Social Network Structure and Counterinsurgency/Counterterrorism: Using Theory to Limit Causal Links and Aid in Strategic Planning*

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This version July 3, 2008.

Abstract

Both qualitative and quantitative methods have utility in political forecasting, yet they are often treated independently. I argue for an approach that formalizes the insights inherent to qualitative models, and so provides for their quantitative measurement and their broader generalization. The modeling approach I offer treats individuals as heterogeneous in intent, and influenced by their interactions with others in their social networks. One's location within these networks affects one's individual behavior; the large-scale structure of the networks influences aggregate behavior. I offer a typology of qualitative network types to classify how different networks affect aggregate outcomes, and incorporate the actions of an external repressor to explore the way in which participation in collective actions may be limited by outside pressure. After analyzing the role of both violent and non-violent repression, I illustrate which types

*Prepared for the National Defense University Human Social Cultural Behavior Workshop July 28 - 29.

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of data on social networks are most useful to forecasting within each network type. The essay concludes with an application, using information known prior to the event to forecast the differential effect of repression on turnout in the 2005 Iraqi Legislative elections.

1 Introduction

The degree to which quantitative political forecasting models are able to achieve their intended goals—the prediction of the onset of a particular political behavior such as instability—rests upon the validity and the generality of the predictors used in the forecasts. If these predictors do not correlate highly with the behavior in question across a large range of substantive cases, then prediction will be poor. Given variation in real-world cases, the most effective predictors are likely to be those that can abstract away from fine-grained detail while still capturing important aspects of society. For example, the rate of infant mortality can be an effective measure of poverty, even though it abstracts away from the distribution of the mortality rate in society, among other things.

Typically, quantitative measurement is limited to those predictors for which quantitative data are present. Nations tally GNP and infant mortality rates, and gathering these provides common measures of the states of economies. "Softer" measures, such as social cleavages or elite interests, are often ignored in such analyses, or at best imperfectly captured by proxies. Common quantitative measures that assess these more accurately either do not exist, or require data that are available only rarely.

Qualitative factors, when they are considered at all, usually only enter as a comparison to or explanation for the quantitative prediction. If the prediction does not hold, the failure can be attributed to a qualitative factor such as social context. If it does hold, then one can argue that the predictors used were adequate proxies for the qualitative factors others might think of as important.

The inability of most quantitative predictive models to directly incorporate qualitative factors comes with two limitations. First, predictive accuracy will be limited in cases where the qualitative factor does in fact matter. Second, the causal mechanism underpinning the prediction—whether or not the prediction is accurate—will tend to be poorly understood, and will often be *post hoc*. This last is particularly important. However good one's predictions are, if one does not understand the reasons why the event occurred, it will be difficult to generalize to cases sufficiently different from the one predicted (Goldstone 2008).

This essay offers a means by which to bridge the gap between the qualitative and quantitative. The abstract behavioral model it introduces provides the causal logic underlying the effect of social context—specifically, the structure of the social networks linking society—on the degree to which aggregate participation in collective activities is achieved. These collective actions can be protests, rebellions, insurgencies, terrorism, (or more prosaic things), and are at the heart of conflict the world over. In addition, the social networks used by the model are delineated by factors often viewed as important by qualitative scholars; individual influence, elite interests, and social construction all have places in the model. Thus it answers in part the qualitative criticism of quantitative work.

At the same time, underlying the model's qualitative social network types are well-specified quantitative measures. These combine with an abstract behavioral model and an external repressor to produce quantitative predictions on participation levels, and on the response of participation to repressive action such as counterinsurgency and counterterrorism. The level of detail in prediction is determined by available data. When data are sparse, rough qualitative measures of network properties can produce improvements in quantitative forecasting models. When data are more plentiful, improvements can be even greater. Thus, despite including qualitative aspects, hypotheses drawn from the model may be incorporated directly into existing quantitative forecasting models. The theory provides the causal story; the variables in the model provide additional predictors in the forecasting model.

The rest of the essay proceeds as follows. First, I discuss the abstract behavioral model underlying the full model. Second, I introduce social networks, defined by both qualitative and quantitative aspects that complement each other. Third, I introduce the concept of repression, and how it interacts with network structure and individual behavior in determining participation. Finally, I conclude with an application of the model to predicting the level of participation one might have expected in the 2005 Iraqi Legislative elections, using information that was available prior to the election.

2 Abstract Behavioral Model

Motivation

A requirement of quantitative forecasting models is that the predictors they used must be relevant across most if not all cases present in the data, both in-sample and out-of-sample. If a model incorporating qualitative aspects, as this one does, is meant to be meshed with these quantitative forecasting models, its base assumptions also must possess this same degree of generality. Otherwise, the addition of the qualitative factors will decrease the degree of applicability of the forecasting model or, in other words, decrease its external validity.

The first and perhaps most important step in creating an externally valid qualitative model, then, is to postulate underlying behavioral rules that apply widely. As any social scientist will attest to, however, this is a troubling requirement. Understanding behavior is messy. Rational-choice-based models get around this by assuming global rationality. This is usually followed, for tractability reasons, by assumptions limiting the range of motivations across the population, often to the point where all individuals have the same utility functions, which are usually fairly simple. Assumptions like this are often criticized by empiricists for being unrealistic. Since the goal of this exercise is empirical prediction, the theory I present does not go down this path.

Instead, the theory uses the notion of an abstract behavioral model (Siegel 2008a). The idea behind these is straightforward: rather than ignore complexity, as rational-choice models tend to do, or incorporate specific complexities, as psychological and some agent-based models do, we will instead average across complexity.

To understand how this works, consider the classic Condorcet Jury Theorem (Ladha 1992). The setting is simple: N jurors sit in a room, and must decide the fate of the accused. They have only two options, guilty or innocent, and they vote via majority rule to convict or acquit. One option in approaching this problem would be to assume rationality on the part of the jurors. This entails adding motivations to their decisions; typically this involves assuming that they desire only to get the majority-rule decision right, that they all have some measure of private information, and that they are able to condition their decisions on the possibility that theirs is the pivotal vote (Austen-Smith and Banks 1996). While this approach certainly yields important insights, it is limited in its applicability to cases where all these assumptions hold. If, for instance, jurors just want the trial to end as soon as possible so that they can go home to their families, the same outcome might no longer obtain. Since the distribution of motivations across the population is unknown and likely unknowable, we cannot assess the external validity of this approach.

Now consider the original statistical Condorcet Jury Theorem. Here the assumptions are simpler: each individual has some chance p to come to the correct verdict. If $p > 1/2$, the theorem states, then the more people who are in the jury, the better the jury does. Note that this assumes nothing about how or why people might be correct; it just provides them with a probability of being so and aggregates behavior accordingly.

This approach is not without limitations, of course. It doesn't explain how or why individuals might come to be correct. It also ignores interactions between individuals, so that one person's vote has no effect on any other person's vote, though later work has indicated that some statistical correlation in votes still allows the theorem's conclusions to go through (Ladha 1992). This latter issue was the one that inspired Austen-Smith and Banks' aforementioned paper, which illustrates the non-rationality of voters in the statistical Condorcet Jury Theorem setting.

