

The Mechanisms of Protest Recruitment through Social Media Networks*

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Abstract

The protest mobilization literature has long suggested that social ties influence a persons decision to protest, yet previous research has not clearly established why this is the case. We consider four possible mechanisms: networks mobilize because they a) provide logistical *information*, b) *motivate* people about the cause, c) solve *coordination* problems, and d) apply social *pressure* to attend. We test these with novel protest attendance data. We identify Twitter users who participated in the 2018 U.S. Womens March, categorize the tweets they could have seen, and compare these and their network positions to those of individuals who were similar but did not participate. We find strong evidence that networks indeed mattered for mobilization. Furthermore, we show that even after controlling for a variety of confounders, exposure to messages providing information, helping to coordinate, and applying pressure predicted protest attendance while exposure to messages seeking to motivate did not.

*The authors thank the members of the Social Media and Political Participation (SMaPP) lab for early feedback on the project, as well as Emily Constance Moffa, Shiva Darshan, Megan Brown, and Nick Kuegel for their assistance. We would also like to thank and knowledge the financial support of the Moore and Sloan Foundations, the Bill and Melinda Gates Foundation, and the John S. and James L. Knight Foundation. Corresponding author: Andreu Casas (andreu.casas@rhul.ac.uk).

1 Introduction

On January 21st 2017, more than four million people joined the Women’s March that took place in hundreds of cities around the United States to demand a more equal and safe society for women.¹ In conjunction with other movements and events that happened shortly thereafter (such as the #MeToo and the #TimesUp movements), this (and subsequent Women’s) march contributed to building a stronger coalition around gender equality and to increasing the salience of existing gender disparities – illustrating the ability of social mobilizations to set political agendas and eventually influence policy (Walgrave and Vliegenthart, 2012), begging the question, what influences people’s decision to protest?

A long-standing argument in the mobilization literature is that the decision to protest is in large part a function of the activity of others in one’s social network. Put another way, people are more likely to attend a protest if people with whom they have social ties attend as well – a claim supported by findings based on self-reported data (Opp and Gern, 1993), real-world behavior (Larson et al., 2018) and both (McAdam and Paulsen, 1993).

However, why do social ties play such a mobilizing role? This crucial yet unresolved question has received an increasing amount of attention in the last two decades. As Kitts (2000) points out, “networks may presumably channel *disengagement* as well as *recruitment*”. In other words, our networks can also prevent us from participating in a protest, and so “there is no guarantee that a tie will increase participation in any given group” (Kitts, 2000, 242). As a result, a wide range of scholars have called for a more careful analysis of the network mobilizing effect. Among others, McAdam (2003) argues that “without specifying the mechanisms that account for the affect, movement researchers are guilty of assaying a structurally deterministic explanation of movement recruitment”; Passy (2003) argues that

¹There were demonstrations in other countries around the World, but the 4-5 million estimate is only for the United States. The following news article in Vox.com contains information about the head count: *The Women’s Marches may have been the largest demonstration in US History*.

“we are now aware that social ties are important for collective action, but we still need to theorize on the actual role of networks”; and [Diani \(2004\)](#) states that “over the last few years it has been increasingly argued that we ought to look for mechanisms rather than correlations, that is, we should clarify how networks really operate, and what impact they have on participation.” In sum, a stronger understanding of the reasons why and how networks mobilize in the current digital era is needed and particularly crucial to social activists and practitioners as well as to social scientists interested in political mobilization, agenda setting, policy change, and political behavior more generally.

We build on a wide range of literature to put forward four theoretically informed hypotheses regarding the *mechanisms* by which personal networks can mobilize people to participate in political activities: (a) by providing basic logistical *information* needed for attendance ([Olson, 1965](#); [Kitts, 2000](#); [Passy, 2003](#); [Diani, 2004](#)), (b) by presenting reasons and *motivation* for others to attend ([Katz and Lazarsfeld, 1955](#); [Passy, 2003](#); [McAdam, 2003](#)), (c) by contributing to solving *coordination* problems ([Opp and Gern, 1993](#); [Kuran, 1995](#); [Passy, 2003](#)), and (d) by putting social *pressure* on others to participate ([Tajfel, 1981](#); [della Porta, 1988](#); [Opp and Gern, 1993](#); [Kitts, 2000](#); [Gerber et al., 2008](#)).

We test these hypotheses using behavioral social media data related to the 2018 Women’s March and state-of-the-art machine learning techniques. We use geolocated Twitter accounts to find a set of Twitter users who attended one of the 249 separate events in the U.S.: we refer to them as the *Attender* group. Then, as a comparison set, we identify Twitter users who could have – but did not – attend one of the marches. These are users who also geolocated their tweets, also tweeted about the Women’s March, and did so from an area that was close enough to a march (and during the time of that march) that they could have plausibly participated. We refer to them as the *Non-Attender* group. In the first part of the analysis, this allows us to test whether the attender and non-attender networks vary in a way that aligns with the presence of a network mobilizing effect ([Larson et al., 2018](#)), which

they do. Then we also collect all the march-related tweets that both our attenders and non-attenders could have seen the week before the march (i.e., the messages sent by the accounts on Twitter they follow, or, in the parlance of network theory, their “ties”). After training machine learning classifiers to predict the presence of the four mobilizing mechanisms in each of the messages (information, motivation, coordination, and pressure), we assess whether, among the set of potential protesters, exposure to the four mobilizing message types on Twitter was predictive of attending the march. This analysis reveals that, after controlling for many confounders (e.g. gender, ideology, prior interest in the movement/march, and media consumption), exposure to a larger number of information, motivation, coordination and pressure messages was predictive of attending the protest.

This is the first study to date to combine real world protest attendance, information about participants and non-participants’ networks, and the messages these networks exchanged prior to protest, in order to test relevant theoretical hypotheses regarding why social networks can be mobilizing. In addition, the study contributes to the literature on social media and political mobilization by showing that social media can in part be mobilizing by channelling crucial communications between personal networks.

2 The Mobilizing Role of Networks

An extensive social science literature finds that personal networks play a crucial mobilizing role in protest participation (Granovetter, 1978; Marwell et al., 1988; Siegel, 2008; Centola, 2013; Larson et al., 2018). Some focus on the contagion effect of networks: information about a given collective action can travel more easily through existing personal connections, making those connected to people who are central to the organization more likely to participate than others (Marwell et al., 1988; Centola and Macy, 2007); while others study the interaction between network characteristics and exposure, and people’s propensity to protest: given that

not all people are initially equally likely to participate in a given action, what kind of personal interactions can make them reach their individual participation ‘thresholds’ (Granovetter, 1978; Chwe, 2000)?

This existing literature makes two main claims. The first one is that **personal ties matter**. As an example, Opp and Gern (1993) find that participants in the 1989 Leipzig rebellion were more likely than non participants to recall having a tie with other people that protested. The second main point is that the quality or **strength of the personal ties** are also important. To give one example, in a study of participation to a high-risk action, the 1964 Mississippi Freedom Summer Project (where students went to the South of the United States to combat racial segregation), McAdam and Paulsen (1993) find that people who applied for and joined the program had stronger ties (Granovetter, 1978) than other participants who applied but did not show up.

Pre-social media era research on the mobilizing role of social ties has had to rely on self-reported information from those who attended (and did not attend) a protest action, and/or had limited data on the composition of the networks of the people being studied, significantly limiting the scope of the analysis and the generalizability of the findings. The emergence of networked technologies and social media, however, has transformed the study of networks and collective action (Gonzalez-Bailon et al., 2011; Barbera et al., 2015; Larson et al., 2018). Some social media studies focus on the diffusion of a protest movement online in order to pin down what network characteristics allow for their online diffusion (Gonzalez-Bailon et al., 2011; Barbera et al., 2015). More recent research goes one step forward and uses geolocated social media accounts to combine rich network data with real-world protest participation. As an example of the latter, Larson et al. (2018) study the Twitter networks of a group of users who attended the 2015 Charlie Hebdo protest in Paris, who are then compared to a group of users who were supportive of the action but decided not to attend; the authors find the group of attenders to be more connected among themselves than the

non-attender group. Attenders had a higher proportion of ties, ties of ties, reciprocated ties, and triadic ties within the group.

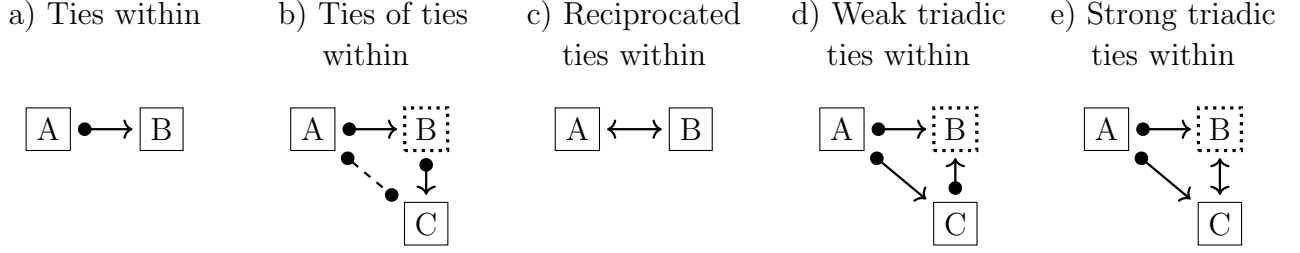
We build on the method developed by [Larson et al. \(2018\)](#) and use Twitter geolocated accounts to detect a set of users who attended, and construct a comparison group of users who, despite showing interest, did not attend the 2018 Women’s March in the United States. We also build on [Larson et al. \(2018\)](#)’s analytical strategy to assess whether a similar general network-mobilizing effect existed during the 2018 Women’s March. Then we move to the novel contribution of this paper and use the content of the tweets to explore the mechanisms and the conditions under which personal networks can indeed play a mobilizing role in the current digital environment.

2.1 Testing for the Presence of Network Mobilization

Before moving onto the mechanism analysis, we first need to assess whether a general network-mobilizing effect can be observed at all for the 2018 Women’s March. We build on [Larson et al. \(2018\)](#)’s work to accomplish this goal. Their theoretical framework holds that people’s social ties may play a role in motivating them to protest. Some people may be eager to protest regardless of what others plan to do, but other people’s willingness to attend may depend at least in part on their exposure to others. The theory is agnostic about why exactly. Regardless of the mechanism, if networks mobilize, then the networks among attenders should look different than the networks among those who did not attend. In particular, the authors suggest that these networks should differ on the five features described below (and Figure 1).² Their framework assumes two sets of data: one collected on people who attended a protest, another collected on people who are as similar as possible as the attenders and who could have attended but did not. We use Twitter data collected for the 2018 Women’s March to measure the networks *among* a set of protest attenders and

²These theoretical expectations are formally derived in [Larson et al. \(2018\)](#).

Figure 1: Visual representation of the network measures we use to test the network mobilization argument.



Legend:

B User in same group	B User might be in same group
— A connection exists	--- A connection might exist
→ Receiving user is friend	—● Receiving user might be friend

the networks *among* a set of non-attenders (the details of the data collection are in the next section). The ties in the network come from a particular feature of the platform: Twitter users can “follow” other users, and by doing so, expose themselves to messages from these people.

