

Spontaneous Collective Action: Peripheral Mobilization During the Arab Spring

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Abstract

Who is responsible for protest mobilization? Models of disease and information diffusion suggest that those central to a social network (the core) should have a greater ability to mobilize others than those who are less well-connected. To the contrary, this paper argues that those not central to a network (the periphery) can generate collective action, especially in the context of large-scale protests in authoritarian regimes. To show that those on the edge of a social network have no effect on levels of protest, this paper develops a dataset of daily protests across 16 countries in the Middle East and North Africa over 14 months from 2010 through 2011. It combines that dataset with geocoded, individual-level communication from the same period and measures the number of connections of each person. Those on the periphery are shown to be responsible for changing levels of protest, with some evidence suggesting that the core's mobilization efforts lead to fewer protests. These results have implications for a wide range of social choices that rely on interdependent decision making.

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1 Introduction

Large groups of people acting without centralized leadership can organize protests. Protests occur as a result of decentralized coordination of individuals, and this coordination helps explain fluctuating levels of protest. Individuals in the core of a social network - those such as activists, members of the media, or civil society organizations - do not mobilize protests. Instead, those on the periphery of the network communicate with each other about the near future (where and when to protest) as well as events as they unfold (the presence of police, what the police are doing, supplies needed, and so on). While those at the center of the network do engage in the same behavior as others, their effect is washed out in comparison to that of the masses they try to lead. I call the ability of the periphery to mobilize *spontaneous collective action*.

There exist two competing explanations for how individuals decide to undertake action. Whether deciding to vote (Downs 1957, Riker & Ordeshook 1968, Quattrone & Tversky 1988), join a political organization (McAdam 1986, Klandermans & Oegema 1987, González-Bailón, Borge-Holthoefer, Rivero & Moreno 2011), or protest (Moore 1995, Lichbach 1998, Goldstone 2001), individuals may decide to do so as a result of effort from centralized, well-connected individuals (the core) or those on the periphery. Those at the center of a social network can provide focal points for action, alternative policies for voters, new information about policies, or demonstrate a regime is weaker than previously thought, all contributing to individuals taking collective action (Taylor 1988, Shachar & Nalebuff 1999, Dalton, Greene, Beck & Huckfeldt 2002, Gerber, Karlan & Bergan 2006). On the other hand, individuals can decide to vote (or protest or join a movement) based on the influence of those they know (Schussman & Soule 2005, Gerber, Green & Larimer 2008), beliefs in their own ability to affect an outcome (Finkel, Muller & Opp 1989, Goldstone 1994, Opp 2012), or from observing the behavior of others (Granovetter 1978, Lohmann 1994). These others are the peripheral members.

This argument is tested using data from the Arab Spring, the protests which started in Tunisia in December 2010 and soon spread through North Africa and the Middle East. The events of the Arab Spring, the most prominent large scale, widespread protests since the collapse of the Soviet Union, provide an ideal situation in which to test this theory. “Arab Spring” refers to the series of protests which started in Tunisia on December 14th, 2010 (leading to the resignation of

that country’s president), slowly spread to neighboring countries over the following 6 weeks, and inspired massive turnout in Egypt that caused President Hosni Mubarak to resign on February 11th, 2011. This paper will show that these protests were not driven by the people who had tried for years to organize them. Instead, they were organized by large groups of individuals discussing amongst themselves where to go, how to get there, when to go, and what was going on once there. This paper does not seek to explain the Arab Spring, but it does, in the course of developing the spontaneous collective action theory, present the first large-scale, systematic evidence on how individuals behaved in each country.

To test the core versus peripheral hypotheses, this paper connects two large-scale datasets. First, a machine-coded events dataset, the Integrated Conflict Early Warning System (ICEWS) is combed to measure the number of protests per day across 16 countries from November 1st, 2010 through December 31st, 2011. Second, a dataset of geolocated tweets in the same countries from the same period is built. These 13,754,998 tweets show what was being said, when it was being said, where, and how many connections each tweet author had. Combining these datasets and using a wide range of models and operationalizations, mass mobilization is shown to occur through peripheral individuals.

This paper proceeds in 8 sections. Section 2 compares and contrasts existing theories of protest mobilization with the one developed here. In Sections 3-5, the empirical strategy is discussed. Section 6 presents the main findings and a battery of robustness checks to reinforce them. Section 7 undertakes a case study of Twitter use across countries to provide qualitative evidence of mass mobilization, and Section 8 concludes with final thoughts and suggestions for future research.

2 Theory

Peripheral members of a network drive protest mobilization through two mechanisms. First, they provide a credible signal that large numbers of people are protesting, suggesting that the cost of protesting is low. Second, once protests have started, they provide more relevant information than those in the core of a network, and this information sustains a protest movement. These mechanisms exist because individuals at the core of a network - those connected to many more people than the average person - are socially distant from most of those connections and few in

number. This distance attenuates the weight of the signal the core sends (Centola & Macy 2007, pgs. 725-726), while their rarity limits the influence of their action and relevance of the protest information they provide.

Networks provide a framework for understanding how a phenomenon spreads between items; when these items are people, the network is a social network, and connections represent two people between whom a phenomenon can spread. These phenomena fall into two categories, simple and complex. A simple contagion is a phenomena which can spread between individuals after one exposure, such as illness or information about job opportunities (Granovetter 1973). Disease transmission or news are canonical examples: John only needs to meet one person with the flu to catch it, and Jane only needs to talk with one person to learn tomorrow's weather. John does not become more sick from meeting a second infected person, and Jane does not become more knowledgeable receiving the same weather report from a second person. Except for rare cases, simple contagions always spread in a network (Newman 2003). Simple contagions spread quickest when core nodes are affected since those nodes can spread the phenomena in question to many nodes at once, regardless of the structure of the underlying network (Watts 2004, pgs. 257-260). In simple contagion models, diffusion of a phenomena is less likely when the diffusion starts on the periphery.

Complex phenomena are those whose transmission requires an individual to observe that phenomena in two or more people. Contact with two or more sources is required when the phenomena possesses positive externalities, gains credibility or legitimacy when multiple people partake, or have an emotional component (Centola & Macy 2007, pgs. 707-708). Models of complex contagion are often called threshold models since they require an individual to be exposed to a defined amount of other people in the network before switching states (Granovetter 1978, Schelling 1978).¹ The existence of thresholds makes the spread of complex contagions less certain, as network structure - the distribution of thresholds - can cause a contagion to stay trapped in one part of the network (Watts 2002). Because contact with more than one source is required for complex contagion's spread, core members do not automatically lead to the spread of the phenomenon in question. The

¹The threshold is sometimes defined as a constant and sometimes as a fraction of network size. This distinction matters for small networks but large ones. For example, in a network of 8 individuals, a threshold of 1/8 does not represent complex contagion because an individual will switch states when only 1 person it knows has has; in a network of 800,000, a threshold of 1/8 would correspond to a late mover. Because mass protest involves large groups of people, the difference between numeric and proportional thresholds is moot. See Centola and Macy 2007 for an extended discussion on the difference between fractional and numeric thresholds.

existence of that phenomena in peripheral parts of the network becomes essential for its spread throughout the network.

Protests are a complex contagion phenomenon because increasing participation makes others more likely to join. Individuals are more likely to protest as others protest, since the cost of protesting decreases as a function of group size. Individuals are especially more likely to protest when they know others who are protesting (Opp & Gern 1993), and those on the periphery of a network are more likely to know others on the periphery than in the core (McPherson, Smith-lovin & Cook 2001, Kwak, Lee, Park & Moon 2010). Since there exist many more individuals on the periphery of a network than in the core, protest is therefore more likely to occur when those on the periphery of a network mobilize.

The first mechanism through which the periphery of a social network mobilizes protest is through providing a credible signal about participation in the protest. Peripheral members mobilize other participants better than those in the core because they provide a more credible signal that the protest enjoys widespread participation. If a protest is dominated by core members, the signal suggests that the policy disagreement does not affect many people who do not usually protest. This insight is similar to that made by Susanne Lohmann: she argues that unexpected participation of “moderate activists” drive protest mobilization because “extreme activists” always protest, so their participation is not a credible signal about the severity of a grievance (Lohmann 1994). A larger than expected turnout of “moderate activists” signals to others that grievances are widely shared, leading to the expectation that one’s action will decisively lead to a policy change. In discussing the effect of network structure on collective action, David Siegel explains that:

[...] the people at the bottom of the network – the proletariat, if you will - can [mobilize] if they have enough connections among themselves. The key here is to obtain a sufficiently large and well-connected group of people at the bottom of the hierarchy who [...] are highly internally motivated to participate. If these requirements are achieved, the bottom of the hierarchy can spur the network on to very high levels of participation. (Siegel 2009, pgs. 134-135)

Peripheral mobilization dominates core mobilization because there are more people on the periphery.

The second mechanism through which the periphery of a social network mobilizes protest is

by providing more information about a protest as it unfolds, and this information has the effect of coordinating protestor movement and tactics. One type of information is situational awareness, knowledge about unfolding events, and peripheral members, because of their number, provide this awareness in ways the core cannot. Situational awareness entails knowing the size of the police presence, which routes police block, whether or not police engage with protesters, paths around police, and where other protest groups find themselves. Protestors are also more likely to reach and hold onto their desired site if they can approach it from multiple directions and coordinate their action, as doing so makes it harder for police to contain the protesters (Gunning & Baron 2013, 168-174). But, since there exists a finite supply of core individuals, splitting a protest into subcomponents means the ability of core members, who are few in number, to control them is lessened.

Moreover, once engagement with state forces commences, order often dissolves; a protest is a quickly shifting series of actions occurring in an area too big to be observed by a few individuals. During a street engagement with government forces, protestors may require reinforcements on some streets and not others, while supplies such as gas masks necessary in one place but not elsewhere. If a group is able to cause police to retreat, communicating that advantage to nearby protestors can provide reinforcements to exploit this development. But relying on core members, who are few in number, to coordinate these reactions decreases the efficacy with which protestors can react to new developments. Situational awareness therefore increases the likelihood of protest success, and situational awareness is increased when information flows from and between as many individuals as possible.

Situational awareness also entails providing logistical support for a protest. During the initial march to a protest site, one key piece of information is what kind of equipment individuals need. Gas masks, onions, and soda mitigate the effect of tear gas, while hammers, slingshots, and shields are necessary if projectiles are to be employed. Individuals also need to know to where these supplies need to be delivered, as some groups of protestors may be marching peacefully while others in different neighborhoods confront the police. The same logic holds once a protest site, such as a city's main square, is established. At this point, the protest site becomes a miniature city; the provision of food, medical supplies, sanitation, communications equipment, and security needs to be coordinated.

A comparison with military tactics clarifies the importance of situational awareness. The chief advantage of German armored divisions at the start of World War II was coordination enabled by new communication technology. Equipped with radios, unit commanders could communicate with their tanks in real-time, maintaining tactical awareness throughout a battle and so allowing them to exploit enemy weaknesses or cover their own (Citino 2004). Iraqi forces in the first Gulf War had not learned this lesson: battlefield commands flowed through centralized headquarters in Baghdad, and Coalition forces were able to bomb these facilities, hindering the ability of Iraqi frontline forces to respond to battlefield developments (Press 2001). In protests, it is the police who have traditionally had the coordination advantage because of their distributed communication, while protesters have often lacked a similar ability.

Peripheral individuals are better positioned to coordinate than the core. Even in authoritarian setting, the existence of widespread discontent is often not a surprise. In Tunisia and Egypt, for example, it was widely known that the regimes were unpopular. In Tunisia, oligarchic elites and weak rule of law alienated large segments of society, from students to the working-class, especially outside of Tunis, and desperation suicides were not uncommon events (Breuer 2012, Al-Zubaidi & Cassel 2013). In Egypt, police indiscretion, religious persecution, and economic instability similarly dispirited a majority of the population (Gunning & Baron 2013, 97-127). It was well-understood in these countries that dissent was widespread and a minority of a society benefited from current policies at the expense of most others. Widespread, commonly understood dissatisfaction means that latent desires for policy change are known to exist, rendering the task to one of coordinating protest. The periphery then drives mobilization because it signals that disparate, numerous groups of individuals are acting on this discontent.

