, Jon Kleinberg, and Christos Faloutsos. 2005. "Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations." In *Proceedings of SIGKDD International Conference on Knowledge Discovery in Data Mining*, 177–87. New York, NY, USA.

Lillis, Nashelly Chavez, Tony Bizjak, Cathy Locke, Ryan; Sangree, Hudson. March 22, 2018. "Protesters of police shooting shut down I-5 and block entry to Sacramento Kings game". *The Sacramento Bee*.

Lowery, Wesley. 2016. *They Can't Kill Us All: Ferguson, Baltimore, and a New Era in America's Racial Justice Movement*. New York: Little, Brown and Company.

Macy, Michael. 1991. "Chains of Cooperation: Threshold Effects in Collective Action." *American Sociological Review* 56(6):730–47.

Manzo, Gianluca, Simone Gabbriellini, Valentine Roux, and Freda Nkirote M'Mbogori. 2018. "Complex Contagions and the Diffusion of Innovations: Evidence from a Small-N Study." *Journal of Archaeological Method and Theory* 25(4):1109–54.

Marwell, Gerald and Pamela Oliver. 1993. *The Critical Mass in Collective Action*. New York: Cambridge University Press.

Marwell, Gerald, Pamela Oliver, and Ralph Prahl. 1988. "Social Networks and Collective Action: A Theory of the Critical Mass. III." *American Journal of Sociology* 94(3): 502–34.

McAdam, Douglas. 1986. "Recruitment to High-Risk Activism." *American Journal of Sociology* 92(1):64–90.

Mendes, Kaitlynn, Jessica Ringrose, and Jessalynn Keller. 2018. "# MeToo and the Promise and Pitfalls of Challenging Rape Culture through Digital Feminist Activism." *European Journal of Women's Studies* 25(2):236–46.

Mische, Ann. 2003. "Cross-Talk in Movements: Reconceiving the Culture-Network Link." Pp. 258–80 in *Social Movements and Networks*, edited by M. Diani and D. McAdam. New York: Oxford University Press.

Oliver, Pamela. 1993. "Formal Models of Collective Action." *Annual Review of Sociology* 19(1):271–300.

Ott, Brian. 2017. "The Age of Twitter: Donald J. Trump and the Politics of Debasement." *Critical Studies in Media Communication* 34(1):59–68.

Pariser, Eli. 2011. *The Filter Bubble*. New York: Penguin.

Pfaff, Steven. 1996. "Collective Identity and Informal Groups in Revolutionary Mobilization: East Germany in 1989." *Social Forces* 75(1):91–117.

Poell, Thomas and José van Dijck. 2018. "Social Media and New Protest Movements." Pp. 546–61 in *The SAGE Handbook of Social Media*, edited by J. Burgess, A. Marwick, and T. Poell. London: Sage.

Poell, Thomas, Rasha Abdulla, Bernhard Rieder, Robbert Woltering, and Liesbeth Zack. 2016. "Protest Leadership in the Age of Social Media." *Information, Communication and Society* 19(7):994–1014.

Purbrick, Martin. 2019. "A Report of the 2019 Hong Kong Protests." *Asian Affairs* 50(4):465–87.

Schelling, Thomas. 1978. *Micromotives and Macrobehavior*. New York: Norton.

Semertzidis, Konstantinos, Evaggelia Pitoura, and Panayiotis Tsaparas. 2013. "How People Describe Themselves on Twitter." Pp. 25–30 in *Proceedings of the ACM SIGMOD Workshop on Databases and Social Networks, DBSocial '13*. New York, NY, USA.

Siegel, David. 2009. "Social Networks and Collective Action." *American Journal of Political Science* 53(1):122–38.

Siegel, David. 2011. "When Does Repression Work? Collective Action in Social Networks." *Journal of Politics* 73(4):993–1010.

Snow, David, Burke Rochford, Steven Worden, and Robert Benford. 1986. "Frame Alignment Processes, Micromobilization, and Movement Participation." *American Sociological Review* 51(4):464–81.

Steinert-Threlkeld, Zachary. 2017. "Spontaneous Collective Action: Peripheral Mobilization During the Arab Spring." *American Political Science Review* 111(2):379–403.

State, Bogdan, and Lada Adamic. 2015. "The Diffusion of Support in an Online Social Movement: Evidence from the Adoption of Equal-Sign Profile Pictures." Pp. 1741–50 in

Proceedings of the ACM Conference on Computer Supported Cooperative Work & Social Computing. New York, NY, USA.

Strang, David and Sarah A. Soule. 1998. "Diffusion in Organizations and Social Movements." *Annual Review of Sociology* 24(1):265–90.

Strogatz, Steven. 2001. "Exploring Complex Networks." *Nature* 410(6825):268–76.

Taylor, Verta. 1989. "Social Movement Continuity: The Women's Movement in Abeyance." *American Sociological Review* 54(5):761–75.

Tilly, Charles. 1978. *From Mobilization to Revolution*. Reading, MA: Addison-Wesley.

Tufekci, Zeynep and Christopher Wilson. 2012. "Social Media and the Decision to Participate in Political Protest." *Journal of Communication* 62(2):363–79.

Valenzuela, Sebastián, Arturo Arriagada, and Andrés Scherman. 2014. "Facebook, Twitter, and Youth Engagement." *International Journal of Communication* 8:2046–70.

Vasi, Ion Bogdan and Chan S. Suh. 2016. "Online Activities, Spatial Proximity, and the Diffusion of the Occupy Wall Street Movement in the United States." *Mobilization* 21(2):139–54.

Watts, Duncan J. 1999. *Small Worlds*. Princeton: Princeton University Press.

Wellman, Barry, Anabel Quan Haase, James Witte, and Keith Hampton. 2001. "Does the Internet Increase, Decrease, or Supplement Social Capital?" *American Behavioral Scientist* 45 (3): 436–55.

ENDNOTES

[10] Twitter users can follow accounts and receive information when the account posts articles.
[11] As isolates have no interactions with other nodes, their participation probability will always equal the baseline probability ($\boldsymbol{\alpha}$ in the model). Comparing the BLM network with isolates with other network configurations with isolates is equivalent to lowering the participation rate for both, leaving the relative order of participation rates intact.

[12] I use the *igraph* package in *R* (Csardi and Nepusz 2006) to simulate networks.
[13] In Siegel's typology, there is a fourth type – the hierarchical network which I did not simulate. Such networks often arise because of formal organizational arrangements that restrain certain actors to form ties with other actors, which is unlikely on social-networking sites where any user can follow others, losing empirical relevance for this study.
[14] Note that each network type can have alternative configurations. The small network has different configurations via three parameters -- number of nodes, connection radius, and rewiring probability. To create a comparable counterfactual, I set number of nodes to 655 and connection radius to 4, resulting in a density of 0.012. The rewiring probability of 0.15 is to reflect the concept of the small world with moderate clustering and spanning ties, but changing the rewiring probability yields similar results (S1 in Supplementary).

Village networks can vary by the number of clusters, size of cluster, probability of ties within cluster, and number of cross-cluster ties. I set the probability of ties within cluster to 1 (i.e., everyone is connected with everyone). The reason for this extremeness is theoretically driven. Scholars have argued that small networks with dense clusters are particularly effective in creating norms or collective identity, which can then scale up into collective action (Pfaff 1996). I can then test the mobilization power of the BLM network compared to such network configurations with a strong mobilization power within clusters.

Because the density of the BLM network is very low, it was not possible to create large clusters without significantly increasing the density. To create a comparable counterfactual, I set the number of clusters to 81 with a cluster size of 8, and randomly add 81 * 2 = 162 cross-cluster ties. This results in a network with the density of 0.012.

The opinion leader network has three parameters – the number of actors, power of preferential attachment, and the number of ties added in each step. To create a comparable counterfactual, number of actors is 655, and the number of ties to add in each generating-step is 4, resulting in a density of 0.012. Changing the preferential parameter yields similar implications (S2 in Supplementary).
[15] There are some differences with Siegel. First, the outcome is a probability rather than an absolute threshold. While both models lead to similar conceptualizations, I followed others (Leenders 2002; Friedkin 2006) as this study incorporates empirical data to inform parameters, and the network autocorrelation model has been widely used in such settings.

Also, while Siegel calculated influence in terms of the proportion of alters, the present study used the number of alters. This is because in low-density networks such as the BLM network, it would be unrealistic to use proportions because of the mathematical problems of small denominators. Many actors had only one tie, and if the tied alter participated, one might infer a participation proportion of 100% (1/1) and incorrectly conclude that influence was extremely high. This model was also more realistic, as Twitter users normally follow multiple users, who may or may not follow the Sacramento chapter. If a focal user had one following user signifying participation, it would would not completely dominate the focal user's Twitter information.
[16] Note that 20% is not an increase in participation probability, but the odds of participation.
[17] Estimation was conducted in *NetLogo* with the *R*-extension.
[18] As seen in Figure 6, at iteration 50 the outcomes are stable.

CONCLUSION

How does social media affect collective action? This dissertation shows that the answers to this seemingly straightforward question are rather complex.

For any social inquiry, the critical issue is to define the phenomenon. For the current question, both the concept “social media” and “collective action” point to the multiplicities of social phenomena. The “social” part of social media refers to different types of social relationships, including interactional ties and informational ties; and the “collective action” part of digital activism signifies many types of behavior, ranging from e-petitions, tweets, to long-term demonstrations. Such heterogeneities require social scientists to carefully define the scope conditions of the proposed theories. Thus, a first set of questions are: which aspect of social media are we referring to? What type of digital activism are we referring to?

After defining the social phenomenon, defining the level of social theory is also critical. Is the scholar examining the macro effects of mobilization at the group level, or the micro-level incentives at the individual level?

This dissertation embarked on such a journey to disentangle these questions. In Chapter Two, I started with the form of digital activism closest to past forms of collective action – street demonstrations. Then in Chapters Three and Four I extended the scope of study to include newer forms of activism – online-only activism. Putting the three chapters together, Chapter Two showed that at the individual level, social media generates psychological incentives that motivate people to participate in activism; Chapter Three extended the findings from chapter one and showed that the extent to which social media creates mobilizing power depends on the type of social relationships and the type of activism; Chapter Four moved to a macro perspective and demonstrated that even under the same mobilizing power at the individual level, the scope of mobilization at the macro level further depends on the network configuration of social media networks.

Because both social relationships and activism forms in the social media age are complex and new, a significant question would be how much past theories of collective action are applicable to understand new forms of digital activism, especially given the emergence of new theories? This dissertation demonstrated that while the forms and relationships of digital activism are different, the fundamental factors that lead to collective action are similar: Psychological factors such as efficacy, grievances, or identification still incentivize people to participate in protests, and network relationships still generate the basis of behavioral diffusion. Nonetheless, the dissertation contributes by specifying the mechanisms that connect these broad factors to social media. Specifically, the dissertation pinpointed the psychological factors that are elicited by social media, the types of networks on social media, and the network configuration of digital networks. The dissertation further connected these factors to different forms of political activism, specifically by employing a risk framework. Depending on the risk/cost of the activism, different types of networks and network structures can promote or inhibit the mobilization process.

