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their new forms of politics through struggle. In the process, they forged new relationships to national centres of power.

NOTES

1. Manchester masters contested, for example, any rights of free labourers to form unions and to strike. In common with their fellows elsewhere in Britain and North America, they advocated individual-to-individual contracts as the basis of employment (see Steinfeld 2001).
2. For technical details and closely related research, see Munger (1979, 1981*a,b*); Schweitzer (1979); Schweitzer and Simmons (1981); Tilly and Schweitzer (1982); Steinberg (1999*a,b*).
3. A full 38% of the catalogue's 6884 contentious gatherings from 1828 to 1834 occurred in Middlesex, a proportion inflated by London-centred sources, yet still indicative of London's primordial place in national politics.
4. The category Constable brings together different varieties of regularly established local police; Middlesex attacks of crowds on constables in 1828-31 consisted largely of resistance to Robert Peel's New Police.
5. Many workers participated in formations here classified as Crowds, but we persist in using the names our sources assigned to formations rather than second-guessing the sources. We treat the assertion and attribution of public names as consequential political acts, expressions of political identities (see Jenson 1993; Tilly 1998*a,b*).

Networks, Diffusion, and Cycles of Collective Action

Pamela E. Oliver and Daniel J. Myers

This chapter shows how different 'network' arguments about how protest spreads imply quite different underlying mechanisms that in turn produce different diffusion processes. There is considerable ambiguity about the relationships among networks, diffusion, and action cycles and the way these can be identified in empirical data. We thus both seek to unpack the 'network' concept into different kinds of processes, and then show how these different network processes affect the diffusion processes we are studying. We sketch out some formal models to capture some of these distinctions.

This chapter extends recent work (Oliver and Myers forthcoming) that develops diffusion models of protest cycles, and focuses on discussing links between network concepts and diffusion concepts in understanding protest cycles. We conceive of social movements as diffuse action fields in which actions affect other actions and the action repertoires of the different actors coevolve through time and through interaction with each other. Movement activists and regimes engage in strategic interactions, each responding to the actions of the other. Different organizations within a movement respond to the actions of others, as successful tactical innovations and movement frames diffuse to new organizations. News media cover or fail to cover particular protests, and thus encourage or discourage future protests. Each of these processes affects the others, in a complex, multifaceted set of interactions. Over time, the action set of each actor evolves in response to the actions of the others and, thus, the whole field is one large coevolving environment in which the characteristics and actions of any actor is constrained and influenced by the characteristics and actions of all other actors in the environment.

One central concern about understanding diffusion and networks in protest waves is that we do not actually have straightforward data about the underlying social networks or mobilization processes. Protest event data usually just contain records of the timing and location of events along with some (often incomplete) information about the participants in the event, their forms of action, and their stated claims or other rhetoric (McAdam 1982; Olzak 1992; Kriesi *et al.* 1995;

Tilly 1995a-d). Rarely, if ever, will the data contain information on the social relationships or communication processes that were involved in organizing and mobilizing that event. Lacking this kind of data, we want to know whether different patterns of social organization will give rise to different patterns in protest event data, and how what we already know about how protests get organized might influence our analysis of protest event data.

After a brief review of the interplay between diffusion concepts and network effects, we develop some important distinctions among different processes often lumped together as 'network effects'. We then develop preliminary models for three empirically important network processes in movements: the flow of information, the flow of influence, and the construction of joint action. All of these models are built on a core modelling 'engine' which we explain. Our models of information flow are most complex, as we stress on the importance of two kinds of networks: broadcast networks, and node-to-node networks. Finally, we show how the models we are constructing are capable of representing the strength of network ties, not just their presence or absence, and of permitting network ties themselves to evolve and be dependent on other processes.

DISAGGREGATING PROTEST WAVES TO GET AT MECHANISMS OF DIFFUSION

The ideas of cycles of protest, diffusion, and network effects are often discussed without making clear distinctions among them. Diffusion is the process whereby past events make future events more likely. In 'classic' diffusion models, there is a transmission of some innovation between people, and it is impossible to have any diffusion without some kind of contact or network tie between individuals. But this equation between networks and diffusion arises because of the assumption of permanent and irreversible 'adoption' in classic diffusion models, an assumption that is inappropriate for the diffusion of collective action (Myers and Oliver 2000; Oliver and Myers forthcoming). Individuals and groups or populations can and do protest or riot on multiple occasions, and the performance of an action by an individual or group often makes a repetition of that action more likely. One could insist on using the word 'diffusion' only when demonstrably *different* people are protesting or rioting, but this definition is problematic for at least two reasons. First, empirical data on protest events almost never contain sufficient detail to distinguish clearly between new actors and repeaters. If repeated events of the same type occur in the same geographic area (e.g. riots), the rioters are quite likely a mixture of previous and new participants. Available data generally provide only numerical counts of numbers of participants and perhaps the names of a few key leaders. They would never provide sufficient detail to track exactly how many new people are entering a form of action and where they came from. Data of that level of detail are only available in detailed case studies of well-structured events,

not in data across a large number of events or more amorphous events. The second reason is theoretical. The reinforcement process, whereby an actor's own actions and its consequences influence that actor's future actions, is theoretically almost identical to a diffusion process, whereby one actor's actions and their consequences influence other actors' future actions. Most of the same processes and factors are involved in the repetition of actions by the same actors and the adoption of actions by new actors. Either way, the 'diffusion' effects of an action are mediated by whether the action is repressed, whether it gets media coverage, whether it affects policy, and so forth. The only difference is that actors presumably know about their own actions and its immediate consequences, while others cannot be affected by a group's actions unless they know about them. Only the 'network processes' themselves are different between self-reinforcement and diffusion to other actors. Because protest is a repeatable, reversible action, diffusion models of protest must focus on the spread of actions, not the spread of actors (Myers 1996, 1997, 2001).

An additional distinction needs to be made between diffusion and cycles. Diffusion processes tend to generate waves or cycles of events, but not all waves of events arise from diffusion processes. Waves of protest can also arise from rhythms and from common responses to external events. A major event such as a disaster or an act of war may trigger independent responses in many locales. Rhythms are what the term 'cycle' most often means in other contexts, periodic rhythms of physical or social life that structure time. The ordinary rhythms of life structure protest just as they structure any other activity, so that protest generally occurs when people are awake and around the constraints of work, school, and political schedules. Beyond these quotidian rhythms are the rhythms of protest itself. There is a recovery or regrouping interval after most actions before a group is ready to act again. At a minimum, people must eat and sleep. Big events such as marches on Washington necessarily require relatively long intervals between them for organizing the logistics. Ritualized protests are often held at regular intervals. The presence of rhythms and external shocks does not, however, mean that diffusion processes are absent. Empirical research has often demonstrated diffusion processes in the spread of information about a major event (Shibutani 1966) and Myers (1996) found clear evidence of diffusion effects within the 'long hot summers' of the 1960s riots and after the assassination of Martin Luther King, Jr.

Finally, we need to recognize the importance of diffusion processes nested within other diffusion processes. Long multi-year protest waves are the accumulation of smaller protest waves arising from particular campaigns and the smaller-scale diffusion processes that occur within them. McAdam (1983) showed that the bursts of activity in the civil rights movement followed tactical innovations. The diffusion of collective action across national boundaries also shows evidence of waves within waves, a general wave of mobilization that transcended national boundaries, and nation-specific waves (Kriesi *et al.* 1995). Similarly, a broad social movement is always made up of smaller campaigns in particular localities or involving particular issues. These smaller campaigns usually arise either from

a burst of repeated actions by one group or in one locality, or the diffusion of a particular movement issue, frame, or tactic between groups or localities. The term 'network' is often used in both cases, but in the former, it tends to refer empirically to the existing social and political ties within a community that permit a set of people to act in concert, while in the latter, it refers empirically to communication channels through which information is spread between different local networks.

Specifying these nested diffusion processes is theoretically critical, as it is clear that big protest waves are built from smaller campaigns that have their own logics, while influencing each other in the larger wave. These campaigns implicate network processes. A wide variety of network forms are involved in campaigns. The most basic is a series of events around the same issue involving the same people in a single locale. If no new people are brought in, this is a simple case of repetitive action by the same actors, a pure 'reinforcement model' process, in which the consequences of earlier actions influence the rate of subsequent actions by these same people, but there is no interpersonal diffusion process involved. However, if these events become larger over time, then we would say that some kind of between-person diffusion has occurred. Of course, even if the number of participants stays constant, there could well have been turnover in the participants. We have developed an approach that is capable of being modified to capture these waves within waves, but we will not be developing such modifications in the scope of this chapter.

SPECIFYING NETWORK EFFECTS

As we dig into the mechanisms of diffusion, it is important to specify the very different kinds of 'network' relations that are involved in different kinds of diffusion. A very wide range of specific phenomena has been lumped together under the rubric of 'network effects' or 'social ties'. If we are going to understand the role of network effects in diffusion, we need to unpack the concept. There are at least three distinct (although related) processes that occur through network ties: communication, influence, and joint action. The relation among these three processes is somewhat hierarchical. A communication tie provides a basis for disseminating information that something has occurred. An influence tie provides a basis for one actor to affect the opinions or actions of another actor; influence requires communication but involves additional social processes beyond mere communication. Joint action may be considered an extreme case of influence, in which initially separate actors come to make joint decisions and act in concert. Influence requires communication, but not all communication entails influence. Joint action requires both communication and influence. It is important to recognize the concept of joint action because empirically researchers may not be able to distinguish multiple acts from concerted joint actions. Many protest event series exhibit huge 'spikes' in which a very big action 'suddenly' occurs or many different actors

'suddenly' engage in the same kind of action at the same time, and these spikes cannot possibly be modelled with standard diffusion models. However, we will show that a model of 'hidden organizing' outside the view of the data collectors can quite readily model such spikes. This chapter will provide detailed discussion of some of the issues involved in each of these three kinds of processes, and outline some approaches to formal modelling of each. In each case, we will give special attention to the question of how the process might be reflected in observed empirical data on protests. However, before moving to these three sections, it is important to consider some other distinctions and dimensions among network processes.