Signalling and situational awareness allow peripheral members to coordinate their action. For example, a message such as “#jan25 protests will take place all throughout cairo, including shubra, mohendessin, in front of cairo university and on arab league street” issued on the morning January 25th, the first major day of protests in Egypt, provides information about where individuals who want to protest can join others (Idle & Nunns 2011, pg. 33). Information less explicitly about coordination can also have a coordinating effect. A large amount of the communication leading up to a protest focuses on supplies needed, how to dress, how to behave towards the police, and the identity of protesters. This communication does not tell people when or where to go, but it

helps them estimate levels of support in the population and danger they may face (Lohmann 1994, Gerbaudo 2012). The more people that provide this information, the easier protest coordination becomes.

The importance of peripheral participation as a signal of broad support is found in the experience of Egyptian mobilization on January 25th. As groups of protesters marched through outlying neighborhoods, they urged onlookers to leave their shops, apartments, and workplaces. Many did, and the protest size snowballed [pg. 51](Cambanis 2015). Protesters also emphasized the different parts of society they represented, with particular care taken to recruit outside of the middle-class as well as emphasize independence from the Muslim Brotherhood (Gunning & Baron 2013, pg. 180). The initial mobilization therefore included youth, members of football fan clubs, the poor and working class, in addition to individuals who were habitual protesters. Moreover, these habitual protesters were situated in the core of the Egyptian social network and had tried to initially protest on January 18th; only 5 activists protested, reflecting the importance of mobilization from the periphery (Gunning & Baron 2013, pg. 91).

That peripheral members of a social network provide more information than the core finds support in other settings as well. In a study of diffusion on Facebook, Bakshy et. al (2012) find that weak ties are responsible for most information diffusion because they are more numerous than strong ties (individuals who interact frequently), just as those on the periphery are more numerous than those in the core. Recruitment to Spain's indignados movement, which started less than 4 months after Egypt's first protests, was characterized by individuals' exposure to the same information from different sources (González-Bailón et al. 2011). Adoption of political attitudes is also increased after exposures from different sources (Romero, Meeder & Kleinberg 2011), and controlled experiments have confirmed the importance of multiple sources of exposure for changing health attitudes (Centola 2010). Complex contagion also drove mobilization processes during the collapse of the Soviet Union (Opp & Gern 1993) and the American Civil Rights movement (McAdam 1986), though scholars at the time did not use that language.

That protest is a complex contagion explains why many states have large domestic intelligence apparatuses and fear mass public gatherings. If an individual desiring to protest is concerned that sharing that information will lead to punishment, individuals are less likely to form connections with other individuals. In network terms, there will be fewer bridges between communities, inhibiting

the spread of protest mobilization information. (If protest were a simple contagion phenomenon, a few number of protestors could have a large effect, and governments would have to make the costs of protest so high to prevent any display of anti-regime sentiment.) Large public gatherings therefore provide one of the few occasions individuals have of bridging their immediate social communities; these bridges may cause individuals' protest thresholds to be surpassed, and a chain reaction of protests may ensue. For example, protests in Egypt against the Iraq War and marking the third anniversary of the Second Intifada led to the first large-scale public chants against Hosni Mubarak and started the process by which previously disconnected groups of individuals began to coordinate their anti-regime actions (Gunning & Baron 2013, pgs. 39-47). In Russia in 1917, an industrial lockout, International Women's Day, and military leave brought together tens of thousands of workers, women, and disgruntled soldiers into the streets of St. Petersburg; the Romanovs fled 4 days later (Kuran 1989, pg. 63). China even allows criticism of government officials and policy so long as it does not lead to appeals for collective action (King, Pan & Roberts 2013).

That protest is a complex contagion phenomenon also does not render core members unimportant in terms of protest mobilization. There are at least 3 mechanisms by which core members can facilitate protests: convincing individuals to blame their dissatisfaction on government policies, revealing the state is weaker than commonly believed, and fostering group-identity. First, a core member can help those on the peripheral ascribe their policy dissatisfaction to specific policies of those in power because the information to assign blame is a simple contagion phenomenon. As Javeline summarizes: "individuals faced with any grievance should be more likely to protest if they can make specific attributions of blame for the grievance and that one mechanism by which entrepreneurs [core individuals] might solve collection action problems is by first solving blame attribution problems" (Javeline 2003, pg. 119). Second, core members can engage in violence which, if not terminated, reveals that anti-regime preferences are widespread and the regime may be weak (De Mesquita 2010). Third, core members can create norms of solidarity, causing individuals to calculate their participation based on group gains (Goldstone 1994). Once individuals see themselves as part of a larger group, the benefits of protest increase while the costs decrease, making them more likely to mobilize when the opportunity arises.

These core-based mechanisms are not related to protest mobilization, however, as they occur before mass protests. They predispose individuals to be ready to mobilize, but they do not directly

mobilize. In the language of Timur Kuran, they cause preferences to change, but they do not provide the initial spark (Kuran 1989, pgs. 63-66). The theory of spontaneous collective action also treats the spark as exogenous.

Scope Conditions

There are two primary scope conditions to the theory of spontaneous collective action. First, a country's regime type may determine whether or not protest is a complex contagion phenomenon. Second, mobilization is bounded by the costs a state imposes on protesting.

Authoritarian regimes are likely to repress individuals who impugn them, as targeted repression is a more effective tactic than its indiscriminate killing (Siegel 2011). Arbitrary jailing, torture, forced exile, and threats to family are all common tactics used to silence anti-regime individuals. In countries where those who desire policy change and are central to a network are routinely intimidated or silenced, they may not have the ability or desire to engage in coordination activities, and coordination would necessarily occur through those on the periphery. Moreover, in countries tolerant of mass gatherings, individuals may have lower thresholds of participation since they do not fear repression. If an individual does not expect protest to be large to be safe, he or she may join a protest alone or after hearing about it from a core social network member. In these cases, protest is more likely to be a simple contagion event and so be more affected by core members of a social network.

Second, any state can stop protests if it is willing to impose high enough costs. In March of 1988 in Burma, protests started over an event just as random as a fruit vendor lighting himself on fire: a youth arrested for fighting other youth was released from jail through political connections. Tension boiled over the summer, a general strike started on August 8th, and the state engaged in ambiguous amounts of repression. On September 18th, repression became less ambiguous as a result of an army coup; the ensuing repression resulted in at least 1,000 deaths in Rangoon, 3,000 nationwide (Ferrara 2003). Protests, which had been stronger throughout August but were tapering by mid-September, ceased. In 1989, a protest movement in China grew over the course of several months; by the end of May, Beijing hosted 250,000 soldiers, and multi-day violent repression began on June 3rd. That repression, in conjunction with the arrest of party leaders and Communist Party reformers, squelched the movement. In 2011 in Egypt, individuals soon realized that the

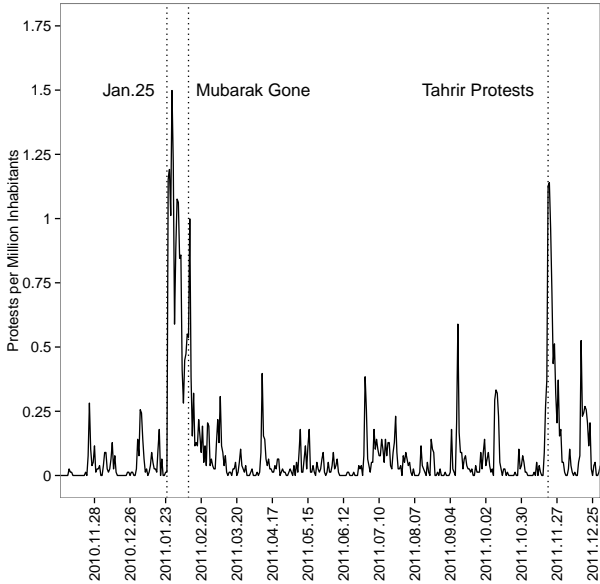
armed forces were not going to repress protests, yet in August 2013, the Egyptian army massacred hundreds, perhaps thousands, of pro-Muslim Brotherhood supporters who were staging long-term sit-ins at two Cairo squares after the July 3rd coup against President Mohamed Morsi. Repression against secular activists also increased, with those continuing to protest facing lengthy jail sentences or death (Mackey 2015). Bahrain’s security forces killed protesters at the Pearl Roundabout, after welcoming a coalition of forces from Gulf states; leaders of al-Wefaq, the main Shia opposition party that participated in government before the start of protests, are now in jail, and the party’s leader faces a 4 year sentence for inciting violence against the monarchy (Kerr 2015). While a state faces internal and external costs from repression, the ultimate success of any protest mobilization depends on the state’s willingness to repress.

3 Data

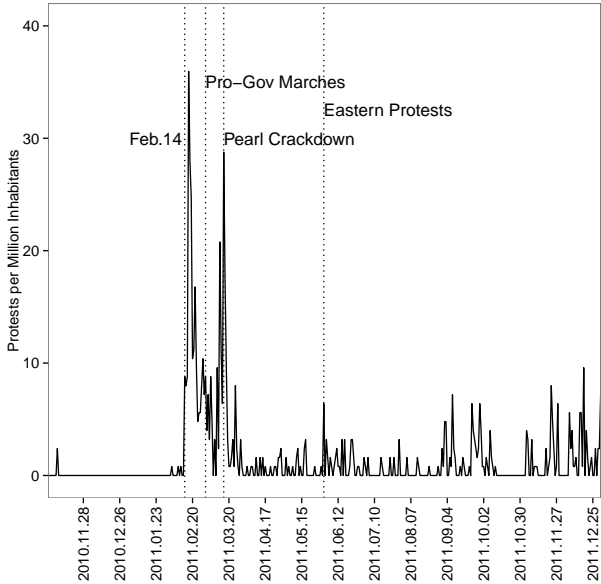
The Integrated Conflict Early Warning System, a machine-coded events dataset that reads newspaper articles, provides the dependent variable, number of protests across 16 countries in the Middle East and North Africa from November 1st, 2010 through December 31st, 2011 (Boschee, Lautenschlager, O’Brien, Shellman, Starz & Ward 2015). ICEWS codes 20 categories of events of increasing severity, from public statements through unconventional mass violence. All events coded as protests where the event occurs in one of these 16 countries are kept. These countries are Morocco, Algeria, Tunisia, Libya, Egypt, Lebanon, Syria, Jordan, Saudi Arabia, Oman, Yemen, Bahrain, the United Arab Emirates, Kuwait, Iraq, and Qatar; Israel is excluded. Figure 1 shows the ICEWS recording of protest in two high-protest (Egypt, Bahrain) and low-protest (Morocco, Qatar) countries.

Twitter, a global social media platform, provides data on daily, individual-level communication. Twitter is a global social network with over 500 million users generating almost 500 million daily messages (tweets). Anyone with an internet connection or phone can access it, and most users create and consume content using their mobile devices; contrary to popular belief, one can compose and consume tweets from any kind of phone, though smartphones greatly facilitate the process. Twitter the company does not edit or censor its users’ tweets, so the content of the network reflects what

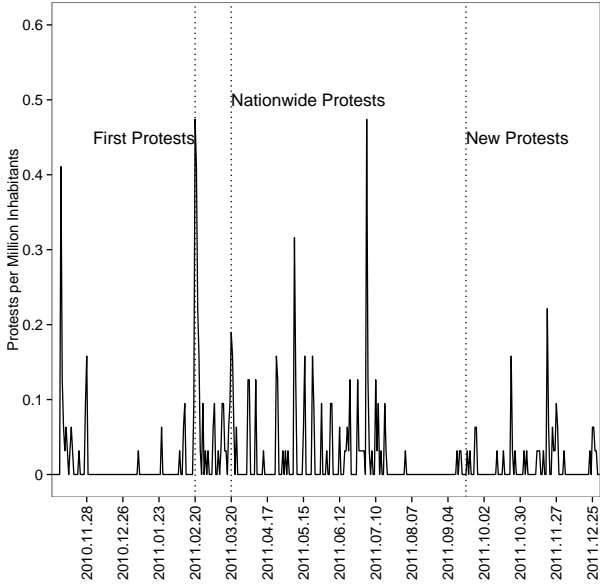
Figure 1: Protests per Million Inhabitants



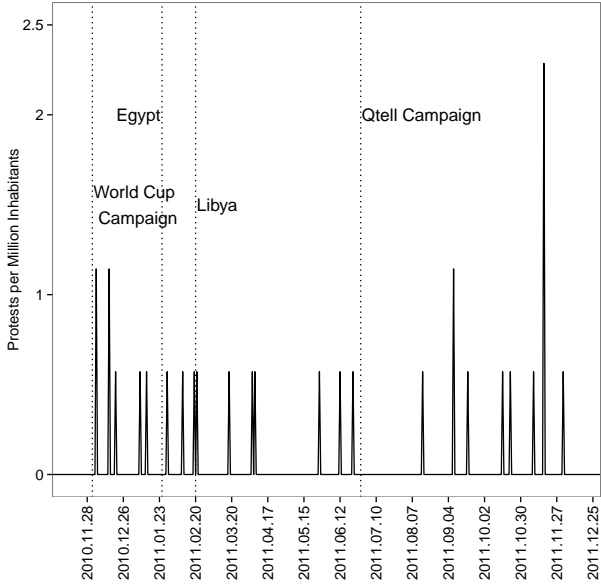
(a) Egypt



(b) Bahrain



(c) Morocco



(d) Qatar

This figure shows that ICEWS captures different levels of intensity of each country’s protests, both temporally and in cross-section. Egypt, which experienced sustained, widespread protesst, has more recorded protests than Qatar but less than Bahrain, which experienced the most per capita protests. ICEWS’ count of protests also varies during days they are expected to.

individuals are discussing at any moment.² Only China and North Korea have completely blocked access to it, though countries have temporarily blocked it at different times.