Implications

Digital activism is an ever-evolving form of political action around the globe, and newer and newer forms of social media and activism will continue to arise. In 2019, Hong Kongers used the platform *LIHKG* to coordinate democratic and longstanding protests against the Extradition Bill. In 2020, another wave of the Black Lives Matter Movement rose due to the death of George Floyd, further awakening consciousness on racial injustice in the United States. Again, Twitter and other social media were critical in spreading the movement. In the same, year, protestors in Thailand use Facebook and multiple types of social media to organize protests calling for the resignation of the prime minister. In 2021, a group of investors on the digital platform *Reddit* spurred a large movement against Wall Street hedge funds, driving the stock of GameStop an 19,000% increase compared to a year earlier at one point. A theoretical framework that can help allocate the core mechanisms of change is critical to understand these innovative forms of digital activism. By pinpointing the axes of psychological incentives, network types, network structure, and activism forms, the dissertation provides propositions that can be tested in such various types of social media in various countries.

By pinpointing the psychological factors and network conditions, the dissertation answers the general question I outlined in the Introduction chapter – why are there people, despite using social media, not willing to participate in collective action? And relatedly, why do some attempts of social media mobilization fail? At the micro level, if social media usage fails to elicit the critical psychological incentives, especially individual efficacy, then the individual is unlikely to participate. Instead, "slacktivism" is the more likely outcome since the individual does not believe that she/he can contribute to movement success anyway (Kristofferson, White, and Peloza 2014). At the meso and macro levels, if the types of networks and network structures are not conducive to the type of activism, then the scope of mobilization would not be large.

By focusing on these mechanisms, the dissertation may also provide some insight on how to generate collective action. As outlined in each chapter, focusing on the critical factors that aid mobilization could be a priority for grassroots building. How to elicit emotions, build deep networks, and include peripheral people who are not embedded in the core network of activists would be tasks for collective action. These tasks would be especially relevant for activism types that require higher costs/risks.

Future directions

The data limitations specific to each chapter's data are already mentioned, so I focus on general limitations and future directions on the topic of social media and collective action.

One general limitation is that each chapter addressed a different dimension of the relationships between social media and collective action – psychological incentives, network types, and network structure. However, it is very possible that these dimensions have interaction effects. As a few examples, the types of emotions elicited by social media may depend on the type of the relationships; the psychological incentives generated by network relationships may depend on where the individual is embedded in the network structure; the type of network could determine the network structure of social media. Building models that incorporate interactions between factors at different levels would be a next task.

Another future direction would be to explore how social media relates to different repertoires of activism, especially regarding protest violence. All activism types in the cases of this dissertation were peaceful tactics, yet in many cases violent tactics, such as attacking the police or property damage, are part of routine collective action repertoires (DeLuca, Lawson, and Sun 2012; Paret 2015). While this dissertation does not provide direct answers to which participants resort to violent tactics rather than peaceful ones, psychological incentives and network embeddedness would likely be critical factors that link social media usage and activism types (Thompson 2011). For instance, the psychological incentives that trigger radical action differ from those that motivate peaceful tactics (Tausch et al. 2011), and how social media relates to action of radicalization would be a fruitful avenue of investigation.

A final remark on future directions is how resistance and counter-movements spread on social media. In the Sunflower Movement, Black Lives Matter, the Hong Kong anti-ELAB movement and many other cases of digital activism, the movement was met with counter-movements that opposed the movement goals. Why did some citizens choose to join one movement rather than the other, and what role did social media play in the process? Again examining the psychological factors and network relationships would be fruitful avenues. Regarding psychological incentives, I would anticipate that identification would play a crucial factor as a distinguishing psychological factor (Klandermans 2014), and how social media shapes the identification of different users would be an interesting inquiry. Why do people from different social backgrounds formulate different identities that may be in conflict with one another, and what is the role of digital media in such processes? Are such identities merely a transformation of offline "life-worlds" (Elder-Vass 2018), or are they newly minted and formulated through online interactions (Kavada 2015)? Regarding network relationships, how people sort into polarizing network structures (Baldassarri and Bearman 2007), and the role of social media in this process, would be another line of inquiry. Again the critical inquiry would be how much social media allows for the formation of new relationships (Bennett 2012), and how much are such networks a reflection of offline social networks (Bisbee and Larson 2017). A network perspective would help us not only understand mobilization, but group conflict as well.

Concluding remarks

Societal changes are often associated with technological advancements. The prevalence of social media has allowed every citizen to potentially become simultaneously an influencer and subject of influence. While the rosy picture that social media can bring democratic change is possible, the pathway to achieve democracy largely depends on how people, governments, and social media firms utilize such social media to achieve their own goals. Sparks of democratic change have occurred, but so has mobilization for undemocratic action. Explaining how technological change links to the action of people calls for sociological research that pays special attention to theory-building, gathering innovative data, and careful specification of the phenomenon of examination. The field of digital activism would continue to be central in the political arena, and draw interest from numerous disciplines like computer science, communication, psychology, information schools, political science, and of course, sociology. In my view, understanding the complex mechanisms associated with digital activism is a formidable task. While conventional theories and methods of sociology can provide much insight, restricting to disciplinary boundaries would hinder the ability to comprehend new forms of digital activism. It is the social phenomenon, not the discipline, that drives the inquiry of social action.

References

Baldassarri, Delia, and Peter Bearman. 2007. "Dynamics of Political Polarization." *American Sociological Review* 72(5):784–811. doi: 10.1177/000312240707200507.

Bennett, W. Lance. 2012. "The Personalization of Politics: Political Identity, Social Media, and Changing Patterns of Participation." *Ann. Am. Acad. Pol. Soc. Sci.* 644(1):20–39. doi: 10.1177/0002716212451428.

Bennett, W. Lance, and Alexandra Segerberg. 2012. "The Logic of Connective Action: Digital Media and the Personalization of Contentious Politics." *Inf. Commun. Soc.* 15(5):739–68.

Bennett, W. Lance, Alexandra Segerberg, and Shawn Walker. 2014. "Organization in the Crowd: Peer Production in Large-Scale Networked Protests." *Inf. Commun. Soc.* 17(2):232–60. doi: 10.1080/1369118X.2013.870379.

Bisbee, James, and Jennifer M. Larson. 2017. "Testing Social Science Network Theories with Online Network Data: An Evaluation of External Validity." *The American Political Science Review* 111(3):502.

Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam D. I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. 2012. "A 61-Million-Person Experiment in Social Influence and Political Mobilization." *Nature* 489(7415):295. doi: 10.1038/nature11421.

Boulianne, Shelley. 2015. "Social Media Use and Participation: A Meta-Analysis of Current Research." *Inf. Commun. Soc.* 18(5):524–38. doi: 10.1080/1369118X.2015.1008542.

Castells, Manuel. 2015. *Networks of Outrage and Hope: Social Movements in the Internet Age*. Cambridge: Polity.

Centola, Damon. 2018. *How Behavior Spreads: The Science of Complex Contagions*. Princeton University Press.

Coleman, James S. 1994. *Foundations of Social Theory*. Harvard university press.

DeLuca, Kevin M., Sean Lawson, and Ye Sun. 2012. "Occupy Wall Street on the Public Screens of Social Media: The Many Framings of the Birth of a Protest Movement." *Communication, Culture & Critique* 5(4):483–509. doi: 10.1111/j.1753-9137.2012.01141.x.

Earl, Jennifer, Katrina Kimport, Greg Prieto, Carly Rush, and Kimberly Reynoso. 2010. "Changing the World One Webpage at a Time: Conceptualizing and Explaining Internet Activism." *Mobilization* 15(4):425–46.

Elder-Vass, Dave. 2018. "Lifeworld and Systems in the Digital Economy." *European Journal of Social Theory* 21(2):227–44.

Eltantawy, Nahed, and Julie B. Wiest. 2011. "The Arab Spring| Social Media in the Egyptian Revolution: Reconsidering Resource Mobilization Theory." *Int. J. Commun. Syst.* 5(0):18.

Foa, Roberto Stefan, and Yascha Mounk. 2016. "The Danger of Deconsolidation: The Democratic Disconnect." *Journal of Democracy* 27(3):5–17.

Gerbaudo, Paolo. 2012. *Tweets and the Streets: Social Media and Contemporary Activism*. London: Pluto Press.

Gonzalez-Bailon, Sandra, Andreas Kaltenbrunner, and Rafael E. Banchs. 2010. "The Structure of Political Discussion Networks: A Model for the Analysis of Online Deliberation." *J. Inf. Technol. Impact* 25(2):230–43. doi: 10.1057/jit.2010.2.

Howard, Philip N., and Muzammil M. Hussain. 2011. "The Role of Digital Media." *Journal of Democracy* 22(3):35–48. doi: 10.1353/jod.2011.0041.

Hsiao, Yuan. 2018. "Understanding Digital Natives in Contentious Politics: Explaining the Effect of Social Media on Protest Participation through Psychological Incentives." *New Media & Society* 20(9):3457–78. doi: 10.1177/1461444817749519.

Hsiao, Yuan. 2020. "Evaluating the Mobilization Effect of Online Political Network Structures: A Comparison between the Black Lives Matter Network and Ideal Type Network Configurations." *Social Forces*.

Kavada, Anastasia. 2015. "Creating the Collective: Social Media, the Occupy Movement and Its Constitution as a Collective Actor." *Inf. Commun. Soc.* 18(8):872–86. doi: 10.1080/1369118X.2015.1043318.

Kharroub, Tamara, and Ozen Bas. 2016. "Social Media and Protests: An Examination of Twitter Images of the 2011 Egyptian Revolution." *New Media & Society* 18(9):1973–92.

Kim, Hyojoung, and Steven Pfaff. 2012. "Structure and Dynamics of Religious Insurgency: Students and the Spread of the Reformation." *Am. Sociol. Rev.* 77(2):188–215. doi: 10.1177/0003122411435905.

Kitts, James. 2000. "Mobilizing in Black Boxes: Social Networks and Participation in Social Movement Organizations." *Mobilization: An International Quarterly* 5(2):241–57.

Klandermans, Pieter G. 2014. "Identity Politics and Politicized Identities: Identity Processes and the Dynamics of Protest." *Polit. Psychol.* 35(1):1–22. doi: 10.1111/pops.12167.

Kristofferson, Kirk, Katherine White, and John Peloza. 2014. "The Nature of Slacktivism: How the Social Observability of an Initial Act of Token Support Affects Subsequent Prosocial Action." *Journal of Consumer Research* 40(6):1149–66.

McAdam, Douglas. 1988. *Freedom Summer*. New York: Oxford University Press.