But consider the strengths of the approach. It makes few assumptions on behavior, and so has increased external validity. Cultural, educational, and psychological differences can all be incorporated into the formation of these probabilities. Further, it produces a prediction despite these few assumptions. Not as to the effect of cultural, educational, and psychological differences, of course, since they are not in the model. But aggregate outcomes are predicted cleanly, and these predictions could be incorporated easily in a larger forecasting model of jury accuracy simply by adding an N to the list of predictors.

The statistical Condorcet Jury Theorem is also eminently expandable. It is often difficult to maintain tractability when adding new factors to or weakening assumptions in rational choice theories, but the same is not true here. If one wants to posit *how* these probabilities of being correct change with others' actions, one need only do so. To make this explicit, one could assume that individuals vote in order, and that each person's p increases the wider the gap between guilty and innocent votes in the jury. The hidden assumption here is that the wider the gap, the more likely it did not occur by chance, and so the more likely it is that others' votes signal actual knowledge. Or one could assume that individuals vote simultaneously, but in multiple rounds of straw polls.

I call models like the statistical Condorcet Jury Theorem abstract behavioral models because they do not posit exact behavior, but rather abstract away from it to focus on the outcome of that behavior. They are in some sense minimal; to discern how likely it is the jury is correct while still maintaining some level of causality, one must at least know what the chances are that each person is correct, even if one does not know why.

Model

The model I discuss here, first introduced in Siegel (2008b), shares certain aspects with the statistical Condorcet Jury Theorem. It makes minimal behavioral assumptions for its setting, and it abstracts away from individual characteristics to focus on the outcome of these characteristics, as expressed in the aggregate. Yet it is more complex than the statistical Condorcet Jury Theorem, with stronger causal links between behavior and action. Importantly, though, despite this increased complexity it still displays strong external validity, and is quite expandable, as we will see in later sections.

The abstract behavioral model focuses on the willingness of individuals to participate in some collective action. Much as with the Condorcet Jury Theorem, individuals in the model will have two possible choices. There these were vote to acquit or to convict. Here they are to participate or not. The model employs two central assumptions in regard to individuals' motivations toward participation. The first is that individuals are heterogeneous in interests. That is to say, individuals are varied in their motivations toward participation. An analogous assumption in the Condorcet Jury Theorem would have the jurors possessing different likelihoods of being correct *a priori*. The second assumption is that individuals adjust their motivations over time, in response to the actions of those to whom they are connected via local social networks. I consider each assumption in turn.

Heterogeneity in motivations helps ensure ensure external validity, since we do not need to assume that all people are the same. However, this implies that either we specify all individuals' specific motivations—an effectively impossible task—or we find some way to average across them. I take the latter route, and separate each individual's motivations to participate at a given time into two components.

The first component is the *net internal motivation*, and I label it $b_{i,t}$ for each individual i at each time t. Within this component are all potential motivations both for and against participation that are *independent* of the participation of others. This includes interests typically thought of as benefits from taking part in the collective action, such as a personal desire to effect social change, a preference for "rabble-rousing," or a hatred for the opposition. It also includes motivations more typically classed with the costs of participation, such as an opportunity cost for missing work while protesting, or the price of acquiring weaponry or false identification. Despite the substantive differences between these things, however, others' participation generally does not affect them, at least in the short term.

The second component is the *net external motivations*, and I label it $c_{i,t}$ for each individual i at each time t. Within this component are all potential motivations both for and against participation that are *dependent* on the participation of others. This includes any possible incentive for or against participation that varies with the participation of others.

A wide variety of potential behaviors fall under this second component, and before moving on, it is worthwhile to delineate some of them, as they illustrate exactly how this abstract behavioral model is able to achieve wide generality.

Firstly, others' participation might increase (or in some cases decrease, if the action is covert) the chance of success of the action, particularly if such group participation involves pooled resources and the action is resource-intensive. Second, others' participation might pass information on to you, which you can then use to learn better about some state of the world (e.g. Lohmann 1994). For example, consider an array of loosely-connected terrorist cells who are waiting for the "right" moment to strike. Each action by a cell suggesting their intent to strike provides information about the cell's belief as the the "rightness" of the moment, information that other cells can utilize in their own decisions. In this example, each cell's actions increase the likelihood that other cells will strike as well. This directionality is not necessary, though; in general, information spurs people to update their beliefs about the worth of participation, and possibly change their decisions in consequence.

Third, others' actions can transmit direct influence (e.g. Friedkin and Johnsen 1999). This is particularly important when individuals are enmeshed in a leader/follower dynamic. The leader's actions can often effectively force his followers to act as well, regardless of their individual interests. Fourth, others' participation can affect one's reputation (Kuran 1995), in that social punishment becomes possible if one does not join in some collective action. Fifth and relatedly, others' actions can induce worries about fairness (Gould 1993), as one fears that one is not pulling one's weight in the movement or group activity. Sixth, there is the safety in numbers argument; you are safer the more people who join your actions (e.g. Kuran 1991). Finally, the credibility or legitimacy of the activity might be enhanced with others' participation, particularly those in a leadership role (Centola and Macy 2007).

Though detailed, this list is not exhaustive; many other casual stories might play a role. The model, by abstracting away from them, maintains its generality without losing the ability to address these types of behaviors. It is important to note that the two components in the model are mutually exclusive. All motivations whose change depends on others' participation are by definition *external* motivations; all others are necessarily *internal* motivations. Which fall into each component can depend on context and the collective action in question. The model assumes that what falls into each component is constant across time.

Behavior—represented by the choice of whether or not to participate—is determined by a simple rule: individual i participates at a given time t if and only if $b_i + c_{i,t} > 0$. That is to say, one participates if one's net motivation to do so is positive.

A straightforward generalization of this rule has decisions made stochastically: $b_i + c_{i,t} > \varepsilon_{i,t}$ with $\varepsilon_{i,t}$ a random variable. The random variable here represents uncertainty in the action, due to events outside the knowledge of the analyst, or to misperception of others' actions by the person making the decision. Though this perhaps would add to the model's realism slightly, it has little else to recommend it, and so is not considered further. In general, the addition of such a random component tends to increase levels of participation in models in which behavior becomes more likely the more others take part in it. The reason is that misperception (or probabilistic behavior) creates moments of high participation that feed on themselves to become self-sustaining.

This specifies motivations in a static context. Yet such a focus ignores the fundamentally dynamic nature of the processes we care about here. If others' participation alters one's own decisions, we must give these others the chance to act, after all. This entails specification of how each component changes in time. The first step in doing so is determining the initial conditions on each component.

Internal motivations are assumed heterogeneous, and so they must be distributed in some fashion. I assume that this distribution is normal (Gaussian), with parameters b_{mean} and b_{stdev}. This assumption is not without content. As noted by Granovetter and Soong (1983) and Yin (1998), the distribution of interests can have a large effect on the expected level of participation in a collective action. Thus it is important to justify the choice of a normal distribution.

We start by noting again that one's net internal motivations are the sum of factors distributed across the population independently of all other such elements. If they are weighted in a certain way, a central limit theorem implies that their net, b_i, is distributed normally. If all the assumptions of the central limit theorem are not true, of course, then the normal distribution might not obtain. Even so, one can still treat net internal motivations as a single value, albeit one with a different distribution across the population, or one drawn from distributions that vary across members of the population.