- a) **Ties within:** a user A follows another user B that is part of the same attender/non-attender set. User B might (but not necessarily) follow user A back.
- b) **Ties of ties within:** a user A is connected to a user C located in the same (attender/non-attender) set through an intermediate tie B. A follows B, and B follows C. A might follow C, C might follow B and/or A, and B might follow A. B might be (but not necessarily) part of the same attender/non-attender set.
- c) **Reciprocated ties within:** a user A follows another user B that is part of the same attender/non-attender set; and user B also follows user A.
- d) **Weak triadic ties within:** a user A follows another user C that is part of the same attender/non-attender set, and with whom A has a “friend” B in common (both A and

C follow B). C might also follow A, B might follow A and/or C, and B might be part of the same attender/non-attender set. The key difference with *Ties of ties within* is that in this case A must follow C.

- e) **Strong triadic ties within:** same as in *Weak triadic ties within*, but in this case the triadic connection between A and C is stronger because C has a reciprocal relationship with the common friend B.

Given that users may differ on the number of friends/ties they have, and that the interest is mainly in comparing how attenders are connected among themselves *versus* non-attenders, the authors calculate and compare the *proportion of* of all {ties | ties of ties | reciprocated ties | weak triadic ties | strong triadic ties} that are to users within the same attender/non-attender set. Higher values for the attender (v. non-attender) set would be in line with the existence of a general network-mobilizing effect.

3 The Mechanisms of Network Mobilization

Literature from a variety of fields point to several possible reasons for why personal can be mobilizing. But to date there has been very little empirical research disentangling these possible mechanisms (see Kitts (2000) as an notable exception)³. This is in part due to data limitations faced by previous studies. Disentangling and/or adjudicating between mechanisms requires the analyst to find people who participated in a collective action (and people who could have participated but did not), to observe the composition of their networks, and to have access to the relevant communications taking place within the network. We take advantage of a very rich dataset containing the Twitter networks (ties and ties-of-ties) for a group of participants and non-participants in the 2018 Women’s March, as well as

³Kitts (2000)’s work brought the field forward by not only theorizing about potential mechanisms but also putting them to test. However, as discussed by the author, the scope of the paper and findings are limited due to the use of self-reported measures and qualitative interviews.

the communications related to the march that these users’ networks exchanged the week before the protest. As previous studies have shown, Twitter networks are a good reflection of people’s real-life networks (Bisbee and Larson, 2017). And the messages people are exposed to on social media are often responsible for the diffusion of protest movements online (Gonzalez-Bailon et al., 2011; Barbera et al., 2015; Casas and Webb Williams, 2018), indicating that social media communication offer an excellent opportunity to uncover different types of network effects (Jost et al., 2018).

Scholars have laid out and coined several mechanisms as to why personal networks play a mobilizing role. As some examples, McAdam (2003) talks about the ‘recruitment attempt’, ‘identity-movement’, and the ‘positive influence’ mechanisms, and Passy (2003) highlights the ‘socialization’ function, the ‘structural connection’, and the ‘decision-shaping’ mechanism. We build on these and other literature to put forward four main mechanisms that take into account the functionalities highlighted in previous work. We call them the *information*, *motivation*, *coordination*, and *pressure* mechanism. We see them as “*non-exclusive*”, meaning that a single message can contain more than one of these mechanisms.

3.1 The Information Mechanism

Personal networks provide basic logistical information needed to participate. Information costs are a potential impediment for the success of collective actions (Olson, 1965). In order for people to decide whether to join a protest, they first need to be aware that such an action is taking place, where and when, and how to get there. Communicating, discovering and consuming this logistic information has some costs attached to it. Other scholars have previously theorized about this particular mobilizing function of personal networks: Kitts (2000) also refers to it as the ‘information’ mechanism, Passy (2003) as the ‘structural connection’ (ties connect people to recruitment efforts), and McAdam (2003) as the ‘recruitment attempt’ function.

One of the non-attenders in our datasets tweeted the following the day of the march: *“I’m kinda surprised by the #WomensMarch2018 photos and video from throughout the country. I admit I had a busy work week so I didn’t consume much news, so I didn’t even know about it. But clearly a lot of people did!”*

This anecdotal evidence raises three main points. First, it illustrates the importance of exposure to basic logistic information. In a counterfactual scenario where this person had been exposed to information about where and when the march was taking place, she might have chosen to attend. Second, this example highlights the costs attached to consuming basic logistic information. Although these are rather low, our potential protester could have learned about the 2018 Women’s March by watching the news on TV, reading a newspaper, or even searching online; however, not everybody is willing or able to bear such costs. We also note the passive nature of the delivery of the information. If one is on social media regularly – and this information is being shared in one’s network – then this logistical information just flows to the individual. The person need not make any conscious attempt to find out if a march exists, or details of how to attend.

Finally, in this scenario one can also see how personal ties could have lowered the costs of obtaining the basic logistic information needed. This person could have easily learned about the march in a simple conversation with a friend who already possessed the information, or via a social media message from a friend in her network. A substantial number of existing studies stress that personal networks are mobilizing in part because they contribute to the transmission of necessary organizing information (Gould, 1991; Lohmann, 1994; Opp and Gern, 1993; Gonzalez-Bailon et al., 2011; Theocharis et al., 2015). Building on this literature, we formulate the following hypothesis:

Information_(H₆): *Users whose friends sent Twitter messages containing basic logistical information related to the 2018 Women’s March were more likely to protest.*

3.2 The Motivation Mechanism

Personal networks provide motivation to participate. Studies of opinion formation and political attitudes show that people often do not pay attention to politics (Hibbing and Theiss-Morse, 2002) nor do they have clear policy positions on a wide range of issues and policies (Converse, 2006). When it comes to making political decisions, such as voting and attending a protest, people often rely on cues they receive from their networks to form their own opinion. For example, Katz and Lazarsfeld (1955) and Page and Shapiro (1992) find that media often influences public opinion by first influencing the views of attentive publics, who then influence the views of those in their networks. In the political mobilization context, Passy (2003) underlines that personal networks have a ‘decision-shaping’ function, meaning that core protest participants inform people in their networks about the correctness of the action, motivating them to participate.

For example, Lohmann (1994) argues in particular that cascades of negative information about the regime that spread through personal networks provided important motivation for citizens to join the demonstrations that took place in Leipzig in 1989-1991, prior to the collapse of the German Democratic Republic (GDR).⁴ In a context of total repression, where people knew very little about the performance of the regime, the initial demonstrations encouraged early core and informed activists to spread information about the true ‘nature of the regime’ (Bikhchandani et al., 1992), – which was responsible for “environmental damage, political repression, corruption, and the luxurious lifestyles of the SED elite” (Lohmann, 1994, 44). These revelations then provided the motivation necessary for East German citizens to take to the streets.

Some of the messages that people sent on Twitter about the Women’s March in the days before the protest can be read in this vein, as providing motives for others to protest. The

⁴Note that although we use the term “information” here, it is not information about the logistics of the protest, as in the previous section, but rather information about the regime’s behavior, which is in turn providing motivation for action.

Figure 2: Example of a Tweet sent the week before the Women’s March that had some of the theorized mechanisms.



message shown in Figure 2 for example, apart from providing basic logistical information about the march (e.g. the day the march is taking place in Los Angeles and a link to further logistic information), also lays out reasons why people should care and attend the march. The text stresses the importance of supporting “diverse and powerful woman” and the images highlight some of the unequal conditions women face, such as only being paid on average 81% of the salary men receive for similar positions. To be clear, in this paper we are interested in explaining behavior (why people actually *protest*), not attitude change. However, as Lohmann (1994) notes, finding reasons to care about a given issue is a crucial step towards acting on it, strengthening the importance of studying communications around reasons to care as well as reasons to attend the march.

Hence, we build on the described literature on the mobilizing role of personal networks, opinion formation, and political participation to formulate the following hypothesis:

Motivation(H_7): *Users whose friends sent Twitter messages providing reasons to care and attend to the 2018 Women’s March were more likely to protest.*

3.3 The Coordination Mechanism

Personal networks solve coordination problems. One of the other main reasons for why collective actions often fail is because potential participants are uncertain about whether other people will join the action. This is particularly relevant, although not exclusive of, authoritarian regimes, where being the only one (or one of the few) to protest means being a clear repression target. In more democratic settings, people are also more inclined to participate in well attended actions because of a desire to be part of relevant (and sometimes iconic) mobilizations that can have a meaningful societal impact (Klandermans, 1997).

The literature on the role of personal networks in solving coordination problems became particularly salient after the unexpected collapse of the Soviet Union in the late 1980s. Kuran (1991) argues that people against the regime had clear incentives to falsify their preferences and to not show their private beliefs publicly until others around them had already done so. When people with a very high mobilization propensity started protesting on the streets, they ‘infected’ those in their personal networks with a lower propensity to participate by showing that more people were willing to protest, generating a ‘bandwagon’ effect that ended up with the collapse of the regime. Other models of network contagion corroborate Kuran (1991)’s work by also showing that personal networks can be mobilizing in part because they solve these type of coordination problems (Opp and Gern, 1993; Lohmann, 1994; Chwe, 2000).

In a democratic context such as the United States, the works of others also show that the coordination role of networks can also play a mobilizing effect. Proponents of the *expectancy-value* theory in social psychology argue that people are particularly likely to participate in a protest action if they expect it to be successful (in terms of attendance and political/policy outcomes) (Klandermans, 1984). In a recent empirical study of the online diffusion of the

Black Lives Matter movement, after controlling for a battery of alternative explanations, Casas and Webb Williams (2018) find that images shared online that showed people already protesting and supporting the movement on the street were in part responsible for an increase in attention to and diffusion of the movement online, thus illustrating the strong relationship between expectation of success and protest participation. What remains unclear is whether messages from friends that contribute to solving coordination problems have an effect on actual protest attendance. In addition to providing basic logistical information and reasons to protest, the message in Figure 2 also contributes to solving coordination problems by letting people know that the friend who sent the message will be attending the march in Los Angeles on January 20th. Therefore, in line with the expectancy-value theory and bandwagon models, we should expect exposure to messages communicating that other people will attend, and/or that the march will be a success in terms of attendance, to be predictive of protest attendance. Hence, based on the rich literature on the matter, we formulate the following hypothesis:

Coordination(H_8): *Users whose friends sent Twitter messages stating that they would attend the 2018 Women’s March, or that the march would be successful in terms of participation, were more likely to protest.*

3.4 The Pressure Mechanism

Personal networks put pressure to participate. Classic collective action theory predicts pressure mechanisms to increase the likelihood that an action will succeed (e.g. Olson (1965)’s “negative incentives”). A sense of social belonging explains a wide range of political attitudes: people do not desire to deviate from their group’s behavior and they often emulate actions perceived as valued by people in their social network (Tajfel, 1981). This social/peer pressure can go as far as encouraging people to behave in ways that conflict with their own

interests and/or preferences (Sinclair, 2012).

Gerber et al. (2008) work provides a clear example of how social pressure can significantly influence political participation. In a study of voting behavior during the 2006 primary elections, the authors run a field experiment where a group of citizens received a letter (previous to the election) telling them that their neighbors would know whether they had voted or not in the upcoming election, putting peer pressure on them to vote.⁵ The participation rate among these voters was about 10 percentage points higher than the average voter.