Dimensions of Proximity or Connection

Information and influence flow through social networks. But there are different ways in which actors can be 'connected'. There are at least three dimensions to network proximity that are relevant to the study of social movements: spatial, organizational, and other social. These may be expected to play different roles in protest and social movements.

Spatial/social: Movement actions are space-bound: people often congregate in the same place at the same time to act in concert. Riots and 'spontaneous' protests most often diffuse spatially: individuals become aware of the riot or protest because they are near it. However, there is no 'pure' space, and space itself is always socially organized. Neighbourhoods are usually segregated by class, ethnicity, or race, and are often segregated by political orientation, so that different 'kinds' of people are found in different kinds of public spaces. Social etiquette rules about class or ethnicity or gender, as well as language differences may create communication barriers that are the practical equivalent of great distances. A wide variety of routine social structures can create network ties. For example, Oberschall (1989) shows that early sit-ins in North Carolina after the first Greensboro sit-in diffused as black colleges played basketball games against each other. The mass media also have a decided spatial component. Mass media have clear geographic and linguistic catchments. Although there is 'national' news, which is usually broadly available, that 'national' news always has a bias toward events occurring near the site of publication or broadcast (Mueller 1997; Myers and Caniglia 2000). Myers (2000a) found for example that although large riots diffused nationally, presumably by way of national news coverage, smaller riots diffused within the boundaries of television broadcast ranges. Prior to electronic communication, collective disturbances diffused along transportation routes and took longer to diffuse (Rudé 1964; Hobsbawm and Rudé 1968; Charlesworth 1979; Myers 2000b).

Movement/organizational: Even within spaces, the participants in particular actions usually have additional ties to each other beyond mere proximity. Between spaces, actions may be coordinated through political/movement ties between movement organizations. Local chapters of the same national organization would

be expected to have high political ties. Different organizations with similar political/movement goals would tend to have positive ties, although they would also have some elements of competition between them. There obviously has to be some actual mechanism of communication between spatially dispersed elements of the same organization, such as organization newsletters, or telephone calls or e-mail among members. But these actual mechanisms of communication are most often invisible to the protest events researcher, who merely notes that events were organized in five different cities by local chapters of the same organization.

Relational/social: Movement organizations may have ties to nonmembers through their members' 'other' social relationships and memberships. These other ties include kinship and friendship, attendance at the same school, membership in the same recreational club or religious congregation, employment at the same workplace, or membership in some secondary association that has no direct relation to the movement. In many cases, these 'other' ties become the basis for recruitment into a movement organization or its actions, as well as for increased support for the movement's opinions (Ohlemacher 1996). Movements whose members have social connections to the larger society through many different social ties are likely to be better able to mobilize support than those that lack such ties. However, as we consider influence models below, it will become apparent that these external ties can have both 'positive' and 'negative' effects on movement mobilization.

In the work that follows, we will not be able to explore the effects of these different kinds of proximity, but have set up general schemes that should be able to capture the structures that the different kinds of relations would imply.

Sizes of Networks and Numbers of Actors

If we are looking at the total numbers of participants in collective action, we often conceive of the network diffusion as reaching down to individual people. But it is well established that most people enter protest movements as parts of relatively cohesive groups, and that whole groups make decisions together about whether to participate in particular actions. This means that it is often most reasonable to think of the 'actors' as groups, not individuals. But when this is so, we will then also want to be able to consider the 'size' of each of these actors, which is the number of people it mobilizes. Although capturing this complexity in its totality is beyond the scope of this chapter, we will discuss how our models can be modified to deal with group size issues.

Network Structures and Collective Action

Network theorists have devoted a fair amount of attention to measuring and categorizing qualitative differences in network structures, as well as quantifying the position of any one actor in a qualitatively-defined network (Knoke and Kuklinski 1982; Wasserman and Faust 1995). The same number of ties in a network has

different effects depending upon their distribution, so that star-like structures in which one central person has links to other actors who have no links to each other are, for example, quite different from circles in which each actor has exactly two ties to other actors and all actors are connected. Similarly, cliques can be defined within larger networks. Unless one wants to stay at the level of the case study, however, it is difficult to use these concepts in the study of the diffusion of collective action across a large and complex population. Instead we need to have summary measures of a movement group's network ties. In this chapter, we will give some simple examples of how structural effects can be incorporated, but will not pursue this dimension in any depth.

The Basic Model

In this model, each actor has a probability p_k of acting at each time period. The number of people who actually act at each time period varies stochastically around the mean p_k , where N is the number of actors. Each actor's p_k may change across time as a function of the past actions of themselves or others. Elsewhere (Oliver and Myers 2001), we explore the question of the form of the underlying model for the diffusion of collective action. Plausible models for mobilization cycles that go up and down are not straightforward. Collective action always declines, and the question is whether this should be specified as arising from a natural tendency within actors that occurs regardless of outside influences, or whether it is a process of outside factors such as repression. Addressing these questions is beyond the scope of this chapter. Here, we will simplify the individual decision model and focus only on the upswing or accelerative phase (Oliver *et al.* 1985) of a protest cycle, where the feedback effect from others' actions is entirely positive. This underlying model does not produce event distributions that look like real protest cycles, which always come down again, but it will give us a basis for evaluating network effects.

Models in this chapter are developed using the Stella simulation programme from High Performance Systems, Inc.¹ The program has a graphical interface to represent differential equations. An appealing feature of Stella is that it generates a list of the equations implied by the graphical connections.² The programme can handle one- or two-dimensional arrays with sizes constrained only by the capacity of the computer. The acting probability and other characteristics of each actor are captured by one-dimensional arrays, while network links and inter-actor influences are captured by two-dimensional arrays. The programme accepts hot links to inputs and outputs, so it is possible to set up a who-to-whom matrix of network linkages in a spreadsheet that can be read by the programme. All of the models in this chapter could readily be programmed in some other way, but we have found Stella to be a very useful development tool as it hugely reduces the ratio of programming to thinking in the process of model development.

For analysis, we have set up several fixed network configurations as well as a random network controlled by a random number generator and can choose between network configurations with a user-controlled switch. For this chapter, the arrays are fixed at size 10, which is large enough to show some of the effects of random variations, but small enough to be manageable in a development phase. Substantively, an N this small could be understood as actions in different cities or by different groups in a movement. Representing a city of a million inhabitants as a matrix would tax our computer systems and be unlikely to be informative. The more reasonable way to proceed for representing large populations is to conceive them as subgroups with varying sizes, where the group's size is another variable in the model. Such an extension is beyond the scope of this chapter.

Baseline Model with No Communication

For baseline comparisons, we begin with a group of N actors who have no awareness of each other. Each group may randomly emit an action. We tally the plot of all actions. Initially, we have all actors with the same low probability. Because actors do not influence each other, this probability does not change. Because of its random component, each iteration of this model produces a slightly different outcome plot. Figure 8.1 shows plots of the baseline model for a system of 10 actors. Even though there is a constant probability of action, because it is a random model, there are varying numbers of actors at any given time, and the frequency plot exhibits a spiky sawtooth form with waves typical of protest event plots. The cumulative count, however, shows a different story: in a purely random model with a constant probability, the total rises essentially linearly with time. We will be using the total counts across five periods in subsequent models because they damp out some of the random variations of one-period counts. These five-period counts are roughly equivalent to the kinds of patterns you would get if you aggregate daily event counts to weeks, or weekly counts to months. This is shown in the bottom panel of Fig. 8.1. Note that this purely random process generates cycles and even small diffusion-like S-curves in the cumulative count.

To model information diffusion effects, we have to provide some specification of how one actor's probability of acting is affected by the actions of others. Here, we will assume that the tendency to repeat this action is a function of how many others are doing it. Although verbal theorists can relax into vague discussions of positive effects, and even quantitative empirical researchers can just specify a regression coefficient on the lag of prior action, when we write a mathematical model, we have to say exactly how we think people respond to others' actions, and this is not at all clear from empirical research. Shall we assume that others' actions always increase our own probabilities, no matter what? And, if so, in what functional form? Linearly in a power relationship? With rising and then falling marginal returns? Or should we assume that actors respond not to the absolute level of others' actions, but to whether it is increasing or not? The former assumption, that