The parameters of the normal distribution correspond to the mean net internal motivation and the dispersion of the net internal motivation within the population. Higher mean values are representative of collective actions in which people are more likely to participate, all else equal. Note that using only two parameters here, b_{mean} and b_{stdev}, the model represents different forms of participation, some of which may be less costly or more beneficial than others.

Each individual's $b_{i,0}$ is thus given by a draw from the distribution $N(b_{mean}, b_{stdev})$. What about each person's net external motivation? One option would be to distribute this as well. However, note that behavior is determined by a comparison between these two components. As the sum of two normal distributions is itself a normal, adding an additional two parameters to distribute external motivations adds little of content to the model. Thus I keep things simple, and set all $c_{i,0} = -1$. This value is assumed to be the lowest value possible for external motivations, which range from -1 to 0. In setting initial external motivations to their minimum, I fashion the model to focus on breakouts of participation and what actions may be taken to stop them before coming to fruition, a more proactive approach in the realm of counterterrorism and counterinsurgency that the alternative. However, little would change in the model if the focus were to turn to ending mass participation, and the model's results should generally carry over to that case.

Now we turn to the ways in which each component changes over time. First consider internal motivations. These cannot, by definition, vary based on the actions of others. This leaves two possibilities for their changing. One, they could vary based on exogenous, un-modeled effects. Two, they could vary based on endogenous effects arising from actors internal to the model, but other than those participating or potentially participating in the collective action. The first is no different than adding $\varepsilon_{i,t}$, which we have already discussed. The second requires the introduction of some other entity. As yet we have none. Thus, until a repressor is discussed in Section 4, I assume that net internal motivations, $b_{i,t}$, are constant.

Next consider external motivations. These by definition change as others' actions change. For simplicity, I assume that they change *only* as a result of others' actions; nothing exogenous to this has any effect. But how do they change? We could just postulate a general function, $f(\cdot)$, but little insight would be gained from the resulting model. Accordingly, the model assumes that the greater the percentage of other individuals who participate, the more one desires to participate oneself. This does reduce generality somewhat. For instance, the model no longer does well addressing collective actions focusing on the provision of public goods, since once sufficient contributions have been given so as to provide the good to all, people might become *less* likely to want to contribute. However, the model still applies to many other collective actions, many other behavioral referents. In particular, all seven of the behaviors listed above naturally lend themselves to this assumption, with more participation by others implying a greater desire to participate oneself.

Individuals respond to others' participation via the vehicle of the local participation rate, $lpr_{i,t}$. In this section, we first assume that the participation rate that matters is that of the population as a whole. In the next section, once social networks have been introduced, we will see that this simple term captures a great deal of complexity; different individuals within a population can observe very different local participation rates based on their positions within the network.

I assume that the updating rule that relies on this rate is $c_{i,t+1} = \lambda c_{i,t} - (1-\lambda)(1 - lpr_{i,t})$. Thus, one's external motivations tomorrow are a weighted average of one's today, and the local participation rate. Higher values of the weight λ indicate less responsiveness to local participation levels, or equivalently, slower "learning." Varying the weight allows for variation in the speed of learning, and the capability of such variation is one reason why this adaptive form was used rather than something like Bayesian updating. A second reason can be found in the variety of behavioral referents the rule must address; Bayesian updating makes far less sense outside the realm of information transfer and acquisition. Note that the updating rule has external motivations be a linear function of the local participation rate, so that there are no diminishing marginal returns to others' participation.

The introduction of the updating rule completes the assumptions on individuals. As the model itself will become analytically intractable once networks are introduced, we must now specify how the model progresses, and how results are to be derived from it. Consider the former first. The model's dynamics are split up into periods of indeterminate length. These may be agreed-upon meetings of prospective protesters or members of nascent terrorist cells, or may instead delineate the moments one gives to thought of participation. Regardless, during each period each individual simultaneously decides whether or not to participate based on the above decision rule. Between periods, each person updates his or her net external motivations according to information about others' participation during the preceding period, as per the above updating rule.

Without repression, and without other exogenous events, individuals start in period zero not participating. Individuals begin by receiving their internal and external motivations; they are also placed in a network when such are present. Then time in the model begins. The first event of interest is that "rabble-rousers" with $b_i > 1$ start to participate. Depending on the distribution of internal motivations (and the structure of the network), these rabble-rousers might spur others to participate, potentially leading to a cascade, or they might not. Without a network the model mimics other cascade-type models, such as that of Granovetter (1978). Eventually a steady-state is reached, after which time no participant wants to stop, and no non-participant wants to start. These steady-state values serve as the preferred dependent variable in the analysis when repression is not present. Other variables such as the speed at which the steady-state is reached may also be taken; however, since the connection of the rate of updating, λ, to real-world temporal progression is undetermined, the utility of such a measure is not obvious.

The connection to forecasting can now (finally) be made clear. If the degree of participation in a collective action is positively correlated to the success of that action, then the number of participants in protests, rebellions, or insurgencies should be positively correlated with instability, and the number of participants in terrorist activities should be positively correlated with the frequency and intensity of terrorist attacks. The model's contribution, then, is to indicate what variables affect the number of participants one can expect in any collective action, and to provide a causal logic for how they do so. The first—and only—three such predictors offered thus far are the number of people, N, and the internal motivation distribution parameters, (b_{mean}, b_{stdev}).

Due to the presence of stochasticity in the assignment of internal motivations, the best we can do in deriving forecasts from these predictors is to produce expected values of the steady-state participation level. Absent a network we can solve for the expected steady state exactly in an infinite population, and fairly easily extend the analysis for finite N using standard simulation methods. We find that participation is increasing in b_{mean} always, increases in b_{stdev}) save when b_{mean} is high, and displays non-monotonic behavior in N, largely due to the additional power of chance present in the model when the number of people is small (Siegel 2008b). Since none of these are particularly surprising, it would behoove us to move on to the addition of network structure. Doing so requires not only the introduction of networks, but also a more complex methodology for deriving results from the model.

3 Social Network Structure

Model

Multiple options exist for the modeling of social network structure. One focuses on purely quantitative measures of network connections. By constructing graphs of the detailed linkages between individuals, one can measure aggregate statistics of interest such as the path length and the clustering coefficient, which correlate to the speed at which information and influence can traverse the network, and the degree to which individuals have connections in common, respectively.

This is certainly a productive technique when data are plentiful, but it has several problems when conditions are less than ideal. One is that data are usually *not* plentiful. This is particularly true in areas that are inherently risky, such as insurgencies and terrorist activities. Further, the most careful social analysis of a particular setting can often only discern group-level structure (e.g. Petersen 2001). This lack of data also occurs in more peaceful settings; as Fowler (2005, p. 15) notes, "No one knows the true average path length for a typical political discussion network." Any theory that requires the entire social network to be known will be of limited use, therefore, to scholars who only have qualitative network data.

A second problem is that, even when data on network links are plentiful, they are rarely accompanied by knowledge as to *what* individuals are discussing. It may be the case that a particular network of ties engages in frequent political discussion, for instance, and thus its members are driven to vote, but it may also be the case that the network is purely social and never entertains political discussions due to a strong social norm. Without information as to the content transmitted by the network ties, the causality underlying their role is likely to be hidden.

