THE COEVOLUTION OF SOCIAL MOVEMENTS[*]

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Movements develop in coevolution with regimes and other actors in their environments. Movement trajectories evolve through stochastic processes and are constrained, but not determined, by structures. Coevolution provides a theoretical structure for organizing existing understandings of social movements and sharpening future research. Stochastic thinking is essential for recognizing the both the volatility and path dependence of collective action and its underlying structural constraints. Formal models of diffusion, adaptive learning, mutual reinforcement, and inter-actor competition are developed and compared with empirical protest series. Responses to exogenous reinforcement, mutual adaptation in which failure is as important as success, and inter-actor competition are the most plausible mechanisms to account for empirical patterns. Trajectories of action depend upon the number of discrete random actors. Overall, the analysis suggests that movement dynamics are shaped more by interactions with other actors than by processes internal to a movement, and that empirical analysis must be sensitive to the level of aggregation of the data.

This article advances two arguments. First, that coevolution can provide a theoretical structure for organizing existing understandings of social movements and sharpening future research. Second, that developing formal models of movement coevolution is a crucial part of a total research program for understanding social movements. The first argument largely involves renaming and reframing existing concepts and may be viewed by some as merely an incremental advance over what has gone before, although we believe it is an important one. In particular, this work is entirely consistent with a recent shift toward emphasizing mechanisms and processes rather than inputs and outputs. However, we will demonstrate that stochastic or random processes and adaptation and competition are crucial to movement dynamics, elements of a coevolution structure which have been absent in prior theorizing.

The second argument involves demonstrating that the very act of attempting to model movement coevolution forces sharper and clearer theory at many points and that it raises important new research questions. In particular, we will show that although there are many theories which can account for the rise of a protest cycle, there are very few which adequately account for its decline, and even fewer which provide plausible accounts of the repeated ups and downs of protest event cycles. We show that adaptation to external reinforcement and competition among movement actors provide accounts for aspects of movement dynamics inexplicable through other mechanisms.

We begin with the fundamental observation that in social movements, actions affect other actions: Actions are not just isolated, independent responses to external economic or political conditions—rather, one action changes the likelihood of subsequent actions. This broad understanding of inter-action effects encompasses relations often seen as qualitatively distinct. The term "diffusion" is used when prior actions affect the future probability of similar actions, including the spread of ideas or language. The term "strategic interaction" used when the actions of movements and their opponents (regimes or countermovements)

affect each other. The vocabulary for other kinds of interactions is less clear, such as resource flows from institutions to movements or the mutual shaping of frames and tactics; but they also involve actions (e.g., giving money, publishing pamphlets), which affect other actions. These interaction influences have long been recognized. Examples include McAdam's (1983) work on tactical diffusion, Meyer and Whittier's (1994) work on movement spillover, Tarrow's work on radicalization and inflationary tactical spirals (1994), and work on organizational ecology (Minkoff 1993; Minkoff 1997; Olzak and West 1991).

Our second core observation is that the mixes of actions emitted by different kinds of actors evolve (change) over time, and that the action sets of actors coevolve with each other. For example, protest strategies have coevolved with policing strategies (Della Porta 1996; McCarthy, McPhail, and Crist 1999; McPhail, Schweingruber, and McCarthy 1998), peasant insurrections coevolved with antiseigneurial legislation in revolutionary France (Markoff 1997), counter-movement pairs coevolve with each other (Meyer and Staggenborg 1996), and non-oppositional collective discussions create a climate which makes later oppositional action possible (Deess 1997). Species coevolve when they change and adapt over time in response to each other. Diffusion and coevolution are closely related. Species which adapt well tend to diffuse, and so do successful actions. Conversely, species can be driven to extinction (negative diffusion, if you will) by the actions of other species. Diffusion processes change the environments to which actions and species adapt. In fact, coevolutionary relationships can most often be conceived as relations between diffusion processes. Coevolutionary relationships may vary in their forms, including predator-prey, niche competition, and symbiosis, as well as the indirect relations that arise from sharing a common environment (e.g., habitat destruction). There are limits to the biological analogy, specifically because the core mechanisms for selection are learning and decision rather than mortality and sexual selection, although chance events play key roles in both. Nevertheless, the insight that movements coevolve with other actors permeates movement scholarship even when that language is not used. Serious attention to the underpinnings of coevolutionary theory provides new and powerful ways of theorizing relations among social movements and other actors.

