The Mechanisms of Protest Recruitment through Social Media Networks*

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Abstract

The literature on protest mobilization has long suggested that social ties have a strong influence in the decision to protest. Recent literature on social media mobilization also shows that in the current digital environment these social ties effects often take place online, particularly in social media. However, previous research does not provide clear evidence for why personal ties play a mobilizing role. In this paper we lay out four main theoretical mechanisms and we test them using real-world protest attendance data: social networks mobilize because a) they provide basic logistic *information* that is vital to protest coordination, and b) they create *motivations* for others to protest, c) they solve *coordination* problems, and d) they put *pressure* on others to participate. We collect data on Twitter activity during the 2018 Womens March that took place in many cities in the United States on January 20th and 21st. We then use geolocated accounts to find a set of users who attended a march and a set of users who did not. We use machine learning techniques to determine the amount of information, motivation, coordination, and pressure frames to which they were exposed through their Twitter networks. In line with current theories, we find users who protested to be more connected among themselves than those who did not. In regards to the mechanism analysis, we find that users whose friends sent a larger number of information, coordination, and to a lesser extent, pressure frames, were more likely to protest, but find the opposite effect for motivation frames.

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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 right after (such as the #MeToo and the #TimesUp movements), the march contributed to build a stronger coalition around gender equality and to increase the salience of existing gender disparities – illustrating the ability of social mobilizations to set political agendas and eventually influence policy. But how did this protest become to be the "largest demonstration in US history" (Frostenson, 2017)? In other words, what influences people's decision to protest?

Social scientists have been long debating about this question. A long-standing argument in the literature is that people's networks are partially to blame: people are more likely to attend a protest if their social ties also do so – 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, and through what channels? Scholars have argued that personal networks influence one's decision to protest because they: a) provide basic logistic *information* needed for attendance (Olson, 1965), b) present reasons and a *motivation* for others to attend (Katz and Lazarsfeld, 1955a), c) contribute to solving *coordination* problems (Kuran, 1995), and d) put *pressure* on others to participate (Gerber et al., 2008). Nevertheless, empirical research using real-world data to explore the validity of these mechanisms is nonexistent. Moreover, recent research points to social media as a channel through which these network effects occur (Gonzalez-Bailon et al., 2011; Barbera et al., 2015; Jost et al., 2018; Larson et al., 2018; Langer et al., 2018). This literature

[1] There 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*.

however does not study in detail the content of the social media messages networks of potential participants exchange previous to protest – leaving questions about why personal ties influence people's decision to protest unanswered.

We assess whether and the reasons why personal networks have a mobilizing effect by studying real-world participation to all Women's March that took place on January 20th 2018, on the anniversary of the first march. We use geolocated Twitter accounts to find a set of users who attended one of the 249 marches in the United States that day, and a set of users who did not (but showed interest in the march). We then obtain information about their Twitter networks and collect the march-related messages sent by their friends the week before. After training machine learning classifiers predicting the presence of the four mobilizing mechanisms in each of the messages (information, motivation, coordination, and pressure), we use the network data to evaluate whether protesters were indeed more connected among themselves than non-protesters, and whether people exposed to the four mobilizing frames on Twitter were more likely to protest.

We first find that, although users in the non-protester set had on average a larger number of social media ties (friends), ties of ties (friends of friends), reciprocated ties (friends who follow the user back), and triadic ties (friends among their friends' friends), protesters were indeed more connected than non-protesters among each other: they had a larger proportion of ties, ties of ties, reciprocated ties and triadic ties within their own (protester) group.

Then, when exploring the messages that protesters and non-protesters's networks exchanged the week before the march, we find that those whose friend's sent a larger number of messages containing *information*, *coordination*, and to a lesser extent,*pressure* frames were more likely to protest. Contrary to our initial expectations however, we find that exposure to *motivation* frames had a negative participation effect. The findings are robust to different model specifications and controls.

The contribution of the paper is two-fold. First, building on Larson et al. (2018)'s strategy, we use real-world network and participation data to empirically test the validity of the network-participation argument (Granovetter, 1978; Marwell et al., 1988; Siegel, 2008; Centola, 2013) in the context of a highly decentralized (and somewhat divisive) mobilization. Then, we bring the analysis one step forward and disentangle some of the reasons why social networks can be mobilizing. This is the first study up to date that combines real world protest attendance, information about participants and non-participants' networks, and the messages and frames people received the days previous to protest. Overall, the paper provides an exhaustive picture of the conditions under which personal networks influence people's decision to protest.