Another option would be to discount networks entirely. This, however, is clearly an empirical mistake. As noted particularly often in the sociological participation literature, individuals' decisions depend strongly on their social contexts (e.g. Gould 1991; McAdam and Paulsen 1993; Opp and Gern 1993; Snow et al. 1980). Mississippi's Freedom Summer is one example; McAdam (1986, p. 80) writes: "Participants were much more likely than withdrawals to have had ties—especially strong ties—to other volunteers." Social structure thus should and does alter outcomes. This is seen theoretically as well; the pattern of network connections (e.g. Centola and Macy 2007; Chwe 1999; Gould 1993) and the position of individuals (e.g. Gould 1993; Kim and Bearman 1997) both play roles in individuals' desires to participate or not.

Accordingly, I take a third path, and adopt a different methodology for addressing the role of social networks. It builds off of the abstract behavioral model described in the previous section. The local participation rate, $lpr_{i,t}$, determines the signal to which individuals respond. Note that, while one may observe the participation of individuals outside one's local network, this does not affect one's external motivations because one is not connected to these others, and so receives no influence or (credible) information from them. There is always the chance that they are plants, designed to smoke out the opposition, after all (Petersen 2001).

Changing one's local network alters the set of behaviors to which one responds, changing the incentives for participation that one experiences. This, in turn, affects aggregate outcomes. How this works can be seen in the following example, taken from Siegel (2008b):

> Let us begin by assuming that there are six people arranged in what is typically called a "star" formation, with one in the center and the other five tied only to her. Further, let internal motivations be such that the central person's b_i exceeds one, while everyone else's are between zero and one, exclusive. In the first period the points of the star will not participate, since the central individual is not yet participating, and so $b_i - 1 < 0$ for them at this point. The central person will, however, begin participating immediately; she is a rabble-rouser. Once this has occurred the local participation rates for all other individuals become one, since all are connected only to the center by assumption. This drives their external motivations to the maximum of zero, causing them to participate as well. All individuals thus participate within two periods.
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> Now assume the same setting, save that the central, influential person is a less-

motivated type, rather than a rabble-rouser. Further, let the sole rabble-rouser in the network be located at one of the points of the star. As before, the rabble-rouser participates in the first period. However, in this network configuration only one person is affected by this decision—the central person. One-fifth of his local network is participating, driving his external motivation to negative four-fifths. If his internal motivation is greater than this he participates, triggering a cascade as in the earlier case. If it is not, however, he does not participate, and the movement stalls at one person. In short, initial distributions of motivations that produce identical levels of participation in the first period can lead to very different subsequent behavioral dynamics, due to the way in which the shape of the network structures the way individuals perceive others' participation. Though simple, this example is illustrative of the two paths the evolution of this model generally take. In the first, participation spreads sufficiently widely so as to cause a cascade, leading to very high levels of participation in equilibrium. In the second, participation spread stalls at some point, and only lower levels are achieved. Which path is taken depends on both the distribution of motivations within the population, and on the structure of network ties.

The structure of the network is thus clearly important, and must be specified. The specification I employ offers a way to get at the comparative impacts of empirically-realistic social networks, other than via detailed measurement. It is based on a typology of qualitative network structures. These are not an exhaustive list of all possible networks types, but rather a typology of commonly-observed social structures that display differences that are observable on purely qualitative grounds. Two of these represent populations in which each person's individual influence, as measured by one's number of ties (equivalently connectivity or network size), is roughly equal to the average. The other two represent societies in which individuals are differentially influential, either due to many more ties, or to a privileged place within the network.

Each network is defined in two ways. The first is by type. Each of the four network types—the Small-World, the Village (or Clique), the Opinion-Leader, and the Hierarchy—has certain behaviors that are common to it. All a researcher need do to make use of these predictions is to identify the type of network in place. As we can see in Figure 1, which is a visualization of the four network types, this is designed not to be difficult, or to require significant data.

[Figure 1 about here]

The second way they are defined is via one or two network parameters. Though these usually do require quantitative data to fit, it is often the case that variation of these parameters, within a reasonably large range, has little effect on aggregate outcomes. Accordingly, data may be sparse yet still useful for forecasting.

In keeping with the tone of this essay the descriptions of each network below are largely qualitative. Each tie in these networks is symmetric, implying that anyone you influence also influences you. Thus the model is most applicable to situations in which influence or information transfer requires some level of trust, as is typically true in the settings of insurgency and terrorism. Of course, symmetric ties do not imply symmetric influence. Just because two people influence each other does not mean they have equal influence on each other. If one of the pair has many other connections, but the other does not, the first person will be far less influenced by the second than the reverse, owing to the dependence on the local participation rate. The networks below are also static. Though this does somewhat limit the model's applicability to behaviors that occur quickly as compared to the speed of network formation or alteration, by providing a detailed analysis of the role of network structure, one can determine what effect networks have at any point along variation in their parameters, even if the networks' structure changes endogenously. Thus the model retains utility in this case. Further detail can be found in Siegel (2008b), and additional information about networks in general can be found in surveys such as Strogatz (2001).

The first network is the Small-World network (Watts 1999). It represents modern cities and suburbs, and all individuals within it are more or less equal in influence, with none holding particular sway over their peers. The network is formed in two steps. First I create a ring substrate, defined by the parameter *Connection Radius.* This parameter determines the number of other individuals to each side of one to which one is connected. A radius of one would therefore be a simple circle. Second, each of these ties has some chance of being severed and reconnected somewhere else. This is done stochastically, with probability given by the parameter *Rewire Probability.* The first parameter thus dictates average connectivity in the network, while the second alters the rate at which information and influence flows within it. This network is typically associated with such phenomena as the six degrees of separation effect, due to its usual encouragement of rapid information spread across it. Yet it also displays a fair bit of clustering, if less than normally observed in modern society. Such networks can have their substantive origins when existing tightly-connected groups are broken up due to spatial movement of the groups' members, either by choice, as in going away to college, or by necessity, as in forced migration.

The second network is the Village, or Clique, network. This has some similarities to the Small-World network, but is much more highly clustered, as one can see in Figure 1. It represents small towns, villages, and cliques. The Village network's defining characteristic is that everyone knows everyone else within the village or clique, and all have equal influence in that regard, but only a few people in each village influence anyone outside that village. One parameter, *Village Size*, determines the size of each village or clique. (If a population does not divide evenly by this parameter, all left over individuals are placed into a last, smaller village.) This determines almost completely the level of average connectivity in the network, and is a direct correlate to Putnam's notion of "bonding" social capital (2000). A second parameter, called *Far Probability*, is the probability that a tie between members of different villages is made; it is checked once per possible connection. This dictates substantially the rate of information and influence spread within the network, since it determines the ability of behaviors to pass beyond the boundaries of a clique or village. It also is a direct correlate to Putnam's notion of "bridging" social capital. Behavioral spread typically first occurs within a village, only expanding outward once that village or clique is nearly all participating. When repression is involved, this can lead to spatially targeted violence and the perception of inequality.