Moeller, Judith, Claes De Vreese, Frank Esser, and Ruth Kunz. 2014. "Pathway to Political Participation: The Influence of Online and Offline News Media on Internal Efficacy and Turnout of First-Time Voters." *American Behavioral Scientist* 58(5):689–700.

Morris, Aldon D. 1984. *The Origins of the Civil Rights Movement*. New York: The Free Press.

Opp, Karl-Dieter. 2009. *Theories of Political Protest and Social Movements: A Multidisciplinary Introduction, Critique, and Synthesis*. New York: Routledge.

Paret, Marcel. 2015. "Violence and Democracy in South Africa's Community Protests." *Rev. Afr. Polit. Econ.* 42(143):107–23. doi: 10.1080/03056244.2014.995163.

Pfaff, Steven. 1996. "Collective Identity and Informal Groups in Revolutionary Mobilization: East Germany in 1989." *Social Forces* 75(1):91–117. doi: 10.1093/sf/75.1.91.

Polletta, Francesca, and James M. Jasper. 2001. "Collective Identity and Social Movements." *Annu. Rev. Sociol.* 27(1):283–305. doi: 10.1146/annurev.soc.27.1.283.

Shirky, Clay. 2011. "The Political Power of Social Media: Technology, the Public Sphere, and Political Change." *Foreign Affairs* 28–41.

Tausch, Nicole, Julia C. Becker, Russell Spears, Oliver Christ, Rim Saab, Purnima Singh, and Roomana N. Siddiqui. 2011. "Explaining Radical Group Behavior: Developing Emotion and Efficacy Routes to Normative and Nonnormative Collective Action." *Journal of Personality and Social Psychology* 101(1):129.

Thompson, Robin. 2011. "Radicalization and the Use of Social Media." *Journal of Strategic Security* 4(4):167–90.

Valente, Thomas W. 1996. "Social Network Thresholds in the Diffusion of Innovations." *Soc. Networks* 18(1):69–89. doi: 10.1016/0378-8733(95)00256-1.

Valenzuela, Sebastián, Arturo Arriagada, and Andrés Scherman. 2012. "The Social Media Basis of Youth Protest Behavior: The Case of Chile." *Journal of Communication* 62(2):299–314.

Valenzuela, Sebastián, Arturo Arriagada, and Andrés Scherman. 2014. "Facebook, Twitter, and Youth Engagement: A Quasi-Experimental Study of Social Media Use and Protest Behavior Using Propensity Score Matching." *International Journal of Communication* 8:2046–70.

Vasi, Ion Bogdan, and Chan S. Suh. 2016. "Online Activities, Spatial Proximity, and the Diffusion of the Occupy Wall Street Movement in the United States." *Mobilization* 21(2):139–54.

Watts, Duncan J. 1999. "Networks, Dynamics, and the Small-World Phenomenon." *Am. J. Sociol.* 105(2):493–527.

van Zomeren, Martijn, Tom Postmes, and Russell Spears. 2008. "Toward an Integrative Social Identity Model of Collective Action: A Quantitative Research Synthesis of Three Socio-Psychological Perspectives." *Psychol. Bull.* 134(4):504–35. doi: 10.1037/0033-2909.134.4.504.

APPENDICES

APPENDICES FOR CHAPTER TWO

Appendix A: logic and details of survey design

Overview

Informed by the research questions of selection bias and psychological incentives, the design of the survey incorporates two essential elements. First, it includes personal histories of potential confounders *before the issue of protest*. This would isolate the effect of SM activity related to the issue net of sources of selection bias. Second, it informed by previous work on psychological incentives (Opp and Gern 1993; Van Zomeran et al. 2008), the questionnaire includes five key factors: anger, social incentives, identification, group efficacy, and individual efficacy. This would survey a broad range of psychological incentives that have shown to be predictors of protest.

As any survey should be aware of issues of reliability and validity, the design includes various methods to enhance the quality of the research, which is described below. In the first part of this Appendix the detailed logistics of the survey is described. In the second part of this Appendix I discuss various implementations to reduce potential issues that may undermine the quality of the survey.

Details of the survey

Pretest procedures and implementation

Before the questionnaire was distributed, three pretests were conducted (Groves et al. 2011). First, to ensure that the measures aligned with the theoretical constructs, the questionnaire was distributed to experts in the fields of collective action or survey design. Second, to verify that the respondents interpreted items correctly, ten Taiwanese citizens were recruited through personal networks, and cognitive interviews were conducted using a “think aloud” procedure. Respondents elaborated what they were thinking while completing the questionnaire. Third, a field test was conducted. A draft version of the questionnaire was distributed through personal networks to 27 respondents. In contrast to the cognitive interviews, feedback was obtained after the respondents completed the questionnaire. Thus, the latter two methods complement one another in that one involves dense interaction with the researcher and the other mimics the field situation. Respondents for the cognitive interviews and field tests were recruited from personal networks to prevent contamination of the final sample since information on the Internet is easily transmitted. All pretest results were excluded from the final analyses.

The questionnaire was posted online on PTT, a large Bulletin Board System (BBS) forum site in Taiwan (described below). The survey was posted from May 5, 2015 to June 25, 2015. As an incentive, a lottery was conducted randomly and respondents were selected to win an IPad or convenience store coupons.

Since Taiwan's official language is Mandarin, the questionnaire was translated by the author. The questionnaire consisted of approximately 50 questions (varying due to skip patterns) and took approximately 10-15 minutes to complete.

Validity Checks

To prevent repeated responses, a cookie restriction on the website was implemented. Additionally, respondents were asked to provide their PTT ID and email address for contact purposes for the lottery. Finally, upon contact, the respondents were asked to provide their name and address for prizes to be mailed. Therefore, a respondent would have to own two PTT IDs and emails as well as two names and addresses and to remove previous cookies to provide a repeated response. The number of repeated responses should be low or none.

A total of 948 respondents completed the survey. Two validity checks were conducted before the analysis. First, respondents who completed the survey in an extraordinarily short time (i.e., less than four minutes; the median response time was approximately 10 minutes) were excluded. Second, to exclude respondents who were not paying attention to the questions, the questionnaire included two questions that were contradictory to one another: "In general, I felt angry towards those who physically attended the movement" and "In general, I admired those who physically attended the movement." Respondents who answered "Agree/Strongly Agree" on both questions were excluded from the analysis. After the checks, the effective sample size is 913.

Measures of control variables

Demographic variables

Several demographic variables were measured, including gender (0 = male, 1 = female), age, status as college student (0=not student, 1=college/graduate student) father's education and mother's education (1 = less than elementary school, 7 = doctoral).

Previous political behavior (before the issue of protest)

Previous political behavior was measured, including "On average, how often did you discuss political or social issues with others?" and "On average, how often did you read political or social news?" (1 = less than once a month, 5 = everyday). Additional items measured whether the respondent ever had the experience of attending a protest, attending a political rally, attending a community meeting, working for a politician, working with an NGO, or solving community problems with others (0 = no, 1= yes).

Previous social media behavior (before the issue of protest)

Previous social media behavior consisted of a series of items: “On average, how often on your social media site did you post comments on political or social issues?”, “On average, how often on your social media site did you comment on other people’s posts on political or social issues?”, “On average, how often on your social media site did you repost or re-share other people’s posts on political or social issues?”, “On average, how often on your social media site did you ‘like’ other people’s posts on political or social issues?”, and “On average, how often on your social media site did you encourage others to take action to support political or social issues by posting or responding posts?” (1 = less than once a month, 5 = everyday).

Discussions on study design

On sample selection

Related to the goals of statistical inference is the selection of the sample. Because this study was not a random probability sample, there may be concerns about selection on the dependent variable, such as those who attended the protest were more inclined to respond the survey. Multiple procedures were implemented to reduce this possibility.

First, by including various controls of selection bias, such as political interest and political experience, the bias in estimating the key independent variable (i.e., SM activity) is reduced. In other words, in regression settings, the impact of selection bias originates from the violation of *conditional independence* between the independent variable and the error term (also known as omitted variable bias) (Wakefield 2013). By including variables on selection bias in the model, the unexplained correlation between the error term and SM activity is accounted for.

Second, the survey was intentionally posted on boards that were *unrelated to politics* with the aim of sampling a population that had little association with protest.

The information statement and the recruitment post explicitly asked people to complete the survey *regardless of* whether they were supportive of, against, or did not care about the Sunflower Movement. The aim was to recruit a sample consisting of heterogeneous groups, which reduces the probability of only recruiting respondents interested in the Sunflower Movement. Moreover, a lottery was drawn to increase the motivation of people who were not interested in politics. Thus, we would expect people who were interested in politics as well as those who were not to be interested in completing the survey. As approximately 60% of the sample *did not* participate in the Sunflower Movement allows the analyses to have enough cases on both sides to distinguish effects.

Finally, suppose the issue of selection bias existed, we would like to understand the direction of the bias. In a case with more protest participants than expected, the regression coefficients should be downward biased towards zero (see King, Keohane, and Verba 1994). For instance, SM activity may have a stronger effect on protest participation than estimated, which does not change research implications.

On retrospective questions

Because retrospective questions were included in the questionnaire, multiple procedures were implemented to reduce recall bias.

As scholars have noted, the specification of landmark events significantly reduces recall bias (Loftus and Marburger 1983; Shum 1998). *By design,* this survey asked about people's experience regarding a landmark event. The Sunflower Movement marked the largest student protest ever in Taiwanese history and was intensively report by the mass media.

Second, the time of recall is not very long since the survey asked about an event one year earlier, which is not a long time compared with other surveys that ask about life histories

(Freedman et al. 1988; Berney and Blane 1997). Before the respondents answered any questions about politics, two questions about daily life (how often the respondent went shopping and how often the respondent played electronic games at the time) were implemented to help respondents locate their memory at the time. The percentage of respondents answering "don't know" was below 3% on both questions, suggesting that recalling memory was not a difficult task.

Third, in the pretest cognitive interviews, interviewees were asked whether they had difficulty recalling memory, and none expressed such concerns.

Finally, to prevent respondents from telescoping backward through their experience during the Sunflower Movement, questions about previous experience or attitudes before the movement were placed before any items about the Sunflower Movement were asked.

Appendix B: On causal endogeneity between SM activity and psychological factors

Results indicate that SM activity triggers a variety of psychological incentives. However, because SM activity and psychological factors were measured in the same time frame, one may question the direction of the causal relationship. For instance, it might be possible that after seeing the issue of protest, a user first became angry and identified with protestors, then due to these emotions the user had lots of activities on SM. To address this problem, this analysis utilizes the set of questions regarding participants' SM activity on social/political issues *prior to the issue of protest*.

The logic is that psychological incentives triggered due to the issue should have no effect on previous SM activity. Therefore, if SM activity does have an effect, we should see a positive relationship between prior SM activity and the psychological factors (a lagged effect). On the other hand, if it is psychological factors that lead to increased SM activity, we should not see such a positive association. Structural equation modeling on the same model was used, except that SM activity items are now regarding the individuals' previous behavior on SM.