Some of the people messaging the days preceding the march were explicitly putting pressure on other to attend (see some examples in Table 1). According to the discussed arguments, those exposed to these messages (particularly if the messages were sent from strong ties) should be more likely to attend the march. Hence, building on this existing literature on group dynamics and social pressure, we formulate the following hypothesis:

Pressure_(H₉): *Users whose friends sent Twitter messages putting pressure on others to participate to the 2018 Women’s March were more likely to protest.*

4 Data & Methods

We test our hypotheses by studying real-word attendance at the 2018 Women’s March in the United States, and the Twitter networks and communications of a group of users who attended one of the marches and a group of users who, despite showing support for the movement and be close to one of the marches, did not attend. The first Women’s March took place on January 21th 2017. On the anniversary of this first march, the organizers called for a second march in 379 U.S. locations (plus other locations around the World) on January 20th and 21st.

⁵Other randomized group of voters received other letters containing different treatments and placebo tests.

Three types of data were needed in order to test the hypotheses proposed in this study: a) to find a group of people who attended one of the marches and a comparison group of potential protesters that did not attend any of the marches, b) detailed information about these people’s (Twitter) networks, and c) information about the communications and type of messages people exchanged through their networks via this social media platform the week before the protest. Before presenting our findings, we first describe in detail how we collected and processed the data in order to have these three crucial pieces of information.

4.1 The Attender and Non-Attender Groups

To find a group of Twitter users who attended a march and a comparison group who did not, we needed to collect all Twitter messages related to the march, look for users who geolocateed their tweets, and then check whether they sent a tweet from the march at the time the march closest to them was taking place – or whether they were in another location where no march was taking place.

Before and during the march we used the Twitter Streaming API to collect all Twitter messages mentioning a set of hashtags associated with the demonstrations.⁶ 15,679 users used a geolocated account (10,828 on January 20th and 4,851 on January 21st) – meaning that we had information about the place (city) from which these messages were sent.

In order to know whether they sent a message at the time the march closest to them was taking place, and whether they sent it from the march location, we first needed to obtain detailed information about the location and time of each march. So the week following the march we scraped the Women’s March website to collect information about all the marches that took place on January 20th (N=249) and January 21st (N=65), building a dataset with

⁶We included in our search terms hashtags the organization asked supporters to promote as well as hashtags we saw (two weeks before the march) that users were using in relation to the demonstration: #womensmarch, #womensmarch2018, #powertothe polls, #togetherwerise, #whywemarch, #whyimarch, #imarchfor, #marchingforward, #womensunite, #unitedresistance, #resisttrump.

the following information: day of the march, locality, start time, and address and coordinates of the starting point of each march.

We proceeded to match each user to a march by finding the march closest to any of the tweets sent by a user.⁷ Then, as a first filter to find users for the attender and non-attender groups, we checked whether the 15,679 users with a geolocated account tweeted between the start time of the closest march and 8 hours after.⁸ Out of the ones that did, we then considered the users who tweeted at least one message from the municipality where the closest march was taking place as a *potential attender*, and the ones that did so from another place as *potential non-attender*.

At this point we were still uncertain about whether all the users in these two groups were actual attenders and non-attenders for three main reasons: a) some *actual* non-attenders could be in the group of *potential* attenders if they tweeted from the locality of their closest march but did not attend the march, b) some *actual* attenders could be in the group of *potential* non-attenders if they tweeted about their attendance to the march afterwards from another location, and c) some non potential participants could be in the *potential* attender and non-attender groups if they tweeted against the Women’s March when the march closest to them was taking place, or if they were supportive of the Women’s March but the closest march was too far away to feasibly attend the demonstration.

We used a three-fold strategy to address these issues and build the final attender and the comparison non-attender set. First, we constrained the inclusion in the non-attender

⁷By comparing the distances between the coordinates of each march starting point and the center of the 4-coordinate bounding box from each tweet.

⁸In this step we used a wide 8-hour time range for two main reasons. The first one is that some of the large marches lasted very long. The second is because the messages from users who tweeted from large marches, such as New York City, could not be actually sent during the march due to large concentration of Internet user in the same spot. As these tweets were automatically sent hours later and the time-stamp of the tweet corresponds to this later time, we elected to use a wider time window to avoid missing these protesters. We are not worried about errors in precision (i.e., false positives) because, as we describe below, we hand checked all of the accounts, so the consequence of this decision was simply creating more accounts for us to hand check.

group to users who sent at least one message from within 50 miles of the closest protest, removing some non potential participants from the non-attender group (because they were too far away to attend). Second, one of the authors manually went through the messages the remaining users sent and checked whether they sent at least one message against the Women’s March (see some examples in [Appendix A](#)): these non potential participants were also excluded from the dataset (these users were not of interest because they would have never attended a march no matter what). Finally, a research assistant went through the messages of the remaining users and indicated whether she thought they had attended a march, had not attended any, or she was not able to say based on the messages (3-class variable).⁹ She also indicated whether the user was an organization such as a media outlet or a company (binary variable). The organizational accounts were removed from the dataset and we only kept in the *final* attender and non-attender groups those users that the research assistant considered that had and had not attended a protest, respectively. Finally, to simplify the rest of the data collection process and analysis, we focused next only on protesters who attended a march on January 20th (the day most of the marches took place) and the non-attenders who did not participate in a march in any of the two days (January 20th or 21st).

As a result, we ended up with two ***final groups*** of 2,878 and 1,352 people for whom we were highly confident that the person either attended or did not attend, respectively, one of the 2018 Women’s Marches, respectively.¹⁰ These 4,230 users composed the final sample of our analysis.

⁹A second research assistant also coded about 30% of the messages to check for inter-code reliability. On these cases they both coded the two coders agreed about 80% of the time. Cohen’s Kappa, Scott’s Pi, and Krippendorff’s alpha were all ≥ 0.7 .

¹⁰Having examined each of these accounts by hand, we are also confident that they are indeed people and not bots.

4.2 Protesters and Non-Protesters' Ties

The next step toward having all the necessary data to be able to test our hypotheses was to collect information about the Twitter networks of each of these 4,230 users.

Most works studying the mobilizing role of networks using real-world data tend to focus on people's immediate network (their friends) and do not take into account the effects that other further connections can have (such as friends of friends and triadic ties). An advantage of using social media data is that one can collect not only the list of users one follows (friends or ties) but also the list of followers for those followed by a given user (ties of ties). Moreover, as previously mentioned, Twitter networks have been found to be a fair representation of people's network on real life (Bisbee and Larson, 2017).

Hence, the week after the weekend of the Women's Marches took place, we collected the lists of people these 4,230 users followed (a total of 4,800,584 friends, 2,116,038 of them unique), and the lists of users these 2,116,038 unique friends followed (298,526,026 unique users). This allowed us to build a comprehensive graph of the networks of the attenders and non-attenders in our sample.

4.3 Pre-March Network Communications

As we mentioned, during the week before the Women's March and while the demonstrations were taking place, we collected all Twitter messages mentioning the key hashtags related to the protest.¹¹ After collecting the list of friends of the users in the attender and non-attender sent, we went back to the message collection and pulled all the march-related messages that each user's friends sent during the week before the march (71,291 unique messages). Two sets of messages were ignored: a) messages against the march (see Appendix A for some examples), and b) messages related to a pro-life protest (that took place the day before,

¹¹See Footnote 6 for a list of the hashtags.

on January 19th) that shared a couple of the mobilizing hashtags with the Women’s March (#WhyIMarch and #WhyWeMarch). Using the machine learning techniques that we will discuss next, these messages were detected and removed. We ended up with a final dataset of pre-march communications containing a total of 712,413 messages, 54,728 of them unique.¹²

The next step was to detect the presence – or lack thereof – of each of the four mobilizing mechanisms in these tweets. First, we drew a random sample of 3,300 messages for two manual coders to label. Each manual coder labeled 1,850 tweets, with a set of 400 they both coded (see codebook in [Appendix B](#)). 200 of the 400 were coded multiple times and were used for coder training and calibration. The other 200 were used to calculate inter-rater reliability (IRR) measures (see [Appendix C](#) for detailed IRR statistics), which were satisfactory. [Table 1](#) shows some example tweets coded as containing each of the theorized mechanisms.

Then we used this labeled dataset to train machine learning classifiers to predict six tweet-level outcomes: whether the tweet was against the march (sentiment), whether it was related to the pro-life mobilization that took place the day before (prolife), as well as whether the messages contained each of the mobilizing mechanisms (information, motivation, coordination and pressure). We trained an ensemble of six machine learning models using different types of tweet-level features as input: unigrams from the tweet text, unigrams from the text that is visible when reading a tweet as a result of a shared link, text embeddings, image embeddings, and joint text and image embeddings (see [Appendix D](#) for a detailed description of the models).

We assessed the ability of the six machine learning classifiers to predict each of the six binary outcomes, and for each outcome we selected the most accurate one. In [Table 2](#), the *Class Prop.* column on the left describes the proportion of tweets in the training set that were labeled as containing each outcome, whereas the most right column describes the proportion

¹²In the 712,413 message count we count a friend’s message as many times as users in our sample follow her.

Table 1: Example tweets for each of the theorized mechanisms.

Information
On 1/21, @womensmarch kicks off a year-long #PowerToThePolls campaign to win in 2018! The rise of the woman IS the rise of the nation. In 2018, lets rise together! https://t.co/O9sqO9ZXDU
The speakers lineup has been released for the #PowerToThePolls #WomensMarch in Huntsville this Saturday, 20 January, 11 am! #p2phsv https://t.co/I7okJ7KwVF
If you plan to ride any bus line being diverted to Mission Street, reconsider your options. Taking the 6-Parnassus was slow and wait times was 40+ minutes. This also affects Golden Gate Transit that regularly runs on Mission. #WomensMarch #SFMuni #SFMTA #Muni #GoldenGateTransit https://t.co/nSHgzrbsPA
Motivation
RT @ACLU_Mass: Tomorrow, we are taking to the streets for #WomensMarch2018 and organizing to fight Trump’s anti-immigrant agenda.
Why would any citizen not register and vote? People died to give us this right! C’mom people! https://t.co/oXpNCIY5TK #PowerToThePolls
History was made when more than 5M people across the world rallied in the #WomensMarch for equality. Here is some of last year’s best moments that launched us towards progressive strides for equality from #MeToo & #TimesUp, to making bids for public office in the thousands. https://t.co/8Tkn30Z6z6
Coordination
What should my sign say for @womensmarch DC? #WomensMarch2018 dc
Front and back of signage. Carried it last year and carrying it again this year. #WomensMarch @womensmarch_sd @womensMarch #WomensMarchSD https://t.co/VaesZT3JZf
Marching with my 75-year-old mom! #WomensMarchNYC https://t.co/Pr2RBBZkIw
Pressure
@AoDespair "Liberty, Equality, Justice" is the motto of #AmericanVelvetRevolution we must start the #AmericanVelvetRevolution now! to the streets... join with #WomensMarch2018 in two days, do not obey dictates of #TrumpFascism, #VoteBlue every chance you get from local on up!
Are you marching Jan. 20? #WomensMarch https://t.co/7w5NXXKt1t8
We all need to take to the streets tomorrow. Not just women. ALL Resisters. #resist #TrumpShutdown #womensmarch2018 Cleveland

of *all* pre-march tweets predicted as having each outcome. In the rest of the columns we report the accuracy of the models selected to predict each outcome. The overall accuracy for all models is about 80% or higher. For the information, motivation, prolife and sentiment classifiers, precision and recall is also high (between 60 and 100%). The coordination and pressure classifiers are a bit noisier, precision and recall is about 50%. However, these are

Table 2: Accuracy of the machine learning classifiers predicting the 4 mobilizing mechanisms (Information, Motivation, Coordination, and Pressure).