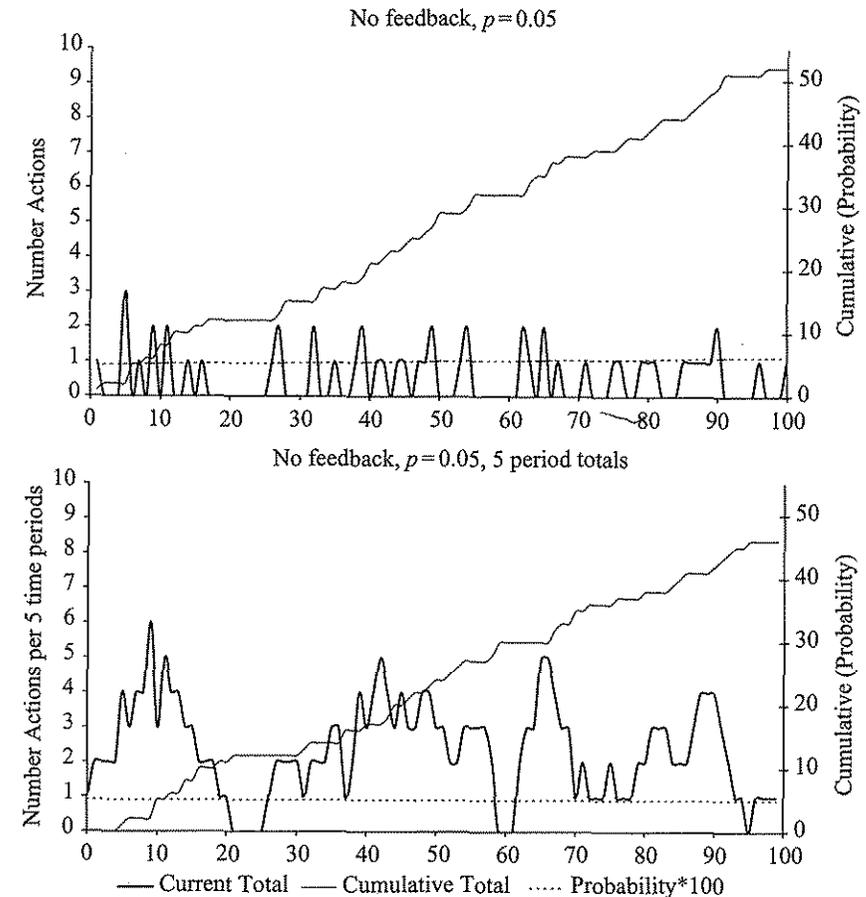


FIG. 8.1. Random processes produce apparent cycles. Top panel is number of events per time period, bottom panel is 5-period moving average (used in other models)

actors respond to the level of others' actions, would arise if there is an accelerating production function or if actors' behaviour is principally determined by influence or imitation processes. However, in the long run, such models produce unanimous action in which everyone is protesting with certainty forever, something that never happens. The latter assumption, that actors respond positively to the increases in others' actions, and negatively to decreases, would arise from an S-shaped production function that first rises then falls, which seems consistent with an underlying process in which initial action obtains benefits, but there are declining marginal returns to action after it has been at a given level for some time. Our initial work with this second model indicates that, while interesting, it produces volatile results that are very sensitive to initial conditions, which makes

it unsuitable as a platform for investigating network effects.³ For this reason, in this chapter we use models employing the assumption that actors respond to the level of prior action.

The model we use assumes that actors respond to the total level of others' action in a diffusion-like fashion. The basic elements of this model are: p_t = probability of acting at time t ; n = number of actors—a random process determines whether each actor actually acts on a given trial; $r_{k(t)}$ = recent total number of actions across all actors within the past k trials, at time t ; and k = the number of trials considered.

The algorithm for changing the probability of action as a function of past actions is

$$p_t = p_{t-1}(1 + w_1(kn - r_{t-1})(r_{t-1}/n)),$$

where w_1 is a weighting coefficient on the feedback term. Actors simply respond to the total of others' actions, which means that 'full information' is assumed so that there are no network effects. This simple model produces an S-shaped growth in the probability until a probability of 1.0 is reached, when it stabilizes with everyone acting. The weighting factor determines how quickly this happens; if the weighting factor is small enough relative to the time span of the model, the probabilities may remain essentially unchanged for the duration of the model. The distribution of current action exhibits random variation around an S-shaped rise until unanimous action is reached; unanimous action is an absorbing state. The cumulative distribution is S-shaped until unanimity is reached, and thenceforth rises linearly. In Fig. 8.2 we show examples of the effect of feedback from others' actions in this algorithm. The plot of cumulative protests clearly shows the S-shaped growth pattern diagnostic of a diffusion process in the first phase, until unanimous action is achieved, and then it becomes a linear curve like any other constant-probability model. We have parameterized the baseline model so that it has a low level of action if there is no feedback and a relatively rapid rise toward unanimity if there is 100 per cent feedback through all possible network ties. This will give us a backdrop against which to consider the effects of various network constructs. The upper panel shows the current action rate as well as the cumulative event count and the probability for a homogeneous group in which everyone's initial probability is 5 per cent and the feedback weight is 0.005. The lower panel provides two variants of the initial probability of action. In the homogeneous case, all actors begin with a 5 per cent probability of acting; in the heterogeneous case, actor 1 has a 40 per cent chance of acting, while the other nine actors each have a 1 per cent chance. The average probability is about the same in the two cases. The lower panel compares the homogeneous and heterogeneous cases for the full feedback and zero feedback models. When there is no feedback, the heterogeneous group has slightly more action, due to the one high-probability actor. When there is full feedback, the heterogeneous group reaches unanimous action a little more slowly than the homogeneous group.

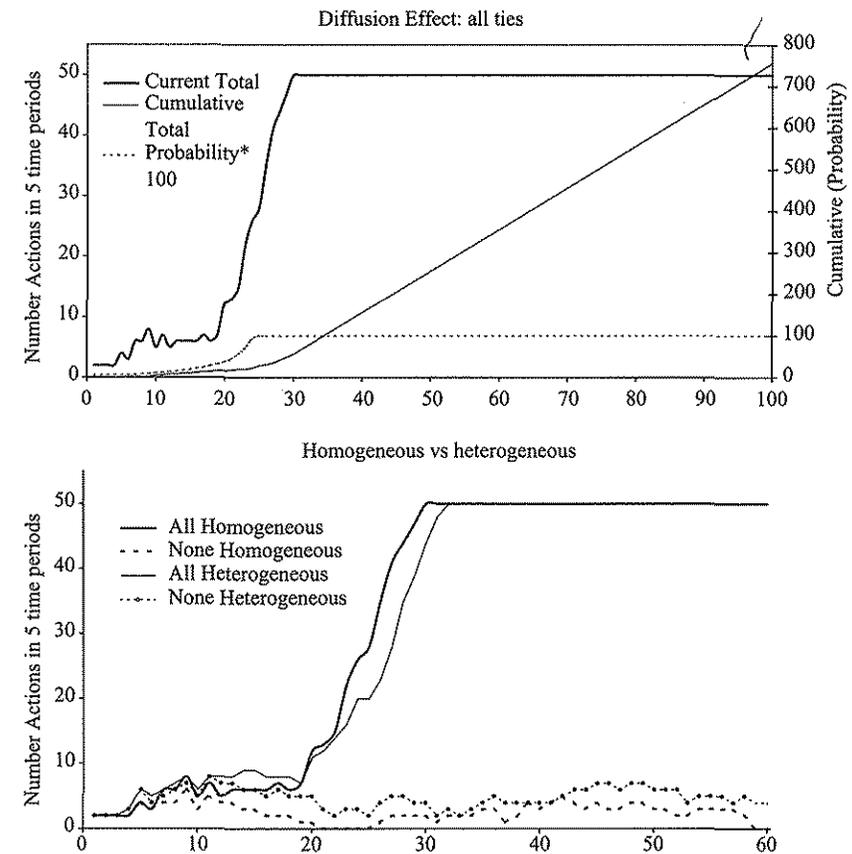


FIG. 8.2. Diffusion in networks with all ties. Top panel shows diffusion in a homogeneous group (all have $p_0 = .05$) with all ties present. Bottom pane contrasts all ties with no ties for homogeneous and heterogeneous groups (one actor has $p_0 = .4$, all others $p_0 = .01$). Feedback weight is .005.

INFORMATION FLOWS

When ideas or actions are diffusing between actors, the 'thing' that is transmitted is information. Broadly speaking, there are two types of networks through which information may flow, node-to-node and broadcast. Node-to-node paths are the kind usually implied by the use of the term 'network'. Actor A communicates with actor B, who communicates with actor C, and so forth. Many network analysts examine the efficiency of communication across node-to-node networks with different properties, such as overall density of ties, the tendency to cliquing, or the extent to which communication is channelled through a few key actors. By contrast, a broadcast network involves a single communication source that is directly

received by a very large number of people. In our era, this is the mass media. But previous eras also had broadcast communication on a smaller scale, in the form of town criers and travelling messengers.

Although hard-core network analysis focuses on the effects of network structure and chains of indirect ties (Knoke and Kuklinski 1982; Wasserman and Faust 1995), any 'network' analysis of communication in protest waves in the modern era is sterile if it does not treat the mass media. Large numbers of people who otherwise have no connection at all can be 'connected' by their responses to a common news or entertainment source. When the actions of one group are covered in the mass media, communication effects can spread as far as the media are broadcast, without prior connection between the actors. Myers (1996, 2000a) shows that large riots that received national television coverage increased riot propensities nationally, while smaller riots increased riot propensities within their local television catchment areas. Protest event data based on newspapers, especially if it is drawn from a single 'national' news source, is, by definition, data on the events that can be assumed to have been communicated to a broad population.

But, of course, the news media are not unbiased samplers of events. They are rather intentional actors who select news stories for reasonably well-defined reasons, and it is well established that the size and disruptiveness of an event increase its probabilities of news coverage, as does the proximity of the event to the news organization (Snyder and Kelly 1977; McCarthy *et al.* 1996; Mueller 1997; Myers and Caniglia 2000). More recent research also suggests that news media cover some kinds of issues much more than others (Oliver and Myers 1999; Oliver and Maney 2000). The media themselves are subject to diffusion processes, both within one news organization, and between them. If a news organization has already published several stories about a particular issue, it is less likely to publish another because it is not 'news,' although there is some evidence that for at least some issues, the recent publication of one article about an issue will raise the probability of another article about the same issue, as the news organization follows the 'story'. Between news organizations, once one outlet picks up a story, other outlets may pick it up. If enough outlets begin to cover the story, it becomes news, and the media will begin actively seeking more stories on the same theme. The result is the 'media attention cycle' which has been shown to under-represent movements at the beginnings and ends of their cycles, and over-represent them in the middle, when the issue is 'hot' (Downs 1972; Cancian and Ross 1981; McCarthy *et al.* 1996).