Fit indices of the model suggest a good fit ($\chi2$ (38) = 89.957, $p < .001$; CFI = 0.995; TLI = 0.991; RMSEA = 0.039). In addition, none of the residual correlations have an absolute value of 0.1 or higher.

As seen in Table B1, the results are similar except that the effects from SM activity to the psychological factors are smaller. This is expected since the items measure SM activity on social and political issues in general rather than specific to the Sunflower Movement, while the psychological factors are those regarding the Sunflower Movement. However, the chronological nature of the variables gives confidence to the finding that SM activity influences psychological incentives.

A notable difference is that while the effect of SM activity on social incentives, anger, individual efficacy and identification remain robust, the effect of SM activity on group efficacy is not significant. Therefore, group efficacy did not pass the robustness test, while other effect pathways appear to be robust.

Table B1. Unstandardized, Standardized, and Significance Levels for robustness model in Appendix B (Standard Errors in Parentheses; N = 879)

Parameter Estimate	*Unstandardized*	*Standardized*	*p-value*
Measurement Model Estimates			
Previous Social Media Activity → X_1	1.00	0.85	
Previous Social Media Activity → X_2	1.17 (0.12)***	0.89	.00
Previous Social Media Activity → X_3	1.37 (0.13)***	0.91	.00
Previous Social Media Activity → X_4	0.77 (0.07)***	0.78	.00
Previous Social Media Activity → X_5	1.13 (0.10)***	0.88	.00
Identification → X_6	1.00	0.92	
Identification → X_7	0.70 (0.13)***	0.85	.00
Structural Model			
Path coefficients			
Previous Social Media Activity → Social Incentives	0.15 (0.03)***	0.24	.00
Previous Social Media Activity → Anger	0.08 (0.03)**	0.13	.01
Previous Social Media Activity → Individual Efficacy	0.15 (0.03)***	0.24	.00
Previous Social Media Activity → Group Efficacy	0.01 (0.03)	0.01	.86
Previous Social Media Activity → Identification	0.32 (0.08)***	0.22	.00
Previous Social Media Activity → Protest	0.08 (0.04)	0.11	.05
Social Incentives → Protest	0.13 (0.08)	0.12	.09
Anger → Protest	-0.03 (0.11)	-0.03	.75
Individual Efficacy → Protest	0.42 (0.08)***	0.38	.00
Group Efficacy → Protest	-0.11 (0.06)	-0.10	.08
Identification → Protest	0.01 (0.06)	0.05	.69
Covariances			
Social Incentives ←→ Anger	0.26 (0.04)*	0.26	.01
Social Incentives ←→ Individual Efficacy	0.40 (0.04)***	0.40	.00
Social Incentives ←→ Group Efficacy	0.16 (0.05)*	0.16	.04
Social Incentives ←→ Identification	1.12 (0.18)***	0.49	.00
Anger ←→ Individual Efficacy	0.43 (0.04)***	0.43	.00
Anger ←→ Group Efficacy	0.24 (0.04)***	0.24	.00
Anger ←→ Identification	1.60 (0.24)***	0.70	.00
Individual Efficacy ←→ Group Efficacy	0.37 (0.04)***	0.37	.00
Individual Efficacy ←→ Identification	1.28 (0.19)***	0.56	.00
Group Efficacy ←→ Identification	0.64 (0.12)***	0.28	.00
Residual variances for Identification	5.24 (1.50)***	0.95	.00

Note: a. $\chi2$ (38) = 89.957, p < .001; CFI = 0.995; TLI = 0.991; RMSEA = 0.039
b. *p<.05; **p<.01; ****p<.001

Appendix C: Addressing causal endogeneity between psychological factors and protest

Similar to Appendix B, one may question the causal relationship between the psychological factors and protest. Although *by survey design* items on the psychological variables were chronologically before protest participation, it is still possible that respondents telescoped backward based on whether they participated in the Sunflower Movement. Therefore, a robustness check was performed using *future intentions to protest* as the dependent variable. The item was measured by "If an issue you consider unjust happens in the future, are you inclined or not inclined to participate in relevant street protests?" (0=inclined to not participate, 1=no inclination, 2=inclined to participate). The model specification is the same as Table 5, except protest participation is replaced with future protest intentions.

If the psychological factors do lead to protest, we should see a positive relationship between psychological factors and future intentions. However, if the causal relationship is reversed, we shall not observe such a relationship. Structural equation modeling was used to model the same model, except that the dependent variable is now future intentions to protest instead of protest participation.

Fit indices suggest good fit ($\chi2$ (37) = 145.339, $p < .001$; CFI = 0.993; TLI = 0.987; RMSEA = 0.058). In addition, none of the residual correlations have an absolute value of 0.1 or higher.

As seen in Table C1, we see that the correlations between psychological factors remain statistically significantly. More importantly, in addition to the significant relationship between individual efficacy and future intentions, identification seems to be a strong predictor of future intentions as well. Note again that since there are reciprocal relationships between the psychological factors, this does not mean that other incentives have no effect. More disentanglement of the psychological factors should be left for future studies, although it seems that individual efficacy is more robust to different specifications. The key is that the chronological nature of the variables give confidence to the results that psychological factors mediate the relationship between SM activity and protest participation.

Table C1. Unstandardized, Standardized, and Significance Levels for robustness model in Appendix C (Standard Errors in Parentheses; N = 879)

Parameter Estimate	*Unstandardized*	*Standardized*	*p-value*
Measurement Model Estimates			
Social Media Activity → X_1	1.00	0.86	
Social Media Activity → X_2	1.38 (0.14)***	0.92	.00
Social Media Activity → X_3	1.32 (0.12)***	0.91	.00
Social Media Activity → X_4	0.79 (0.05)***	0.80	.00
Social Media Activity → X_5	0.93 (0.05)***	0.84	.00
Identification → X_6	1.00	0.93	
Identification → X_7	0.66 (0.05)***	0.85	.00
Structural Model			
Path coefficients			
Social Media Activity → Social Incentives	0.26 (0.03)***	0.40	.00
Social Media Activity → Anger	0.30 (0.03)***	0.45	.00
Social Media Activity → Individual Efficacy	0.36 (0.03)***	0.52	.00
Social Media Activity → Group Efficacy	0.10 (0.03)***	0.17	.00
Social Media Activity → Identification	0.78 (0.13)***	0.54	.00
Social Media Activity → Protest Intentions	0.18 (0.04)***	0.21	.00
Social Incentives → Protest Intentions	0.12 (0.07)	0.09	.06
Anger → Protest Intentions	0.05 (0.08)	0.04	.53
Individual Efficacy → Protest Intentions	0.39 (0.08)***	0.32	.00
Group Efficacy → Protest Intentions	-0.00 (0.07)	-0.00	.99
Identification → Protest Intentions	0.13 (0.06)*	0.22	.02
Covariances			
Social Incentives ←→ Anger	0.12 (0.05)*	0.12	.01
Social Incentives ←→ Individual Efficacy	0.28 (0.04)***	0.28	.00
Social Incentives ←→ Group Efficacy	0.10 (0.05)*	0.10	.04
Social Incentives ←→ Identification	0.79 (0.15)***	0.39	.00
Anger ←→ Individual Efficacy	0.27 (0.05)***	0.27	.00
Anger ←→ Group Efficacy	0.19 (0.05)***	0.19	.00
Anger ←→ Identification	1.25 (0.21)***	0.61	.00
Individual Efficacy ←→ Group Efficacy	0.33 (0.04)***	0.33	.00
Individual Efficacy ←→ Identification	0.86 (0.15)***	0.42	.00
Group Efficacy ←→ Identification	0.45 (0.11)***	0.22	.00
Error X_3 ←→ Error X_4	-0.30 (0.09)***	-0.30	.00
Residual variances for Identification	4.19 (1.31)***	0.71	.00

Note: a. $\chi2$ (37) = 145.339, p < .001; CFI = 0.993; TLI = 0.987; RMSEA = 0.058
b. *p<.05; **p<.01; ****p<.001

APPENDICES FOR CHAPTER THREE

Appendix A: Correlations between variables

Since the main concern is to explain participate/not participate in activism, I dichotomize the dependent variables to calculate tetrachoric, biserial, and Pearson correlations and presented in Table S1-1.

Regarding the dependent variables, the correlation between *BLM Expression* and *BLMSacramento Events* is .65, indicating that the two types of activism often co-occur.

Regarding independent variables. *BLM Expression* is positively associated with both interactional tie centrality and informational tie centrality, while negatively associated with interactional tie isolate status. However, network similarity from interactional ties appears to be the strongest covariate ($\rho = .52$). *BLMSacramento Events* is positively associated with interactional tie centrality and informational tie centrality, and network similarity from interactional ties also appears to be the strongest predictor ($\rho = .89$). Such results preliminarily suggest that network similarity from interactional ties creates larger incentives for activism regardless of the activism form.

For interactional ties, consistent with the framework that network structures affect network similarity, isolates, centrality, and clustering all have a moderate association with network similarity. For informational ties, we still observe such associations, but the associations are smaller.

Table S1-1. Tetrachoric, biserial, and Pearson correlations.

	1	2	3	4	5	6	7	8	9	10	11	12
1 BLM Expression	1.00											
2 BLMSacramento Events	.65	1.00										
3 Isolate (Interactional tie)	-.62	-.54	1.00									
4 Centrality (Interactional ties)	.22	.31	-.21	1.00								
5 Clustering (Interactional ties)	.41	.12	-.62	-.04	1.00							
6 Isolate (Informational ties)	-.21	-.29	.17	-.13	-.12	1.00						
7 Centrality (Informational ties)	.29	.23	-.31	.74	.02	-.23	1.00					
8 Clustering (Informational ties)	.01	-.03	.05	-.06	.07	-.45	-.03	1.00				
9 Network similarity: BLM Expression (Interactional ties)	.52	.66	-.47	0.52	.29	-.21	.59	.00	1.00			
10 Network similarity: BLM Expression (Informational ties)	.26	.11	-.08	.24	.06	-.39	.44	.16	.26	1.00		
11 Network similarity: BLMSacramento Events (Interactional ties)	.42	.89	-.40	.25	.26	-.09	.30	-.04	.65	.09	1.00	
12 Network similarity: BLMSacramento Events (Informational ties)	.11	.31	.01	.08	-.03	-.34	.11	.10	.02	.39	-.01	1.00

Appendix B: Count model coefficients

This section presents the count model coefficients on the hurdle autoregressive models. To reiterate, the main manuscript presented the binomial coefficients, which tests the hurdle of moving from non-participation to participation. The count model coefficients in this section present coefficients explaining which users participate more once they have decided to participate. As the literature review main concerns participation/non-participation, there are no hypotheses to guide results from this section. However, discussions would be provided.