The third network is the Opinion-Leader network, also called a Scale-Free network. Unlike the previous two networks, in which individuals generally have equal numbers of connections to others, the Opinion-Leader network is meant to represent situations in which a small number of social elites—those with many connections to others—drive the spread of information and influence throughout the network, in large part determining the behavior of their many followers. The "star" network used in the example above is a small-scale version of such a network. These networks are defined by only one parameter, γ, which simultaneously determines both the number of opinion-leaders, and the number of connections each has. The creation of such a network occurs in two steps. First, individuals are assigned a number of ties according to the distribution $p(k) \propto k^{-\gamma}$, where k is the number of ties a particular individual has. Smaller values of γ thus correspond to greater average connectivity. Second, connections are made randomly so as to approximate as closely as possible this distribution of ties. Though not exact, this method provides good performance when γ is not too small, and allows for variation in the parameter in a way that preferential attachment methods have more difficulty achieving. Studies of internet susceptibility have recently encouraged the common use of these networks (Albert et al. 2000).

The fourth and final network in the typology is the Hierarchy. Unlike the Opinion-Leader network, in which the power of elites lies in their greater number of network ties, the power of elites within the Hierarchy rests in their placement at its top. Hierarchies are typically observed in bureaucratic settings, as well as in terrorist (and insurgent) groups whose concerns with security are outweighed by the desire for efficiency (Shapiro 2007). Two parameters represent the hierarchy. The first, the *Expansion Rate*, dictates the width of each level, as each level of the hierarchy contains a number of individuals equal to the *Expansion Rate*, raised to the power of the level, beginning at 0 for the top. Each person is connected to a number of people below her equal to the *Expansion Rate*; each of these latter people are connected to her immediate superior as well. So, for example, if the expansion rate is 5, there is 1 person at the top, 5 people on the second level, 25 on the third, 125 on the fourth, and so on. Each person in the second level is connected to the person at the top, and each also is connected to five people in the third level. Note that this doesn't lead to full levels for all values of N; thus the bottom level might have fewer members. (Figure 1 displays a top-down picture of a Hierarchy.) The second parameter, *Level Connection*, is the probability that any person within the same level is connected to another person in that level. Each possible connection is checked randomly once. The first parameter captures the command structure of the network, the second the connections that form endogenously between people who work in close quarters.

As the example of the star network above illustrated, the placement of individuals in the network can play a complimentary role to that of network structure in determining aggregate participation levels. Thus, I explore different methods of distributing internal motivations within networks. The first way is to leave them uncorrelated with position. Individuals receive internal motivations randomly, as described in the previous section. The second way, available mainly for the latter two network types, which possess elites, is to preferentially give the elites either the highest internal motivations (denoted positive correlation) or the lowest internal motivations (denoted negative correlation). The third way, used most naturally in networks without elites, is to correlate internal motivations with proximity within the network. In each case, the way motivations are distributed is just as much a part of network structure as is the manner in which connections are arranged.

Methodology

Before the introduction of networks, analysis was fairly straightforward, and in some cases could even be accomplished via direct numerical solution. The same is not true in the context of networks within this typology. As such, a different methodology must be employed. As in most things there are multiple options, but here we are constrained by the likelihood that non-linearities and non-monotonicities will be present in the model's dynamics.

Ordinarily, a useful approach for deriving comparative statics in the presence of a complex model that is not analytically solvable is to sample randomly across the parameter space, and then use either regression analysis or explicit computational testing of directional hypotheses at each sampled point (e.g. Kim and Bearman 1997; Smirnov and Fowler 2007). However, this method is limited in the domain of this model for two reasons. One, the sampling approach does comparatively poorly when one expects important non-monotonicities and conditional dependencies, as we do here. Dealing with these within the sampling approach would require one to sample sufficiently in the regions of nonlinearity, which is hard to do when one does not know *a priori* where these might be. The uniform random samples used typically in such analyses are often poorly suited to such cases. Two, specification of regressions and/or directional hypotheses is difficult given this same lack of foreknowledge regarding conditional dependencies and non-monotonicities.

Thus, I take a different tack in analyzing the model, and focus on limiting the dimensionality of the parameter space to the point where directly sweeping the space becomes possible. Here direct sweeping equates to evaluating the dependent variable(s) at a number of points fine enough to illustrate non-linearities and non-monotonicities. Effectively, I split the model into pieces small enough to analyze in the same way one could analyze the model absent networks.

To accomplish this trick, I do two things. First, I build and analyze the model in stages. Networks are added only after an analysis of the system without networks has been completed, and the model of repression introduced in the next section is only added once the role of networks has been independently understood. Second, I utilize extant theory to direct the analysis. This entails attention to the work of scholars such as Granovetter and Soong (1986) and Yin (1998), who illustrate that in a Fully-Connected network, as was present in the previous section, an infinite population should produce up to three equilibria. These correspond to low, intermediate, and high levels of participation on average. As the model generally displays a bimodal outcome, as mentioned earlier, such averages are more statements about how often cascades occur in which nearly everyone participate.

Which equilibrium (here steady-state) obtains depends on the values of the parameters b_{mean}, b_{stdev}, and N. Splitting up the space spanned by these three parameters according to the level of participation they produce in a Fully-Connected network provides a baseline of expectation for participatory outcomes in other networks. In further analysis, I find that network structure has a similar effect on participation levels within each of these three regions of parameter space (Siegel 2008b), but that different regions have different responses to adding networks. Accordingly, the first stage in the analysis entails separating the parameter space corresponding to internal motivations and population size into three regions, denoted "motivation classes." The classes are called "weak," "intermediate," and "strong," and they produces on average (in a Fully-Connected network) low, medium, and high degrees of participation, respectively.

The second stage in the analysis considers the role of network structure on each of these three classes. Because each network is defined by one or two parameters, plus the discrete parameter that dictates how internal motivations are correlated with position in the network, I am able to obtain comparative statics for the effect of varying each network parameter on the steady-state participation level. Though this can be computationally intensive, the payoff is the ability to describe non-monotonicities and conditional dependencies that would otherwise be difficult to discern.

A Few Results

Though this essay focuses on methodology, it is worth stating a few of the most notable of these dependencies before extending the model one last time. Network size (equivalently connectivity or social capita) proves hardly a panacea. Adding network ties (or social capital) when internal motivations are low, or when confronted with a hierarchy displaying positively correlated motivations (i.e. the elites are positively disposed to participate), can depress participation levels. This finding has direct relevance in assessing the potential utility of policies that focus on building social capital without full consideration of the social context, such as USAID's Iraq Community Action Program's (CAP).[1]

The power of elites is similarly conditional on network structure. The influence of elites makes sense only when viewed in light of other elites' motivations and the larger structure of the network, and cannot be assumed simply from the number of connections. Unfavorable network structures (e.g. hierarchies with levels neither too wide nor too narrow, and well-connected subordinates) can greatly limit the ability of elites to enforce their desires. This is particularly relevant in executive-branch bureaucracies, where the appointed upper echelon frequently has differing goals than the rank-and-file employees, and cannot control the growth of network ties among the latter.

4 Repression

Model

Thus far the model's focus has been on the growth of participation within a social network. Though this is a useful endeavor in understanding the role social structure plays in encouraging participation, it is divorced from the practical problem of counterinsurgency and counterterrorism, both of which focus on *stopping* participation in certain events, ideally before they really start. This last methodological section, drawn from Siegel (2008c), details the effect of adding repression to the model, where repression is defined as any activity which is intended to decrease the rate of participation in some collective action.