	Class Prop. (training set)	Accuracy	F-Score	Precision	Recall	Class Prop. (full dataset)
Information	0.42	0.87	0.84	0.83	0.86	0.38
Motivation	0.39	0.77	0.71	0.70	0.72	0.34
Pressure	0.20	0.85	0.64	0.62	0.66	0.24
Coordination	0.19	0.84	0.62	0.58	0.66	0.18

still substantively accurate classifiers: these are infrequent classes and by random chance we would correctly predict a tweet with these two mechanisms only about 20% of the time. In sum, these classifiers provide a meaningful signal that allow us to detect the presence of and study our mechanisms of interest.

5 Results

We begin by testing whether personal networks played a particular role in the mobilization of attenders to the Women’s March. Following the method of [Larson et al. \(2018\)](#), we test whether the group of attenders were indeed more connected among themselves than were users in the non-attender group (they were). Then, we transition to explore the Twitter communications of the attenders and non-attenders’ networks in order to address the rest of the hypotheses and uncover the reasons why personal networks played a mobilizing role. We first look at the number of messages related to the Women’s March that Twitter friends from users in both groups sent the week before the protest. We then explore the presence in these messages of the four mechanisms of interest, and we conclude by estimating their effect on protest mobilization when controlling for other relevant covariates. In the final section we will discuss the implications of the findings as well as potential steps for future research.

In Table 3 we provide a summary of the network attributes of the non-attenders ($N = 1,352$) and attenders ($N = 2,878$), as well as group comparisons (t-tests) for each of the

attributes. The goal of these comparisons is to evaluate the extent to which attenders were more connected among themselves than non-attenders. If personal networks have no effect on people’s decision to protest (null hypothesis for $H_{1,2,3,4,5}$), we should see no differences in group connectivity.

Table 3: Network attributes for the 2,878 Attenders and the 1,352 Non-Attenders.

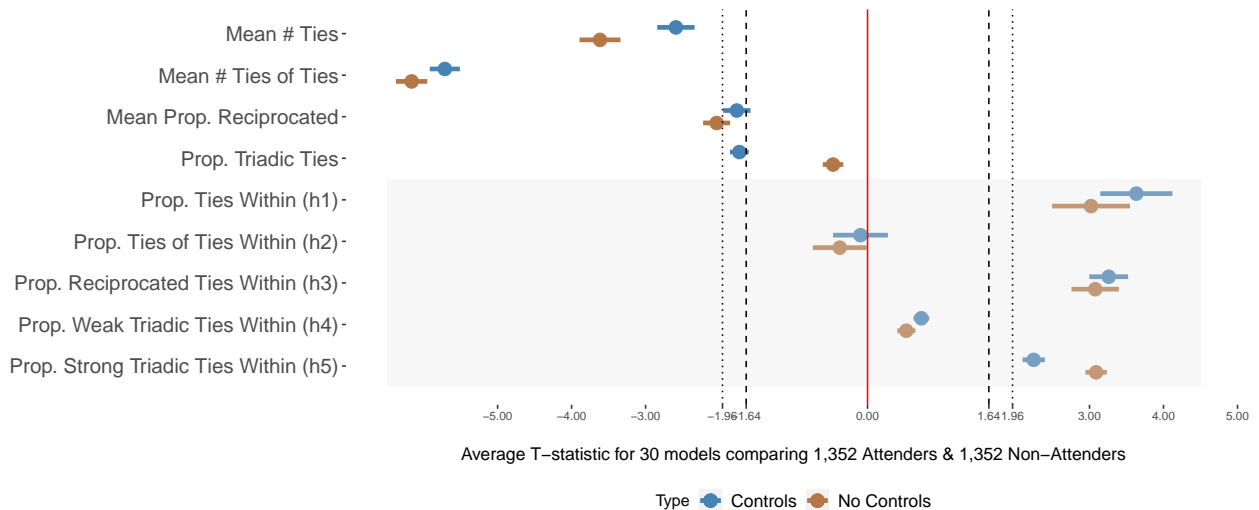
	ATTENDERS	NON-ATTENDERS	Tstat
Mean # Ties	1,018	1,304	-4.10
Mean Prop. Reciprocated Ties	0.30858	0.32511	-2.36
Mean # Ties of Ties	4,875,507	6,951,308	-6.77
Mean # Triadic Ties	44,598	48,679	-0.40
Prop. Ties Within (H_1)	0.00146	0.00051	18.17
Prop. Ties of Ties Within (H_2)	0.00022	0.00010	28.92
Prop. Reciprocated Ties Within (H_3)	0.00216	0.00050	7.83
Prop. Weak Triadic Ties Within (H_4)	0.00386	0.00129	3.34
Prop. Strong Triadic Ties Within (H_5)	0.00097	0.00054	3.81
<i>T-statistic</i> tests the null hypothesis that attributes for Attenders and the Non-Attenders are the same.			

Two main points stand out from Table 3. First, non attenders had larger networks than users in the attender group. On average, they had a greater number of ties (1,304 *versus* 1,018 for attenders), ties of ties (about 7 million *versus* 4.8 million for attenders), and triadic ties (48,679 *versus* 44,598 for attenders). Moreover, non-attenders had a reciprocated friendship with a larger proportion of their friends (.33 *versus* .30 for attenders).

However, despite having smaller networks, the Twitter users that attended one of the Women’s March on January 20th were indeed more connected among themselves. As the bottom half of Table 3 indicates (rows in bold), their ties were more likely to attend than were the ties of non-attenders. A larger proportion of their ties was also present in the attender group (.001 *versus* .0005 for non-attenders) as well as a greater proportion of their ties of ties (.0002 *versus* .0001 for non-attenders), reciprocated friends (.002 *versus* .0005 for non-attenders), weak triadic ties (.004 *versus* .0001 for non-attenders), and strong triadic ties (.001 *versus* .0005 for non-attenders). These differences are all statistically significant

at conventional levels. Hence, we find strong support for the first five hypotheses, jointly making the claim that networks played some kind of mobilization role in the Women’s March.

Figure 3: Bootstrapped T -statistics testing the null hypothesis that network attributes for Attenders and Non-Attenders are the same.



Note: Controls: Female (binary), Media attention (# top media accounts followed), Political interest (# members of Congress followed), and Ideology (# of members of Congress from each party followed + follows FoxNews + follows MSNBC). The coefficient table for the linear models predicting these network features as a function of being an attender or non-attender plus a set of controls, are available in Appendix G

To be certain that the differences in the last five rows in Table 3 are not an artifact of differences in group sizes, we use a bootstrapping procedure to check robustness. Since the attender group is about two times larger than the non-attender one, users in the attender group have more chances to be connected to another user in the same set. To make sure the results are not a simple function of group size, we decided to draw 30 samples of attenders of the same size of the non-attender group ($N = 1,352$), and to then compare each of these samples to the network characteristics of the full non-attender group.

Figure 3 shows the average T-statistics for these 30 comparisons. Overall, we observe the patterns from Table 3 to hold: on average non-attenders have larger networks (as indicated by

the negative four bootstrapped t-statistics at the top) while attenders remain more connected among themselves (as indicated by the bootstrapped statistics in the bottom gray rows). However, we observe one relevant difference. Although in Table 3 we saw attenders to be more connected among themselves both via strong and weak ties, in Figure 3 we observe the findings for ties in general (proportion of ties within $-H_1-$) and for strong ties to hold (proportion of reciprocate ties within $-H_3-$ and proportion of strong triadic ties $-H_5-$), but we do not find clear evidence supporting that attenders were more connected among themselves through weak ties than the users in the non-attender group (H_2 and H_4). The patterns hold when, instead of simply calculating differences in means between the attender and non-attender group, we use a linear model to predict each network feature as a function of being (or not) an attender plus a set of relevant confounders such as gender, media attention, political interest, and ideology. These controls account for the possibility that users in the attender and comparison non-attender group differ on other dimensions (the coefficient table for these models is available in Appendix G).

However, what explains these differences? Why are personal networks mobilizing? Can we gain some leverage by exploring the communications that the attenders and non-attenders networks exchanged the week before the protest? In the rest of the analysis we explore the communications that networks of attenders and non-attenders exchanged the week before the march. In an initial descriptive exploration, we find that the average non-attender (who had substantively larger networks) was exposed to a larger number of messages about the Women’s March and a larger number of messages containing each of the theorized mechanisms. However, the median attender was indeed more likely to be exposed to messages on each mobilizing mechanism, indicating that the average values are mostly driven by some outliers. These findings are finally corroborated in a multivariate analysis, which reveals that, after controlling for other potential confounders, the number of tweets containing the information, coordination, and social pressure mechanism were strong predictors of attending

the march (we find null results for the motivation mechanism).

Figure 4: Number of messages that the friends of the average and median attender and non-attender sent the week before the march.

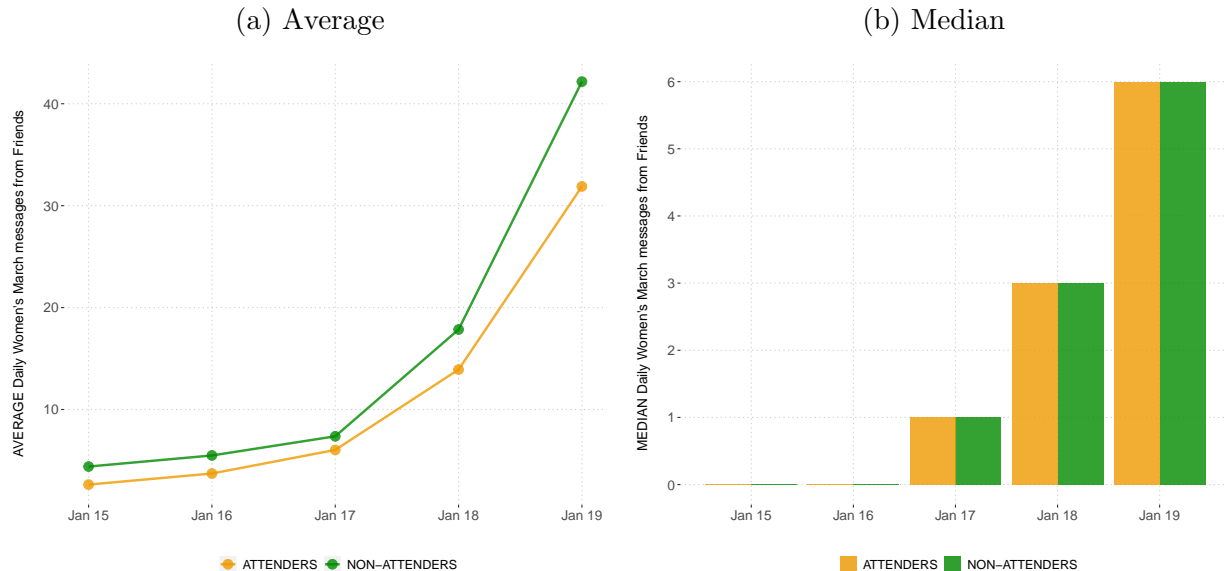


Figure 4 shows the number of tweets related to the Women’s March that the friends of the average (a) and median (b) attender (in yellow) and non-attender (in green) sent the week before the march. As one would expect, the amount of discussion about the march increased as the demonstration was closer in time, particularly during the two days preceding the demonstrations (January 18th and 19th).¹³ On average, during these preceding days, users in the non-attender set were exposed to more messages than the users in the attender group. However, as Figure 4 illustrates, the average is driven by some outlier in the non-attender set. Despite having smaller Twitter networks, the median attender was actually exposed to the same amount of march-related messages during the proceeding week; indicating that friends of attenders actually sent more tweets about the Women’s March.