Table S2-1 presents the count model coefficients on *BLM Expression*. As seen in Model 3, contrary to the general trend found in the manuscript that interactional ties have stronger effects, in the count model coefficients we find that informational tie isolates, centrality, and local clustering all have a significant effect. Furthermore, as seen in Models 4-5, the difference in network similarity effects between interactional ties and informational ties is substantially reduced compared to the binomial model. The results echo the discussion in the main manuscript in that informational ties may have substantial effects on the degree of participation in online-only activism once one has decided to participate. Drawing from theories of how humans filter information (Broadbent 1958; Miller 1956), perhaps before one decides to participate interactional ties provide the social incentives to participate but informational ties are merely noise, but once the threshold of participation is crossed "preaching to the converted" is much easier and the information from informational ties become reinforcing mechanisms rather than noise.

Table S2-1. Hurdle autoregressive model on BLM Expression (count coefficients).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model 1	Model 2	Model 3	Model 4	Model 5
Network Position					
Interactional Ties					
Isolates	-.78***		-.35**		-.09
	(.14)		(.13)		(.09)
Centrality	.61***		-.15		-.18*
	(.16)		(.11)		(.08)
Local clustering	.27+		.32**		.02
	(.15)		(.12)		(.07)
Informational Ties					
Isolates		-.30**	-.25**		-.06
		(.09)	(.09)		(.07)
Centrality		1.21***	1.21***		.21+
		(.19)	(.18)		(.11)
Local clustering		.33**	.21*		.17**
		(.11)	(.10)		(.06)
Network Similarity					
Interactional Ties				1.03***	.94***
				(.07)	(.08)
Informational Ties				.72***	.64***
				(.06)	(.07)
Age	.10	.17**	.17+	.23**	.24***
	(.10)	(.06)	(.09)	(.07)	(.07)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-counts
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Table S2-2 presents the count model coefficients on *BLMSacramento Events*. One can first notice that the standard errors for the structural network characteristics are either NA or are enormous for many estimates. The point refers to the concern mentioned in the main manuscript that although we have the statistical power to estimate the threshold of participation/non-participation, the data does not permit sufficient power to distinguish who participates more once they have decided to participate. Still, we can see in Models 9-10 that even with limited power, Interactional tie network similarity has a statistically significant effect on *online-mobilized offline activism*, echoing the main point in the manuscript since it is by far the strongest predictor in the binomial model.

Table S2-2. Hurdle autoregressive model on BLMSacramento Events (count coefficients).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model 6	Model 7	Model 8	Model 9	Model 10
Network Position					
Interactional Ties					
Isolates	-11.37		-6.55		-4.46
	(NA)		(176.73)		(82.87)
Centrality	.05		-.16		-.08
	(.15)		(.24)		(.32)
Local clustering	-1.75+		-.97		-.17
	(.90)		(.94)		(.82)
Informational Ties					
Isolates		-6.10	-3.44		-2.55
		(NA)	(307.60)		(91.44)
Centrality		.67*	.67		.75
		(.27)	(.47)		(.66)
Local clustering		.50	.44		.44
		(.48)	(.49)		(.46)
Network Similarity					
Interactional Ties				.55***	.44***
				(.14)	(.15)
Informational Ties				.47*	.10
				(.21)	(.25)
Age	1.13**		1.19**	-.17	.53
	(.35)		(.41)	(.41)	(.46)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-counts
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Appendix C: Robustness checks on influential points/outliers

Since the dependent variables are relatively rare events, especially for *BLMSacramento Events*, one may be considered that there are a few data points that are mainly driving the results. To address this concern, this section presents re-estimates of Model 3 and Model 5 in the main manuscript since these are the two models that are most relevant to the article.

For each model, I identify the points with either the top five highest leverage, top five highest Pearson residual, or the top five highest deviance residual. For each of the data points in the list, I leave the data point out and re-estimate the model. The *R* package *LogisticDx* (Dardis 2015) was utilized to identify the potential influential points.

Table S3-1 presents the results for *BLM Expression*. The table presents the range of the estimates, and the range of the p-values obtained. As seen, the statistically significant coefficients remain significant even if we delete influential points, and the conclusions of the models remain.

Table S3-1. Hurdle autoregressive model on BLM Expression (binomial coefficients).

	Network characteristics		Network characteristics & Network similarity	
	Model 3 Estimates	p-values	Model 5 Estimates	p-values
Network Position				
Interactional Ties				
Isolates	-.531~ -.526	.000 ~ .000	-.447 ~ -.439	.000 ~ .000
Centrality	.516 ~ .532	.043 ~ .049	.168 ~ .178	> .10
Local clustering	.503 ~ .508	.000 ~ .000	.10 ~ .107	> .10
Informational Ties				
Isolates	-.094 ~ -.092	> .10	-.052 ~ -.048	> .10
Centrality	.388 ~ .399	.013 ~ .015	-.275 ~ -.265	> .10
Local clustering	.001 ~ .005	> .10	-.065 ~ -.058	> .10
Network Similarity				
Interactional Ties			2.238 ~ 2.260	.000 ~ .000
Informational Ties			.466 ~ .470	.000 ~ .000
Age	.177 ~ .183	.006 ~ .008	.301 ~ .307	.000 ~ .000
n of observations	1215		1215	

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds

Table S3-2 presents the results for *BLMSacramento Events*. Same as the case for *BLM Expression*, the statistically significant coefficients remain significant even if we delete influential points, and the conclusions of the models remain.

Table S3-2. Hurdle autoregressive model on BLMSacramento Events (binomial coefficients).

	Network characteristics		Network characteristics & Network similarity	
	Model 6 Estimates	p-values	Model 8 Estimates	p-values
Network Position				
Interactional Ties				
Isolates	-1.225 ~ -1.222	.008 ~ .008	-.975 ~ -.956	.038 ~ .043
Centrality	.245 ~ .251	.049 ~ .057	.216 ~ .258	.061 ~ .124
Local clustering	.049 ~ .052	> .10	-.027 ~ -.021	> .10
Informational Ties				
Isolates	-.417 ~ -.416	> .10	-.246 ~ -.243	> .10
Centrality	-.048 ~ -.042	> .10	-.241 ~ -.232	> .10
Local clustering	-.119 ~ -.117	> .10	-.017 ~ -.014	> .10
Network Similarity				
Interactional Ties			.656 ~ .689	.000 ~ .000
Informational Ties			.395 ~ .410	.000 ~ .000
Age	-.007 ~ -.003	> .10	-.117 ~ -.109	> .10
n of observations	1215		1215	

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds

In sum, the robustness checks on influential points suggest that the results are not driven by a few influential points.

Appendix D: Weighted network models

Since the models on network similarity (i.e., Models 4, 5, 9, 10) utilize a binary network for interactional ties (mention/not mention), one may be concerned that such a binary network may not capture the processes of network similarity. For instance, if user *i* mentions user *j* more than user *k*, we may hypothesize that user *i* draws more influence from *j* than from *k*. To test this possibility, this section re-estimates the models utilizing a weighted network for interactional ties, which is constructed by counting the number of tweets users mention one another.

To compare whether such weighted network models fit the data better than the original models, this section then calculates statistics of model fit, including the McFadden pseudo-R^2, the Tjur pseudo-R^2, AIC, and BIC. For the pseudo-R^2 statistics, higher numbers indicate better model fit, while for AIC and BIC lower numbers indicate better fit. The package *DescTools* (Signorell, A. et al 2017) in *R* was used for calculating the fit statistics.

Table S4-1 presents the estimates of Models 4 and 5 using the weighted network. The substantial results are the same as the original model in that statistically significant effects were found for interactional tie isolates, interactional tie network similarity, and informational tie network similarity, while the other structural network statistics remain insignificant. Furthermore, it seems that in the weighted network models the difference between interactional tie and informational tie network similarity effects are even more pronounced than in the original models.

Table S4-1. Hurdle weight matrix autoregressive model on BLM Expression (binomial coefficients).

	Network similarity	Network characteristics & Network similarity
	Model 4	Model 5
Network Position		
Interactional Ties		
Isolates		-.49***
		(.08)
Centrality		.02
		(.25)
Local clustering		.20*
		(.08)
Informational Ties		
Isolates		-.02
		(.07)
Centrality		-.25
		(.18)
Local clustering		-.07
		(.07)
Network Similarity		
Interactional Ties	32.69***	21.19***
	(3.49)	(3.35)
Informational Ties	.35***	.51***
	(.08)	(.10)
Age	.31***	.30***
	(.07)	(.07)
n of observations	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

However, Table S4-2 indicates that the binary network model fits the data better than the weighted network model across all four fit statistics. It suggests that network similarity may not scale up with the number of mentions in the research case.

Table S4-2. Comparison of fit statistics on Model 5.

	Binary network model	Weighted network model
McFadden pseudo-R^2	.27	.26
Tjur pseudo-R^2	.32	.31
AIC	1225.50	1243.21
BIC	1276.52	1294.23

Table S4-3 presents the weighted network model results for *BLMSacramento Events*. Results are similar to the binary network model, as statistically significant effects were found for interactional tie isolates, interactional tie network similarity, and informational tie network similarity, while the other structural network statistics remain insignificant. However, we do not see the large difference in interactional tie network similarity and informational tie network similarity effects as in *BLM Expression*.

Table S4-3. Hurdle weight matrix autoregressive model on BLMSacramento Events (binomial coefficients).

	Network similarity	Network characteristics & Network similarity
	Model 9	Model 10
Network Position		
Interactional Ties		
Isolates		-1.19*
		(.47)
Centrality		-.06
		(.19)
Local clustering		.06
		(.16)
Informational Ties		
Isolates		-.28
		(.30)
Centrality		-.19
		(.23)
Local clustering		-.09
		(.21)
Network Similarity		
Interactional Ties	.52***	.55***
	(.10)	(.12)
Informational Ties	.45***	.44***
	(.10)	(.10)
Age	-.04	-.07
	(.16)	(.16)
n of observations	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Again, the fit statistics in Table S4-4 again suggest that the binary network model in the main manuscript fits the data better than the weighted network model across all four fits statistics.

Table S4-4. Comparison of fit statistics on Model 10.

	Binary network model	Weighted network model
McFadden pseudo-R^2	.26	.18
Tjur pseudo-R^2	.20	.12
AIC	313.74	344.83
BIC	364.77	395.86

In sum, this section shows that the results from binary network models and weighted network models are largely similar, but the fit statistics indicate that the binary network models may have a better fit. Thus, the binary network models are presented in the main manuscript.

Appendix E: Robustness check using protests in Sacramento

Although the results from *BLMSacramento Events* suggest that for online-mobilized offline activism, interactional ties have a much larger effect than informational ties, two concerns may arise. First, one may wonder whether the results are generalizable to other online-mobilized offline activism. Second, since *BLMSacramento Events* is a rare event, one may wonder whether the results hold for non-rare events. Thus, this section uses protests in Sacramento as the dependent variable.