Social media data are ideal for understanding protest for three reasons. First, in states that control information disseminated through newspapers, radio, and television, social media are one of the few independent sources of information (Edmond 2013). Social media have therefore become a tool for citizens to gather and disseminate information in information-scarce environments such as authoritarian regimes. Second, state actors belatedly realized the power of social media, leaving it unregulated; lack of regulation made social media an attractive tool for anyone seeking independent information, and the information contained in social media therefore more closely reflected the offline world than did official news sources (Hamdy & Gomaa 2012). Social media has therefore become a critical component of many protest movements, starting with the 2009 Iran election protests and continuing through the Ukraine civil war (Burns & Eltham 2009, Rahimi 2011). Third, it provides the best temporal resolution of any data source. It is therefore one of the few sources available to researchers interested in dynamic processes that can provide micro-level information on these processes.

There are four reasons to prefer Twitter as a data source to other social media platforms. First, it is one of the most used social media platforms, usually second only to Facebook (Duggan & Smith 2013). Second, it is often used during crisis events to disseminate information, including during protests (Tonkin, Pfeiffer & Tourte 2011, Earl, McKee Hurwitz, Mejia Mesinas, Tolan & Arlotti 2013). Third, though it is used to discuss political events such as protests, it is also used to engage in quotidian topics like celebrity gossip, the weather, and sports (Boyd, Golder & Lotan 2010, Sinha, Dyer, Gimpel & Smith 2013). In the sample of tweets used later to train the support vector machine, *almost 75% were not about political events*. Fourth, Twitter provides a large amount of its data through two programming interfaces, making Twitter data easier to obtain than Facebook's. While other sites with social networking components, such as YouTube or reddit, are also relatively easy to gather data from, none are also used as comprehensively as Twitter.

Moreover, the norms of communication on Twitter makes this the most reliable way to measure coordination across so many countries and days. There are four ways to a user can modify a

²Twitter will censor tweets to comply with countries' laws. For example, it has censored a neo-Nazi group's tweets in Germany and has started to delete accounts from the Islamic State of Iraq and Syria that are deemed to incite violence.

plaintext tweet. The most common is the # symbol, known as the hashtag. Individuals will affix a hashtag to the front of a word to associate it with a certain conversation, e.g. “Eyewitnesses: NDP thugs throwing molotov cocktails inside the Egyptian Museum. I repeat NDP thugs, NOT anti-Mubarak protesters. #Jan25 #fb”. If a different user then searches for messages containing “#Jan25” or “#fb”, this tweet will be returned; employing a hashtag therefore makes the information in one’s message more likely to spread beyond just one’s social network (Romero, Meeder & Kleinberg 2011). Users quickly converge on a few hashtags to use for an event, whether that event is a protest, sporting event, or pop culture meme (Bruns & Burgess 2011, Lehmann, Gonçalves, Ramasco & Cattuto 2012).

Twitter makes it easy to find all tweets containing a hashtag. A user interested in upcoming protests could therefore search, from her smartphone or a computer, for “#jan25”, “#egypt”, or other hashtags and retrieve every tweet containing those hashtags.³ That person is therefore quickly exposed to vastly more information than she could gain from traditional interpersonal communication, and she knows that everyone else searching those hashtags will see the same tweets. She is therefore confident that when she reads about the meeting in Batal Ahmed street, many others have read about it as well, and others who search for “#jan25” know that others have seen that tweet as well. The prevalent use of hashtags, convergence to very few during major events, and ease of finding information related to the hashtag make tweets with hashtags they key coordination mechanism.

Twitter data comes courtesy of researchers at Northeastern University’s Laboratory for the Modeling of Biological and Socio-Technical Systems (Mocanu, Baronchelli, Perra, Vespignani, Gonçalves & Zhang 2013). The tweets involved in this analysis were extracted from Twitter’s 10% API, an unbiased sample of 10% of all public activity on the platform. There are two ways in which country of origin was identified. First, if a Twitter user has enabled location sharing, the tweet will have GPS coordinates, and those coordinates are used to assign country-location for that tweet. If the country-location is one of the 16, the tweet is saved. Second, users can report their location as part of their profile, and that location is reported as metadata with each tweet. The user-reported location is then compared to a dictionary of cities and country names to assign each

³This search is not case sensitive: a user searching for “#jan25” will see the same results as one searching for “#Jan25”. The searched term will not return tweets that use the character string without a hashtag, e.g. a tweet that says “police thugs r everywhere in egypt jan25” will not show up in search results.

tweet to a city or country.⁴ Unlike previous studies that analyze contentious events, tweets were not selected based on hashtags, providing a representative sample of what people were actually talking about, e.g. protests or the weather, during this period. In fact, only 19.74% of all tweets in this sample contain a hashtag, and most are apolitical.

4 Measures

Coordination

A Gini coefficient for hashtags operationalizes coordination. The Gini coefficient, which ranges from 0 to 1, usually measures income inequality, but it can be used on any discrete quantity. Instead of measuring wealth per person, it here measures occurrences per hashtag per day per country; as with income, a 0 means every observed hashtag is observed the same number of times, 1 that one hashtag accounts for all hashtags used in that country on that day. This measure is labeled $Coordination_{i,t}$ for the rest of the paper and is shown in Figure 2b.

Equation 1 shows this calculation. For each day t in each country i , there exist n unique hashtags. $Coordination_{i,t}$ counts the number of times each hashtag j occurs and use those counts to calculate the Lorenz Curve of (hashtag) inequality.

$$Coordination_{i,t} = \sum_{i=1}^{16} \sum_{t=1}^{426} \frac{2 \sum_{j=1}^n j n_j}{n \sum_{j=1}^n n_j} - \frac{n+1}{n} \quad (1)$$

$Coordination_{i,t}$ is preferred to a topic model because it scales easily and is directly comparable across countries. Tweets often contain slang that varies by country, so making a topic model for each country is a large project in its own right. Aside from requiring much more labor, creating a topic model, whether unsupervised or not, risks constricting results to words or topics that the researcher has an *a priori* expectation will matter (Grimmer & Stewart 2013). The measure is agnostic to what words people or say or how many topics they discuss; caring only about the hashtags, it will measure any hashtag used (not just the ones thought of in advance), revealing after the fact which hashtags are most salient. Section 7 provides further evidence that the hashtags identified with $Coordination_{i,t}$ are used for coordination.

⁴For more detail, see the Materials and Methods section of Mocanu et. al 2013

Three other Twitter behaviors that may impact coordination are measured. Retweets, equivalent to forwarding an e-mail to one’s entire contact list, can also promote coordination. An example of a retweet is, “RT @Ekramibrahim: Police, specially in civil clothes are holding electricity sticks. #jan25”. Ekramibrahim is the author of the message after the colon, but the person who sent the tweet read Ekramibrahim’s message and retweeted it to her followers. This secondary message is the retweet, and the reader knows it was seen by at least the followers of Ekramibrahim and the person who retweeted it. A message can be retweeted an infinite amount of times, though a user who sees a retweet only knows that at least one person retweeted it; in practice, most tweets are not retweeted, those that are are not retweeted often, and the retweet rate decays to almost 0% after 24 hours (Kwak et al. 2010, Liere 2010, Starbird & Palen 2012).⁵

A message can also contain a user mention or a link. A message that directly refers to another user by name is said to contain a user mention. If a user writes, “@ramezm i noticed a debate: #25jan or #jan25”, @ramezm will receive a personal notification about the message; a tweet with a user mention is still viewable by the followers of the original author. A retweet is when a user shares the message of someone he follows with those who follow him; it is akin to forwarding an e-mail to everyone in your address book. Tweets also often contain links to photos and articles, though those the messages are rarely retweeted (Suh, Hong, Pirolli & Chi 2010).

Retweets, links, and mentions are not as effective at promoting coordination as hashtags. While more retweets of one tweet means that more people have seen the same set of information, the prevalence of hashtags means the information in a retweet is also available to those searching for hashtags that the retweet happen to contain. The same logic is true of links: if a link is meant to provide coordinating information, it will almost certainly contain a hashtag that is also relevant to coordination. While it is possible that user mentions have a strong coordinating effect outside of their employment of hashtags, they are dyadic and tend to be part of conversations - they are not used to mobilize protesters.

Equation 2 shows the calculation of these other measures of potential coordination. For each day t and country i , the measure counts the number of tweets, K , and tweets with measure M_k . m is a count of tweets with a link, mention of another user, or that are a retweet, depending

⁵With one extra click, a user can see how many times the original tweet was retweeted, but there is no way for the researcher to observe if a user knows how many times a tweet was retweeted.

on the measure in question. Dividing the measure by the number of tweets that day in that country quantifies the amount of other possible coordination that could have occurred in addition to $Coordination_{i,t}$.

$$MPercent_{i,t} = \sum_{i=1}^{16} \sum_{t=1}^{426} \frac{1}{K} * \sum_{k=1}^K m_k \quad (2)$$

Core Coordination

To measure coordination from the core, one has to first identify individuals at the center the network. Identifying this core is difficult. There are too many users - 20,094 in Bahrain and 79,235 in Egypt alone - in the Twitter data to assign manually an identity to each one, and that attempt would result in a low identification rate because Twitter does not require individuals to publicly disclose any identification information. One can measure, however, the number of followers each account has; this measure, in-degree centrality, is not as precise a measure of centrality as those created with complete network data (Kwak et al. 2010, Pei, Muchnik, Andrade, Zheng & Makse 2014), but complete network data are not available. Those in the core are therefore approximated based on the distribution of popularity in each country. For the main model, a tweet belongs to a core member if its author’s number of followers are at or above the 95th percentile for all users in country i . More formally,

$$Core = \begin{cases} 1 & \text{if } PR_i(f) \geq .95 \\ 0 & \text{if } PR_i(f) < .95 \end{cases} \quad (3)$$

where $PR(f)$ is the percentile ranking of the tweet based on the number of followers.

Previous work that manually identified a random sample of users from Tunisia and Egypt informed the selection of this threshold (Lotan, Ananny, Gaffney, Boyd, Pearce & Graeff 2011). Table 1 compares the number of followers and tweet production for the categories identified in Lotan et. al 2011 with this paper’s primary popularity threshold; the threshold used later is bolded. In Tunisia, the core measure appears to roughly be most similar to bloggers; in Egypt, to bloggers and activists, though the manually identified accounts in Egypt are much more popular than any of the popularity measures. Notice though mainstream media account and employees of mainstream

media are the most central in each country and skew the country-level results upwards. The Results section shows that varying the follower threshold does not change the result. The Supplementary Materials also show how tweet production and the ratio of the core’s followers to the periphery’s followers varies by country and threshold; users at the 95% threshold account for 10% of all tweets in Kuwait up to 50% in Syria.