Even though the mass media play a central role in our era, node-to-node networks are also important. Social ties between groups increase and deepen information flows beyond the information presented in the mass media, as posited in the classic 'two step' model for media influence on attitudes. Social influence appears to flow principally through social connections, not the mass media, so that we expect information coming only through news sources to be much less effective in changing opinions and orienting people toward action than information coming through social ties.

In the real world, patterns of diffusion and the ways diffusion uses different networks are messy, to say the least. In fact, the different kinds of networks patterns not only operate at the same time, but also are affected by one another. Recently, a number of scholars studying media coverage of protest and demonstrations have noted that larger events are more likely to get media coverage—and more of it (Snyder and Kelly 1977; McCarthy *et al.* 1996; Mueller 1997; Oliver and Myers 1999; Myers and Caniglia 2000; Oliver and Maney 2000). This means that the larger a protest group's local network is and the stronger the ties in that network, the larger its events will be and the more press coverage it will receive.

When the press covers a protest event, the protest issue and tactic are projected to other potential actors thereby invoking a completely different kind of network. In this way, recruitment through personal networks can piggyback on media coverage. Even if activists in one city have no direct communicative ties with activists in a second, they may be inspired to invoke their local network to produce an imitative event once they hear about the first event through the mass media. Thus the media operates directly through its distribution network to mobilize additional individuals to join existing protest groups and it can also invoke networks indirectly by mobilizing a node in a different activist network that will activate its local network.

Other carriers of diffusing protest also interact with local networks and the media to reinforce and extend their influence. For example, some protest has been tied to travelling activists who give speeches or engage in direct attempts to organize. These activists do not just wander aimlessly, but select targets based partially on the likelihood that their efforts will be successful—as indicated by some level of local organization which has the network ties to support the protest activity. Indeed, these activists may even be called upon by existing organization to come and help rally the troops. Furthermore, media coverage of the speeches and meetings helps to draw new recruits into the fold of potential activists and the ensuing actions give the media more to report.

The messages delivered to individuals by their personal contacts and by the media can also reinforce each other during the critical time when the individual is presented with an opportunity to decide whether or not to act (Oliver 1989). If, when approached by a friend or colleague and asked to act in support of civil rights, and the recruit has recently been watching the news about church burnings, that recruit may be more likely to respond to the personal network. The importance of the cycles of influence among distinct kinds of networks cannot be ignored.

When information is not carried by the mass media, node-to-node network ties determine the targets of action, flows of resources, and flows of information. Spatial, organizational, or relational ties between actors may permit them to know about information not carried in the mass media. Chains of direct ties can indirectly link actors with others who are quite distant from them and lead to the widespread diffusion of information. When indirect ties are involved, it is possible to

track the diffusion over time through successive circles of influence or along well-defined physical paths. Crowd actions in the past have diffused across time from a point of origin along major transportation routes (e.g. Rudé 1964: 25; Shibutani 1966: 103–6). Individuals received communication about developing riots (Singer 1968) and sit-in campaigns (Morris 1984) by direct communication from prior acquaintances. Announcements at church services spread the word about the Montgomery bus boycott (Morris 1984). Activists encounter new ideologies and tactics at conferences with other activists (Rothman and Oliver 1999). Such effects are especially noticeable in prior centuries (Charlesworth 1979), or in the earliest phases of more recent movements. Once action has begun and receives mass media coverage, it becomes difficult to empirically assess the basis of communication and influence flows without directly asking each actor involved, and even when asked, actors may have been subject to multiple sources of relatively redundant information.

Modelling Network Ties with No Media Coverage

Suppose we have a taboo issue that the news media refuse to cover. Or, perhaps, instead of being 'taboo,' it is one of those positive and uplifting kinds of action which lack news value because it is not conflict-oriented and not linked to institutional politics (Oliver and Myers 1999; Oliver and Maney 2000). To add network effects to the baseline model we create a who-to-whom network matrix with entries that are zeroes or ones. A matrix with all 1's is the 'everyone affects everyone' model and produces the same results as a model in which people's actions are affected by totals. Conversely, a matrix with all 0's produces the same result as the independent probabilities model. Because the underlying model is a growth model, where there is no decline, if actors are influenced by others' actions (or their own) there is a gradual increase in the probability of action and, thus, in the average level of total action, but the rate at which the action increases is a function of the density of communication. Between the 'full information' model and the 'no information' model lay the models in which there are some connections between actors. Theoretically, it is important to specify whether the diagonals are 1s or 0s, that is, whether people increase their action as a function of their own actions as well as of others' actions, but exploring these subtleties is beyond the scope of this chapter.⁴

This model can be used to assess the effects of varying network structures. Because it is stochastic, even for exactly the same determinate who-to-whom relationship matrix, there will be different results on each iteration of the model, depending on random fluctuations in exactly who acts when. We may use Stella's ability to use a seed for the random number generator to fix this process and compare network structures. Figure 8.3 compares one random and three fixed structures including a 'star' network in which all ties are through actor, a cliqued network in which all ties are within cliques (1, 2, 3 vs. 4, 5, 6 vs. 7, 8, 9, 10), and a bridged cliqued network in which there is an additional tie between 3 and 4, and

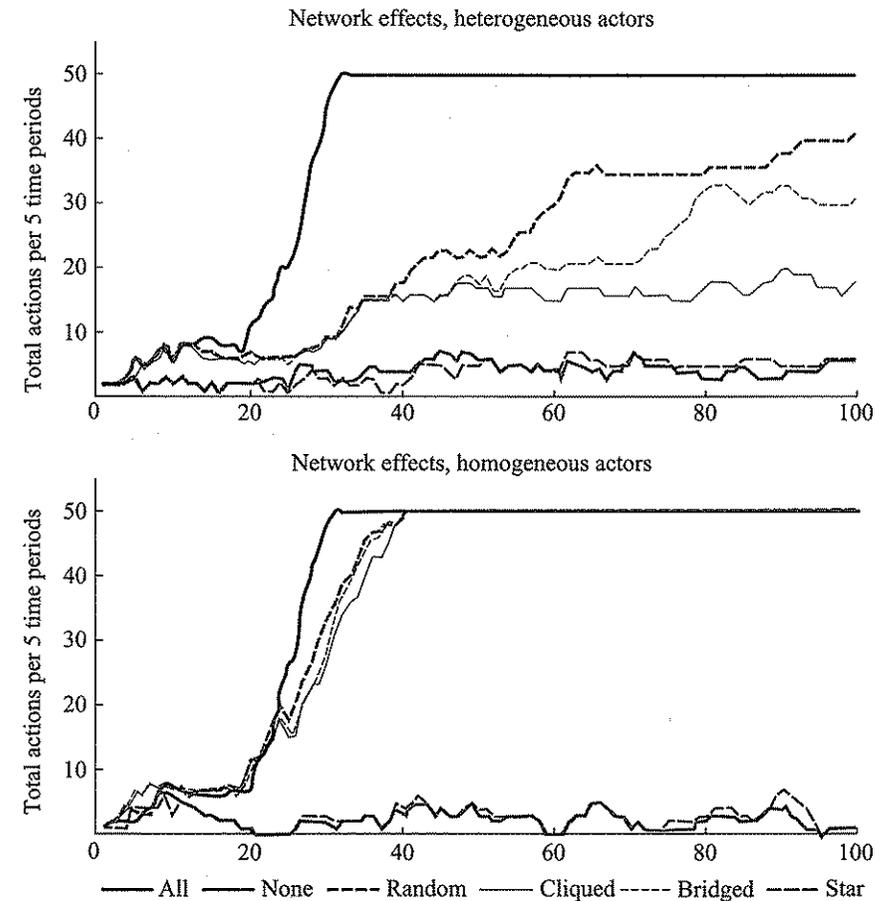


FIG. 8.3. Comparison of different patterns of network ties in the diffusion of action for heterogeneous and homogeneous groups

between 6 and 7. In this model, different random networks vary widely in their results, and the variability of results due to network ties is even greater when the initial probability distribution is heterogeneous. The particular random network in this figure is slightly more effective than the bridged clique network, which in turn is slightly more effective than the fully cliqued network. The 'star' network in this example fares little better than no feedback at all: this arises because the non-stars only have information about one actor's actions and so the total level of action is too small to lead to much increase through feedback. In an influence model, shown later, a star can have a much bigger impact on action.

This approach can be readily generalized to much larger network matrices (e.g. 100×100), but these are quite difficult to analyse without prior theory of what

kinds of structures are relevant or interesting. Obviously, the approach of using a full matrix of who-to-whom ties becomes computationally impossible with very large groups such as the tens or hundreds of thousands in city populations, and seems most appropriate for modelling the relationships between groups.

Modelling Protest and the Media

Protesters generally seek news coverage as the mechanism for having influence on a wider public and the authorities. Protests that receive no news coverage are often construed as failures. Protests that receive news coverage are likely to be invigorated, and activists are likely to prolong their activism and emit more total protests if they have received news coverage. But, of course, the news media do not cover all protests that occur, and their coverage is dependent on the amount of protest. There are 'media attention cycles,' which are diffusion cycles: news media tend to ignore a protest campaign in its small initial phases and then, when they do begin to cover it, there is a flurry of coverage for a while until it becomes 'old news,' and then coverage dies down again.