Sacramento Protests is a count variable defined by counting the number of tweets for each user that mentions the word "Sacramento" (case-ignored), and one or more of the words ["protest", "demonstration", "rally"] (case-ignored). The logic is the word "Sacramento" signifies the geography, and ["protest", "demonstration", "rally"] signifies physical activism. Of course, compared to *BLMSacramento Events*, this is an imprecise measure of offline activism in Sacramento. However, since the frequency of non-zeros is much higher (12.23%) than *BLMSacramento Events* (3.86%), this robustness check trades measurement validity for statistical power, and can complement the results in the main document which has better measurements but lower statistical power.

Table S5-1 presents the model results, again with X-standardized coefficients. As seen in Model S5-3, similar to *BLMSacramento Events*, a significant effect for interactional tie isolates was found. However, negative effects were also found for interactional tie clustering and informational tie clustering. The result can perhaps be explained by research that shows ties to supporters enhance participation while ties to non-supporters inhibit participation (Kitts 2000; McAdam 1986) and local clustering may create structural constraints to expand ties to other groups (Burt 2001). Since we do not know the goals and issues of the measured Sacramento

Protests, they may not be in congruence with the Black Lives Matter group of this study which emphasizes racial issues. Local clustering may create structural constraints to participate in other types of activism that are not related to racial issues, and hence appears as negative coefficients.

The results from Models S5-4 and S5-5 indicate similar trends to *BLMSacramento Events* in the main manuscript, as interactional tie isolates, interactional tie network similarity, and informational tie network similarity have statistically significant effects. Furthermore, similar to the main manuscript, as seen in the comparison of the coefficients, interactional tie network similarity appears to have a much larger effect than informational tie network similarity.

Table S5-1. Hurdle autoregressive model on Sacramento Protests (binomial coefficients).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model S5-1	Model S5-2	Model S5-3	Model S5-4	Model S5-5
Network Position					
Interactional Ties					
Isolates	-1.17***		-1.17***		-.68***
	(.17)		(.17)		(.18)
Centrality	.04		.10		.05
	(.07)		(.11)		(.13)
Local clustering	-.22*		-.21*		-.09
	(.09)		(.09)		(.11)
Informational Ties					
Isolates		-.18+	-.18+		-.03
		(.10)	(.10)		(.11)
Centrality		.11	-.12		-.20
		.07	(.12)		(.16)
Local clustering		-.20*	-.17+		-.29*
		(.09)	(.10)		(.14)
Network Similarity					
Interactional Ties				1.41***	1.26***
				(.13)	(.13)
Informational Ties				.19*	.20*
				(.08)	(.09)
Age	.41***	.41***	.41***	.30**	.30**
	(.09)	(.09)	(.09)	(.10)	(.11)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-odds
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

In sum, results are consistent with results in the main manuscript regarding *BLMSacramento Events* as interactional tie isolates, interactional tie network similarity, and informational tie network similarity have statistically significant effects. While negative effects were found for local clustering, perhaps it may be due to the incongruence between the protest issues and the goals of Black Lives Matter.

Appendix F: Robustness check on temporal sequence

Although the article argues that users in certain network positions are more prone to participate/not participate, because the data in the main analysis is cross-sectional one cannot sort out such a temporal sequence. Quite the opposite could occur – network positions form after one participates (e.g., one becomes more central in the network after one participates in online-only activism).

This section utilizes a second wave of data as the outcome to investigate temporal sequences. The data covers the period of July 2, 2017 to March 28, 2018, which also covers the incident of the killing of Stephon Clark in March 18, 2018 and the subsequent protests. The modeling strategy is to regress the outcome from wave 2 on the network covariates in wave 1, which examines the question: *given the structural network characteristics in wave 1, which users are more likely to participate in wave 2?*

Note that this test addresses only the temporal sequence, not causality. There could be confounding variables that influence both structural network characteristics in wave 1 and participation in wave 2 (e.g., general political interest). A test of causality would require an experimental design.

Table S6-1 shows the results using *BLM Expression* in wave 2 as the outcome. The results are generally similar to the main analysis: Interactional tie structural network characteristics have a much larger effect than informational tie structural network characteristics (Model S6-3), and interactional tie network similarity also has a much larger effect than informational tie network similarity (Model S6-5). In fact, many of the informational tie effects are not statistically significant in this model. The major difference from the main analysis is that the reduction in effect of structural network effects after accounting for network similarity is smaller.

Table S6-1. Hurdle autoregressive model on BLM Expression -- Wave 2 (binomial coefficients).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model S6-1	Model S6-2	Model S6-3	Model S6-4	Model S6-5
Network Position					
Interactional Ties					
Isolates	-.76***		-.73***		-.64***
	(.11)		(.12)		(.12)
Centrality	.95***		.77***		.57**
	(.16)		(.19)		(.20)
Local clustering	.11		.12		-.07
	.07		(.07)		(.08)
Informational Ties					
Isolates		-.28**	-.25**		-.22*
		(.09)	(.10)		(.10)
Centrality		.64***	.13		-.23+
		(.08)	(.11)		(.13)
Local clustering		-.14+	-.13		-.18+
		(.08)	(.09)		(.10)
Network Similarity					
Interactional Ties				1.00***	.76***
				(.09)	(.10)
Informational Ties				.09	.10
				.07	(.09)
Age	-.31***	-.28***	-.30***	-.30***	-.30***
	(.07)	(.07)	(.07)	(.07)	(.08)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-counts
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Table S6-2 shows the results regarding *BLMSacramento Events* in wave 2. Note that because the time period is smaller compared to the main analysis, there are fewer such events and the statistical power is reduced. Still, we see that interactional tie network characteristics of isolates and centrality appear to be associated with the outcome (Model 1), but the standard errors for centrality when accounting for informational tie characteristics are larger (Model 3). Similar to the main analysis, Model S6-10 shows that interactional tie network similarity is strongly associated with the outcome, whereas none of the informational tie covariates are statistically significant. In sum, the general conclusion that interactional ties are much more important remains consistent, although some the covariate effects are different.

Table S6-2. Hurdle autoregressive model on BLMSacramento Events -- Wave 2 (binomial coefficients).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model S6-6	Model S6-7	Model S6-8	Model S6-9	Model S6-10
Network Position					
Interactional Ties					
Isolates	-.72*		-.70*		-.45
	(.34)		(.35)		(.36)
Centrality	.22*		.16		.14
	(.09)		(.16)		(.17)
Local clustering	.04		.10		-.06
	(.19)		(.19)		(.21)
Informational Ties					
Isolates		-.05	-.03		.04
		(.19)	(.19)		(.20)
Centrality		.27*	.07		-.12
		(.11)	(.20)		(.22)
Local clustering		-.54+	-.58+		-.62+
		(.31)	(.33)		(.36)
Network Similarity					
Interactional Ties				.78***	.72***
				(.12)	(.14)
Informational Ties				.20	.26
				(.19)	(.19)
Age	.11	.12	.11	.05	.06
	(.19)	(.19)	(.19)	(.20)	(.20)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-counts
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Appendix G: Re-analysis removing organizational accounts

The main analyses do not distinguish organizational Twitter accounts from regular users since they play a role in connecting users, spread information, and often participate in activism. However, it would be interesting to understand how results may differ if we completely ignore these organizational users.

A total of 26 organizational users (2% of the total sample) were identified. Tables S7-1 and S7-2 show results with these organizational users removed. As seen in the models on network similarity (Models S7-4, S7-5, S7-9, S7-10), the substantive conclusion that network similarity from interactional ties plays a stronger role than network similarity from informational ties does not change.

However, the results regarding structural network characteristics are quite different (Models S7-1, S7-2, S7-3, S7-6, S7-7, S7-8). The effects of interactional tie isolates, interactional tie clustering on *BLM Expression*, and the effect of interactional tie centrality on *BLMSacramento Events* that were observed in the main analyses do not appear here. The 2% of the organizational users greatly affect how we conceptualize structural network characteristics. This is not surprising given the large literature on how social movement organizations (SMOs) connect people for mobilization (e.g., Jenkins and Eckert 1986; Morris 1984), and thus play a significant role in making people structurally embedded in supportive networks. For instance, SMOs disseminate connect supporters widely, and thus removing the role of SMOs results in many "false" *Isolates* who are in fact receiving movement information from SMOs, or "messed-up" *Clustering* calculations as two people may not only be friends but also participate in the same SMO. The results point to the necessity of including SMOs, especially when understanding the effects of structural network characteristics.

Table S7-1. Hurdle autoregressive model on BLM Expression (removing organizational accounts).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model S7-1	Model S7-2	Model S7-3	Model S7-4	Model S7-5
Network Position					
Interactional Ties					
Isolates	-.10		-.12		-.03
	(.08)		(.09)		(.09)
Centrality	1.82***		1.51**		-.65
	(.48)		(.48)		(.79)
Local clustering	-.27**		-.24**		-.26**
	(.09)		(.09)		(.09)
Informational Ties					
Isolates		.02	.05		.04
		(.08)	(.08)		(.08)
Centrality		.65***	.49**		.27
		(.16)	(.16)		(.20)
Local clustering		-.14+	-.11		-.09
		(.07)	(.07)		(.07)
Network Similarity					
Interactional Ties				1.68***	2.58**
				(.43)	(.88)
Informational Ties				.29**	.17
				(.11)	(.15)
Log(Number tweets)	.53***	.54***	.52***	.50***	.52***
	(.05)	(.04)	(.05)	(.04)	(.05)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-counts
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Table S7-2. Hurdle autoregressive model on BLMSacramento Events (removing organizational accounts).