The rest of the paper proceeds as follows. First, in the next section we present the logic behind the network mobilization argument. Then, we build on a wide range of theories to advance a set of four mechanisms that should be to blame for the mobilizing role of networks. We then discuss the data and methods used in the study, and we present the results. We conclude by summarizing the findings and its implications, and by laying out potential next steps for future research.

2 The Mobilizing Role of Networks

An extensive social science literature finds that personal networks play a crucial mobilizing role (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 likely to participate in a given action, what kind of personal interactions can make them reach their individual participation 'thresholds' (Granovetter, 1978; Chwe, 2000).

As Larson et al. (2018) point out, 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 to 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. As few examples, Centola and Macy (2007) find that the "width" of a tie (the number of individuals connecting two people) facilitates complex diffusion, such as the spread of high-risk social movements. And in a study of participation to another high-risk action, the 1964 Mississippi Freedom Summer Project (where students went to the South of the United States to combat racial seggregation), McAdam and Paulsen (1993) also find that people who applied for and joined the program had stronger ties (Granovetter, 1978) to other participants than those who applied but did not show up.

Past research on the mobilizing role of social ties had to rely on self-reported information from those who attended (and not attended) 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-word 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, and a group of users who were supportive of the action but decided not to attend, and find that the group of protesters were more connected among themselves than the non-protester group. Protesters had a higher proportion of ties, ties of ties, reciprocated ties, and triadic ties within the group.

We build on Larson et al. (2018)'s method and use Twitter geolocated accounts to detect a set of users who attended, and a group of users who despite showing interest did not attend, one of the 2018 Women's March in the United States. Our main goal is to go one step forward and to explore some of the mechanisms through which personal networks mobilize. As a first step however we want to replicate Larson et al. (2018)'s findings in another context to see if similar results emerge when studying a more decentralized and divisive protest. Building on research described in this section, and on Larson et al. (2018)'s findings, we expect those users who attended one of the protests to be more connected among themselves than those who did not participate in any of the actions. In particular, we take into consideration both the existence and the quality of ties to formulate the following hypotheses. Given a defined group of protesters and non-protesters, we expect that:[2]

H$_1$: *On average, the proportion of the protesters'* ***ties*** *that are also in the protester group is greater than the proportion of the non-protesters' ties that are in the non-protester group.*

H$_2$: *On average, the proportion of the protesters'* ***ties-of-ties*** *that are also in the protester group is greater than the proportion of the non-protesters' ties-of-ties that are also in the non-protester group.*

H$_3$: *On average, the proportion of the protesters'* ***reciprocated ties*** *that are also in the protester group is greater than the proportion of the non-protesters' reciprocated ties that are also in the non-protester group.*

H$_4$: *On average, the proportion of the protesters'* ***triadic ties*** *that have one tie in the protester group is greater than the proportion of the non-protesters' triadic ties that have one tie in the non-protester group.*

[2] See Larson et al. (2018) for a formal representation of these same hypotheses.

3 The Mechanisms of Network Mobilization

Hence, an extensive literature finds that people are more likely to join a protest movements if they have ties to other protesters – and even more if these ties are 'stronger.' A crucial question that remains unanswered however is: why is this the case? What is about personal networks that make people more likely to protest? What specific functions do networks play?

Literature from a variety of fields provide several answers this question. Empirical research disentangling the validity of these mechanisms however is nonexistent. This is in part due to data limitations faced by previous studies. Disentangling and/or adjudicating between mechanisms requires 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 to the 2018 Women's March, as well as the communications related to the march that these users' networks exchanged the week before the protest. As previous studies show, Twitter networks are a good reflection of people's real-life networks (Bisbee and Larson, 2017), and the messages people are exposed to in social media are often to blame 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 a great opportunity to uncover different types of network effects (Jost et al., 2018).

We focus our analysis on four mechanisms scholars believe are to blame for the mobilizing role of personal ties. We call them the *information*, *motivation*, *coordination*, and *pressure* mechanism. Next, before transitioning to discussing the data and methods used in the analysis and the results, we describe each of them.

3.1 The Information Mechanism

Personal networks provide basic logistic 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 action is taking place, where and when, and how to get there. Communicating and consuming this logistic information has some costs attached to it.

One of the non-protesters 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 would had been able to attend. Second, this example highlights the costs attached to consuming basic logistic information. These costs are low, one could have learned about the 2018 Women's March by watching the news on TV, reading a newspaper, etc. However, despite being low, not everybody is willing or able to bear them.