Adding media effects into a model requires specifying how the media work. This is a complex problem, which will need to be the subject of a separate analysis. We need to consider both how the media affect protest, and how protest affects the media. In this chapter, we will assume that the media are simply a channel of communication, so news coverage of events affects protest by conveying to actors information about the protest rates of others. This means that we will assume that media coverage acts just like full feedback or network communication, in terms of the algorithm for the effect of others' actions on an actor's probability of acting. In terms of the relation between protest and the probability that the protest receives news coverage, there is some information from recent empirical work. We know that there are issue attention cycles that may be functions of factors exogenous to protest, or may be set off by protest; an issue attention cycle raises the probability that an event will be covered. In addition, we know that the probability of an event being covered increases with its size, and recent large events may draw a higher rate of coverage to immediately subsequent events. There are also 'news hole' effects, so that there is a limit on the amount of action that can be reported on one day. Myers and Caniglia (2000) found, for example, that the *New York Times* under-reported riots at the peak of a riot cycle: even though they reported that there was a lot of rioting going on, any particular riot was less likely to be mentioned when there were many riots happening.

In this chapter, we cannot provide a full analysis, but illustrate a possible approach to such a problem by showing the effects of several kinds of media factors separately. We begin by showing the effect of a flat percentage of news coverage on the rate of 'adoption' of action compared to full information. Figure 8.4 shows the rate of action diffusion with news coverage at a constant 50 and 20 per cent probability as compared with the full information model (equivalent to

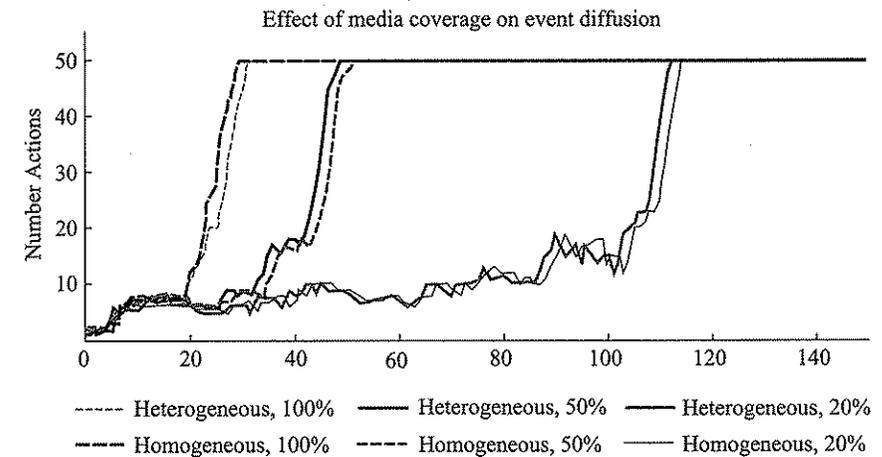


FIG. 8.4. Media coverage as flat percentage provides communication, which promotes event diffusion. There is little difference between heterogeneous and homogeneous groups.

100 per cent probability of news coverage). In this initial model, the specification is that the news media has a single probability of news coverage. If it 'covers' action at all, it covers all the action that is occurring on that round. A more detailed specification would say that the media could be differentially sensitive to different actors, so that actors could have different probabilities of coverage or that different proportions of those acting on a round could be covered. That would yield different patterns of results.

Figure 8.5 shows how the diffusion of action is affected when the probability of news coverage is not a flat percentage, but increases with the size of the action, for example, the number of actors. The 'functional' relation is parameterized so that actions involving all ten actors have a 50 per cent rate of coverage, while the probability for smaller actions is proportionately smaller. This dependence of news coverage on event size markedly slows the spread of action.

In most research, newspapers are the source of data and thus only news coverage of action is empirically observable. Figure 8.6 shows both action and news coverage of action when the probability of news coverage is a constant 50 per cent (upper panel), and when the probability of news coverage is 50 per cent for the largest actions (involving all ten actors) but is proportionately lower for smaller actions. Two patterns are clear in these figures. First, if the probability news coverage is proportional to the size of the events, diffusion is delayed relative to a constant probability of coverage, because the earlier smaller events (involving just one or two actors) are less likely to get news coverage. Additionally, the apparent level of protest from news coverage is even lower than the actual level, due to the lower probability of coverage. Second, note that the cycles of news stories differ

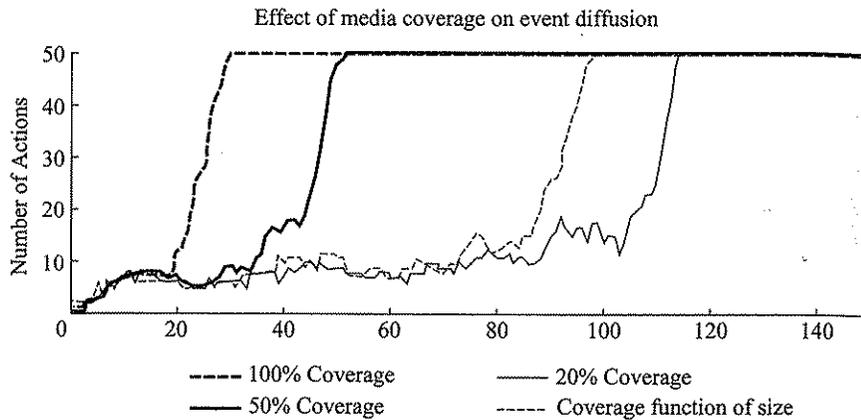


FIG. 8.5. Comparison of action diffusion when news coverage rate is 100%, 50%, 20%, or a function of number of actors. Homogeneous groups.

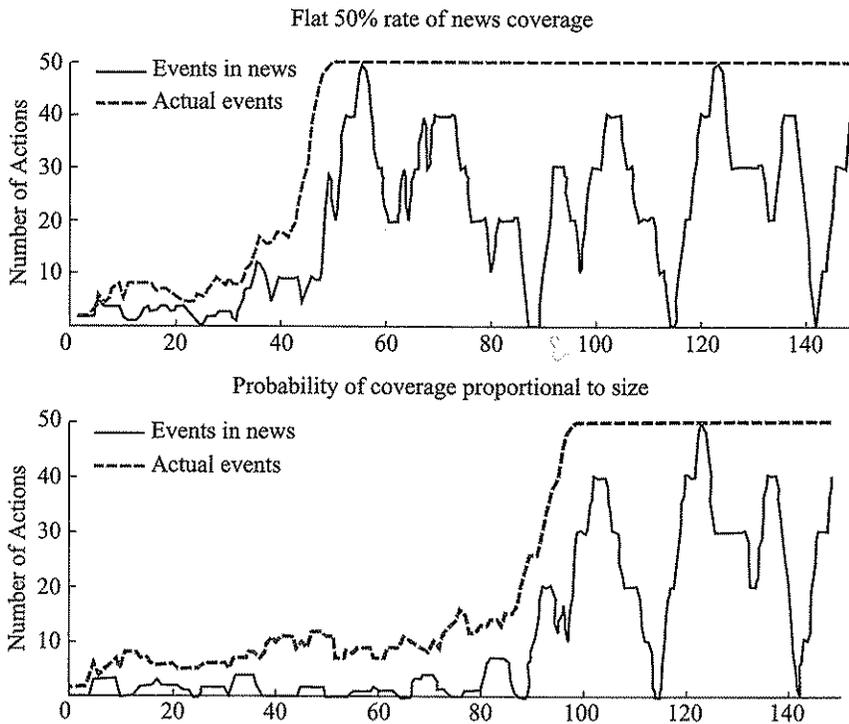


FIG. 8.6. Comparison of actual event series with events reported in the news. Top panel shows a flat 50% coverage rate. Bottom panel shows coverage proportional to the number of actors. Homogeneous groups.

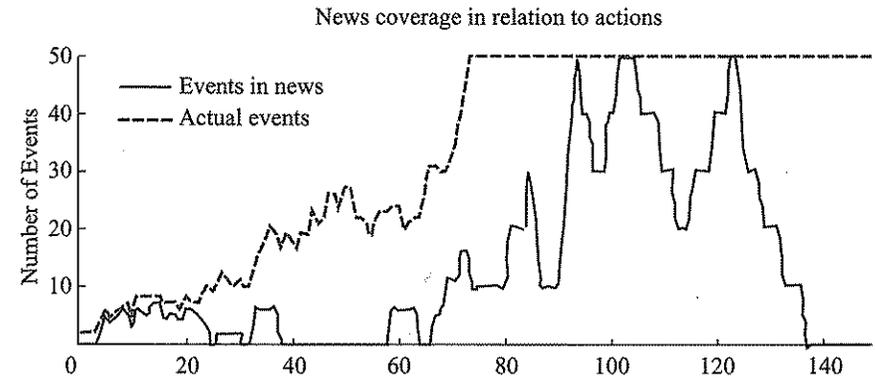


FIG. 8.7. Independent issue attention cycle can distort apparent protest cycle. Dashed line shows actual events, solid line shows events reported in the news.

markedly from the cycles of action. This is especially true when the probability of coverage is a function of event size. But even after action has reached unanimity, random fluctuations in news coverage give the appearance of protest cycles where there are none. However, in both these cases, news coverage does successfully track the difference between high-action and low-action periods.

There is substantial reason to believe that the news media's probability of covering protest is often determined not by the characteristics of the protest, but by external events or political cycles (Oliver and Maney 2000). In Fig. 8.7, the probability of news coverage is exogenously determined as a sine function, that is, a wave that goes up and down independently of protest levels. As before, past news coverage of protest raises future protesting. In this example, there is an early news cycle that helps to spark a diffusion process. Then the news coverage dies down while the protest is still rising. Coverage comes and goes again later when action is unanimous. Because very often the news coverage of protest is the only 'data' we have about protest, it is very important to recognize how easy it is for news cycles to be unrelated to protest cycles, and it is obviously important to do a more detailed study of how protest and news coverage relate to each other.