What remains unanswered however is whether the discussion among the networks of the users in the attender and non-attender set was similar in content. Did the Twitter friends

¹³In Figure 4 we also see that including the tweets sent before January 15th into the analysis would not have made any difference (there was barely no activity before that date).

of the attenders used the theorized mobilizing mechanisms at a higher rate?

To address this question we used the trained machine learning models to predict which of the tweets sent by the attenders and non-attenders’ friends contained each of the mobilizing mechanisms. In Figure 5a we see that for each type of mechanism: users in the non-attender set were exposed to a larger number of tweets about the march (similar to what we saw in Figure 4). This is not necessarily surprising given that, as previously discussed, these are all potential attenders who are likely to be embedded in networks that cared and messaged about the march. However, in Figure 5b we see again that the averages in 5a are particularly driven by some outliers: when we rank by number of messages exposed to of each mechanism, the median attender was exposed to a larger number of messages on each mechanism.¹⁴

The previous figures however do not account for the possibility that people in the attender and non-attender group differ in other relevant dimensions. In Figure 6 we use information from all the users in the attender and non-attender group to fit five multivariate logistic regressions predicting participation to the Women’s March. In Figure 6a we do not yet take into account the content of the messages. Instead, we start by showing the results of a model predicting protest attendance as a function of some key user-level predictors that we will then include as controls in the rest of the models. The findings from this baseline model align with existing research and are fairly intuitive: being a female, previously following the official Women’s March account, and having a liberal ideology are all predictive of attending the march. On the contrary, having a conservative ideology as well as following a large number of people on Twitter is negatively associated with participation. Following a larger number of accounts of media outlets and members of Congress (so higher media and political attention) does not have any particular effect.

Then in Figure 6b we report the marginal effects for the key predictors of interest in four

¹⁴See Appendix F for the distribution of number of messages of each mechanism seen by attenders and non-attenders.

Figure 5: Number of messages containing each mobilizing mechanism that the friends of the average and median attenders and non-attenders sent the week before the march.

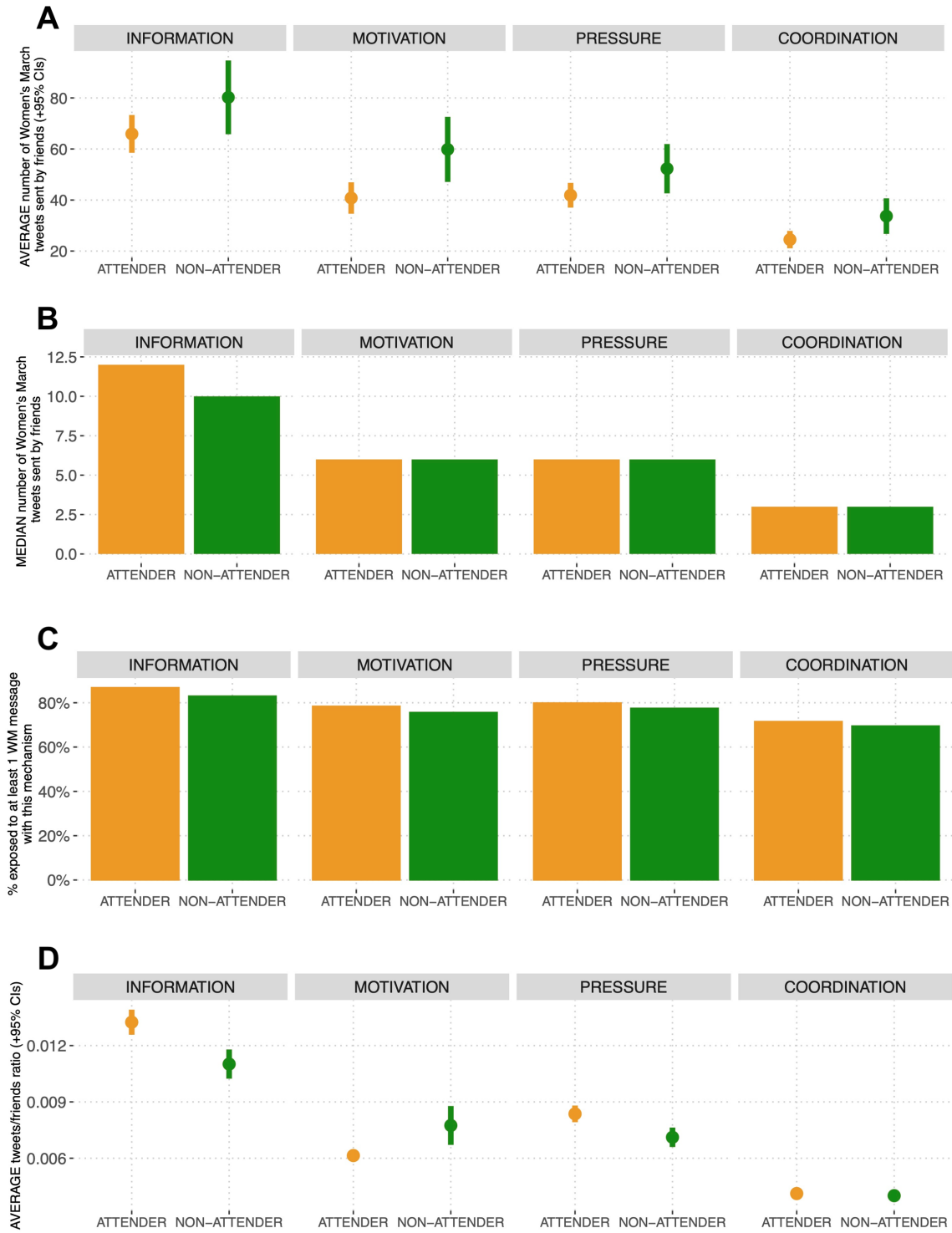
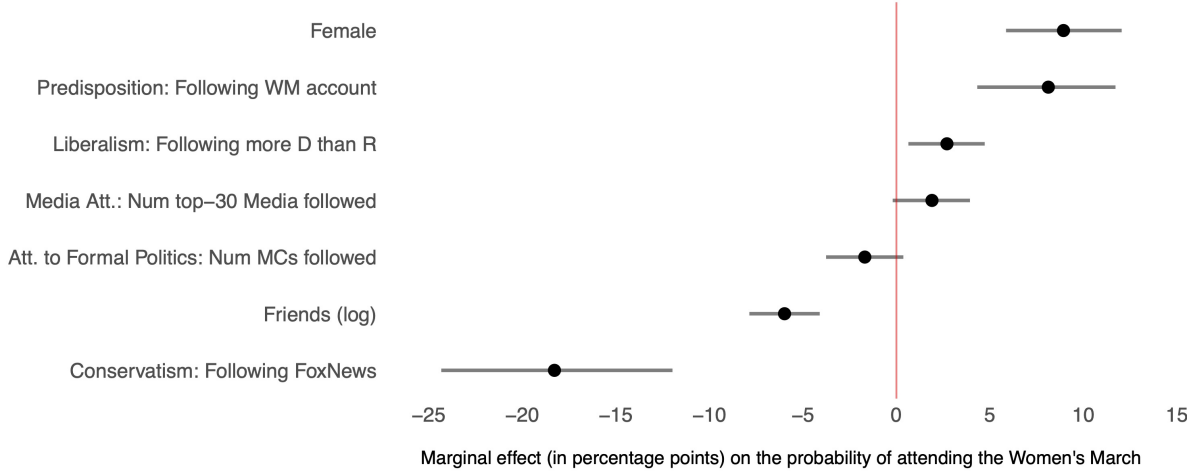
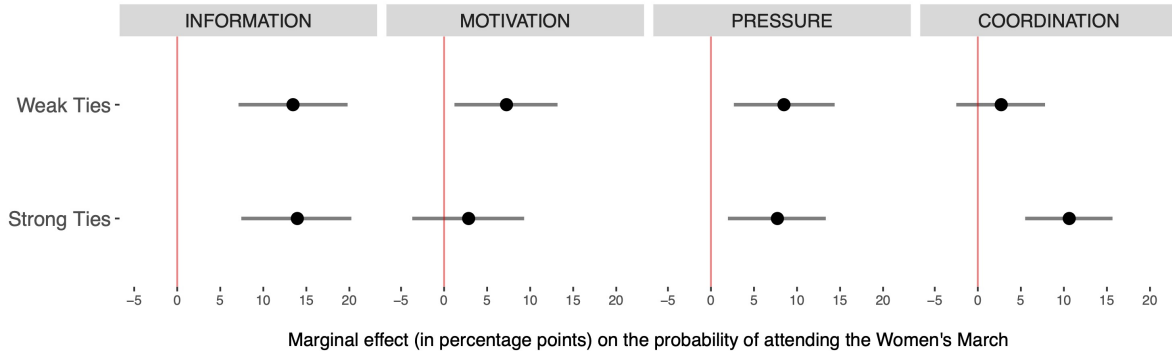


Figure 6: Logistic regressions predicting protest attendance.

(a) Model 1: Only including controls.



(b) Models 2, 3, 4, and 5: Predicting attendance as a function of the number of messages containing each of the theorized mechanisms, plus the controls in Model 1.



Note: The marginal effects for binary variables indicate the change in probability of attending the Women's March (in percentage points) when going from 0 to 1. The effect for continuous variables indicate the change in probability when going from the average value for that variable to 1 standard deviation above. The coefficient table for these models is available in Appendix E.

new logistic regressions (coefficient tables for all the models are available in Appendix E). In each regression we assess the role of each theorized network-mobilizing mechanism when controlling for the confounders in Figure 6a (plus the total number of messages related the Women's March sent by friends). Moreover, given that in Figure 3 we observed attenders to be particularly more connected among themselves via strong ties, in these additional

mechanism models we account for the strength of the tie with the friends who sent the pre-march tweets containing each mechanism.¹⁵

As stated in hypotheses $H_{6,8,9}$, exposure to a larger number of information, coordination, and pressure messages does indeed predict protest attendance. In particular, we observe that exposure to a larger number of pressure messages sent by *strong* (but not weak) ties is positively correlated with attendance, whereas information and coordination type message from both weak and strong ties had a significant effect on protest participation.