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 had 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 substantive 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($_{H_5}$)**:** *Users whose friends sent more Twitter messages containing basic logistic information related to the 2018 Women's March were more likely to protest.*

3.2 The Motivation Mechanism

Personal networks provide motivations to participate. Studies of opinion formation and political attitudes show that people often do no pay attention to politics (Hibbing and Theiss-Morse, 2002) nor 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 (1955b) 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.

Lohmann (1994) also argues that cascades of information providing reasons for people to protest was one of the main triggers of the demonstrations that took place in Leipzig in 1989-1991, previous to the collapse of the German Democratic Republic (GDR). 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 'nature of the regime' (Bikhchandani et al., 1992): "environmental damage, political repression, corruption, and the luxurious lifestyles of the SED elite" (Lohmann, 1994, 44) – cascades of motivation spread through personal networks and others decided to join the protests after learning what was actually going on in the country.

Some of the Women's March related messages that people sent on Twitter the days before the protest clearly provided motives for others to protest. The message shown in Figure 1 for example, apart from providing basic logistic information about the march (e.g. the day

Figure 1: Example of a Tweet sent the week before the Women's March that had some of the theorized mechanisms.

the march is taking place in Los Angeles and a link to further logistic information), it also lays out reasons for 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 man receive for similar positions.

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($_{H_6}$): *Users whose friends sent more Twitter messages providing reasons to 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.

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 believes 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 like the United States, the work of others also show that the coordination role of networks can also play a mobilizing effect. In a 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 to blame of an increase in attention to and diffusion of the movement online. What remains unclear is whether messages from friends that contribute solving coordination problems have an actual effect on real-world protest attendance. Apart from providing basic logistic information and reasons to protest, the message in Figure 1 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. Hence, based on the rich literature on the matter, we formulate the following hypothesis:

Coordination($_{H_7}$): *Users whose friends sent more 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, and ingroup-outgroup dynamics, explain a wide range of political attitudes: people do not desire to deviate from their group's behavior (Tajfel, 1981).

Gerber et al. (2008) work provides a clear example of how peer 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.[3] The participation rate among these voters was about 10 percentage points higher than the average voter.

Building then on this existing literature on group dynamics and social pressure, we formulate the following hypothesis:

Pressure($_{H_8}$): *Users whose friends sent more Twitter messages putting pressure on others to participate to the 2018 Women's March were more likely to protest.*

[3]Other randomized group of voters received other letters containing different treatments and placebo tests.

4 Data & Methods

We test our hypotheses by studying real-word attendance to 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 showed support but did not attend. The first Women's March took place on January 21th 2017, right after Donald Trump's inauguration, with the goal of "harnessing the political power of diverse women and their communities to create transformative social change."[4] More than 650 demonstrations were organized all around the World, most of them in cities in the United States – about 400, with a principal march on Washington D.C..[5] Experts estimate that more than 4 million people participated to the U.S. protests alone, making it the largest demonstration in U.S. history.[6] 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, with the epicenter being the march in Las Vegas.[7] Apart from pursuing the main mission of the organization, under the motto "Power to the Polls", this second march had as a particular goal to foster the election of political candidates all around the United States that supported gender equality and other movement demands.

Three main pieces of data were needed in order to test the hypotheses proposed in this study: a) to find a group of people who protested and a group of potential protesters (users who positively messaged about the movement) that did not attend any of the marches, b) detailed information about these people's (Twitter) networks , and c) information about the

[4] Extracted form the Mission statement in the Women's March website.

[5] Number and location of the 2017 demonstrations obtained from the Women's March website. The link has now expired but an archived version can be accessed via the Web Archive in this url. We scrapped the data from the website before it disappeared, so we also have the information in dataset format.

[6] See the attendance data collected by Erica Chenoweth (University of Denver) and Jeremy Pressman (University of Connecticut) reported in this news article in Vox: *The Women's Marches may have been the largest demonstration in US History.*

[7] We downloaded the list of locations, and meta data about each of them, from the Women's March website. As mentioned in Footnote 5, the information for the 2018 marches is not available in the website neither. We however have a dataset containing all the march data for replication.

communications and type of frames people exchange through their networks via this social media platform the week before the protest. Before transitioning to discussing the results, in the rest of this section we describe in detail how we collected and preprocessed the data in order to have these three crucial pieces of information.