INFLUENCE

There are many network theorists working on influence models which assume that people's attitudes are shaped by those of the people to whom they have network ties, and in particular that the degree of influence will be affected by the homogeneity/heterogeneity of the opinions in the networks to which one is tied. If virtually all of one's acquaintances share the same political perspective, one's mobilization level or attitude extremity will be greater than if one's acquaintances

vary in political perspectives (Pfaff 1996; Kim and Bearman 1997; Soule 1997; Van Dyke 1998; Chwe 1999; Sandell 1999). This suggests that there is an interesting dynamic in the way networks affect mobilization. The same factors that create higher influence (all one's acquaintances are similar) are likely also to reduce the extent to which a group has network ties into nonmovement organizations. Thus relatively closed, politicized networks tend to increase diffusion through self-reinforcement processes, while relatively open networks have more potential to foster diffusion through mobilizing new participants, although the force of such a diffusion effect is likely to be weaker. Of particular concern is whether a group is relatively inbred, with ties only to itself or to other movement groups, or whether it has ties out into the general population of people who are not already mobilized. For example, Ohlemacher (1996) develops the concept of the social relay to distinguish the networks in two communities, one in which the protesters were relatively isolated, and the other in which protesters had substantial ties to non-protest organizations in the community: the relatively isolated protesters were viewed as more radical and failed to generate a broad mobilization, while the protesters with substantial non-protest ties built a broader, less marginalized, mobilization.

We may begin to model these processes by adapting Gould's (1993*a,b*) influence model, in which each person's probability of action is affected by the average of the action level of all the others to whom she/he is tied. If there are zero network ties, each person's probability stays the same; if there are 100 per cent of all possible network ties, everyone's probability fairly rapidly converges to the same probability, with the initially higher probabilities dropping and the initially lower probabilities increasing. If we put a simple who-to-whom matrix in this system, network ties affect the speed with which these processes occur, but not the final outcomes. We can see how this works by setting up a two-clique network with radically different initial values of opinions. If the cliques are completely unconnected, they will each reach their own equilibrium, as in the top panel of Fig. 8.8. Here, then, we have the gap between the isolated radical terrorist cell, for example, and the larger population. The radical cell can maintain its radicalism, but at the cost of having no influence on the larger population. If there are any bridges between the networks, however, influence will 'leak' across the system and the two cliques will move toward each other and will ultimately reach system-wide equilibrium, as in the middle panel of the figure. However, the move toward equilibrium can take quite a while to happen and, in the mean time, there can be radical disjuncture between subnetworks. These two cliqued cases may be compared with the bottom panel, which shows how one random network fairly rapidly converges to a system-wide equilibrium. In this particular case, it happens that one actor has no ties to other actors and so remains unchanged while everyone else converges toward equilibrium.

Network analysts usually treat the structure of network ties as fixed and unchanging. But, of course, movement actors devote a great deal of effort toward

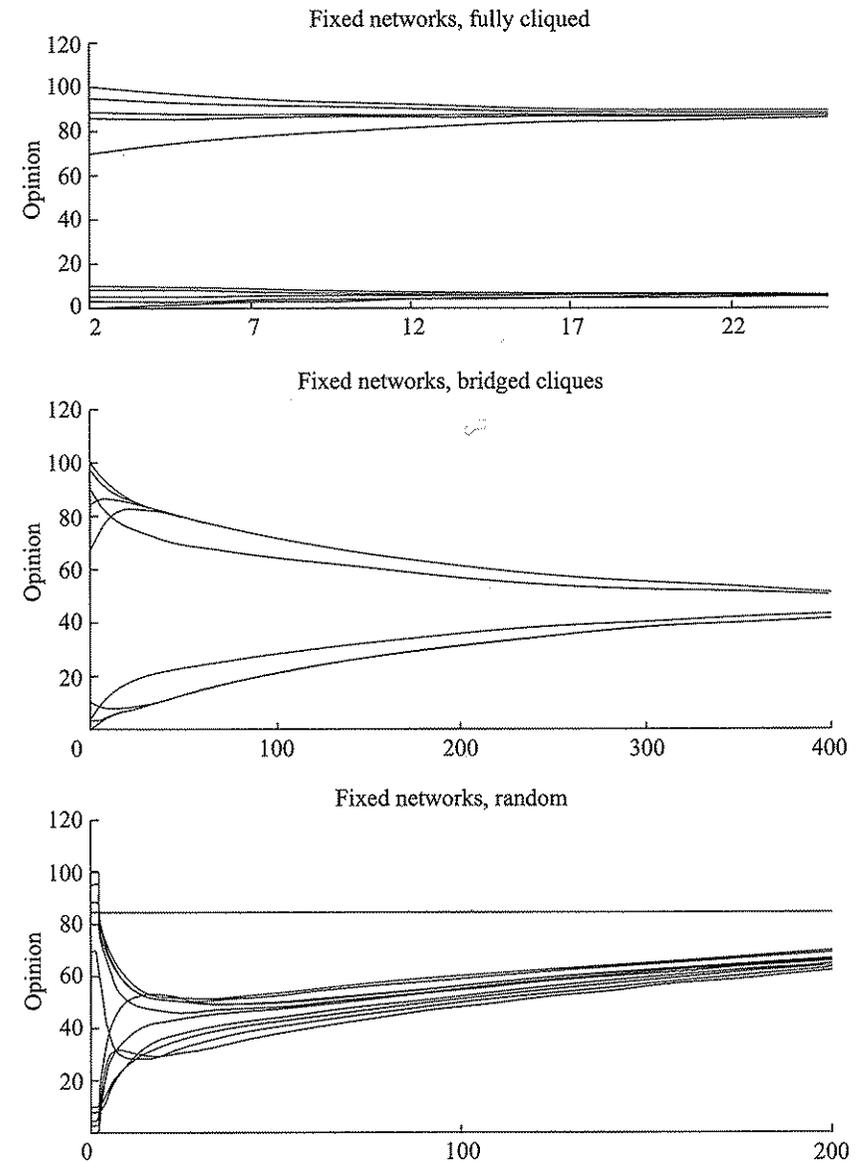


FIG. 8.8. Influence processes in cliqued, bridged and random networks. Network ties fixed. (In the random network, one actor happens to have no ties to others.)

creating new ties, and even the less planned forms of social interaction create new ties. In a formal modelling approach, it is quite feasible to make the ties themselves change over time in response to prior interaction. We may demonstrate this with a modified influence model. Instead of fixed present/absent ties, we begin with a who-to-whom matrix in which each entry is the probability that two actors will come into contact and influence each other. In this model, a matrix of 0,1 network ties is generated on each round probabilistically as a function of the given probabilities of influence. In addition, we add a feedback to these probabilities so that if a contact actually occurs (i.e. if there is a 1 in the matrix, even if it arises from a low probability of occurrence) that contact raises the probability of future contact by a given amount. To demonstrate how this model works, we set up an

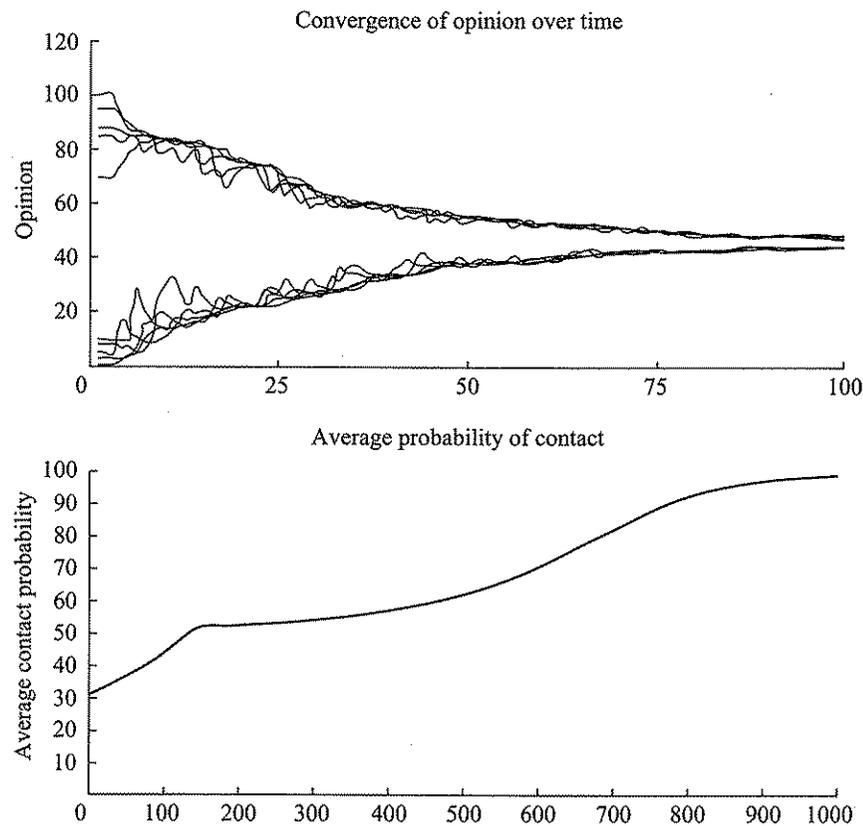


FIG. 8.9. Network ties are probabilistic and can be increased by contact. Each clique of five actors initially has 50% probability within clique and 5% between cliques. Upper panel shows opinion convergence as actors come into contact. Lower panel shows that the average probability of contact gradually rises across many time periods

input matrix with two cliques, each of which has a 50 per cent probability of making contact within the clique and only a 5 per cent chance of making contact between cliques. As before, we give the two cliques widely different starting values on the opinion measure. As Fig. 8.9 demonstrates, this model also generates convergence toward an equilibrium value, although it happens more slowly and with random fluctuations around the trend. As the bottom panel of Fig. 8.9 indicates, the average overall density of ties within the network gradually increases as well, approaching saturation as a limit. The irregular shape of the plot exhibits the influence of the cliquing. There is an initial rapid increase in the average contact probability arising from increases within cliques. After this phase, there is a classic S-shaped diffusion curve arising from the gradual increase in the probability of contact between cliques, which accelerates in the middle of the process, and then slows again as the network approaches saturation.