As the focus of this model is on the growth and repression of collective action, rather than on the causes for repression, I do not incorporate the repressor into the model explicitly. Instead, it is an exogenous entity whose sole purpose and desire is to minimize participation

[1] URL: http://www.usaid.gov/iraq/accomplishments/cap.html; last accessed July 1, 2008.

in a collective action. Though repression is a loaded word, no moral implication is meant by its use here. The unitary actor engaging in repression may be an oppressive state seeking to halt a protest, terrorists or insurgents looking to stop others from voting (as in the example of the next section), or a state seeking to halt violent terrorist or insurgent activity. The theory, as stated, represents any of these situations equally well. This is in keeping with the tone of the abstract behavioral model introduced in Section 2.

The commonality between these repressive entities is in the mechanisms they use to repress. Here I consider two broad types of repression, which I term "mild" and "harsh," though the former is only mild in comparison to the latter. I also consider two different repressive technologies: random/equal and targeted. I describe each of these now.

Mild repression consists of methods like the application of selective incentives, the alteration of property rights, or the use of limited violence, such as with a water cannon. In short, anything that does not actually involve exiling, killing, incarcerating, or otherwise removing an individual from society falls under this type. Formally, I model mild repression via a direct decrease to an individual's $b_{i,t}$, his net internal motivations. Thus these now become time-dependent under the influence of repression, though at this point they can only decrease. (This will change shortly.) Note that repression is applied only to participants. Though one can easily set the model up to repress even those not participating, it is generally not beneficial for the repressor to do so, and so I do not consider it here.

Two different repressive technologies are available to the repressor employing mild repression: equal and targeted. Equal mild repression diminishes each participant's internal motivation by the same amount. Targeted mild repression reduces the internal motivations of people with more connections more, proportionally to the ratio of their connectivity to the total number of ties in the network.

Harsh repression covers all those methods that mild repression does not, such as assassination or imprisonment, and so often involves more overtly violent means. All methods which remove an individual from society fall into this category. I model harsh repression by removing the repressed individual from the network entirely, and cutting all his ties. Such repression thus has a dual effect: it both reduces aggregate participation due to the removal of the participating individual, and also removes the *influence* of the participating individual on other people who were formerly tied to him.

Harsh repression also has two associated technologies: random and targeted. In random harsh repression, participants are removed randomly from the network. In targeted harsh repression, individuals are removed in the order of their connectivities, with the highest connectivity individuals removed first.

Both types of repression are limited in strength. For mild repression, this limitation is modeled by setting a maximum amount that the repressive entity can change internal motivations over any time period. For harsh repression, the limitation is modeled by setting a maximum rate at which individuals can be removed from the network. Note that an entity whose sole goal is to limit participation will always choose to repress at the maximum level, given assumptions to this point.

Though the two types of repression are an exhaustive characterization, by definition, the technologies are not. However, they do represent the extremes well. Random/equal repression corresponds to a low-information or a low-capability environment, in which the repressive entity is unwilling or unable to target the presumptive leaders of the collective action. It is also the presumptive technology when there are no real elites to lead, as in Small-World and Village networks. Targeted repression corresponds to a full-information or a high-capability environment, in which the repressive entity is both willing and able to repress more influential participants more strongly. Most real-world scenarios should fall somewhere in this range, so outcomes at these two extremes demarcate the space of likely aggregate responses to repression.

Thus far the model has had a certain detached quality. Individuals risk their lives and are possibly repressed with deadly force, and yet people continue to respond more or less logically. Since we know watching close social connections be killed or imprisoned is likely emotionally traumatic, the last model aspect I introduce here is the capability of individuals in the model to respond emotionally to the harsh repression (i.e. removal) of those (formerly) in their local networks.[2] This emotional response can take one of two forms. People can grow angry at the martyrdom of their compatriots, or they can grow fearful at the loss of their fellows.

Formally, the model incorporates emotional responses as follows. Under anger, internal motivations increase, under fear they decrease. The amount and timing of these changes depends on the actions of the repressive entity. Each person removed from one's network causes an emotional response in all subsequent periods, and the more people removed, the greater the response.

Methodology

The methodological requirements of the model including repression are largely similar to the model without repression. However, it bears repeating that each new factor in the model is only added after the previous ones have been understood. Here that means that repression is only added after having explored the role of network structure absent repression. Much as exploration of the abstract behavioral model absent networks yielded insights that were then exploited to vary network parameters carefully across the three motivational classes, in exploring repression I exploit generalities across networks discovered in analyzing the previous section's model. In general, there is an "optimal" parameterization of each network that produces that maximum level of participation achievable in a particular motivation class, and we can separate network parameterizations into sub-optimal, optimal, and greater-than-optimal groupings, with each label roughly corresponding to the number of network ties relative to the optimal.

Given these dependencies on network parameters, one can vary the strength of repression

[2] A natural extension I do not consider here is for people to respond emotionally to mild repression as well. Given the results reported below, my conjecture is that the same outcomes will obtain as under harsh repression.

under both types and both technologies. Once this analysis has been completed, one can then explore the impact of emotional responses, varying their strength under both anger and fear.

One further change needs to be addressed. When one lets repression act indefinitely, the steady-state participation level is always zero. Eventually the repression gets to everyone. Thus I instead use the dependent variable corresponding to the maximal participation level achieved during a history. This represents the strongest point in an insurgency or in terrorist activity, and thus measures the maximal degree to which the collective action affects the repressor.

A Few Results

As in the previous section, though the focus of this essay is on methodology, it is useful to provide some illustrations of what benefit for forecasting the model can provide. Two classes of results bear mentioning. The first is substantive: the model makes several predictions on how participation changes as a function of repressive strength, type, and technology, as well as of the level of emotional response on the part of the populace. The second is practical: the model indicates which predictors will likely have the largest impact on outcomes, and thus can help direct costly, time-consuming, and sometimes even dangerous data-gathering projects.

First, the substantive results. The broadest of these, which has consequences even beyond prediction, is that participation levels decrease similarly when subjected to mild or harsh repression. Repression type has no independent effect on outcomes. In addition to implying that the type of repression is a poor predictor in forecasting models, controlling for the strength of repression of course, this result has significant consequences for counterterrorism and counterinsurgency. Depending on the relative costs of the application of harsh and mild repression, it may be more cost effective to engage only in the latter, *even absent externalities induced by harsh repression.* When these externalities are present, in the form of an anger response, mild repression is *far* more effective. Even a comparatively weak anger response results in massive backlash that swamps any decrease in participation due to harsh repression. In some cases, harsh repression can *increase* participation rates six-fold in the presence of an anger response, as the network spreads and multiples the anger in a path-dependent manner.

A second substantive result, is that the technology of repression matters only when elites are present in the network, and only significantly when these elites are not uniformly motivated to participate, i.e. when their internal motivations are not positively correlated. Networks without elites naturally respond equally to both technologies of repression, since individuals all have roughly the same amount of influence. Networks with elites are more robust to random/equal repression and far less robust to targeted repression when elite interest is uncorrelated with network position. Elite networks where the elites all have high motivations, however, are extremely robust to both technologies of repression, implying that any attempt at repression in such networks will be extremely costly and potentially still ineffective.

Practically, not all data are useful predictors in all cases. We have already seen that it is not necessary to know the type of repression. Which data are useful varies by network type. In Small-World and Village networks, a rough order of data importance is: the strength of repression; the motivation class of the population (measured possibly by dissatisfaction with the repressor); the average connectivity; and the level of rewiring or inter-village connections, respectively.