4.1 The Protester and Non-Protester Groups

To find a group of Twitter users who attended and a 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.

Before and during the march we collected Twitter messages mentioning a set of hashtags associated with the demonstrations using the Streaming API (from now on when we talk about tweets/messages we are only referring to those related to the Women's March).[8] 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 from which these messages were sent (locality and 4-coordinate-point bounding box around the locality).[9]

In order to know whether they sent a message at the time the march closest to them was taking place, and whether they sent if from the march location, we first needed to obtain detailed information about the location and time of each march. So the week following the

[8]We 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, #powertothepolls, #togetherwerise, #whywemarch, #whyimarch, #imarchfor, #marchingforward, #womensunite, #unitedresistance, #resisttrump.

[9]In the past, geolocated Twitter messages used to reveal the specific coordinates from which a geolocated tweet was being sent (Larson et al., 2018), but after recent changes made by Twitter to increase user privacy, most of the time one can only access the name of the locality from which a given geolocated tweet is sent, and a 4-coordinate-point bounding box delimiting that locality. We use the information in the 'place' endpoint provided for each tweet by the Twitter API. Although this 'place' endpoint has a 'coordinates' field in it, for most tweets from geolocated accounts this field is empty, whereas the other fields providing information about the locality from which the user is sending the tweet (e.g. 'place_type', 'name', 'full_name', 'country_code', 'country', and 'bounding_box' around the location) always contain information.

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

We proceeded to match each user$_i$ to a march$_j$ by finding the march$_j$ closest to any tweet$_{i,z}$.[10] Then, as a first filter to find users for the protester and non-protester 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.[11] 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 *potential* protester, and the ones that did so from another place as *potential* non-protesters.

At this point we were still uncertain about whether all the users in these two groups were actual protesters and non-protesters for three main reasons: a) some *actual* non-protesters could be in the group of *potential* protesters if they tweeted from the locality of their closest march but did not attend the march, b) some *actual* protesters could be in the group of *potential* non-protesters if they tweeted about their attendance to the march afterwards from another location, and c) some non potential participants could be in the *potential* protester and non-protester 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. First, we constrained the inclusion

[10] By comparing the distances between the coordinates of each march$_j$'s starting point and the center of each tweet$_{i,z}$'s 4-coordinate-point bounding box.

[11] In 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. These tweets were automatically sent hours later and the time-stamp of the tweet corresponds to this later time – we decided to go with a wider time window to avoid missing these protesters.

to the non-protester group to users who sent at least one message from 10 to 50 miles away from the closest protest, removing some non potential participants from the non-protester 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 are not of interest becuase they would had 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).[12] 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* protester and non-protester groups those users that the research assistant also considered that had and had not protested, respectively. Finally, to simplify the rest of the data collection process and analysis, we focus next only on protesters who attended a march on January 20th (the day most of the marches took place) and the non-protesters who did not participate in a march in any of the two days (January 20th or 21st).

As a result, we end up with two *final* groups of 2,607 and 507 people for whom we are highly confident that attended and not attended one of the 2018 Women's Marches, respectively. These 3,114 users compose the final sample we study in our analysis.

4.2 Protesters and Non-Protesters' Ties

The next step toward having all the necessary data to be able to test our hypotheses is to collect information about the Twitter networks of each of these 3,114 users.

[12] A 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 about 80% of the time.

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). An advantage of using social media data is that one can easily collect not only the list of user one follows (friends or ties) but also the list of followers for those followed by a given user (ties of ties). Moreover, as we already 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 the Women's Marches took place, we collected the lists of people these 3,114 users followed (a total of 3,417,056 friends, 1,642,218 of them unique), and the lists of users these 1,642,218 unique friends followed (about 17 billion users).[13] This allowed us to build a comprehensive graph of the networks of the protesters and non-protesters in our sample.

4.3 Pre-March Network Communications and Frames

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.[14] After collecting the list of friends of the users in the protester and non-protester set, 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: a total of 486,007 messages, 45,717 of them unique.[15]

Then the challenge was to detect the presence of each of the mobilizing mechanisms in these tweets. First, we draw a random sample of about 5,000 of them, and we split

[13] Due to computation restrictions, we have not yet computed the exact number of friends of friends involved in the study, nor the number of these that are unique. The 17 billion is an estimate based on the average number of ties of ties the users in our sample have: see Figure 1

[14] See Footnote 8 for a list of the hashtags.