	Network characteristics: Interactional Ties	Network characteristics: Informational Ties	Network characteristics	Network similarity	Network characteristics & Network similarity
	Model S7-6	Model S7-7	Model S7-8	Model S7-9	Model S7-10
Network Position					
Interactional Ties					
Isolates	-.66***		-.53**		-.38*
	(.16)		(.17)		(.18)
Centrality	-.04		-.04		-.40*
	(.14)		(.16)		(.20)
Local clustering	-.29		-.28		-.31
	(.18)		(.18)		(.22)
Informational Ties					
Isolates		-.73***	-.62**		-.64**
		(.19)	(.21)		(.22)
Centrality		.02	.02		.06
		(.14)	(.15)		(.15)
Local clustering		-.66+	-.72+		-.58
		(.39)	(.41)		(.39)
Network Similarity					
Interactional Ties				.39***	.46***
				(.07)	(.11)
Informational Ties				.22**	.19*
				(.07)	(.07)
Log(Number tweets)	.19	.22+	.15	.23	.16
	(.13)	(.12)	(.13)	(.12)	(.14)
n of observations	1215	1215	1215	1215	1215

Note:
a. Coefficients are standardized by the independent variables
b. Coefficients are presented in log-counts
*c. +p<.10; *p<.05; **p<.01; ***p<.00*

Appendix H: Pseudo-code on variable operationalization

```
Obtain list of all users following @BLMSacramento
Remove all users that have no public tweet available
Obtain all tweets for remaining users
Exclude all tweets that are after November 4, 2015

For each user in dataset:
    If user follows another user in dataset:
        create informational tie edge between the two users

        For each tweet by user:
                If tweet contains hashtag #BlackLivesMatter | #blacklivesmatter | #BLM |
                #blacklivesmattersacramento:
                        count for BLM Expression += 1

                If tweet contains url of events hosted by @BLMSacramento:
                    count for BLMSacramento Events += 1

                If tweet mentions another user in dataset:
                    create interactional tie edge between the two users

Calculate centrality for each user
Calculate local clustering coefficient for each user
Calculate indegree and outdegree for each user

For each user in dataset:
    If user's indegree and outdegree are both zero:
        define user as isolate

Calculate interactional tie network similarity for BLM Expression based on product of
interactional tie network matrix and vector of BLMExpression

Calculate interactional tie network similarity for BLMSacramento Events based on product of
interactional tie network matrix and vector of BLMSacramento Events

Calculate informational tie network similarity for BLM Expression based on product of
informational tie network matrix and vector of BLM Expression

Calculate informational tie network similarity for BLMSacramento Events based on product of
informational tie network matrix and vector of BLMSacramento Events
```

Appendix I: References

Broadbent, D. E. 2013. *Perception and Communication*. Elsevier.

Dardis, C. 2015. "LogisticDx: Diagnostic Tests for Models with a Binomial Response." *R Package Version 0. 2*.

Díaz-Uriarte, Ramón and Sara Alvarez de Andrés. 2006. "Gene Selection and Classification of Microarray Data Using Random Forest." *BMC Bioinformatics* 7:3.

Jenkins, J. Craig, and Craig M. Eckert. 1986. "Channeling black insurgency: Elite patronage and professional social movement organizations in the development of the black movement." *American Sociological Review* 51(6): 812-829.

Liaw, Andy and Matthew Wiener. 2002. "Classification and Regression by randomForest." R News 2(3):18–22.

Morris, Aldon D. 1984. *The Origins of the Civil Rights Movement*. New York: The Free Press.

Miller, George A. 1956. "The Magical Number Seven, plus or Minus Two." *Psychological Review* 63(2):81.

Rokach, Lior and Oded Maimon. 2008. *Data Mining with Decision Trees: Theory and*

Applications. London: World Scientific.

Svetnik, Vladimir et al. 2003. "Random Forest: A Classification and Regression Tool for Compound Classification and QSAR Modeling." Journal of Chemical Information and Computer Sciences 43(6):1947-58.

Signorell, Andri et al. 2017. "DescTools: Tools for Descriptive Statistics." Retrieved (https://cran.r-project.org/package=DescTools).

APPENDICES FOR CHAPTER FOUR

Appendix A: Robustness check on alternative configurations of Small World networks

As mentioned in the manuscript, the small world network can take many alternative configurations if we change the re-wiring probability of the network. This supplementary section tests how the results change as we increase/decrease the rewiring probability. I experiment with a wide range of the rewiring probability, and report the average final participating proportion over 1000 simulations.

Figure S1-1 shows the results. The x-axis is the rewiring probability, while the y-axis the final participating proportion. The red horizontal line is the result for the BLM network, while the black dots are the results for the Small World networks. The nine subplots represent the nine theoretical scenarios in the main analyses. The results are similar to the main analyses. The BLM network outperforms the Small World network (i.e., the red horizontal line is above the black dots) when conditions are unfavorable for participation (i.e., upper and left plots), but underperforms compared to the Small World network (i.e., the red horizontal line is below the black dots) when conditions are favorable (i.e., lower and right plots).

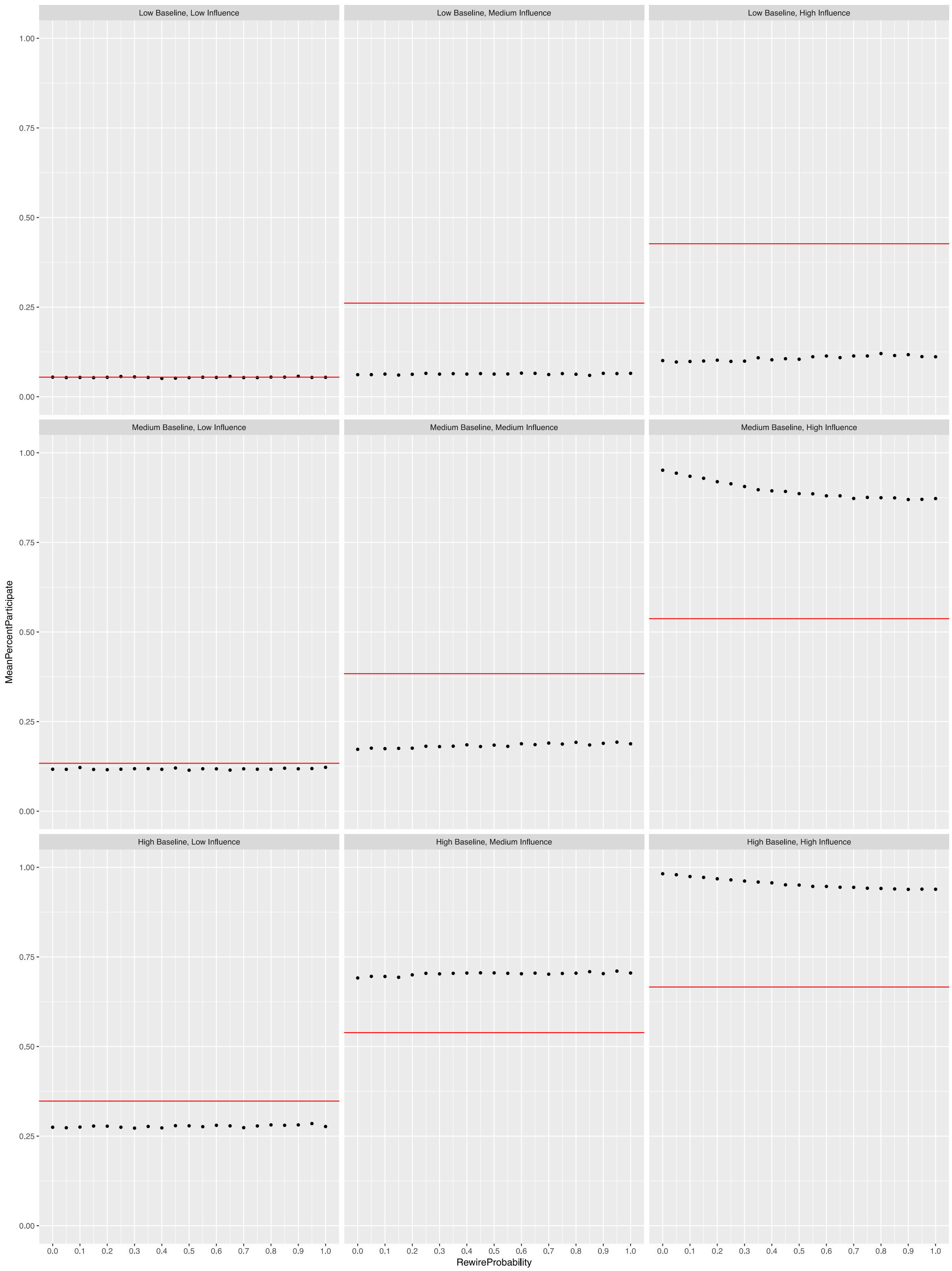

Figure S1-1. Results of robustness check for Small World networks.

Appendix B: Robustness check on alternative configurations of Opinion Leader networks

As mentioned in the manuscript, the opinion leader network can take many alternative configurations if we change the power of preferential attachment of the network. This supplementary section tests how the results change as we increase/decrease the power of preferential attachment. I experiment with a wide range of the power of preferential attachment, and report the average final participating proportion over 1000 simulations.

Figure S1-1 shows the results. The x-axis is the power of preferential attachment, while the y-axis the final participating proportion. The red horizontal line is the result for the BLM network, while the black dots are the results for the Opinion Leader networks. The nine subplots represent the nine theoretical scenarios in the main analyses. The results are in general similar to the main analyses, but with notable exceptions. The BLM network still underperforms compared to the Opinion Leader network (i.e., the red horizontal line is below the black dots) when conditions are favorable (i.e., lower and right plots). However, if the power of preferential attachment is very high (e.g. larger than 2), the Opinion Leader network can outperform the BLM network in certain unfavorable conditions (e.g., Low baseline, Low influence). This is because with very high preferential attachment the Opinion Leader network is starting to exhibit the advantageous characteristic of the BLM network – very high density clusters. As nodes tend to connect to leaders and their surrounding core a lot, dense clusters start to form and thus facilitate participation in unfavorable conditions.