Table 1: Comparing Core Measure with Hand-coded Accounts*

Group	Accounts	Followers Avg.	Tweet Avg.	Mention %	Retweet %	Hashtag %	Link %
Egypt - Lotan	37	15138.71	949.78	0.40	0.06	0.36	0.32
Mainstream Media	1	103927.00	5281.00	0.00	0.00	0.74	0.70
Non-Media Org.	2	23877.40	457.50	0.32	0.07	0.22	0.52
MSM Employee	9	22463.50	650.22	0.41	0.01	0.21	0.21
Blogger	15	8394.17	1070.67	0.52	0.08	0.33	0.22
Activist	10	8036.55	703.40	0.42	0.07	0.28	0.33
Core 99.9 Percentile	80	37001.28	924.69	0.33	0.02	0.39	0.44
Core 99 Percentile	793	7104.31	736.38	0.45	0.05	0.27	0.32
Core 98 Percentile	1585	4033.08	591.71	0.46	0.05	0.25	0.31
Core 97 Percentile	2378	2875.48	515.21	0.46	0.04	0.25	0.31
Core 96 Percentile	3170	2256.03	453.52	0.45	0.04	0.25	0.30
Core 95 Percentile	3962	1868.79	409.94	0.45	0.04	0.25	0.30
Blackout	740	8046.33	650.95	0.22	0.05	0.24	0.61
Tunisia - Lotan	10	7942.94	248.60	0.33	0.12	0.59	0.56
Mainstream Media	2	5604.49	741.00	0.16	0.12	0.77	0.78
MSM Employee	1	52503.00	1.00	0.00	0.00	0.00	1.00
Blogger	3	1910.77	258.33	0.57	0.13	0.30	0.20
Activist	4	2496.28	57.00	0.59	0.09	0.36	0.29
Core 99.9 Percentile	7	17749.31	206.71	0.25	0.06	0.22	0.68
Core 99 Percentile	62	4880.14	410.92	0.37	0.06	0.27	0.55
Core 98 Percentile	123	3095.44	444.93	0.44	0.14	0.31	0.43
Core 97 Percentile	184	2392.96	374.43	0.45	0.13	0.31	0.40
Core 96 Percentile	245	1968.22	337.18	0.47	0.12	0.30	0.37
Core 95 Percentile	307	1681.87	308.22	0.47	0.11	0.31	0.38

*Categories are borrowed from Lotan et. al 2011. They coded for accounts associated with mainstream media organizations, mainstream new media organizations (news sites that exist only online) mainstream media employees, any organization that is not a media organization (Vodafone and Wikileaks are their examples), bloggers, activists, digerati, political actors, celebrities, researchers, bots, and a residual category. Any of those categories not identified here means that no account from that category was found in the data.

The bold rows represent the category used to identify core members. Other categories are used in robustness checks, with no changes to the results. For a discussion of the **Blackout** row, please see Section 7.

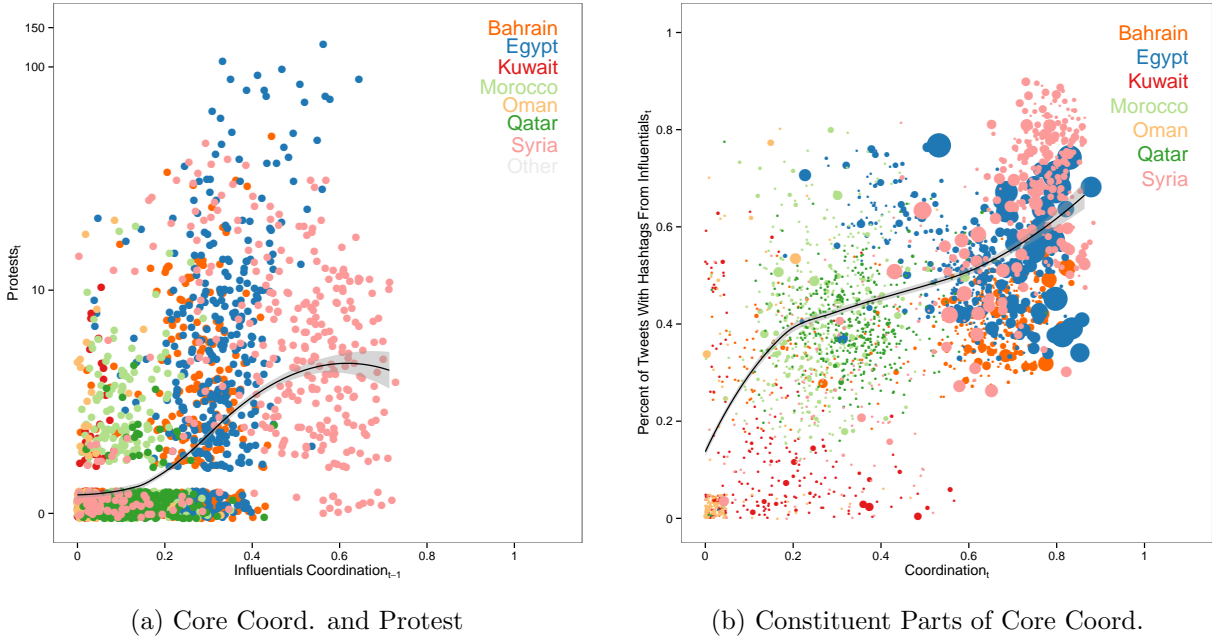
Having identified tweets produced from those in the core, one can then identify when the core engages in coordination. Because hashtags are the primary method of coordination and high levels of coordination lead to protest, the percentage of hashtags per country per day produced from the core is interacted that with the coordination measure. The percent of tweets with hashtags that are created in the core is defined as:

$$Core\ Coordination_{i,t} = \sum_{i=1}^{16} \sum_{t=1}^{426} Coordination_{i,t} * \frac{1}{K} * \sum_{k=1}^K Core_k * Hashtag_k \quad (4)$$

For each country i on each day t , each of the K tweets is read for whether it contains a hashtag and is from a core account. The number of those tweets is divided by the number of tweets in that country-day and interacted that with that country-day’s level of coordination, resulting in a core coordination measure for that country-day. The regression results leave the constituent parts of the variable as the variable name to ease interpretation; the summary statistics use the shortened name to save space.

Figure 2 examines $Core\ Coordination_{i,t}$ in more detail. The first panel shows that the lagged measure correlates highly with subsequent protest, much like $Coordination_{i,t-1}$; this result is not surprising, as the two variables have a .882 correlation. Figure 2b breaks $Core\ Coordination_{i,t}$ into its constituent parts, $Coordination_{i,t}$ and the percent of tweets with hashtags that are from influentials. In that figure, each day is sized by the number of protests.

Figure 2: Core Coordination Variable



5 Model

The base model is:

$$Protests_{i,t} = \beta_0 + \beta_1 * \Omega_{i,t-1} + \beta * \mathbf{X}_{i,t-1} + Protests_{i,t-1} + \epsilon_{i,t} \quad (5)$$

where Ω represents the independent variables of interest in each model, \mathbf{X} represents a series of controls, and ϵ is a stochastic error term. Because the dependent variable is a count of protests, it is an integer always greater than or equal to 0. Since $Protests_{i,t}$ is overdispersed and the zeroes are true zeroes, a negative binomial model instead of a Poisson or zero-inflated negative binomial is used.

Because high levels of coordination are collinear with high levels of hashtag usage, the model controls for the percent of a day’s tweets that have hashtags, ensuring that it measures actual coordination and not a coincidental increase in hashtag usage. The models of peripheral coordination control for the percent of a day’s tweets which are retweets, contain links, or mention another user because those features may have some coordination effect. The models of core coordination similarly control for the percent of all tweets with at least one hashtag that are from accounts of the core; the percent of all tweets that are retweets which are from core members; and so on for links and mentions.

There are three non-individual controls: country fixed-effects, a lagged dependent variable, and a lagged measure of the number of repression events as measured by ICEWS. Repression is any event with a CAMEO of exhibiting military posture (event root code 15), coercion (17), using unspecified unconventional violence (18), a physical assault (182), torture (1822), or death by physical assault (1823).

Every variable on the right hand side is lagged by one day to mitigate any simultaneity effects. All models include country fixed effects but no day fixed effects, as the latter bias the errors and lead to underestimates of protests. Finally, all models are run with country-clustered standard errors.

Table 2 shows the correlation between the main independent variables, and Table 3 shows the average value of each variable per country (along with each’s total tweets and protests).

Table 2: Variable Correlation

	Protest _{t,t}	Coord _{t,t-1}	Hashtag % _{t,t-1}	Retweet % _{t,t-1}	Mention % _{t,t-1}	Protest _{t,t-1}	Core Hashtag % _{t,t-1}	Core Retweet % _{t,t-1}	Core Link % _{t,t-1}	Core Mention % _{t,t-1}	Core Coord _{t,t-1}	Core Protest _{t,t-1}	Core Core Hashtag % _{t,t-1}	Core Core Retweet % _{t,t-1}	Core Core Link % _{t,t-1}	Core Core Mention % _{t,t-1}	Core Core Coord _{t,t-1}
Protest _{t,t}	1	0.281	0.218	-0.012	-0.155	0.785	0.178	0.099	0.149	0.149	0.1	0.571	0.309	0.309	0.309	0.309	0.309
Coord _{t,t-1}	-	1	0.594	-0.038	-0.237	0.295	0.535	0.372	0.519	0.519	0.349	0.269	0.88	0.88	0.88	0.88	0.88
Hashtag % _{t,t-1}	-	-	1	0.203	-0.448	0.231	0.521	0.351	0.405	0.405	0.186	0.185	0.649	0.649	0.649	0.649	0.649
Retweet % _{t,t-1}	-	-	-	1	-0.233	-0.013	0.122	0.279	0.156	0.156	0.098	0.029	-0.051	-0.051	-0.051	-0.051	-0.051
Link % _{t,t-1}	-	-	-	-	-0.659	0.106	0.325	0.232	0.23	0.23	0.024	0.063	0.291	0.291	0.291	0.291	0.291
Mention % _{t,t-1}	-	-	-	-	1	-0.155	-0.344	-0.265	-0.3	0	0	-0.126	-0.351	-0.351	-0.351	-0.351	-0.351
Protest _{t,t-1}	-	-	-	-	-	1	0.175	0.108	0.152	0.152	0.1	0.673	0.317	0.317	0.317	0.317	0.317
Core Hashtag % _{t,t-1}	-	-	-	-	-	-	1	0.656	0.702	0.702	0.545	0.158	0.729	0.729	0.729	0.729	0.729
Core Retweet % _{t,t-1}	-	-	-	-	-	-	-	1	0.583	0.583	0.501	0.152	0.467	0.467	0.467	0.467	0.467
Core Link % _{t,t-1}	-	-	-	-	-	-	-	-	1	0.49	0.49	0.142	0.615	0.615	0.615	0.615	0.615
Core Mention % _{t,t-1}	-	-	-	-	-	-	-	-	-	1	0.155	0.271	0.271	0.271	0.271	0.271	0.271
Core Coord _{t,t-1}	-	-	-	-	-	-	-	-	-	-	1	0.271	0.271	0.271	0.271	0.271	0.271

Table 3: Variables by Country

Country _i	Protests _{i,t}	Tweets _{i,t}	Coord _{i,t}	Hashtag % _{i,t}	Retweet % _{i,t}	Link % _{i,t}	Mention % _{i,t}	Core Hashtag % _{i,t}	Core Retweet % _{i,t}	Core Link % _{i,t}	Core Mention % _{i,t}	Core Coord _{i,t-1}
Egypt	3,379	3,742,648	0.59	0.21	0.04	0.29	0.42	0.52	0.55	0.47	0.48	0.31
Syria	2,057	229,476	0.60	0.34	0.03	0.61	0.22	0.54	0.49	0.48	0.35	0.37
Yemen	1,885	61,517	0.39	0.25	0.05	0.62	0.19	0.52	0.23	0.41	0.24	0.25
Tunisia	882	228,554	0.37	0.25	0.07	0.43	0.40	0.50	0.61	0.37	0.49	0.19
Bahrain	798	1,056,990	0.53	0.22	0.06	0.17	0.42	0.39	0.28	0.46	0.28	0.22
Libya	663	84,991	0.37	0.24	0.11	0.34	0.32	0.42	0.54	0.37	0.38	0.17
Iraq	585	146,113	0.35	0.18	0.09	0.28	0.35	0.44	0.51	0.31	0.43	0.16
Jordan	511	273,227	0.38	0.21	0.06	0.45	0.36	0.45	0.48	0.42	0.38	0.17
Morocco	298	300,454	0.25	0.18	0.07	0.34	0.43	0.40	0.40	0.33	0.34	0.11
Lebanon	261	522,891	0.36	0.21	0.06	0.28	0.41	0.50	0.61	0.50	0.41	0.18
Algeria	248	7,474	0.08	0.21	0.11	0.44	0.34	0.40	0.43	0.36	0.18	0.04
Kuwait	161	29,838	0.09	0.09	0.02	0.13	0.52	0.09	0.02	0.06	0.21	0.01
Saudi Arabia	156	4,425,797	0.48	0.13	0.05	0.16	0.51	0.46	0.37	0.45	0.44	0.23
Oman	150	8,509	0.02	0.09	0.05	0.31	0.48	0.06	0.02	0.11	0.14	0.00
UAE	58	1,531,524	0.35	0.15	0.07	0.20	0.43	0.36	0.37	0.42	0.31	0.13
Qatar	29	1,104,995	0.34	0.12	0.06	0.10	0.43	0.39	0.35	0.37	0.32	0.14

6 Results

The main results are presented in Table 4. Columns 1-2 show coordination only from the periphery, and Columns 3-4 build the models for core coordination in the same way. The main model, used throughout the rest of the paper, is shown in Column 5. Across all models, $Coordination_{i,t-1}$, the measure for peripheral coordination, is significant with a p-value much less than .01. The only other significant variables are a lagged dependent variable (positive), intercept (negative), lagged repression (weakly positive), and non-influential hashtag percent (positive). Note that Model 5, the full model, suggests that coordination from the core is inversely associated with protests.