However, we are not able to find empirical evidence to support the predictions of hypothesis H_7 : we do not see a larger number of motivation messages sent by friends to be predictive of attending the protest. While we can conclusively say that we have not found evidence in support of the hypothesis, we do want to be modest about the extent to which this finding should be interpreted as falsifying the hypothesis. We put our hypotheses to a very hard test by selecting a group of non-attenders who were already sending positive messages about the marches when they were in progress. We did so to make sure that the attender and non-attender group were as comparable as possible.

As for the size of the effects, we observe the information mechanism to be related to the highest increase in the probability of attending the protest. A one standard deviation change in the number of information messages from weak and strong ties to which these users were exposed (+62 and +13 messages respectively) was related to an increase in the chances of attending the protest of around 20 percentage points. The coordination and social pressure type messages had a smaller but still quite substantive effect. A one standard deviation change in the number of coordination messages by weak and strong ties (+24 and +6 tweets) increased the likelihood by 8 and 13 percentage points respectively, and one standard deviation change in the number of social pressure messages sent by strong ties (+6

¹⁵We consider a strong tie when a reciprocal friendship exists between a user and the friend who sent a pre-march tweet related to the march.

messages) increased the chances of attending the protest by about 9 percentage points.

6 Discussion

The argument that personal ties have an effect on people’s decision to protest is a long-standing one in a wide range of social science disciplines (Granovetter, 1973, 1978; Marwell et al., 1988; Siegel, 2008; Centola and Macy, 2007; Larson et al., 2018). Nevertheless, the reasons why personal networks play such a mobilizing role are much less established (McAdam, 2003; Passy, 2003; Kitts, 2000; Diani, 2004). A more clear picture of the network-mobilizing effect is of great importance if we are to understand the conditions under which protest movements emerge, as well as the condition under which social groups can set political agendas and influence policy.

In this paper we shed new light on this question by studying the networks and the network communications of a group of Twitter users who attended one of the Women’s March in the United States on January 20th 2018, and a comparison group of potential protesters who showed interest and were close to a march but decided not to attend.

We tested four hypotheses regarding the mechanism by which personal networks can be mobilizing: they provide basic logistical *information* needed to protest, create *motivations* for others to mobilize, solve *coordination* problems by revealing protest attendance, and put social *pressure* on others to attend. We used state of the art machine learning techniques to measure the presence of these different types of messages in tweets that friends in the attender and the comparison non-attender group sent the week before the march.

Our findings were extremely interesting. Our network based analysis largely matched the findings from (Larson et al., 2018), though we were studying a different country and a different type of protest (in multiple cities and on a more divisive issue): users in the attender group were more connected among themselves than were users in the non-attender

set. A notable difference between ours and (Larson et al., 2018)’s study is that in our case we find that those who attended were more connected among themselves via strong rather than weak ties, highlighting the value of replicating in other contexts those findings based on a single case study. Further research will need to further investigate in which cases weak *versus* strong ties are crucial for protest mobilization.

Then, when studying the communications these users’ networks exchanged the week preceding the protest, we found that people whose Twitter ties sent more tweets containing basic logistic *information*, messages letting people know that others will be at the march (and so *coordinating* participation efforts), and messages putting social *pressure* on other to attend, were more likely to attend the protest. We did not find evidence however to support the argument that personal networks influence peoples decision to protest because they provide a *motivation* to do so. We found a strong positive correlation between exposure to *information* and *coordination* messages and attendance independently of whether the messages were sent by weak or strong ties. However, only *pressure* messages from strong ties were predictive of protest participation. These findings align with the logic of these theorized mechanism. Information messages are important because of the basic logistic cues they provide; so the origin of the messages should not particularly matter for the message to have an informative effect. However, the mobilizing power of pressure cues relies on how much the receiver of the message cares about what the friend who sent the message thinks of her/him. Hence, the stronger the relationship between the sender and the receiver, the more likely the pressure message is to have an effect.

In sum, this paper uses behavioral real-world attendance data and detailed information about the communications personal networks exchange the days before a protest to not only show that networks play a mobilizing role but to also disentangle the reasons why. Beyond making a strong theoretical contribution, the methods and research design presented here can help advance the study of political mobilization even further. As an example, future

research can use similar research designs to explore whether some types of network mobilizing mechanisms are more important than others depending on the type of protest: e.g. do the coordination and pressure mechanism play a stronger role in more violent political contexts?

Finally, the goal motivating this project was to better understand the reasons why personal networks play a mobilizing role, and we used people’s Twitter networks and communications (which have been found to reflect off-line personal networks (Bisbee and Larson, 2017)) to study and explore the predictive power and validity of a set of theoretical explanations. We remained agnostic about whether these Twitter communications were simply a reflection of the conversation these users had with their personal networks offline, or whether Twitter was the solely place where some of these communications took place. We believe however that this is a relevant question that future research will need to address in order to continue building a more complete picture of not only the reasons but also the channels through which personal networks can mobilize.

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Appendix A Appendix A: Examples of Anti Women’s March Tweets

Table A1: Examples of Anti Women’s March Tweets

Hello everyone! We like all humans except white straight males ... and women who dont fans of abortion #WomensMarch2018

#WomenMarch2018 #WomensMarchNYC This movement supports a culture that will RAPE YOU, Stone you, Cover you, and take your car keys, and if that doesnt work, honor kill you, I apologize for mansplaining. <https://t.co/VaQFRDXmL4>

Women’s march not concentrating on REAL women’s issues.,Like being victims of crime.,From both illegal and legal immigrants.,Look at the statistics.,What about 2nd amendment rights for women?,Physically a woman can’t beat a man, but a 230 45 ACP bullet CAN! #WomensMarch2018

I can not take this! I AM NOT THIS KIND OF WOMAN. #WomensMarch2018RT if you’re NOT THIS KIND OF WOMAN!tps://t.co/MW3DaZmnwD

This march is, in general, for misandrists who have made themselves perpetual victims of having a vagina. Freud called it Penis Envy. #WomensMarch2018

Wow! How can I un-see these horrific pics. Democrats out today. Our ugly part of America out today! <https://t.co/xaDa39mMN7>

Two years in a row and the activists at the #WomensMarch have failed to answer one fundamental question. What specific rights do you not have an equality of opportunity towards?

I’ll ask the same question I asked last year: what the hell are these crazy Leftist feminists marching for? Last time I checked women of America are free and liberated! #WomensMarch2018 #WomensMarchDC #SaturdayMorning <https://t.co/D162HxLH1k>

I support #MarchforLife not this made up Liberal #WomensMarch2018 <https://t.co/0ClFFaL4QC>

Appendix B Appendix B: Codebook for Coding Pre-March Tweets from Protesters and Non-Protesters' Friends

Purpose: Coding pre-march tweets for the type information users in our protester and non-protester were exposed few days before the march.

General Instructions:

- Each coder should have access to a Google spreadsheet where they will insert the labels for each message, and also to a folder with html files showing messages in a Twitter-looking format.
- Coders need to click on the html files, judge whether messages in there contain one of the 4 mobilizing mechanisms. [If the message has a link, coders DO NOT need to click on the link and look at the information in the link when judging the presence of the different mechanisms]
- None of these variables are mutually exclusive! So you should consider each variable for each message

Specific Instructions:

VAR 1 [information] Information Mechanism

Logic: In order to decide whether to attend a protest, people first need to have basic logistic information about where and when the protest is taking place, how to get there, etc. Conditional on ones initial predisposition to protest, one should be more likely to do so when provided with such basic information.

Instructions for coders: Is the tweet providing basic practical information about how to participate in a Womens March, such as the time of the march, its route, how to get there, events taking place before-during-after the march, etc?

[label = 1 if this mechanism is present. 0 or blank otherwise]

VAR 2 [motivation] Motivation Mechanism

Logic: Most people do not pay attention to politics and they lack clear policy positions. However, the average citizen often takes cues from more attentive publics when making political decisions. Those who we follow in social media can increase our likelihood of attending a protest by presenting us clear reasons for why we should do so.

Instructions for coders: Is the tweet providing a reason for attending a Womens March? This includes reasons to dislike Trump, Trump administration, Trump policies, and especially Trump policies/comments/preferences towards women. Motivation we are going to be open to reasons that might motivate one to protest, even if they are not specifically about the march.

[label = 1 if this mechanism is present. 0 or blank otherwise]

VAR 3 [pressure] Social Pressure Mechanism

Logic: A sense of social belonging, and ingroup-outgroup dynamics, explain a wide range of political attitudes: people do not desire to deviate from their groups behavior. Those who we follow in social media may send us messages clearly signaling that our network will not appreciate-tolerate inaction; pressuring us to protest.

Instructions for coders: Do you believe that this message is putting pressure on others to attend the Womens March? This includes message instructing people to go: e.g. You should go!

[label = 1 if this mechanism is present. 0 or blank otherwise]

VAR 4 [coordination] Coordination Mechanism

Logic: individuals deciding whether to attend a protest often face a coordination problem. If a large group of people protest, the demonstration is a success and one is not wasting the time by attending. However, since it is hard to know ex ante who and how many people will attend, one may decide to not bare the costs of attending and stay home.

Instructions for coders: Is someone in this message indicating their attendance to the upcoming Womens March? And/or is the message indicating that there will be a high attendance to the March?

[label = 1 if this mechanism is present. 0 or blank otherwise]

VAR 5 [prolife] ProLife-only messages

Logic: some of the hashtags we used to collect Womens March messages were also being used in a ProLife march that took place the day before: “whywemarch” and “whyimarch” mostly. I filtered out messages mentioning: whywemarch, marchforlife, prolife, whyimarch, prochoice, life, unbornlivesmatter, lovesaveslives; AND NOT mentioning “womensmarch”, but some ProLife messages may still be present in this dataset of pre-march messages to code. We want to detect them.

Instructions for coders: Is the message ONLY related to ProLife policy positions, demonstration, action; and not related at all to the Womens March?

[**label** = **1** if only has a ProLife component and its not related to the Womens March, **label** = **0** if its about the Womens March (even if it also has a ProLife component), **label** = **9** if it’s unclear]

VAR 6 [sentiment] Sentiment Category

Instructions for coders: Do you think the message is in support of or against the Womens March?

[**label** = **1** if the tweet is in favor of the Womens March, **label** = **-1** if the tweet goes against the Womens March, **label** = **9** if neutral tone or unclear about the Womens March (for example, tweets against trump that dont directly mention the Womens March, or ProLife tweets that arent necessarily against the Womens March. If a quote is in favor but the quoted message against –or vice versa–).]

Appendix C Appendix C: Inter Rater Reliability

In this Appendix we report information to assess the *inter rater reliability* (IRR) of the two manual coders that manually labeled the tweets for whether they had each of the 4 mobilizing mechanisms (information, coordination, motivation, and pressure), whether they were related to the pro-life organization that took place the day before, on January 19th, and whether they were against the women’s march (sentiment).

We draw a random sample of 3,300 messages sent by friends of users in the protester and non protester set. Then each manual coder labeled 1,850 tweets, with a set of 400 they both coded (see codebook in [Appendix B](#)). 200 of the 400 were coded multiple times and were used for training and calibration. The other 200 were used for IRR assessment.