[15] In the 486,007 message count we count a friend's message as many times as users in our sample follow her.

them in three groups and three research assistants manually coded them for whether they had each of the theorized mechanisms – allowing a given tweet to contain the four of them (see codebook in Appendix B and some exaples of messages falling into each category in Appendix A). Then we used this labeled dataset to train four machine learning classifiers that were able to predict the probability for *all* pre-march messages from friends to contain these mechanisms. We transformed the tweets in the training set to Doc2Vec embeddings (Le and Mikolov, 2014) and we then trained four logistic regressions, using these embeddings as input and the assigned labels as output. The 100-fold average out of sample accuracy for these four machine learning classifiers is 75% for the *information* mechanism, 61% for the *motivation* mechanism, 71% for the *coordination* mechanism, and 77% for the *pressure* mechanism (based on balanced hold out sets of 50% true positives and 50% true negatives).

5 Results

We begin by testing the first four hypotheses and corroborating that users in the protester group were indeed more connected among themselves than were users in the non-protester group. We then transition to explore the Twitter communications of the protesters and non-protesters' networks in order to address the rest of the hypotheses. 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 mobiliziation 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 1 we provide a summary of the network attributes of the 507 non-protesters and a random sample of 507 of the 2,607 protesters, as well as group comparisons (t-tests) for each of the attributes. We create a subsample of protesters of equal size than the non-protesters group (n = 507) to make sure that the results of the group comparisons involving within-group attributes (in gray) are not a function of differences in group size. Positive t-statistics indicate a larger attribute average for the protester group whereas negative t-statistics indicate the opposite.

Two main points stand out from Table 1. First, non-protesters had larger and somewhat 'stronger' networks than users in the protester group. On average, they had a greater number of ties (1,244 *versus* 1,073 for protesters), ties of ties (about 6.4 million *versus* 4.6 million for protesters), and reciprocated ties (502 *versus* 419 for protesters). As for 'strength', non-protester had a reciprocated friendship with a larger proportion of their friends (.32 *versus* .31 for protesters) and they had a larger proportion of triadic relationships –out of all possible triadic connections with their friends and friends of friends– (.11 *versus* .1 for protesters). The group differences for the number of ties of ties and the proportion of triadic connections (rows 2 and 5 in Table 1) are statistically significant at conventional levels.

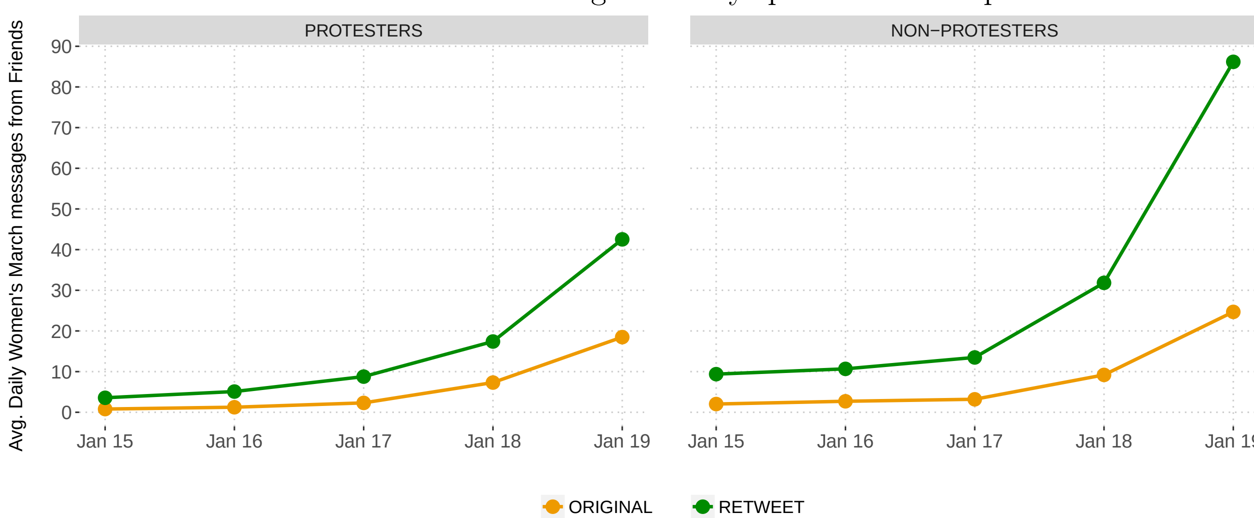
Table 1: Network attributes for Protesters and Non-Protesters (with standard deviation in parentheses). *T-statistic* tests the null hypothesis that attributes for Protester and the Non-Protesters are the same.