Table 4: Peripheral Coordination and Protest

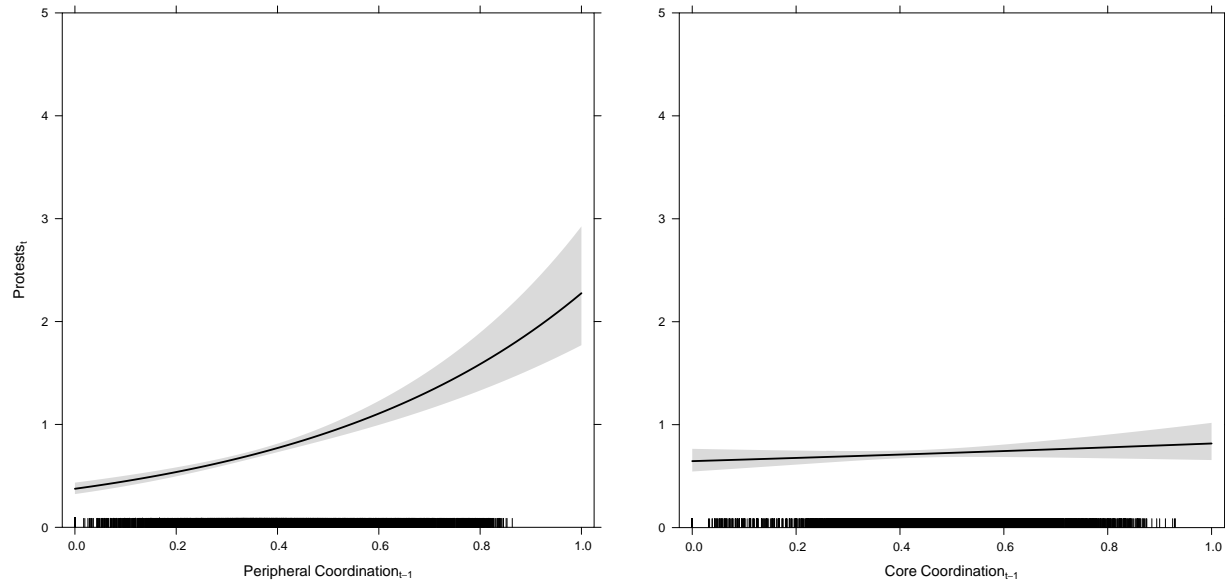
	<i>DV: Protest_{i,t}</i>				
	Coordination		Core Coordination		Full Model
	(1)	(2)	(3)	(4)	(5)
Coordination _{<i>i,t-1</i>}	1.932*** (0.472)	1.936*** (0.469)	1.809** (0.766)	1.830** (0.774)	2.575*** (0.639)
Hashtag % _{<i>i,t-1</i>}		0.707 (0.539)			0.578 (0.616)
Retweet % _{<i>i,t-1</i>}		0.405 (0.876)			-0.362 (1.019)
Link % _{<i>i,t-1</i>}		-0.536 (0.386)			-0.763** (0.378)
Mention % _{<i>i,t-1</i>}		-0.858* (0.512)			-0.921** (0.410)
Repression _{<i>i,t-1</i>}	0.020* (0.011)	0.020* (0.012)	0.021* (0.011)	0.022** (0.011)	0.021* (0.012)
Protest _{<i>i,t-1</i>}	0.127*** (0.010)	0.121*** (0.011)	0.126*** (0.010)	0.125*** (0.010)	0.116*** (0.010)
Core Hashtag % _{<i>i,t-1</i>}			0.600 (0.393)	0.631 (0.441)	0.900** (0.372)
Core Retweet % _{<i>i,t-1</i>}				0.063 (0.398)	0.158 (0.413)
Core Link % _{<i>i,t-1</i>}				0.450 (0.553)	0.711 (0.565)
Core Mention % _{<i>i,t-1</i>}				-0.485 (0.316)	-0.159 (0.258)
Coordination _{<i>i,t-1</i>} *Core Hashtag % _{<i>i,t-1</i>}			-0.313 (1.302)	-0.503 (1.333)	-1.868** (0.942)
Intercept	-0.934*** (0.044)	-0.569** (0.229)	-1.182*** (0.160)	-1.295*** (0.215)	-1.019*** (0.207)
Country FE	Yes	Yes	Yes	Yes	Yes
N	6,800	6,620	6,800	6,800	6,620
Log Likelihood	-8,469.486	-8,296.844	-8,463.422	-8,459.476	-8,280.817

*p < .1; **p < .05; ***p < .01

Model 3 includes $Coordination_{i,t}$ and $Core Hashtag_{i,t-1}$ because those are the constituent parts of the measure of influential coordination.

Because the model is not linear, coefficients do not directly translate into changes in the outcome variable. The marginal effects of $Coordination_{i,t-1}$ & $Coordination_{i,t-1} * Core\ Hashtag\ \%_{i,t-1}$ are shown in Figure 3. Going from no coordination to the maximum observed values leads to about 2 extra protests, a 400% increase, while there exists no effect for core coordination.

Figure 3: Marginal Effects of Peripheral and Core Coordination



(a) Increase in protest as peripheral coordination increases

(b) Coordination does not come through core individuals

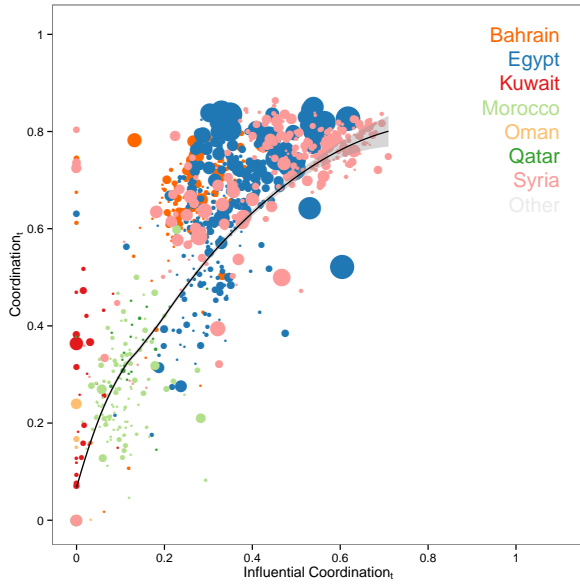
A series of time series diagnostic tests confirm the model specification.⁶ A Durbin-Watson test for serial correlation returns a test statistic of 1.9741 and p-value of .1303, suggesting no serial correlation. The Dickey-Fuller coefficient is -11.25 and has a p-value less than .01, so the dependent variable is stationary (visual inspection also confirms the stationarity). The Breusch-Pagan test statistic is 539.09 with a p-value almost at 0; to control for the heteroskedasticity, I use country-clustered standard errors. Finally, a Lagrange-Multiplier test with the King & Wu test for two-way fixed effects returns a chi-square value of -.81, so it is safe to avoid using time fixed effects.

How is it that the strong correlations shown in Figures 2a and 2b have disappeared? Figure 4 suggests why $Core\ Coordination_{i,t-1}$ does not correlate with protest in a statistically meaningful way. The key insight is that the size of protest does not vary with $Core\ Coordination_{i,t-1}$. Figure

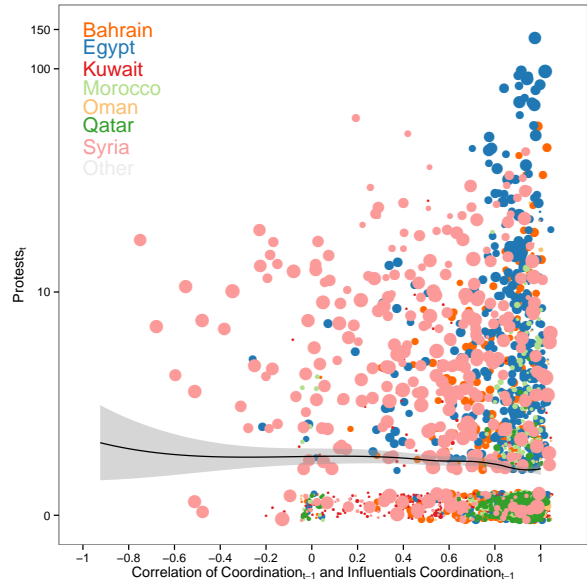
⁶A panel OLS model is used for the diagnostics to ease calculation of the test statistics. The robustness checks that the panel OLS results match those of the negative binomial.

4a reveals the strong collinearity between the two coordination variables, but the distribution of the number of protests (size of points) is stable over most of the range of *Core Coordination* $_{i,t-1}$. In other words, the size of the dots (number of protests) increases from left to right, as coordination increases, but they increase much less as *Core Hashtag %* $_{i,t-1}$ increases. *Core Hashtag %* $_{i,t-1}$ is how *Core Coordination* $_{i,t-1}$ separates itself from *Coordination* $_{i,t-1}$, but it aids little in distinguishing levels of protest. Figure 4b shows how the correlation of the two coordination variables itself correlates with protest. As the two measures become more correlated, the number of protests decreases, though Syria drives this result. Looking just at the x-axis right of 0, there is no correlation between this measure and protest size. Figure 4c shows that there is similarly no correlation, once Syria is excluded, between the coordination variables' correlation and *Core Coordination* $_{i,t-1}$. There are days with many protests across the range of *Core Coordination* $_{i,t-1}$. Finally, notice the shape of the curve in Figure 2a: there is already little correlation between *Core Coordination* $_{i,t-1}$ and the next day's protest at high values of the variable. While *Coordination* $_{i,t-1}$ and *Core Coordination* $_{i,t-1}$ are highly correlated, that correlation appears to be driven entirely by the coordination occurring in the periphery.