Figure C1: Confusion Matrices for 2 manual coders labeling tweets for the 4 mobilizing mechanisms (coordination, information, motivation, and pressure) and 2 other variables of interest (prolife, sentiment)

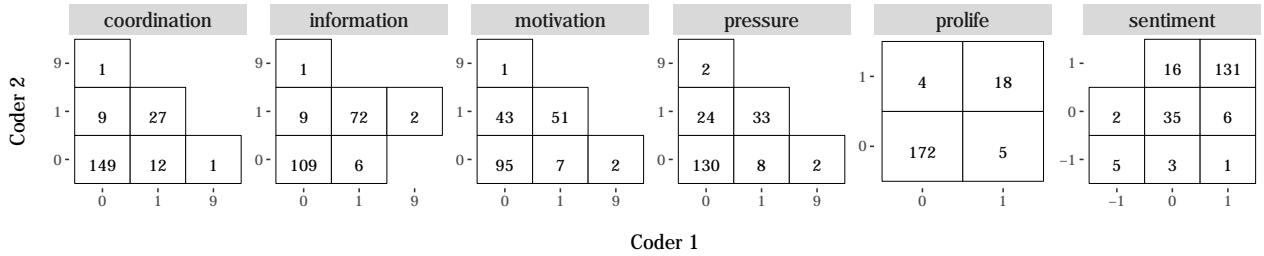


Figure C1 shows confusion matrices illustrating the agreement among the two coders. For the four mobilizing mechanisms, a 0 indicates the mechanism is not present, a 1 indicates the mechanism is present, and a 9 indicates that is unclear. For the prolife variable, a 0 indicates the tweet is about the Women’s March whereas a 1 means that it is about the Pro-Life demonstration that took place the day before. For the sentiment variable, a -1 means the tweet is against the Women’s March, a 0 indicates that it is about the march but has a neutral tone, and a 1 means the tweet is clearly in favor of the march (we collapsed the 0s and the 1s for this last variable when train the binary classifier predicting messages against the march).

In Figure C1 we observe very high agreement for 2 of the 4 mobilizing mechanisms (coordination and information) and the prolife and sentiment coding, and medium agreement for the other 2 mobilizing mechanisms (motivation and pressure). The lower agreement for these two mechanisms is the result of Coder 1 having a slightly more restrictive understanding of what constitutes motivation and pressure.

In Figure C2 we show the agreement rates for the 4 mobilizing mechanisms. A *flexible* agreement means that we consider as an agreement when a coder said that it was unclear whether a mechanism was present and the other coder provided a 0 or 1 label. A *strict* agreement means that we only consider the coders agree when both labeled the tweet as a 0 or as a 1. Overall, we observe the agreement to be higher than 80%. The only exception is the motivation mechanism, for which agreement was around 75%.

Figure C2: Coding agreement for 2 coders labeling 200 tweets for the presence of the 4 mobilizing mechanisms.

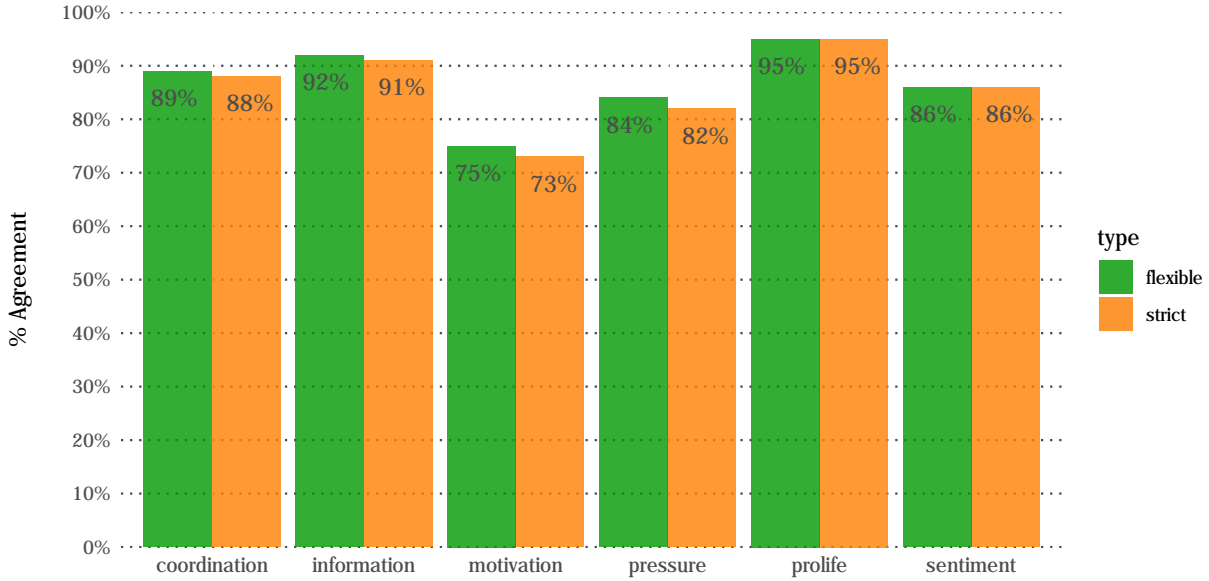


Figure C3: Inter Rater Reliability statistics for 2 coders labeling 200 tweets for the presence of 4 mobilizing mechanisms.

	Prop. Agreement	Krippendorff's Alpha	Cohen's Kappa	Scott's Pi
information	0.92	0.84	0.84	0.84
motivation	0.74	0.46	0.48	0.46
pressure	0.84	0.56	0.57	0.56
coordination	0.89	0.66	0.65	0.65
prolife	0.95	0.78	0.77	0.77
sentiment	0.88	0.68	0.68	0.68

Note: A statistic between 0 and .20 indicates *poor* agreement, .21-.40 *fair* agreement, .41-.60 *moderate* agreement, .61-.80 *substantial* agreement, and .81-1.00 *near perfect* agreement.

Table C3 reports common IRR statistics (Krippendorff's Alpha, Cohen's Kappa, and Scott's Pi) for the 6 variables labeled by the manual coders. We observe that in all cases the IRR statistics are above .4 (indicating at least acceptable *moderate* agreement), but in most cases we observe *substantial* (>.6) or *near perfect* agreement (>.8).

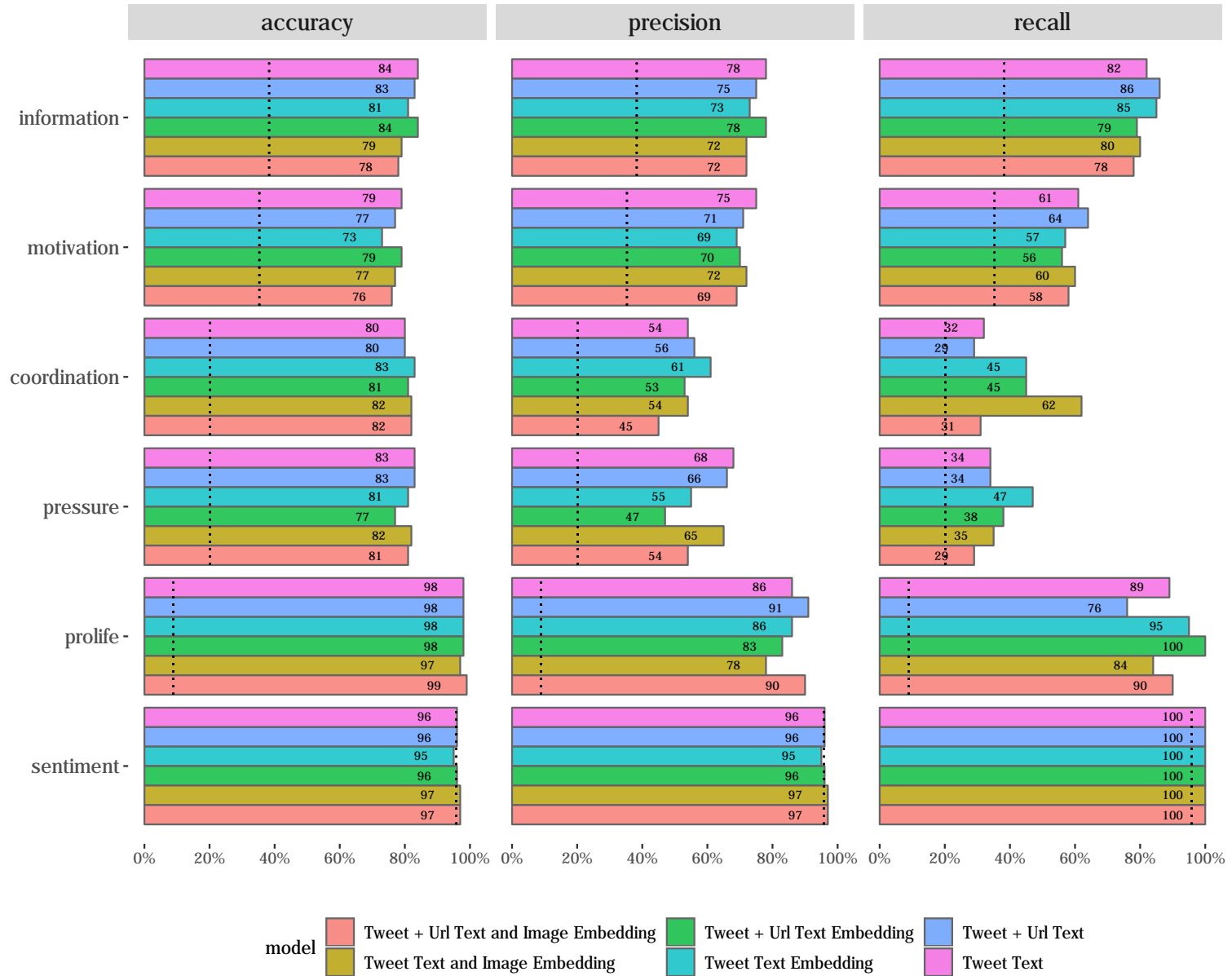
Appendix D Appendix D: Machine Learning Models

Table D1: Description of 6 types of machine learning models trained to predict 6 binary outcomes: the 4 mobilizing mechanism and the two variables of interest (pro-life and sentiment).