In an Opinion-Leader network, a rough order of data importance is: the number and connectivity of elites; the correlation of elite motivations with network position; the technology of repression; the strength of repression; and the motivation class of the population. In a Hierarchy, a rough order of data importance is: the number and connectivity of elites; the correlation of elite motivations with network position; the technology of repression; the strength of repression; the motivation class of the population; and the average connectivity of the subordinates at the bottom of the hierarchy.

Of course, if repression is strong enough, no other piece of data matters. Not even an anger response can overcome a repressor who can crush all participation instantly. For both moral and practical reasons, however, this situation rarely obtains, and so the predictors specified above—all substantially qualitative in nature—are still useful in forecasting.

5 Application of the Model: The January 2005 Iraqi Legislative Elections

I conclude this essay with a real-world example that illustrates the way the model can be applied in forecasting. We open the story with the following quote written by Iraqi sociologist Faleh A Jabar shortly after the January 2005 Iraqi Legislative Elections:[3]

> Voters had expected worse. Early birds showed up before 9:00am to avoid attacks. The more audacious ventured out at what many suspected would be the most hazardous time. The bulk waited. Then, by midday, voters rightly guessed Salafi attackers had deployed all they had. The masses poured into voting stations, amazing themselves and the world.

Note the logic behind the quote—it is precisely that which motivated the model. The repressor here is a combination of the local insurgency and members of Al-Qaida in Iraq. The type of repression was both harsh and mild;[4] luckily, the model does not require one to distinguish between them. The collective activity was voting in the January 2005 Iraqi Legislative Elections and, thanks to the media-favorite purple fingers, it was a public activity, observed by others. People made decisions as to their own participation based on that of others. The risks of subsequent threats or harm implied that one had to know before

[3] `http://weekly.ahram.org.eg/2005/730/re1.htm`. Last accessed 7/2/08.

[4] Multiple suicide attacks election day are classified as "harsh," while the constant threats and the targeting of polling and electricity stations leading up to election are classified as "mild."

participating if the safety of another observed participant was endemic to the process and could be expected to hold for oneself as well, or if some special factor or connection kept that person safe. Hence, social networks played a role.

Detailed network data was certainly not available for the entire Iraqi population before the elections, but the model does not require it. Instead, we need to identify first the type of network in place, and then to specify parameters as best we can. Iraq provides a good test case for this analysis, as Saddam Hussein's brutality created a relatively clean network picture. Internal security agencies intended to crush all state opposition left society deeply disconnected. David Patel writes (2005, p. 3), "Every Iraqi today has stories about children denouncing parents, [and] neighbors settling local disputes through corrupt security officials." Consequently, "the average Iraqi was intimately connected with and confided in only a few other Iraqis" and "[f]riendship networks, therefore, overlapped considerably, often consisting of a couple of brothers and cousins. These clusters of strong friendship networks were often unconnected to one another."

This (qualitative) story matches well with a Village network possessing a low degree of inter-connectivity between villages. This is not the type of network to encourage participation, and even without repression we would have expected little turnout in this case. Since this network description well mirrors the Sunni population at the time, it is not necessary to posit a boycott or repression to explain their lack of participation; the network structure itself did not encourage it. In this context, an inferred (non-Kurdish) Sunni turnout rate of 15% is not surprising.

Shi'a, however, had an additional network overlaid atop this sparse village structure—a religious network in accordance with the dictate to emulate figures of authority (*marja-e taqlid*, effectively Ayatollah). These individuals, chosen by virtue of religious learning and other valued personal characteristics, are in many ways the opinion-leaders in Iraqi Shi'a culture. While people are free to choose which of these favored individuals they follow, they must follow one.[5] These individuals do not always supply direct influence, however; there exist deputies to intermediate. Meir Litvak writes (1998, p. 28):

> patronage networks linking the teacher and his former disciples who resided as 'ulama' in various Shi'i localities came close to the ideal type of radially connected network. In this model each member is directly linked to the central figure, i.e. the teacher, and members communicate with one another only through him.

Together, an Ayatollah and his deputies, along with their followers, make up a Hierarchy. Further, since the followers are poorly connected, as described earlier, all we do not know is the width of each level of the hierarchy. Again, note that all data used has been qualitative in nature.

To make specific predictions, consider two such hierarchies: that of Grand Ayatollah Ali Sistani, and that of Muqtada al-Sadr.[6] The structure of each's network was well-developed, Sistani's because it was inherited from his (prominent) mentor Ayatollah al-Khoei, and Sadr's because it derived from prior emulation of his (prominent) father Grand Ayatollah Muhammad Sadiq al-Sadr. Thus we can assume that the backbone of each Hierarchy is similar; for the sake of this argument we will further assume that the networks were close enough to optimal so as to produce appreciable levels of participation absent repression when the elites were motivated to encourage it.

The correlation between network position and elite interests in the two networks was not so similar, however. In Sistani's case, strong religious credentials and an equally strong hold over his network ensured Sistani's ability to dictate who were his deputies. Further, Sistani came out strongly for voting (and tacitly for voting for the UIA), making it a moral obligation. Consequently we can assume that his network was positively correlated. Sadr, in contrast, did not have the same level of religious credentials and "tremendous variation

[5] `http://www.ccc.nps.navy.mil/si/2004/may/beemanMay04.asp`. Last accessed 7/2/08.

[6] The following argument is taken from Patel (2005). This argument is valid at the time of the elections, but note that Sadr's network in particular has changed substantially since that time.

[was] observed in both rhetoric and action across Sadr offices." (Patel 2005, p. 11). Further, Sadr's message in the context of the elections was ambivalent, with some deputies acting directly against his final boycott message.[7]. Consequently, we can assume Sadr's network was uncorrelated.

This covers network factors. What about individual motivations? Here data are sparser, but, again, we do not need detailed data to make strong predictions. Given the broad gains possible for each group of Shi'ites, and a lack of data indicating either a strong emotional response to repression (beyond that captured by the normal updating dynamic) or a differential level of motivations between rank-and-file members of each Hierarchy,[8] I assume that no emotional response is present, and that both groups are either in the strong or the intermediate motivation class.[9]

Finally, we must consider details of repression. While we don't have a good measure of the exact strength of repression, we do know that no viable repression targeting either Sistani or Sadr was present. Thus we consider the technology of repression to be random/equal, and explicitly vary the strength of repression in the analysis.

Figure 2 presents the results of the analysis, detailing what our expectations about turnout levels should have been, given the information provided, all of which was available prior to the election. Participation by Sistani's followers could have been expected to have been both substantial and robust to repression. In contrast, participation by Sadr's followers (which could have amounted either to boycotting the election or to voting for his

[7]From Juan Cole (`http://www.juancole.com/2005_01_01_juanricole_archive.html`. Last accessed 7/2/08): "Sadr himself has given such mixed signals that it would be hard for [his followers in Sadr City] to follow him if they wanted to. First he said he was neutral about the elections, then more recently that he opposes them. Some of his chief lieutenants have called for a boycott (Shaikh Bahadili in Basra), while others are actually standing for election [in the National Independent Cadres and Elites party]."

[8]Accounts of Sadr City's residents had them enthusiastic to vote. (`http://www.abc.net.au/pm/content/2005/s1290550.htm`. Last accessed 7/2/08.)