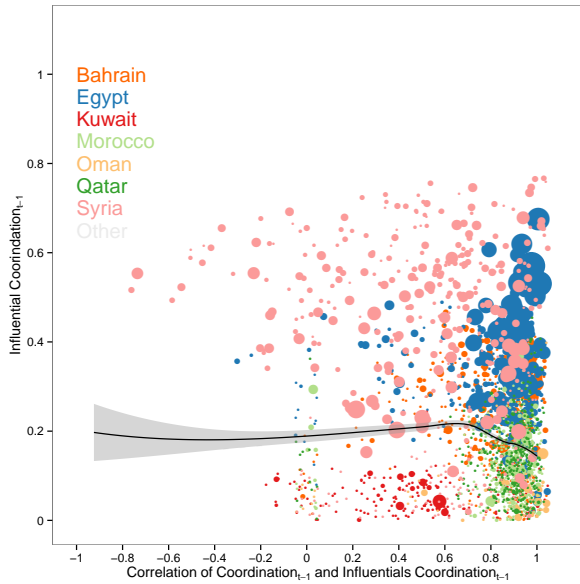
Figure 4: Core Coordination Variable



(a) Coord. and Core Coordination, Sized by Protest



(b) Coordination Measures, Sized by Core Coordination



(c) Coordination Measures, Sized by Protest

Verification

There are 3 possibilities that may undercut these findings. First, the models may use the wrong measure of coordination, both for the core and the periphery. Second, the operationalization of

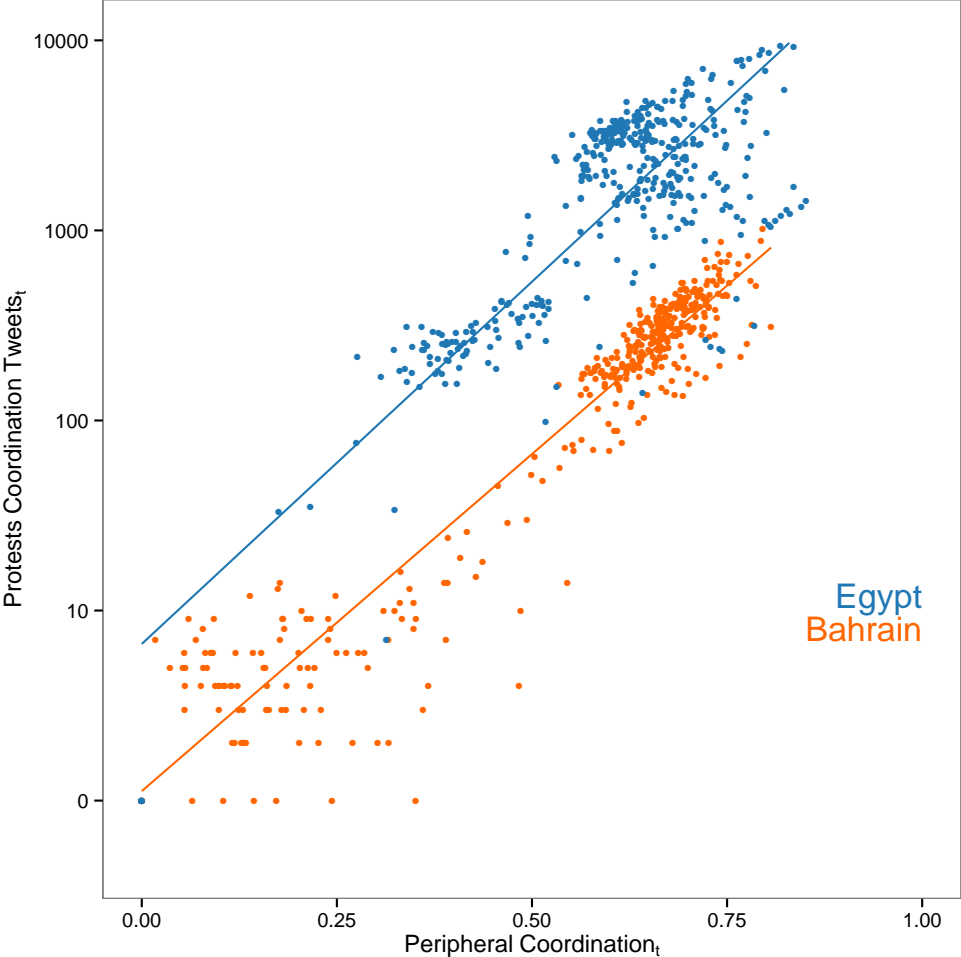
core members may be wrong. Third, reliance on machine-coded data may bias in favor of finding results. In the Supplementary Materials, I address other concerns, such as the nature of time lags and outliers, about the data generating process; all results hold.

Figure 5 allays the first concern. To confirm that $Coordination_{i,t}$ measures coordination, a topic model for Egypt and Bahrain was created. Those two countries were chosen because they experienced widespread protest and have too many tweets to code individually. For each country, 3,000 tweets were randomly selected and coded into overlapping categories, one of which was protest coordination. A naïve bayes classifier was trained on a random 95% of each country’s coded tweets; the other 5% was used to validate out of sample performance.⁷ This process was repeated 30 times, and the results were averaged into a final model; this process is known as bagging and is akin to bootstrapping in regression. The resulting model is applied to each country’s tweets, creating a classification for every single tweet in the sample from Egypt and Bahrain. Once protest coordination tweets are identified, they are aggregated by country-day and compared to the $Coordination_{i,t}$ measure. That result is shown in Figure 5, and there is a strong positive relationship between the measure of coordination and the actual number of protest coordination tweets.

Table 5 addresses the second concern. In column 1, accounts from Lotan et. al 2011 in this sample are identified and controlled for. Accounts from activists or bloggers are called “Online Actors”, while there are not variables for politician, researcher, digerati, or celebrity accounts because those were not found in the sample from either country. It appears that mainstream media accounts (official accounts of news organizations) do positively correlate with subsequent protest. The main coordination measure is still strongly significant, as is retweet percentage; links appear to decrease in rate leading up to protests. The second and third columns of Table 5 show alternative measures of coordination in the core. $Core\ Reachout\ \%_{i,t-1}$ measures the percent of all retweets and mentions that come from those in the core. Core coordination may occur through those in the core engaging with specific individuals (mentions) or acting as information brokers (finding important tweets and retweeting them), not through hashtags. Column 2 controls for this possibility. On the other hand, the core may have a coordination effect simply by being active leading up to protests; their activity may signal a breakdown of support for the regime, a willingness to incur high personal costs that inspires the periphery, or they just may not use hashtags. There appears

⁷See the Supplementary Materials section for the codebook and more details on the topic model.

Figure 5: Verifying Operationalization of Coordination



to be some effect for tweets from the core - *Core Tweet* $\%_{i,t-1}$ is significant at $p \leq 1$. - but their tweet activity on high coordination days does not correlate with subsequent protest. In all three models, coordination from the periphery is still significant and coordination from the core is not.

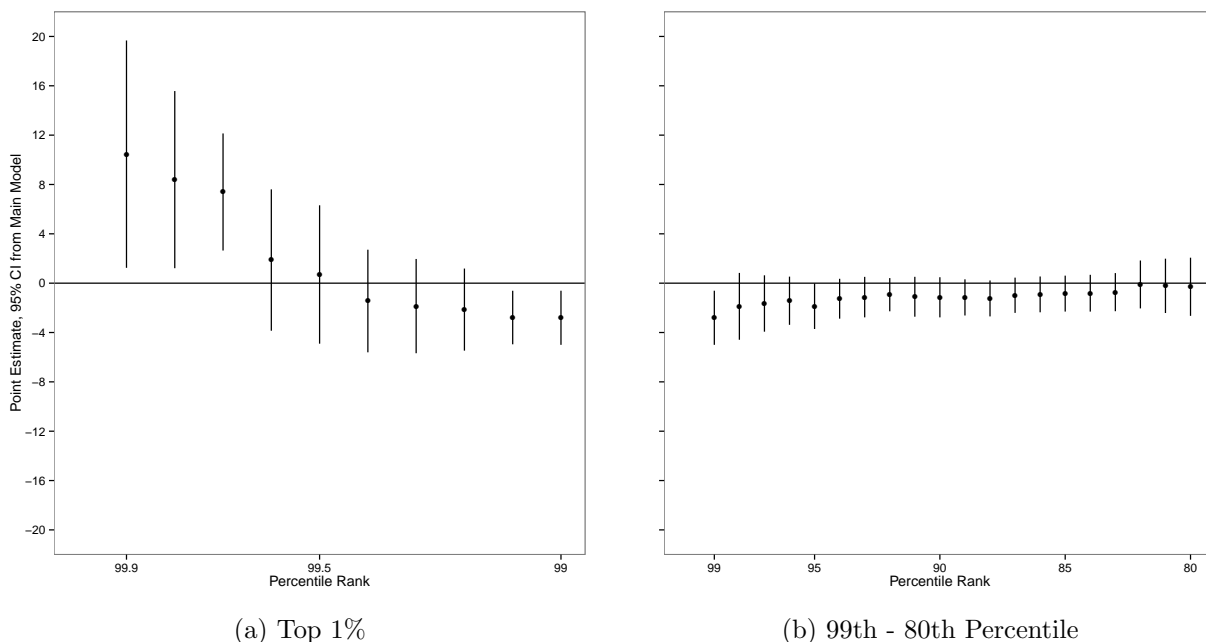
Table 5: Robust to Operationalization of Core

	<i>Protest_{i,t}</i>		
	Core Manual ID	Core Reachout	Core Tweet Share
	(1)	(2)	(3)
Coordination _{i,t-1}	3.041*** (0.419)	1.678** (0.729)	2.308*** (0.772)
Hashtag $\%_{i,t-1}$	-1.728 (7.574)	0.412 (0.641)	0.448 (0.620)
Retweet $\%_{i,t-1}$	12.705*** (1.407)	-0.130 (0.926)	-0.246 (0.934)
Link $\%_{i,t-1}$	-1.525 (1.341)	-0.816** (0.359)	-0.852** (0.374)
Mention $\%_{i,t-1}$	-1.596 (6.119)	-0.701 (0.460)	-0.941** (0.433)
Mainstream Media $\%_{i,t-1}$	18.313*** (5.636)		
MSM Empl. $\%_{i,t-1}$	62.784 (53.143)		
Online Actor $\%_{i,t-1}$	-7.310** (3.191)		
Spam $\%_{i,t-1}$	-7.989 (17.187)		
Repression _{i,t-1}	0.016*** (0.005)	0.020* (0.011)	0.021* (0.011)
Protest _{i,t-1}	0.044*** (0.009)	0.118*** (0.010)	0.116*** (0.010)
Core Reachout $\%_{i,t-1}$		1.358 (1.247)	
Core Tweet $\%_{i,t-1}$			1.078* (0.608)
Core Hashtag $\%_{i,t-1}$		0.416 (0.514)	0.366 (0.518)
Core Retweet $\%_{i,t-1}$		-0.233 (0.580)	0.101 (0.419)
Core Link $\%_{i,t-1}$		0.512 (0.528)	0.365 (0.650)
Core Mention $\%_{i,t-1}$		-1.394 (1.092)	-0.529 (0.370)
Coordination _{i,t-1} *Core Reachout $\%_{i,t-1}$		0.595 (1.074)	
Coordination _{i,t-1} *Core Tweet $\%_{i,t-1}$			-1.276 (1.246)
Intercept	0.335 (4.195)	-0.848*** (0.212)	-0.832*** (0.162)
Country FE	Yes	Yes	Yes
N	830	6,620	6,620
Log Likelihood	-1,712.510	-8,282.427	-8,282.744

*p < .1; **p < .05; ***p < .01

To confirm the 95% threshold used to identify the core, the threshold was varied from the 80th percentile to the 99.9th, and Model 5 from Table 4 is rerun for each threshold. Figure 6 shows how the significance level of $Coordination_{i,t-1} * Core\ Hashtag\ \%_{i,t-1}$ varies as the percentile threshold changes; the horizontal lines are at ± 1.96 to show significance at the 5% level. Figure 6a shows the result from 10 models, where model 1 uses a cutoff at the 99.9th percentile and model 10 is at the 99th; Figure 6b shows the result from 20 models, where model 1 uses a 99th percentile threshold and the 20th uses the 80th percentile. In all iterations, $Coordination_{i,t-1}$, $Repression_{i,t-1}$, and $Protest_{i,t-1}$ remain significant.

Figure 6: Change in Effect Size as Function of Core Threshold



The results in Figure 6 are intriguing. The effect of core coordination hovers around 0 for most of threshold's range and is distinguishable from zero at the 99th and 99.1st percentiles, as well as at the 95th percentile. On the other hand, at the upper extreme of the follower distribution, the 99.7th percentile and above, the sign on $Core\ Coordination_{i,t-1}$ is positive and significant using a 95% confidence interval.