JOINT ACTION

An important phenomenon in any sphere of social action is that individuals come together to form collective actors, and smaller collective actors come together to form larger collective actors. When people organize themselves into groups, they do not show the random patterns of individuals acting independently, but very different patterns that arise from coordinated action. In evaluating protest event data, it is important to recognize that the 'actors' producing the event plots can be of widely different sizes and, in addition, can often be shifting around, grouping and regrouping themselves into temporary coalitions and alliances. No existing models of the diffusion of action have addressed the ways in which these patterns affect the observable event distributions. We cannot provide a detailed analysis of this problem, but we present here one example of it in the empirical data, and show how that kind of phenomenon can be modelled.

Movement Networks and the Problem of Protest 'Spikes'

The typical protest wave is more 'spiked' than standard diffusion models can possibly capture. That is, the empirical waves rise and fall much more quickly than can be accounted for by models of interactor transmission. One possible explanation for this pattern is that much of the protest event data is drawn from media sources and the attention cycle bias makes the peaks of action appear more extreme than they are. Another reason may be the failure to account for repeated actions by the same actor in network models. The density of connections drives diffusion between actors between them. If networks were conceived as operating across time, the network connections to self would increase the overall density of connections within the population and perhaps account for some of the steepness of the empirical curves for protest distribution.

In some cases the 'spike' is generated by a major external shock that has provoked a common response, without explicit coordination. When this occurs, however, the response will be something that requires relatively little coordination and has become a standard action form within a particular population. Identical actions involving complex coordination or novel tactics would not be expected to arise simultaneously in diverse locales simply from an external shock, without explicit coordination and communication through networks. The initial day of rioting after the assassination of Martin Luther King, Jr occurred in a context in which black urban populations were familiar with the 'riot' as an action form. The wave of protests at the beginning of the 1991 Gulf War bombings followed a build-up of mobilization in which it was 'understood' that everyone would protest if the war started.

Pulling out diffusion effects in these cases of closely connected events requires thinking clearly about the nature of the event and the type of coordination involved. In the USA 1960s riots, there was clear evidence of diffusion of small riots to nearby communities within the next day or two. For major protests in Germany, where the demonstrations are generally held on weekends, particularly Saturdays, there would be a seven or more day lag for diffusion effects to occur. That is, there are good reasons to expect different time lags for different kinds of events.

Other problems arise from using the news media as a data source when they are also one of the actors in the process. When the data source is one national news source, it is likely that there will be smaller regional diffusion effects that are not captured in the news source. What appears as a spike in the news accounts may simply be a failure to report the smaller events building up to and following a major event, and media attention cycles may exacerbate this spiking. (In subsequent work with our media models, we can investigate these possibilities.) Myers' riot data is based on newspapers, but was compiled from a large collection of local newspapers by a clipping service and, as a consequence, had much more information about smaller and more localized riot waves. Nevertheless, even Myers' data shows greater peaking than would be predicted by most diffusion models, so there is clearly more work to do.

Joint Action as a Source of Spikes

Many spikes in protest distributions arise from joint action that has clearly been organized. Sometimes this organization is overt and can actually be located in news sources, if it is looked for. Other times it is covert. We examined two data series available to us, Ruud Koopman's data on new social movements' protests in Germany and Kelley Strawn's data on Mexican protests, and identified a large number of cases in which similar events occurred almost simultaneously in multiple locales, often with no prior warning or build-up of action. It is obvious in most of these cases that there has to have been prior communication and coordination,

whether or not it is visible in the data sources. There is clearly some sort of network diffusion process operating, but something else is diffusing other than the final action. Instead, it is an ideology or action plan that is diffusing and the simultaneous coordinated action that follows is an observable expression of a different diffusion process. From a diffusion modelling perspective, such 'multiple event days' create apparent discontinuous spikes in the flow of events.

We have modelled a simple process that generates a 'spike'. Actors have a constant low probability of emitting protest actions. But in addition, actors are organizing. They are linked to other actors through their networks. Each actor has a probability of 'organizing' other actors (which is also assumed to be the probability of acting at the end). Actors 'organize' only those to whom they have a network tie. Each receipt of organizing raises an actor's probability of participating in the 'big event' at the appointed time, as well as of organizing other actors. (In this initial model, these two probabilities are treated as the same, but they could be readily differentiated.) But nothing 'happens' at the big event until the appointed day, when everyone acts at once. In this example, we assume that Actor 1 is the organizer and starts with a 100 per cent chance of organizing/acting, while all the other actors begin with a zero per cent chance of organizing/acting. Each time an actor receives an organizing contact, his/her probability of acting rises 1 per cent. At the specified time period (time = 100 in this example), each actor acts or not with the accumulated probability. This model produces a result that looks like Fig. 8.10. We have added random noise of a low probability of acting, to show how hidden organizing looks against a backdrop of random action. This discontinuous spike is the product of more gradually diffusing influence that is raising the probabilities of action. Figure 8.11 shows these probabilities rising for several different network configurations. The results in Fig. 8.11 differ dramatically from each other: the three random networks have widely different results, and the cliqued

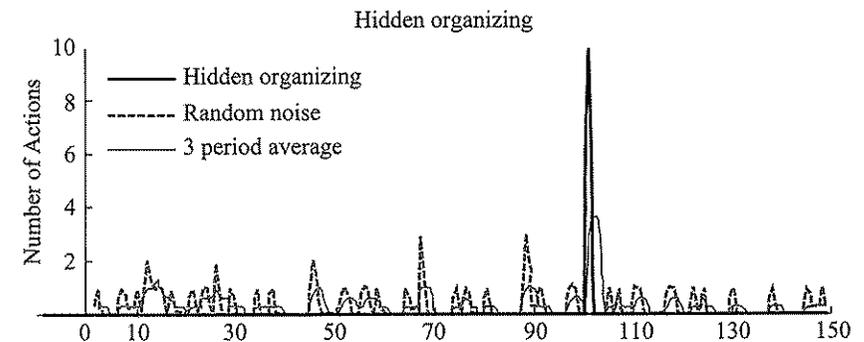


FIG. 8.10. *Hidden organizing, against a backdrop of random noise. Random networks*

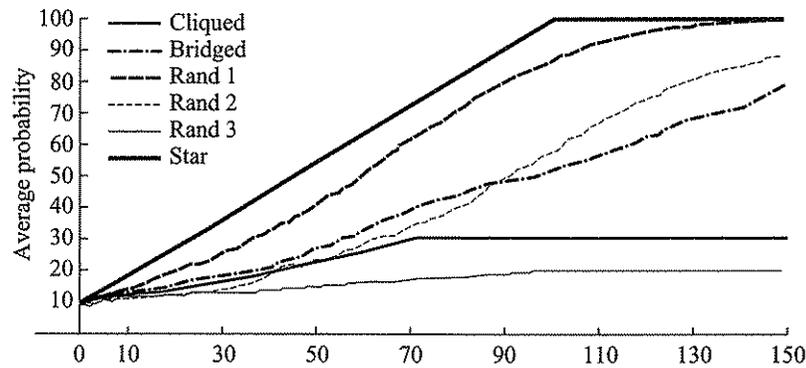


FIG. 8.11. The average probability which is rising in hiding varies tremendously with network structure. Because of the skew in starting values, it is connection to Actor 1 that is especially important

and bridged networks are different from each other. In this model of hidden organizing, the 'star' model is most effective. The size of the 'big event' differs markedly depending on the network organizing it.

Figure 8.12 shows how the effects of network structure can be seen in this process by calculating and plotting the average probability within cliques. Only the bridged cliques show an 'interesting' plot where the spread of organizing through the bridges can be seen. Full cliques have zero probability outside the organizer's clique, while random networks rarely show much cliquing. In a star network, the average probabilities for all the non-stars are about the same. A similar technique of examining different subgroups within a larger network could be used for the information and influence models, as well. It is important to note that the effects of different network structures vary greatly depending on how the network 'works'. Information flows, influence flows, and hidden organizing appear to be impacted differently by different network structures.

This particular specification of hidden organizing assumed that actors were building up to an appointed day, which is the appropriate model for big demonstrations. An alternate specification would be that actors organize until they have mobilized a large enough critical mass, that is, until some size criterion is achieved; this alternate approach would seem more appropriate for the hidden organizing behind a coup or revolution. Hidden organizing mechanisms can be incorporated into an influence model or a communication model. In empirical cases, this behind-the-scenes organizing is occurring simultaneously with other actions. However, it would be expected that actors might have limited resources, which might lead to a decline in other forms of action as organizing increases. Modelling this would require some algorithm for how actors choose between organizing and acting, a complexity that is beyond the scope of this article. Another issue to explore is

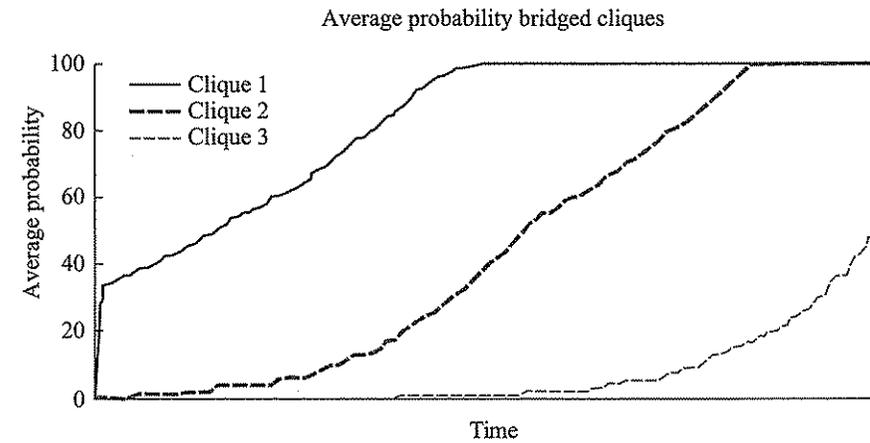


FIG. 8.12. Probability of organizing for a big event. Network structure can be seen in the average probability within cliques. Here the spread of organizing through the bridges can be seen. Full cliques have zero probability outside the organizer's clique. Random networks show wide variability in the degree of cliquing

whether these coordinated actions foster subsequent actions via a diffusion effect, or whether all possible actors act in concert, and action falls off afterwards.