[9]Both yield similar results, though I display only the latter in Figure 2.

deputies' National Independent Cadres and Elites party) could have been expected to have been both lesser and, more importantly, much less robust to repression. Repression which would have barely put a dent in Sistani's influence would have destroyed Sadr's influence.

[Figure 2 about here]

Election-day statistics bear this out.[10] Shi'ite turnout was high (almost 70%) and heavily directed toward Sistani's UIA party. Even Baghdad, location of Sadr city, turned out in sufficient numbers (48%) so that, once the non-voting Sunni population had been removed, one could say with fair assurance that no significant boycott by Shi'ites occurred. Sadr's deputies' party, meanwhile, barely outdrew the Sunni party, The Iraqis.

6 Conclusion

Qualitative and quantitative approaches, though often portrayed as disparate, may be used not only in a complimentary fashion, but explicitly within the same modeling approach. The benefit of doing so is that it enables the direct application of qualitative insights in producing quantitative forecasts. I have described a model of participation in collective actions in which social network structure and repression, both often described qualitatively, interact with individual motivations to produce aggregate outcomes. The model makes clear predictions on participation levels which may be incorporated into forecasting models, and suggests which qualitative (and quantitative) data will be most useful in making these predictions, thus guiding costly data analysis. Further, its generality allows for the easy inclusion of realistic additions like an emotional response to harsh repression. The analysis of this addition illustrates the substantial potential for backlash when even minor anger is likely. The success of the concluding application of the model to the January 2005 Iraqi Legislative Elections, using only rough, approximate, qualitative data, suggests a useful role in forecasting for the methodology introduced here.

[10] `http://www.epic-usa.org/Portals/1/UpdatedElectionResults.pdf`. Last accessed 7/11/07.

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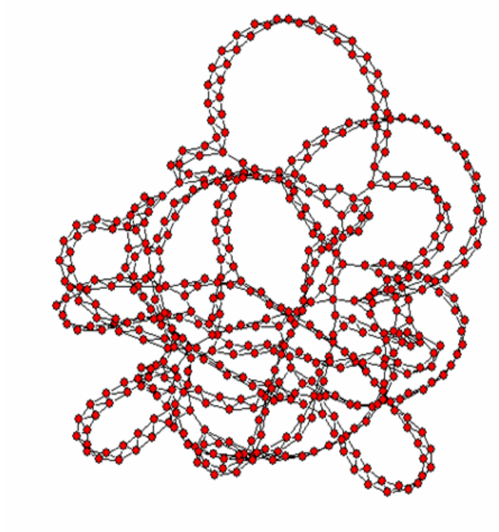
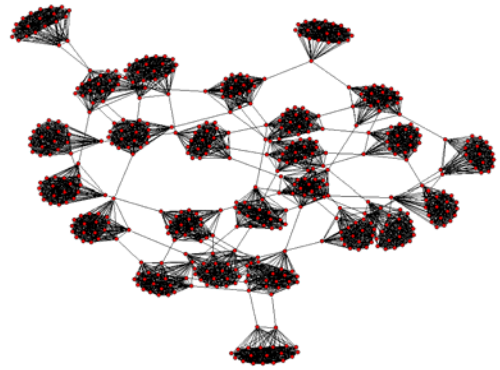
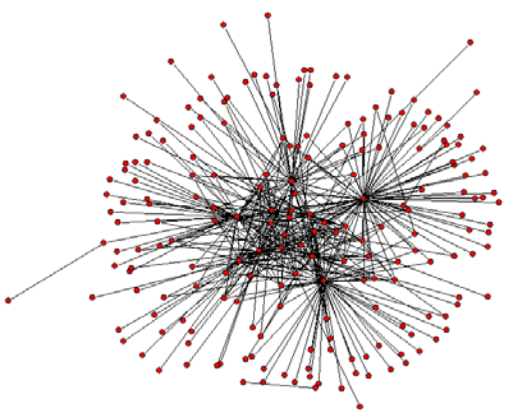


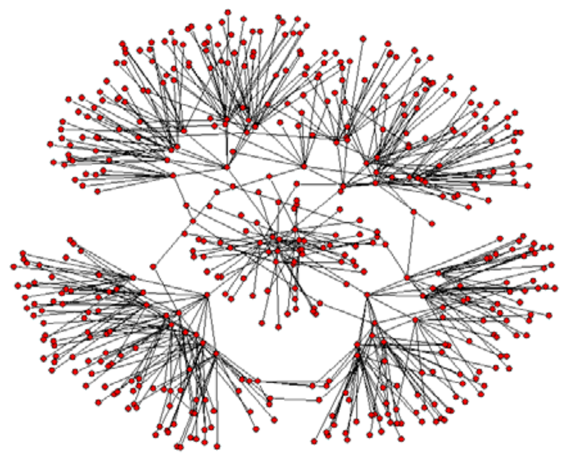
(a) Small-World Network



(b) Village (Clique) Network



(c) Opinion-Leader Network



(d) Hierarchical Network

Figure 1: Network Typology
(Figure 1 in Siegel 2008c)

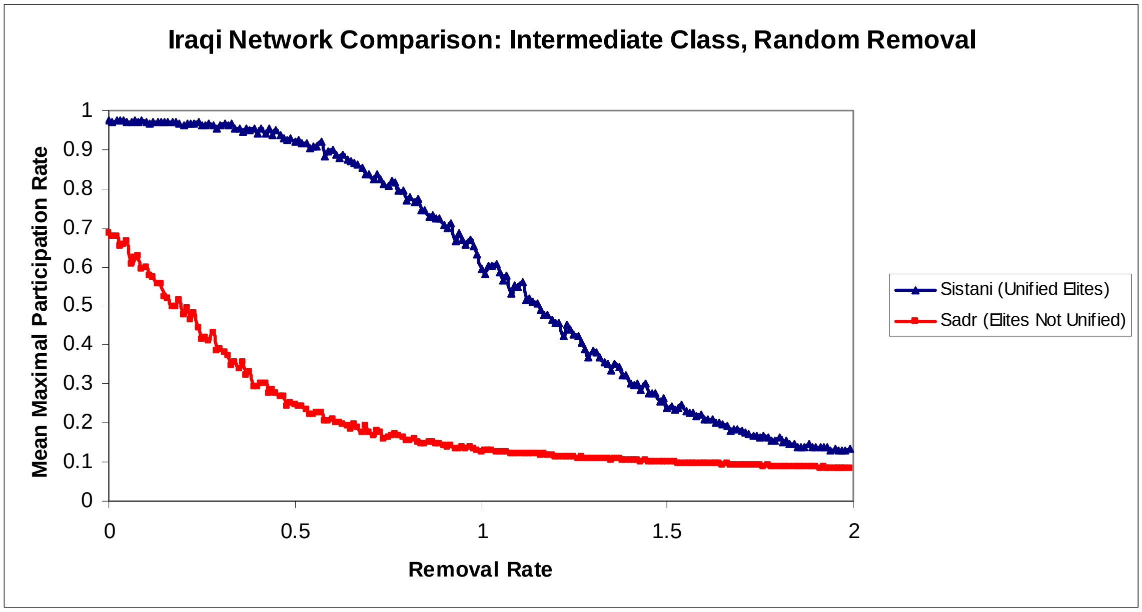


Figure 2: Turnout within Iraqi Social Subgroups
(Figure 6 in Siegel 2008c)