The apparent positive effect from core coordination above the 99.7th percentile should not, however, be assigned much weight, for 3 reasons. First, these models also find that $Core\ Link\ \%_{i,t-1}$ is negative and significant, with an effect from half as strong as to equal with that of core

coordination. Second, the pooled results are driven by outlier countries with few tweets and users at or above the 99.7th percentile threshold. Whether the threshold is 99.7, 99.8, or 99.9, the effect disappears when the model is rerun using only Bahrain, Egypt, Jordan, Lebanon, Qatar, Saudi Arabia, and the United Arab Emirates, the only countries with more than 10,000 tweets from users at or above the 99.7th percentile. All these countries are also the only ones with more than 25 users at this point in the distribution (except for Morocco, with 30). Because the final dataset is at the country-day level, it does not distinguish between a day in Egypt that may have 500 tweets from 20 accounts in the 99.7th percentile core from one in Algeria that has 1 tweets from 1 of the 2 accounts above the same cut off. The resulting models therefore overweight Algerian core users. Rerunning the main model with only the 7 countries just described therefore provides a more accurate understanding of the dynamics this far into the followers' distribution, and models on these 7 countries show no effect for members of the core. Third, it is more likely than not that these accounts represent institutions such as news outlets or non-profit organizations than people.⁸ As Table 6 shows, these accounts are frequent tweeters, and those tweets are more likely to contain hashtags or links. Such behavior is most similar to how news organizations use Twitter (Lotan et al. 2011); Table 1 in Section 4 compares the 99.9th percentile core users to confirmed news accounts in Tunisia and Egypt, showing similarity between the two. The probability that these accounts are news organizations is further increased by rerunning the main model using only Arabic tweets. Using only Arabic tweets when the core is defined at the 99.7th, 99.8th, or 99.9th thresholds, $Coordination_{i,t-1} * Core\ Hashtag\ \%_{i,t-1}$ is not statistically significant. Overall, the positive effect suggested in Figure 6a is probably driven by a few media accounts in countries with less Twitter data than others in the sample.

Table 7 verifies the ICEWS dependent variable. ICEWS relies on news reports, and these reports have well-known biases in coverage (Davenport & Ball 2002, Herkenrath & Knoll 2011, Eck 2012). Machine-coded events data can suffer from event duplication (Caren 2014, Hammond & Weidmann 2014), though one of ICEWS' strengths is its focus on event deduplication. The results could therefore be driven by news media's bias towards major, unexpected events and duplicated events. In the first column of Table 7, ICEWS' count of public statements is the dependent variable. If ICEWS simply picks up news activity, it should record a surge in public statements

⁸I cannot know for sure because the data are anonymized.

Table 6: Core Threshold Descriptive Statistics Across Countries

Country	Group	Accounts	Followers Avg.	Tweet Avg.	Mention %	Retweet %	Hashtag %	Link %
Algeria	99.7 th Percentile	2	6786.50	1.50	0.33	0.00	0.33	1.00
Bahrain	99.7 th Percentile	61	15294.42	530.87	0.17	0.03	0.57	0.49
Egypt	99.7 th Percentile	238	17975.93	992.12	0.37	0.06	0.32	0.42
Iraq	99.7 th Percentile	14	23258.58	455.00	0.74	0.07	0.29	0.05
Jordan	99.7 th Percentile	26	9197.23	436.38	0.19	0.03	0.35	0.73
Kuwait	99.7 th Percentile	10	25240.53	7.00	0.40	0.07	0.07	0.30
Lebanon	99.7 th Percentile	52	7997.13	550.71	0.19	0.15	0.26	0.63
Libya	99.7 th Percentile	11	17287.99	276.36	0.39	0.05	0.59	0.25
Morocco	99.7 th Percentile	30	19132.81	165.03	0.45	0.03	0.27	0.37
Oman	99.7 th Percentile	2	122889.50	1.50	0.67	0.00	0.00	0.33
Qatar	99.7 th Percentile	65	23668.00	428.31	0.42	0.06	0.29	0.33
Saudi Arabia	99.7 th Percentile	266	13375.55	588.77	0.61	0.03	0.19	0.24
Syria	99.7 th Percentile	11	5484.73	630.27	0.14	0.02	0.39	0.74
Tunisia	99.7 th Percentile	19	10068.36	377.95	0.34	0.04	0.31	0.63
UAE	99.7 th Percentile	142	22961.05	261.39	0.33	0.05	0.32	0.36
Yemen	99.7 th Percentile	5	5132.13	371.60	0.05	0.00	0.33	0.75

along with protest, and coordination will then correlate with public statements. Column 1 shows that coordination does not correlate with public statements, suggesting that $Protest_{i,t}$ actually captures protest.⁹

The second column shows that the results do not appear to be driven by duplication. The dependent variable is $Protest\ Rate_{i,t}$, the number of protests on a country-day divided by the number of ICEWS events at that time. If ICEWS duplicates, then the protest rate should not change across the sample and there will be no correlation between $Coordination_{i,t-1}$ and $Protest\ Rate_{i,t}$. $Coordination_{i,t-1}$ is still significant and $Coordination_{i,t-1} * Core\ Hashtag\ \%_{i,t-1}$, in line with the main results.¹⁰

⁹Columns 1 and 2 use an ordinary-least squares estimator because the dependent variable is no longer a count.

¹⁰The Supplementary Materials visualizes the protest rate and shows that it varies in tandem with real-world events.

Table 7: Robust to Dependent Variable

	<i>Public Statements Rate_{i,t}</i>	<i>Protest Rate_{i,t}</i>	<i>Protest_{i,t}</i>	
	All (1)	All (2)	Drop 3 SD (3)	Drop Top Quarter (4)
Coordination _{i,t-1}	0.047 (0.039)	0.100*** (0.036)	2.052*** (0.567)	1.498* (0.794)
Hashtag % _{i,t-1}	-0.051*** (0.013)	0.058 (0.026)	1.127* (0.582)	0.408 (0.579)
Retweet % _{i,t-1}	0.002 (0.032)	-0.035 (0.035)	-0.628 (0.749)	-0.755 (0.587)
Link % _{i,t-1}	0.029** (0.013)	-0.035 (0.025)	-0.069 (0.385)	0.671 (0.464)
Mention % _{i,t-1}	0.003 (0.021)	0.003 (0.021)	0.242 (0.600)	0.726 (0.561)
Public Statements Rate _{i,t-1} 0.099***	(0.013)			
Repression Rate _{i,t-1}		0.047** (0.020)		
Repression _{i,t-1}			0.036*** (0.016)	0.056*** (0.020)
Protest Rate _{i,t-1}		0.356*** (0.035)		
Protest _{i,t-1}			0.122*** (0.011)	0.063*** (0.010)
Core Hashtag % _{i,t-1}	-0.00002 (0.031)	0.029*** (0.018)	0.301 (0.271)	-0.625 (0.697)
Core Retweet % _{i,t-1}	0.011 (0.007)	-0.001 (0.014)	0.112 (0.295)	-0.122 (0.117)
Core Link % _{i,t-1}	0.036 (0.023)	-0.001 (0.014)	0.972** (0.405)	1.252** (0.622)
Core Mention % _{i,t-1}	-0.004 (0.025)	-0.006 (0.017)	-0.227 (0.282)	-0.136 (0.333)
Coordination _{i,t-1} *Core Hashtag % _{i,t-1}	-0.021 (0.059)	-0.068 (0.064)	-1.291 (0.973)	1.119*** (0.343)
Intercept	0.069*** (0.021)	0.041** (0.016)	-2.062*** (0.368)	-3.783*** (0.497)
Model	OLS	OLS	Neg. Binom.	Neg. Binom.
Country FE	Yes	Yes	Yes	Yes
N	6,620	6,620	6,471	2,916
R ²	0.091	0.221		
Adjusted R ²	0.088	0.218		
Log Likelihood			-7,244.759	-1,765.218

*p < .1; **p < .05; ***p < .01

Columns 3 and 4 in Table 7 present the final verification of ICEWS' protest count. Since newspapers overreport major events and ICEWS over reports newspapers, it is possible that the results are driven by the upper end of the protest distribution. Column 3 drops all protest-days that have protests 3 standard deviations above the country's average, and Column 4 drops all protest-days in the upper quartile of each country's protest distribution. In both cases, $Coordination_{i,t-1}$ is significant while elite coordination is not. The main finding of this paper, that coordination occurs along the periphery of a network, is not an artifact of using machine-coded data.¹¹

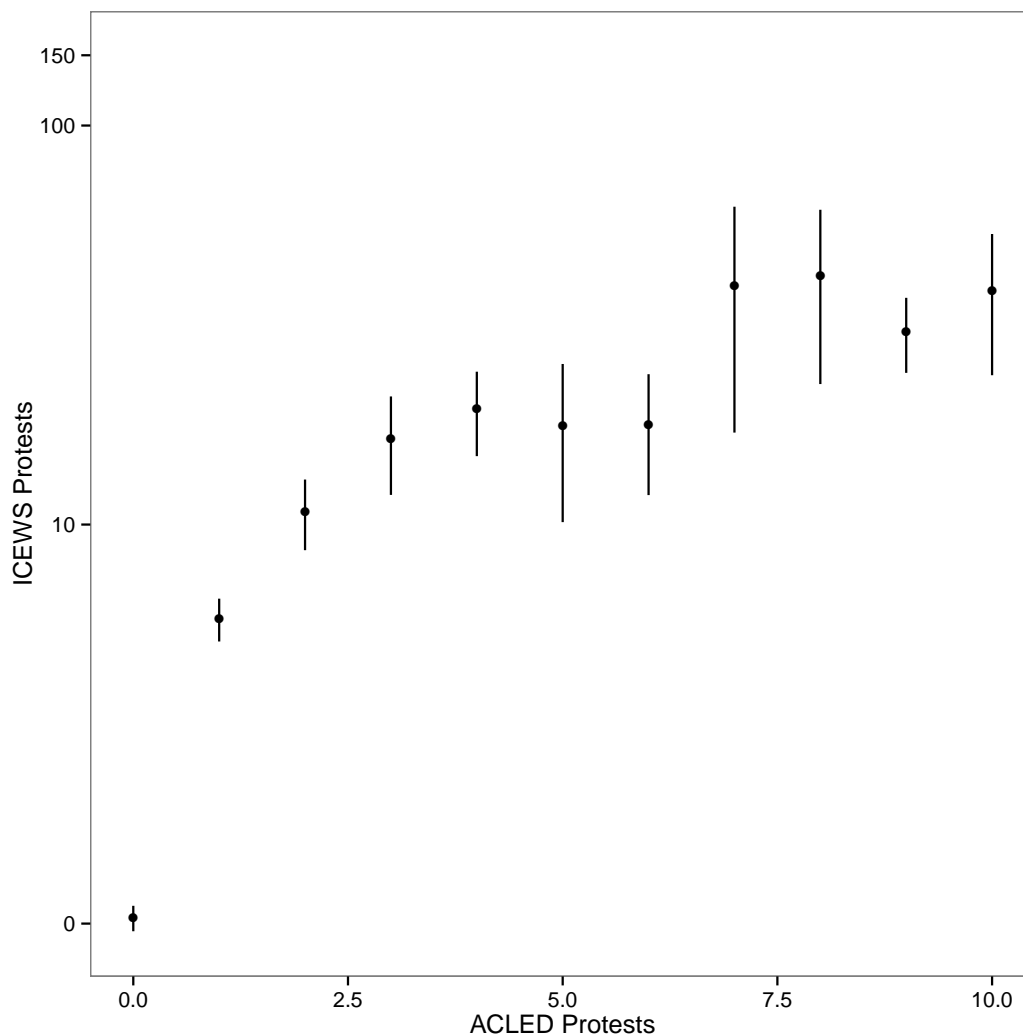
In results shown in the Supplementary Materials, the main model is run while throwing out countries that may have overly influenced results. Removing the 5 countries with the highest levels of protests per capita, the results hold. Removing the 5 countries with the lowest levels of protests per capita, the results hold. Removing the 5 countries with the most tweets per capita, the results hold. Removing the 5 countries with the fewest tweets per capita, the results hold. These results suggest that the coordination patterns are widespread throughout the dataset and not dependent on a few countries.

Further verification of the dependent variable is shown in Figure 7, which shows that ICEWS' count of protests strongly correlates with hand-coded data. The Armed Conflict Location and Event Dataset (ACLED) is hand-coded contains data the number of riots and protests in Algeria, Egypt, Libya, Morocco, and Tunisia for 2010 and 2011 (Raleigh, Linke, Hegre & Karlsen 2010). ACLED provides greater event granularity than the Social Conflict in Africa Dataset, another hand-coded events dataset that contains protests (Hendrix, Hamner, Case, Linebarger, Stull & Williams 2012). The two measures have a Pearson's correlation coefficient of .468.