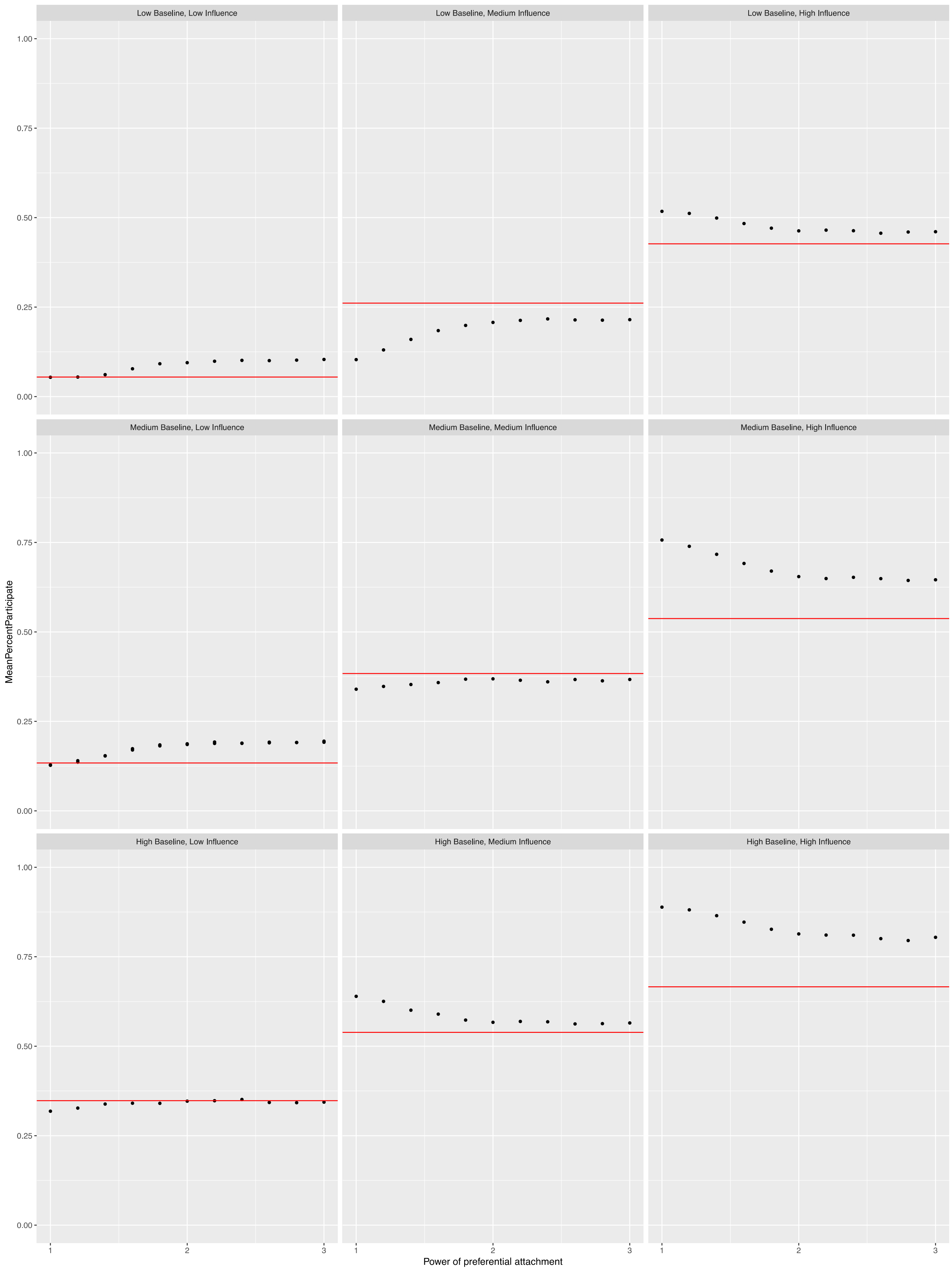

Figure S2-1. Results of robustness check for Opinion Leader networks.

Appendix C: Configurations of supplementary networks

The main analysis identified a “cluster-connective” configuration in the case of BLM Sacramento Twitter. I furthered argued that this configuration is characterized by a moderate degree of transitivity, a large standard deviation in node degree distribution, and a very large diameter. However, one may wonder if this configuration is generalizable to other digital networks. I collect additional data from *BLM Philadelphia*, the Philadelphia chapter of BLM, and *JusticeForImmigrants*, an organization for migration rights. The times of collection are August and September of 2017, which is close to the sampling time of the main analysis. I select these two because *BLM Philadelphia* can inform what other networks in BLM look like, and *JusticeForImmigrants* for comparison in other connective action networks.

The summary statistics of the networks are presented in Table S3-1. Again, for both networks we observe moderate transitivity, very high standard deviations in number of ties, and a large diameter. The configuration of the BLM Sacramento network appears to be similar in other digital networks.

Table S3-1. Summary of supplementary networks

Measure	*JusticeForImmigrants*	*BLM Philidelphia*
Number of nodes	1186	3476
Number of ties	14504	9623
Density	0.021	0.005
Transitivity	0.24	0.17
SD degree	40.23	17.42
Diameter	9	10

Appendix D: Additional Statistics on Simulation Results

In Figure 6 of the manuscript, I showed the mean participation proportion for each iteration for each scenario. However, one might be not only interested in the mean but also the degree of variation. In Table S4-1 below, I show the mean, standard deviation, minimum, maximum, and the interquartile range for the final participation proportion for each network for each conditions. In general, the variations are relatively small compared to the mean, but nonetheless exhibit some differences.

Table S4-1. Summary statistics for final participation proportions.

Scenario	Network	Mean	SD	Min	Max	IQR
Low Baseline, Low Influence	BLM	0.05	0.01	0.03	0.08	0.01
	Small World	0.05	0.01	0.03	0.08	0.01
	Village	0.05	0.01	0.03	0.08	0.01
	Opinion Leader	0.05	0.01	0.03	0.09	0.01
Low Baseline, Medium Influence	BLM	0.22	0.01	0.16	0.27	0.02
	Small World	0.06	0.01	0.04	0.09	0.01
	Village	0.06	0.01	0.03	0.10	0.01
	Opinion Leader	0.06	0.01	0.03	0.10	0.01
Low Baseline, High Influence	BLM	0.39	0.01	0.33	0.44	0.02
	Small World	0.07	0.01	0.04	0.11	0.02
	Village	0.08	0.01	0.04	0.12	0.02
	Opinion Leader	0.23	0.02	0.16	0.29	0.03
Medium Baseline, Low Influence	BLM	0.12	0.01	0.09	0.17	0.02
	Small World	0.11	0.01	0.08	0.15	0.02
	Village	0.11	0.01	0.08	0.16	0.02
	Opinion Leader	0.12	0.01	0.07	0.15	0.02
Medium Baseline, Medium Influence	BLM	0.35	0.02	0.31	0.40	0.02
	Small World	0.14	0.01	0.09	0.19	0.02
	Village	0.15	0.02	0.09	0.19	0.02
	Opinion Leader	0.21	0.02	0.15	0.28	0.03
Medium Baseline, High Influence	BLM	0.51	0.02	0.46	0.56	0.02
	Small World	0.43	0.04	0.3	0.55	0.05
	Village	0.65	0.03	0.55	0.74	0.04
	Opinion Leader	0.53	0.02	0.46	0.61	0.03
High Baseline, Low Influence	BLM	0.32	0.02	0.25	0.38	0.02
	Small World	0.25	0.02	0.20	0.33	0.02
	Village	0.26	0.02	0.21	0.32	0.02
	Opinion Leader	0.27	0.02	0.2	0.33	0.03
High Baseline, Medium Influence	BLM	0.51	0.02	0.45	0.57	0.02
	Small World	0.42	0.02	0.35	0.50	0.03
	Village	0.47	0.03	0.39	0.56	0.03
	Opinion Leader	0.77	0.02	0.72	0.81	0.02
High Baseline, High Influence	BLM	0.64	0.02	0.59	0.70	0.02
	Small World	0.88	0.01	0.84	0.92	0.02
	Village	0.94	0.01	0.90	0.96	0.02
	Opinion Leader	0.77	0.02	0.71	0.81	0.02

Appendix E: Results on analyzing only the connected component in the network

The main paper indicated that the "cluster-connective" structure is comprised of a large connected component but also many independent dyads, triads, or small components. However, one may be wondering that perhaps these unconnected components should not be considered as part of the mobilization network, and one should only examine the structural network effect of the connected clusters. To investigate this possibility, I dropped all these unconnected small components (i.e., retain only the largest component), which yields a network of 614 nodes and 2307 ties. I then constructed the ideal type networks and reran the simulations, and show the results in Figure S5-1. As seen, the implications are substantively the same as the main analyses: The BLM network facilitates participation when conditions are unfavorable but hinders participation when conditions are favorable. This is because even in the connected part, there are many hard-to-reach nodes that are far away from the dense clusters.

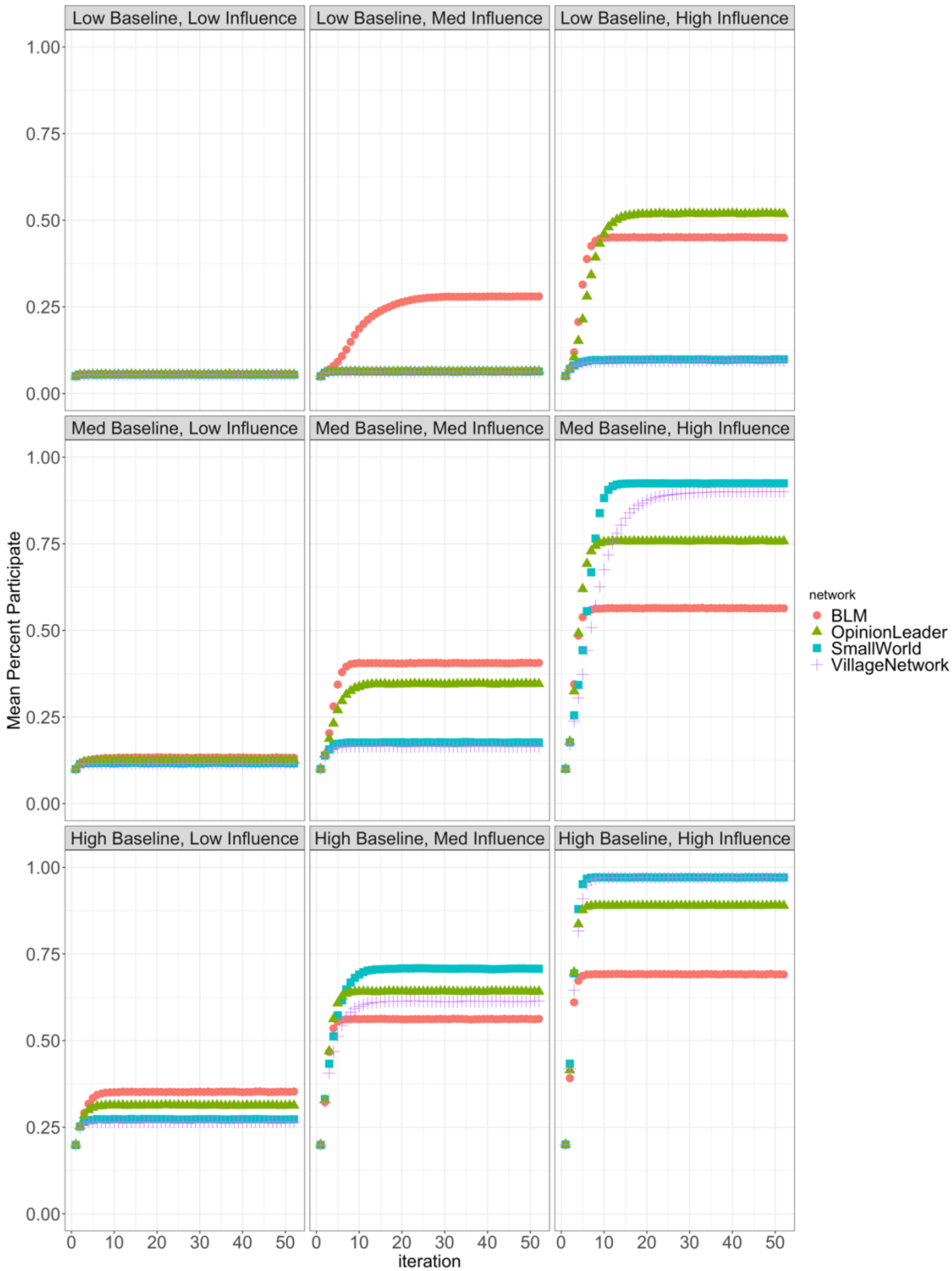

Figure S5-1. Results on robustness check on only the largest component.