Model Label	Model Type	Input Type & Preprocessing
<i>Tweet Text</i>	Naive Bayes	Document Term Matrix ($\#Docs \times \#Unigrams$) <ul style="list-style-type: none"> • use text from tweet (but not text from shared links) • remove urls (<i>http</i>) • remove mentions (@) • remove retweet marks (RT) • all text to lower case • remove all punctuation but exclamation and interrogation signs (!?) • remove stopwords (list from <code>python nltk</code> module) • stem all words (<i>Porter</i> stemmer from <code>nltk</code> module) • same token for all time markers (<i>timemarker</i>) • same token for all day markers (<i>daymarker</i>) • tokenize and use unigrams to build Document Term Matrix
<i>Tweet</i> + <i>Url Text</i>	Naive Bayes	Document Term Matrix ($\#Docs \times \#Unigrams$) <ul style="list-style-type: none"> • use text from tweet • use metadata text from shared links (Title and Description; if appropriate Twitter cards are present) • apply same preprocessing as in the <i>Tweet Text</i> model

<i>Tweet Text Embedding</i>	Logistic Regression	Document Embedding Matrix ($\#Doc \times 100$) <ul style="list-style-type: none"> • use text from tweet • same text preprocessing as in previous models • use pre-trained Word2Vec (Mikolov et al. 2013) model to get 100-size embeddings for each word • average word embeddings within document to get 100-size Doc2Vec embeddings • stack Doc2Vec embeddings to create a Document Embedding Matrix
<i>Tweet + Url Text Embedding</i>	Logistic Regression	Document Embedding Matrix ($\#Doc \times 100$) <ul style="list-style-type: none"> • use text from tweet • use metadata text from shared links • apply same preprocessing as in the <i>Tweet Text Embedding</i> model
<i>Tweet Text and Image Embedding</i>	Logistic Regression	Document Embedding Matrix ($\#Doc \times 612$) <ul style="list-style-type: none"> • use text from tweet • apply same text preprocessing as in the <i>Tweet Text Embedding</i> model • if tweet has an image, pass it through ResNet18 and pull output from second-to-last layer to get a 512-size image embedding • otherwise, build a 512-size image embedding with 0s • append image embedding to the 100-size text embedding, creating 612-size document embeddings • stack document embeddings to create a Document Embedding Matrix
<i>Tweet + Url Text and Image Embedding</i>	Logistic Regression	Document Embedding Matrix ($\#Doc \times 612$) <ul style="list-style-type: none"> • use text from tweet • use metadata text from shared links • apply same text preprocessing as in the <i>Tweet Text and Image Embedding</i> model

Figure D1: Accuracy for an ensemble of 6 machine learning models predicting 6 different outcomes.



In Table D1 we provide a description of the six models trained to predict the 6 tweet-level binary outcomes of the study (the 4 mobilizing mechanisms, plus the anti-march and prolife variables). In Figure D1 we report the accuracy of the models. The dotted vertical lines indicate the percentage of the 200 training tweets that have been found to contain the mechanism. We observe that in most cases overall accuracy is around or above 80%. In terms of precision and recall, for each of the mechanisms there is always a model that yields a precision and a recall above 60% (with the only exception of the recall for the pressure mechanism). This means that the accuracy is satisfactory given that some of the mechanisms are not very frequent (for example, only around 20% of the tweets have been labeled as containing the pressure and coordination mechanism).

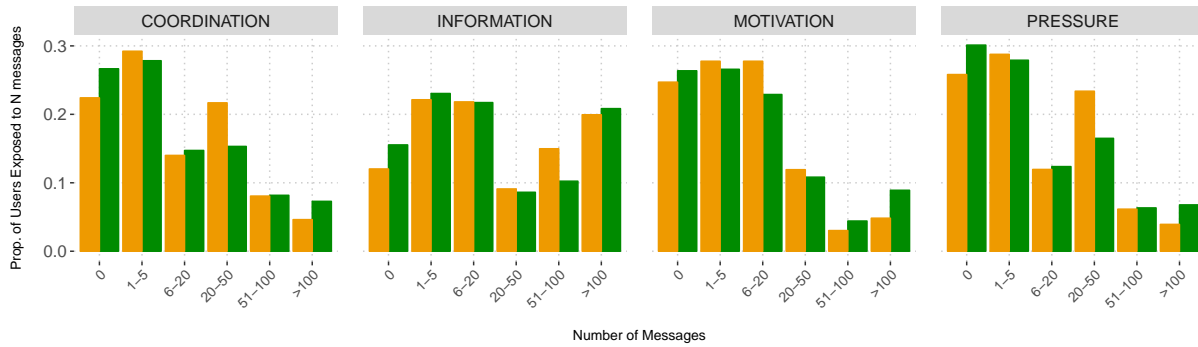
Appendix E Appendix E: Logistic regressions predicting protest attendance.

Variable	Control	Coordination	Information	Motivation	Pressure
(Intercept)	1.806 (0.221)*	1.327 (0.246)*	1.477 (0.249)*	1.377 (0.245)*	1.339 (0.246)*
Friends (log)	-0.221 (0.035)*	-0.184 (0.043)*	-0.207 (0.043)*	-0.194 (0.043)*	-0.187 (0.043)*
Female	0.401 (0.070)*	0.431 (0.071)*	0.419 (0.071)*	0.409 (0.070)*	0.411 (0.070)*
Att. to Formal Politics: Num MCs followed	-0.004 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Media Att.: Num top-30 Media followed	0.014 (0.008)	0.007 (0.008)	0.002 (0.008)	0.005 (0.008)	0.007 (0.008)
Predisposition: Following WM account	0.365 (0.087)*	0.175 (0.140)	0.110 (0.137)	0.263 (0.134)*	0.193 (0.144)
Conservatism: Following FoxNews	-0.743 (0.132)*	-0.633 (0.135)*	-0.487 (0.139)*	-0.723 (0.133)*	-0.652 (0.135)*
Liberalism: Following more D than R	0.010 (0.004)*	0.010 (0.004)*	0.008 (0.004)*	0.015 (0.004)*	0.011 (0.004)*
Num. WM Messages from Weak Ties (log)		-0.151 (0.081)	-0.481 (0.116)*	0.021 (0.086)	-0.072 (0.079)
Num. WM Messages from Strong Ties (log)		-0.483 (0.080)*	-0.651 (0.104)*	-0.115 (0.085)	-0.388 (0.074)*
At least 1 WM Messages from a Weak Tie		0.495 (0.148)*	0.479 (0.141)*	0.326 (0.154)*	0.432 (0.150)*
At least 1 WM Messages from a Strong Tie		0.619 (0.120)*	0.494 (0.106)*	0.287 (0.118)*	0.556 (0.119)*
COORDINATION (Strong tie, logged count)		0.385 (0.088)*			
COORDINATION (Weak tie, logged count)		0.200 (0.080)*			
INFORMATION (Strong tie, logged count)			0.544 (0.105)*		
INFORMATION (Weak tie, logged count)			0.536 (0.110)*		
MOTIVATION (Strong tie, logged count)				-0.044 (0.086)	
MOTIVATION (Weak tie, logged count)				-0.002 (0.085)	
PRESSURE (Strong tie, logged count)					0.279 (0.082)*
PRESSURE (Weak tie, logged count)					0.111 (0.079)
N	4,236	4,236	4,236	4,236	4,236
Log Likelihood	-2,573.159	-2,537.312	-2,514.004	-2,552.195	-2,543.741
AIC	5,162.318	5,102.623	5,056.008	5,132.389	5,115.482

Appendix F Appendix F: Distribution of the number of messages on each mechanism to which Attenders and Non-Attenders were exposed

Figure F1

(a) Proportion of Users Exposed to N Messages



(b) Percentage of users in the Attender and Non-Attender groups who were exposed to at least one message containing each of the mobilizing mechanisms.

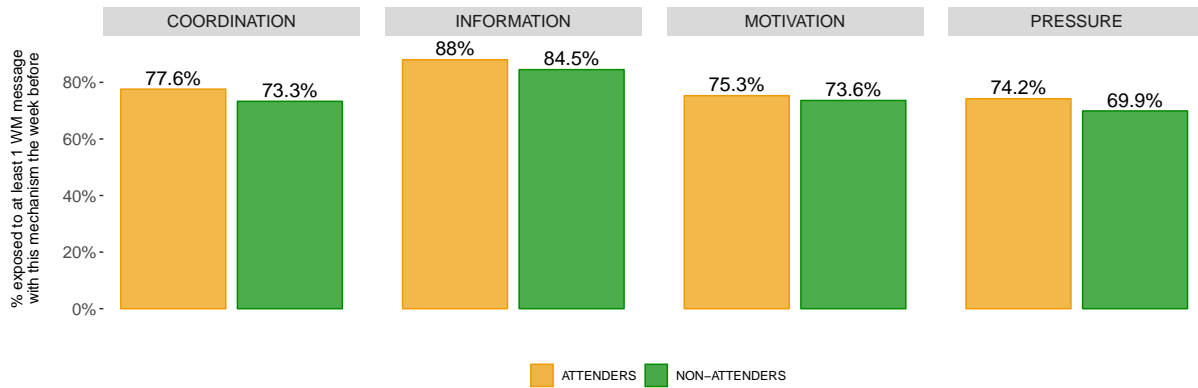


Figure F2: Number of messages containing each mobilizing mechanism that the friends of the average attender and non-attender sent the week before the march.



Appendix G Appendix G: Linear model predicting differences in network attributes

Table G1: Models predicting within-group attributes

Variable	Prop. ties within	Prop. ties of ties within	Prop. reciprocal ties within	Prop. weak triangles within	Prop. strong triangles within
Attender	0.0002 (3.63)*	0.0000 (-0.10)	0.0006 (3.26)*	0.0006 (0.73)	0.0003 (2.25)*
Female	0.0000 (-0.92)	0.0000 (-3.34)*	-0.0002 (-0.76)	0.0006 (0.72)	-0.0001 (-1.03)
Follows FoxNews	0.0003 (2.90)*	0.0000 (-0.85)	-0.0001 (0.12)	-0.0013 (-0.87)	0.0010 (3.82)*
Follows MSNBC	0.0001 (0.66)	0.0000 (0.42)	0.0004 (1.03)	0.0014 (1.06)	0.0000 (0.03)
Num. Democrats Followed	0.0000 (3.05)*	0.0000 (1.57)	0.0000 (1.35)	0.0002 (1.05)	-0.0001 (-4.13)*
Num. Media Accounts Followed	0.0000 (-1.30)	0.0000 (-4.09)*	0.0000 (0.12)	0.0001 (1.54)	0.0000 (-1.10)
Num. Politicians Followed	0.0000 (-1.58)	0.0000 (-0.78)	0.0000 (-0.74)	-0.0002 (-1.12)	0.0001 (5.06)*
Num. Republicans Followed	0.0000 (0.87)	0.0000 (0.18)	0.0000 (0.49)	0.0002 (1.00)	-0.0001 (-5.21)*
(Intercept)	0.0004 (8.67)*	0.0001 (34.73)*	0.0004 (2.49)*	0.0000 (0.05)	0.0005 (3.53)*

Variable	Number of ties	Number of ties of ties	Prop. reciprocated ties	Number of weak triangles
Attender	-209.707 (-2.59)*	-1984285 (-5.71)*	-0.0149 (-1.77)	-19531.2 (-1.73)
Female	-285.632 (-3.53)*	-323153 (-0.94)	0.0120 (1.44)	-19832.7 (-1.77)
Follows FoxNews	41.545 (0.27)	-31392 (-0.05)	0.0053 (0.34)	-438.6 (-0.02)
Follows MSNBC	-11.004 (-0.09)	642012 (1.15)	0.0335 (2.48)*	2802.5 (0.15)
Num. Democrats Followed	19.009 (1.26)	-39217 (-0.61)	0.0025 (1.60)	-16103.8 (-7.74)*
Num. Media Accounts Followed	56.145 (6.21)*	311430 (8.10)*	-0.0086 (-9.19)*	1572.5 (1.26)
Num. Politicians Followed	2.851 (0.18)	76727 (1.16)	-0.0028 (-1.76)	18129.4 (8.42)*
Num. Republicans Followed	1.641 (0.10)	-70854 (-1.03)	0.0029 (1.73)	-13244.2 (-5.95)*
(Intercept)	967.133 (12.14)*	5031742 (14.91)*	0.3601 (44.01)*	38345.2 (3.49)*