	PROTESTERS	**NON-PROTESTERS**	**tstat**
Mean # Ties	1,073 (1,903)	1,244 (1,837)	-1.45
Mean # Ties of Ties	4,618,019 (5,818,521)	6,437,016 (7,689,719)	-4.23
Mean # Reciprocated	419 (1,370)	502 (1,028)	-1.09
Mean Prop Reciprocated	0.31472 (0.20377)	0.32061 (0.20799)	-0.45
Mean Transitivity	0.09789 (0.05982)	0.10676 (0.0797)	-1.99
Prop. Ties Within ($\mathbf{H}_1$)	0.00033 (0.00089)	0.00012 (0.00046)	4.70
Prop. Ties of Ties Within ($\mathbf{H}_2$)	0.00005 (0.00008)	0.00004 (0.00003)	2.19
Prop. Reciprocated Within ($\mathbf{H}_3$)	0.00047 (0.00308)	0.00013 (0.00072)	2.37
Prop. Triadic Ties Within ($\mathbf{H}_4$)	0.00010 (0.00038)	0.00004 (0.00016)	3.39

However, as the information at the bottom half of Table 1 indicates (rows in gray), despite having smaller networks, the Twitter users that attended one of the Women's March on January 20th 2018 were indeed more connected among themselves. A larger proportion of their ties is also present in the protester group (.0003 *versus* .0001 for non-protesters) as well as a greater proportion of their ties of ties (.00005 *versus* .00004 for non-protesters), reciprocated friends (.0005 *versus* .0001 for non-protesters), and triadic ties (.0001 *versus* .00004 for non-protesters). In line with existing network models of protest mobilization (Granovetter, 1978; Marwell et al., 1988; Siegel, 2008; Centola and Macy, 2007; Larson et al., 2018), all these positive and statistically significantly differences in favor of the protester group corroborate the first four hypotheses of the study ($\mathbf{H}_{1,2,3,4}$).

However, what explains these differences? Why are personal networks mobilizing? Could these differences be simply explained by a disproportional discussion of the Women's March among these groups' networks in the days previous to the protest?

Figure 2: Average Daily Women's March related messages the Twitter friends of users in the Protester and Non-Protester sent during the 5 days previous to the protest.



In Figure 2 we begin addressing these questions by exploring the communications that the networks of protesters and non-protesters exchanged on Twitter the week before the protest. Figure 2 shows the average daily original tweets (in orange) and retweets (in green) related to the Women's March that Twitter friends of users in the two groups sent from January 15th to January 19th (both included). As one would expect, the amount of dicussion about the march increases as demonstration are closer in time, particularly during the two days preceding the demonstrations (January 18th and 19th). Nevertheless, during these preceding days, friends of users in the protester group sent fewer messages about the march. The day before the march (January 19th), the Twitter friends of the users in the protester set only sent on average about 20 original tweets and 45 retweets related to the action, *versus* the 25 and 85 by the friends of the users in the non-protester set, respectively. This pattern rules out the argument that protesters were simply influenced by a higher general discussion about the Women's March among their networks.

What remains unanswered however is whether the discussion among the networks of the users in the protester and non-protester set was similar in content. Did the Twitter friends of the protesters used the theorized mobilizing frames at a higher rate than the friends of the non-protesters?

To address this question we use the trained machine learning models to predict the probability of each march-related message sent by a friend of a protester and/or non-protester to contain each of the four mechanisms. In Figure 3 we use these measures to illustrate the average probability of messages sent by the friends of each group to have each mechanism on each of the five days previous to the protest. As we did in Figure 2, we distinguish between original tweets (top four facets) and retweets (bottom facets) to show that the results are robust to these two types of messages. We observe very clear differences across the board. As hypothesized ($\mathbf{H}_{5,7,8}$), Twitter friends of the protester group used *information*, *coordination*, and *pressure* frames at a higher rates than friends of users in the non-protester group. These group differences are relatively constant across time and message type (original messages and retweets). As one could expect, the relevance of information and coordination frames

Figure 3: Average probability of Twitter messages from friends of users in the protester and non-protester set to contain each of the four mobilizing mechanisms.