The Supplementary Materials use the ACLED measures as a dependent variable and shows that coordination may still occur without the core's coordination, though ACLED's little variation on the dependent variable means most results do not attain traditional levels of statistical significance. In results not presented, ICEWS is shown to correlate with GDELT (Leetaru & Schrodt 2013),

¹¹Two new machine-coded projects, the University of Illinois' Social, Political, Economic Event Database (SPEED) and the Open Event Data Alliance's Phoenix project, look to improve on are exciting events data projects. SPEED combines machine-coded data with human verification to achieve human-level accuracy with machine-coded breadth (Nardulli, Althaus & Hayes N.d.). The Phoenix project, an open source system associated with Pennsylvania State University and Parus Analytical Systems, is a major evolution of the TABARI system. Phoenix's main advantage over ICEWS, which also uses a heavily modified version of TABARI, is that it releases new data daily, while ICEWS releases monthly on a one year delay. As of this writing, SPEED's public data only go through 2005, and Phoenix's data starts on June 20th, 2014. Phoenix's Github page is <https://github.com/openeventdata>.

Figure 7: ICEWS Correlates with Handcoded Data



another machine-coded events dataset; their Pearson correlation coefficient is .785. All models presented here and in the Supplementary Materials were rerun using GDELT, and all results hold.

7 Exogenous Identification of the Core in Egypt

This section takes advantage of a sudden increase in the difficulty of accessing the internet in Egypt to identify core members of the Egyptian social network. Those who could access the internet during this period are more likely to be in the core than those who could not, so tracking their communicative behavior throughout the study should more precisely identify any role for the core.

Those in the core according to this identification strategy also do not lead to protest mobilization.

Egypt's January 25th protests surprised everyone - activists, bystanders, and state authorities - with its large mobilization and brief occupation of Tahrir Square. The Mubarak regime had spent the previous days denying that the events in Tunisia would spread to their country, despite a spate of imitation immolations (Khalil 2011, pg. 127). Many Muslim Brotherhood leaders, despite not having sanctioned the protests, were summarily jailed, as the government assumed only it could mobilize such a crowd. With the next major protest called for January 28th after Friday prayers, the government suspended cell phone service and internet access just after midnight on January 28th (the morning of the 28th). The government appears to have figured that people would not protest if they could not communicate with one another; the plan backfired, as Egyptians had no way to communicate except by going outdoors. Instead, the blackout led to more protests (Hassanpour 2014).

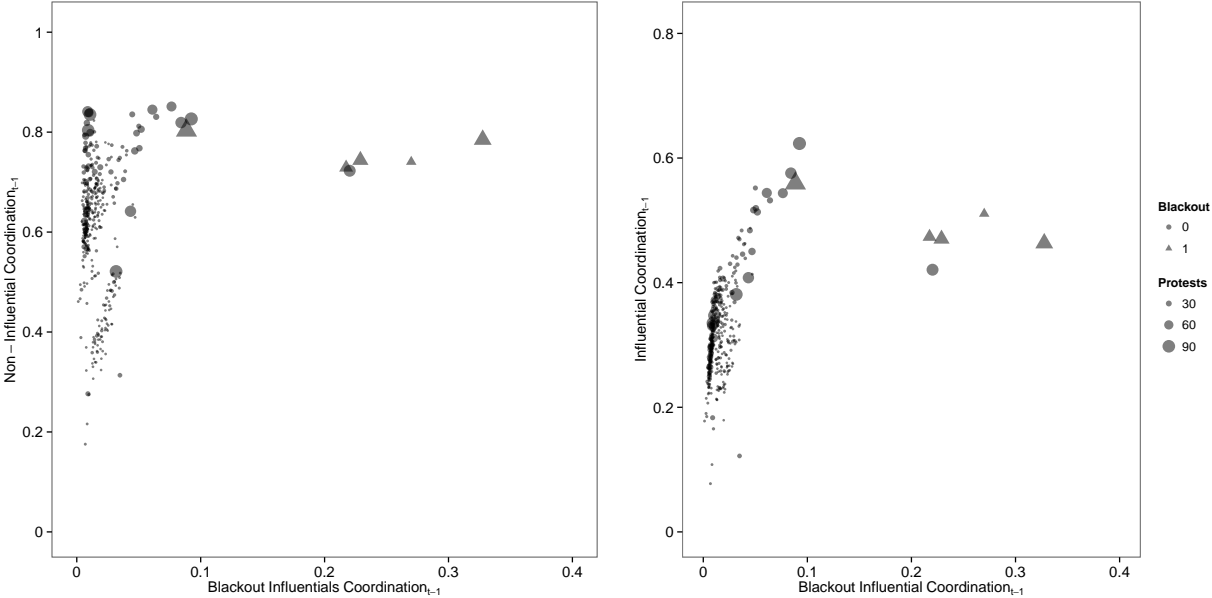
Contrary to conventional wisdom, digital communication was not completely severed. One internet service provider, Noor, functioned through the end of January 31st; it provided connectivity for critical government functions, the Cairo stock exchange, and several international hotels (Glanz & Markoff 2011). Individuals who knew to go to hotels or who had friends with access to Noor could therefore use Twitter; even on the one day without any internet access, February 1st, one could use landlines, dial-up modems, and Google's 'Speak to Tweet' service to get online (Gunning & Baron 2013, pg. 286). The blackout therefore increased the cost of accessing the internet, limiting it to those with expertise or social connections with those who still had access.

Anyone observed tweeting from Egypt between January 28th through February 1st can therefore reasonably be classified as belonging to the core of Egypt's network, regardless of their Lotan et. al coding or number of followers. This dataset observed 740 accounts that used Twitter from Egypt during the blackout, with a maximum of 338 tweeting on February 1st. In terms of Twitter behavior, they are most similar to Egyptian bloggers and activists or those in the 99th percentile of the follower distribution. These users, which I call the *blackout core*, have an average of 8046 followers, and are responsible for an average of 650 tweets and 12.05% of all tweets. How they use Twitter differs, however: they retweet less often (4.74% of their tweets are retweets) than bloggers and activists (8% and 7%) but about as often as those in the 99th percentile, and they mention other users very infrequently - at 21.66%, less frequently than any other group in the sample. They

use hashtags less frequently, in 21.66% of tweets, than bloggers, activists, or those in the 99th percentile. Yet 59.36% of their tweets contain a link, more than any other Egyptian group except Mainstream Media. That the blackout identification accords with the follower-based measure of influence used throughout the paper provides reassurance about the validity of those measures.

Figure 8 shows how the blackout accounts' coordination correlates with $Coordination_{i,t}$ and $Core Coordination_{i,t}$ and protest (size of each point). $Blackout Core Coordination_t$ was calculated the same way as $Core Coordination_{i,t}$ except that having tweeted during the blackout, not number of followers, is the grouping variable. For both measures, shown respectively in Figure 8a and Figure 8b, there is strong correlation in the early part of new measure and the other two coordination variables. The day with the lowest level of lagged blackout coordination is January 28th, the first day of the blackout; this result makes sense since January 27th was a more representative sample of Egyptian Twitter users than later days would be. Just as with Figure 4, they key is to pay attention to the distribution of the size of the points: days with many protests occur across a range of $Blackout Coordination_t$ values.

Figure 8: Blackout Influentials and Protest



(a) Blackout Influentials and Protest

(b) Blackout, Non-Blackout Influentials

Replicating the main models from Section 4 confirms that peripheral coordination drives protest

mobilization. Table 8 shows these results: *Blackout Coordination_{i,t-1}* is not significant in any model. The only stable result from the models is *Blackout Mention_{i,t-1}*, which is positive and significant. Though they infrequently mention other accounts, in comparison to the other categories used to delineate the core, they are more likely to do so during protest events.

Table 8: Blackout Accounts do not Provide Coordination

	<i>Protest_t</i>				
	(1)	(2)	(3)	(4)	(5)
Coordination _{t-1}	0.592 (0.447)	4.420*** (0.952)	4.677*** (1.037)	4.283*** (1.036)	4.904*** (1.176)
Hashtag % _{t-1}		-11.399*** (2.550)			-10.446*** (2.944)
Retweet % _{t-1}		14.286* (7.767)			13.877 (10.516)
Link % _{t-1}		-2.863 (2.606)			2.556 (3.033)
Mention % _{t-1}		-7.604** (3.086)			-8.928*** (3.363)
Protest _{t-1}	0.049*** (0.007)	0.034*** (0.007)	0.043*** (0.007)	0.046*** (0.007)	0.043*** (0.008)
Repression _{t-1}	0.012 (0.018)	0.014 (0.018)	0.011 (0.018)	0.017 (0.018)	0.008 (0.017)
Blackout Coordination _{t-1}			-63.086*** (17.901)	-59.331*** (22.485)	-44.432** (22.651)
Blackout Hashtag % _{t-1}			45.164*** (13.042)	22.291 (18.716)	19.221 (19.351)
Blackout Retweet % _{t-1}				50.241** (22.693)	28.044 (26.984)
Blackout Link % _{t-1}				-3.888 (4.163)	-19.470*** (5.792)
Blackout Mention % _{t-1}				18.620** (7.738)	31.304*** (8.516)
Constant	0.776*** (0.263)	4.493* (2.299)	-1.942*** (0.692)	-1.721** (0.698)	3.390 (2.488)
Country FE	No	No	No	No	No
N	425	415	415	415	415
Log Likelihood	-1,130.493	-1,080.934	-1,088.982	-1,080.382	-1,070.603

*p < .1; **p < .05; ***p < .01

8 Discussion

This paper shows that coordination occurs through those with few social connections, and this coordination leads to protest mobilization. These peripheral network individuals outweigh those in the core because protests diffuse through a complex contagion process, a process which, in the context of protests, requires distributed coordination to spread. These results join a growing body of quantitative work at the intersection of information and communication technology and state repression. Jan Pierskalla and Florian Hollenbach find that, in Africa, cell phone coverage increases the probability of violent conflict (Pierskalla & Hollenbach 2013). Jacob Shapiro and Nils Weidmann find the opposite effect in Iraq; using time-variant data on new cell phone coverage, they find that the provision of cellular coverage decreases insurgent violence (Shapiro & Weidmann 2011). Gary King, Jennifer Pan, and Molly Roberts measure censorship on Chinese blogs; they find that Chinese censors target posts which could generate collective action but are more permissive of writings critical of the Communist Party (King, Pan & Roberts 2013).

Despite the reliance on social media data, this paper does not address whether they, or telecommunications more broadly, affect protest. On one hand, social media may increase subsequent protest if it causes more individuals to learn about the state's actions and those individuals protest when they would not have without the knowledge-providing role of social media. Yet the knowledge-providing role could have counterbalancing effects: as more people learn the resolve of the state against protesters, fewer individuals may protest than otherwise would have. Appropriately answering this question requires data with very precise location information, preferably with temporal variation of social media presence. These data exist and have been used to test violence in Africa (Pierskalla & Hollenbach 2013) and Iraq (Shapiro & Weidmann 2011, Shapiro & Siegel 2015), but the results are contradictory.

No work has been able to show if social media *cause* protest, as it is very difficult to know which countries or regions of countries do or do not have a social media platform and then compare those areas to similar places without social media. Because of the difficulty of isolating social media's affect, this paper has chosen not to ask that question. The point of using social media data is to better understand the observed world. Social media data, especially that which is publicly available, resolves the temporal resolution problem facing previous work, but connecting those data

with detailed spatial data is still a challenge. Because of limits in the data for protests and the paucity of tweets from these 16 countries with GPS coordinates, for example, analysis here was restricted to the country level.

Finally, this paper demonstrates the contributions user-generated data, commonly called "big data", can make to the social sciences (Grimmer 2015, Monroe, Pan, Roberts, Sen & Sinclair 2015, Shah, Cappella & Neuman 2015). Researchers have begun to understand how these data can provide new insights into political phenomena such as voting (Bond, Fariss, Jones, Kramer, Marlow, Settle & Fowler 2012) or ideological sorting (Barbera 2015). These data primarily come from online social networks such as Facebook or Twitter, though anonymized call records, YouTube, or discussion boards (Nielsen 2012) are often used.

Properly used, social media data should become another tool for researchers, but it is most likely to generate knowledge when used as a window into already existing processes (Bennett & Segerberg 2013). It is not clear that social media create new behaviors or fundamentally change social relations. Its main effect is to lower the cost of communication, and lowering the cost of communication also lowers the cost of data gathering. But lower costs do not clearly favor one group of actors over another: the printing press created Martin Luther's *95 Theses* and Russia's *Pravda*, and states have learned how to use the internet and social media to repress (Hoffman 2015, Rod & Weidmann 2015). Using social media data to understand social behavior is therefore the main benefit of "big data". If social scientists have been stuck looking for keys under a streetlight, they now have access to stadium lights. Even stadium lights leave much of the world in the shadows.

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