DISCUSSION AND CONCLUSIONS

The term 'network' needs to be unpacked if it is to move beyond vague heuristic and actually structure research into social movements. We find that attempting to specify network effects in formal models forces us to grapple with the difficult questions of exactly what we think these effects are and how they work, and how they relate to concepts of diffusion. The models we are working with in this chapter are of a particular sort that is rarely attempted in sociology. We are not analysing empirical data and fitting regression coefficients. And we are not specifying elegant deductive models and deriving their formal properties. Both of us have done both of these in other works. But in this project, we are struggling with what empirical data patterns actually look like, and trying to model the underlying processes that could be giving rise to these patterns. This chapter has sketched an approach to this problem and has shown how the flows of information, influence, and joint action can be modelled and how these different processes can yield widely different results.

As we have worked on this problem, we have come to recognize that any empirically valid model needs to have a substantial random or stochastic element. Random fluctuations from constant probabilities produce the kind of spiky, jagged

plots of event counts over time that are characteristic of empirical data. These same random fluctuations frequently produce 'waves' of events, especially when they are aggregated across a few time periods. Once we made the shift to stochastic modelling, we have been forced to confront the huge effect which simple random variation produces in our models. Even with a fixed set of network ties, random fluctuations in who happens to act when can produce large effects on the pace with which action or influence diffuses. Random variations in which actors are tied to each other in a network can produce even larger differences in results. Substantively, this means that sheer chance appears to play a large role in affecting the trajectory of a protest cycle. It will take some time to absorb the theoretical and empirical implications of this result.

As we have unpacked different network processes and sought to pin them down so they could be modelled, we have found that the effect of 'network structure' varies greatly depending upon the nature of a particular network process. This can be seen most extremely with the 'star' networks in which all the network ties are with one central actor. This structure is a severe impediment to mobilization in a model which assumes that actors respond to their direct information about the number of others who have acted recently: because all the actors except the 'star' know about at most one other actor's actions, they do not increase their own probabilities of action to any significant degree. By contrast, the 'star' network is the most efficient in the 'hidden organizing' model, where it is in contact with an organizer that is assumed to increase the probability of behaviour, not the total of prior actions. It would be foolish to try to decide whether 'star' networks are 'good' or 'bad' for mobilization. Instead, it must be recognized that the impact of a network structure is intimately intertwined with exactly how actors affect each others' behaviour. Verbal theorists have talked vaguely for years about information flows and influence, but it is only when you actually try to pin these ideas down to formal representations that you realize how deeply the exact specification of what those relationships are influences not only the gross levels of outcomes, but the ways in which other factors affect outcomes.

We have shown how several different kinds of network effects can be modelled, and why they are important. Our model of information flow focused on the assumption that actors increase their probability of acting as a function of the number of others they know about who have previously acted, an assumption that leads to a gradual rise in everyone's rate of action. In this model, as information diffuses so does action, and we showed that different network structures affect the pace with which this occurs.

Consistent with our other research, we also devoted attention to modelling the effects of news coverage. This is particularly important because most often the *data* we have about protest comes from newspapers. We first show that even if the newspapers are completely unbiased samplers of protests, simple random fluctuations in news coverage produce apparent cycles that are not present in the

underlying protest distribution. But, of course, newspapers are not unbiased samplers. We know that they respond to the size of protest and that they are subject to issue attention cycles that may be independent of protest. Both of these patterns produce additional distortions in the protest cycles in newspapers as compared to the underlying 'real' protest cycle. But, additionally, news coverage itself affects protest and changes the protest cycle. Methodologically, this helps protest researchers, because if news coverage increases protest, it brings the 'real' protest cycle more into line with news coverage of protest. However, if the causal effect of news coverage on protest is not recognized, researchers can draw quite erroneous conclusions about the effect of protest on policy debates. More detailed studies of the interplay between protest and news coverage must be the subjects of other analyses.

Influence models assume that people's opinions change in the direction of those with whom they are in frequent contact. This assumption generates a long-term tendency for a population who has direct or indirect ties to each other to move toward one common opinion, while wholly distinct cliques move toward separate average opinions. We showed how network structures affect these processes. If networks are cliqued, these models provide some way of understanding the relationship between in-group and out-group ties in opinion formation. We also showed how this approach could be readily modified to make the network ties themselves fluid and changing, in response to contacts from others.

The approach we offered for studying influence immediately points to a large number of possible extensions. Our simple models employed only symmetric influence ties, and an obvious extension would be to see how asymmetric influence affects these results. Empirically, populations obviously do not seem to be tending toward a single common opinion, and empirically it is clear that contact between persons of different opinions can generate polarization of opinions rather than convergence. Thus, even though averaging rules like the ones we used are the most common in formal models of influence, they do not seem to generate results that fit empirical patterns. We suspect that the most promising avenue to pursue is a model that says actors will either polarize or converge when they encounter each other, with the probability of doing polarization versus convergence being a function of the distance of their opinions from each other.

Our model of 'hidden organizing' is not necessarily very elegant, but it calls attention to an important empirical phenomenon that cannot be neglected in the analysis of empirically observable protest waves. Protest data are much more spiked than standard diffusion models can accommodate. These spikes violate all the assumptions that undergird standard statistical regression models, as well. Too many scholars have been willing to run models without confronting the implications of these spikes. Yet every social movements researcher knows that 'hidden' organizing (i.e. organizing that is not reported in observable data sources) occurs. This is one example of how important it is to think about what we already know about movement processes as we seek to develop formal theory that speaks to

empirical data, and as we seek to do quantitative analyses of empirical data that are soundly grounded in a theoretical understanding of the underlying processes that give rise to observable data.

Apart from providing an explanation for data spikes, our work on joint action points to the need for conceptual clarity about actors and units of analysis. Separate individuals come together to form groups, and once they are in groups, those groups act with a high level of unity. Thus protest cannot be modelled as if independent individuals are conducting it. But, of course, the groups themselves also may temporarily act together with some unity, and models of independent action of groups will not correctly describe observable data, either. We need to fit the model to the type of action. The black riots of the 1960s had relatively little coordination between communities and relatively little organization within communities, while new social movement protests have a great deal of preplanning and coordination associated with them. We should expect to see different kinds of empirical patterns arising from these different kinds of actions.

We need a middle ground between the statistical analysis of data and the development of pure formal theory. In this project, we are in dialogue with empirical data, seeking to determine the kinds of processes that could produce the patterns we can observe. As we have repeatedly stressed, the discipline of turning theory into equations reveals the ambiguity and imprecision of many past discussions of network effects, and forces us to think more seriously and deeply about just how we think things work.

NOTES

1. Stella is identical to IThink, published by the same firm for business applications, except for the examples included in the manual. The models from this paper are too complex to be printed in this chapter, but are posted on the first author's website, along with links to a free downloadable save-disabled version of the Stella programme which can be used to read and interact with the models. The home page is www.ssc.wisc.edu/~oliver. Follow links to protest research and thence to the modelling projects. A more specific URL is not provided as it is likely to change over time as the web page is updated, but the home page URL will remain the same as long as Pamela Oliver is a professor at the University of Wisconsin. Note: answer 'no' to the question of whether you wish to reestablish links, as the links will not work properly when the files are moved from their original locations, and the save-disabled demo may not have the linking option enabled.
2. However, it does not generate standard mathematical equations for some of the complex modelling constructs available in the programme, such as 'conveyors' and 'ovens,' which are useful for calculating lag effects and moving averages, nor do its equations convey arrays in standard mathematical notation.
3. This algorithm for changing the probability of action as a function of past actions is

$$p_t = p_{t-1}(1 + w_2(r_{t-1} - r_{t-2})/n),$$

where w_2 is a weighting coefficient on the lag term. If the level of action is constant, the difference is zero and $p_t = p_{t-1}$. Otherwise, the probability increases or decreases proportionately to the change in the number of actions expressed as a proportion of the number of actors. This model is very sensitive to the weighting coefficient and exhibits a tipping point: below a critical value, increases cancel out decreases, and the overall probability oscillates around its starting value, but at the critical value, the positive effect of a rising number of actions can trigger a cascade leading to unanimous action. This is a fascinating model for a feedback process, but its very complexity makes it unsuitable for simple demonstrations of network effects.

4. We might also modify this model to make it an 'adaptive learning' model (Macy 1990, 1993; Macy and Flache 1995) by specifying that actors' response to others' actions depends on whether they themselves have acted or not in the previous round. Exploring adaptive learning is also beyond the scope of this paper. We can say, however, that in our very preliminary explorations of a random-action model where the only feedback is from other actors' actions, adaptive learning appears to have no effect in relatively large groups, because the random effects cancel each other out.