(discussing basic logistic information and whether one would attend the march) increases as the march is closer in time, as well as the usage of frames putting pressure on others to protest. However, contrary to what we expected ($\mathbf{H}_6$), *motivation* frames were used at a higher rate by friends of users in the non-protester set. These motivation frames moreover seem to decrease in relevance as the march gets closer.

Finally, one important issue to address is whether the patterns in Figure 3 hold when controlling for other relevant factors that could potentially explain protest attendance.

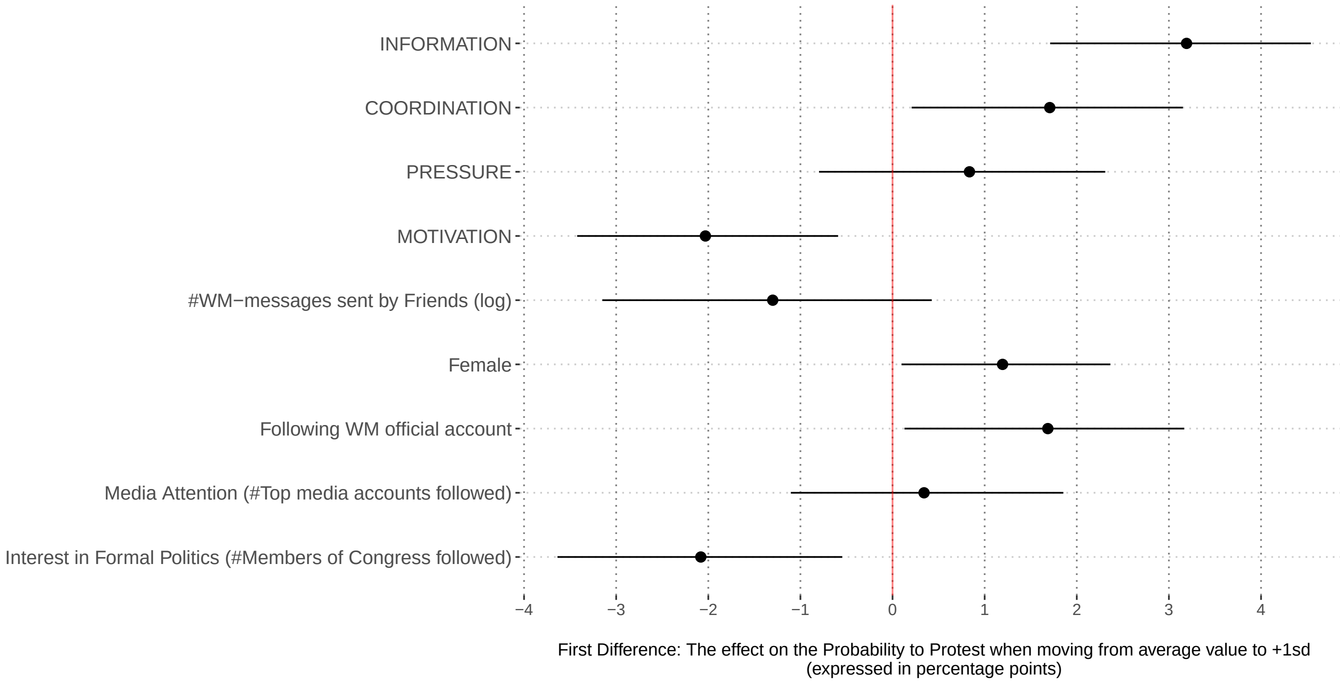
We address this issue by calculating and modeling a larger set of measures for each of the protesters and non-protesters in our sample. First, we calculate four key measures of interest: the average probability that messages from each user's friends had the four theorized mechanisms. Then we build the following covariates: a) a numeric variable accounting for the possibility that users were mobilized by being exposed to a larger discussion among their networks about the Women's March (number of march-related messages sent by their friends the week preceding the action), b) a binary variable indicating whether the user is a woman, to account for the possibility that female attended the march at a higher rate (2,077 of the 3,114 users in the dataset are women),[16] c) a binary variable indicating whether the user followed the official account of the Women's March, to control for differences in the initial propensity to attend the protest, d) a numeric variable indicating the number of top media accounts followed by the user (out of the 50 most followed U.S. mainstream media accounts on Twitter), to account for attentive publics potentially being more likely to attend the demonstrations, and e) a numeric variable indicating the number of members of Congress the user follows on social media, to account for the possibility that attendance was driven by general interest in politics.

Figure 4 presents standardized coefficients (and 95% confidence intervals) for a logistic regression predicting protest attendance among the 3,114 users in both sets as a function of the described variables (plus march-fixed effects to control for potential regional-level predictors. Coefficients table available in Appendix D).[17] The four top coefficients are our main quantities of interest. We observe that after controlling for alternative explanations, we are still able to confidently corroborate two of the mechanism hypotheses ($\mathbf{H}_{5,7}$): users whose friends sent messages with a greater presence of *information* and *coordination* frames were indeed more likely to participate. Increasing by one standard deviation the average information and coordination frames to which users were exposed increased their likelihood of attending the protest by more than 3 and about 2 percentage point on average, respectively.

[16] A research assistant went through the names and Twitter profiles of the users in the sample and coded them for whether they were Female (N = 2,077), Male (N = 938), or Unclear (N = 99: in case she could not tell or classify the gender of a given user in one of the two other categories). To simplify the analysis, we collapse in this analysis the Male and Unclear category. A model with the these three gender categories produces the same exact results.

[17] For the march-fixed effects we take into account the march each protester attended and the closest march to each non-protester.

Figure 4: Standardized coefficients for a logistic regression predicting people's probability to attend one of the Women's March on January 20th 2018



We observe less optimistic results in regards to the two other mechanisms and hypotheses ($\mathbf{H}_{6,8}$). We still see the amount of *pressure* frames sent by friends to be positively correlated with attendance, but the effect is not statistically significant at conventional levels. And as we observed in Figure 3, *motivation* frames are negatively associated with attendance, even after controlling for other potential confounders.

As for the other covariates, we do not see the number of Women's March related messages sent by friends to be of relevance, nor the number of media accounts followed on Twitter. We do see however that women, and people who followed the Women's March official Twitter account, were more likely to attend one of the marches, but the number of members of Congress followed on Twitter to be negatively related to attendance.

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. 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 onto 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 group of users who showed interest by messaging about the march but did not attend.

We argued that four main mechanisms should be to blame for the mobilizing role of networks: personal ties provide basic logistic *information* needed to protest, create *motivations* for others to protest, solve *coordination* problems by revealing protest attendance, and put *pressure* on others to attend. We used machine learning techniques to predict the presence of these mechanisms in the tweets friends of protesters and non-protesters sent the week before the march.

First, using these users' Twitter networks, we corroborated that users in the protester group were more connected among themselves than were users in the non-protester group. Then, when studying the communications these users' networks exchanged the week preceding the protest, we found that users whose friends sent messages with *information* and *coordination* frames, and *pressure* ones to a lesser extent, were more likely to attend. Contrary to our expectations, we found that exposure to *motivation* frames was related to a decrease in the probability to attend the march.

In conclusion, this paper not only provides a very clear picture of the conditions under which personal networks influence one's decision to protest, but it also opens the door to future research on the matter. The methods applied in this paper can be used to study many other protests, particularly mobilizations that have been planned ahead of time, allowing the researcher to start tracking the messages potential protesters exchange the days previous to the action. We found that motivation frames were not important to drive attendance to the Women's March, but that could be a function of the issues motivating the march being already very salient. Could these motivation frames be of greater relevance when a protest movement is still emerging? We encourage others to build on the work presented here to test these network-mechanism effects in other contexts.

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Appendix A Examples of Anti Women's March Tweets

Table 2: 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! https://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 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-proster 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

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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]

Appendix C Examples of Pre-March Messages Containing Each Mobilizing Mechanism

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'mon people! https://t.co/oXpNClY5TK #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/7w5NXKt1t8
We all need to take to the streets tomorrow. Not just women. ALL Resistors. #resist #TrumpShutdown #womensmarch2018 Cleveland

Appendix D Results for a Logistic Regression Predicting Attendance to the 2018 Women's March

	Coefficient	SE	P-Value
(Intercept)	15.66	2782.11	0.996
INFORMATION	3.28	1.39	0.018*
COORDINATION	5.49	2.32	0.018*
PRESSURE	4.83	3.38	0.153
MOTIVATION	-3.12	1.39	0.024*
#Friends who sent WM-messages (log)	-0.05	0.17	0.768
#WM-messages sent by Friends (log)	0.01	0.14	0.974
Female	0.38	0.13	0.004*
Following WM official account	0.34	0.27	0.201
Media Attention (#Top media accounts followed)	0.02	0.01	0.209
Interest in Politics (#Members of Congress followed)	-0.01	0.01	0.021*
March-fixed Effects		Yes	
N = 3,114			
AIC = 2137.4			