FROM SOCIAL MOVEMENT AS ORGANISM TO SOCIAL MOVEMENT AS A POPULATION OF ACTIONS IN A SYSTEM OF ACTIONS

Most social movement theorists recognize that social movements are not coherent entities. Older life cycle models and organic analogies have been rejected, and all theorists sharply distinguish between a single social movement organization and a broader social movement. The problem has been to develop theoretical language for this conception (Oliver 1989). It has been easier theoretically to describe social movement organizations, which are coherent decision-making entities. Theorists have long insisted that movements be studied not in isolation, but in strategic interaction with their opponents and bystanders, but it has been difficult to do this without treating each of the "sides" as if it were a coherent decision-making entity. In fact, neither movements nor states are necessarily coherent: both are collections of actors with different agendas and ideas. Nevertheless, these actors are bound to each other through some kind of common identification, and what they do affects each other. The degree of coherence varies, of course, but even those movements and states which are hierarchical and fairly unified have internal struggles and conflicts. This very general point has been argued in a variety of different ways by scholars from a variety of different theoretical traditions (Gusfield 1981; Melucci 1989; Oberschall 1978).

Social movements are not like organisms, but they are like species. Unlike an organism, which has a distinct set of properties, a species is a breeding population characterized by a statistical distribution of properties. Species evolve when these statistical distributions change. Social movements are not long unitary collective actions, they are populations of collective actions with statistical distributions of properties. However, we

must work carefully even with the analogy to species. For we are not so much concerned about whether the people in a given population survive or grow or multiply, but about shifts in the mix of their activities, in what they do. If exactly the same population of people is emitting a lot of protest at time 1 and is emitting no protest at all at time 2, we would usually say the social movement is active at time 1 and dormant at time 2. When social movements "rise" and "fall," what we are observing are changes in the mix of actions in a population across time. It is straightforward to move from this recognition into current understandings of protest cycle dynamics, which involve shifts in the kinds of actions across time (e.g., from confrontational protests to mass demonstrations to institutionalized politics to clandestine violence), and shifts in the action repertoires across time (Tilly 1978). Returning to the biological analogy, actions are structurally equivalent to genes. Biologically, genes are not selected directly but rather indirectly, through selection on organisms. However, in protest evolution, actions are usually selected directly by actors' choices, not through indirect selection on actors, although indirect selection may also occur.

Thus we understand a social movement as a distribution of events across a population of actors. Social movements rise when the overall frequency of protest events rises in a population, they become violent when they ratio of violent events to non-violent events rises, and so forth. Thinking statistically allows us to talk about the beginning of a particular social movement protest cycle as the point at which action begins to accelerate, and its end as the point at which action falls back to a low steady-state rate of occurrence. The term "event" here is used very generally, so that adopting a belief or writing a document may be thought of as events, as can resource flows from one group to another.

STRATEGIC INTERACTIONS AND COEVOLUTION

Social movements are always shaped by the actions of opponents and bystanders. Actors not only interact strategically at each point in time, they learn over time from past interactions and from information communicated to them by other actors. New dissident tactics diffuse through dissident networks, and new regime responses diffuse through regime networks. These new forms of action influence subsequent interactions. Police in the US and Europe since the 1960s have learned to channel and routinize protests to minimize their disruptive potential (McCarthy and McPhail 1998; McCarthy, McPhail, and Crist 1999; McPhail, Schweingruber, and McCarthy 1998). Political and economic elites may respond to violent or disruptive dissent by encouraging or facilitating nonviolent or nondisruptive forms of collective action (Jenkins and Eckert 1986; Koopmans 1993). Elite money flowing into movement organizations creates jobs for activists and channels their activities into nondisruptive organizational influence strategies. These organizations may, at a later phase, initiate new forms of action, possibly sparking a new cycle of protest. This is related to organizational ecology approaches which build on the concept of "density dependence," in which movement organizations are founded and die off partly as a function of the number of other similar organizations creating legitimate models for action and competing for resources (Minkoff 1993; Minkoff 1997; Olzak and West 1991).

Attempts to theorize the strategic interactions between movements and their opponents have foundered when movements have been conceived as entities, because strategic analyses attribute more uniformity of purpose to both sides than ever is actually found to be true under empirical scrutiny. But a shift to an event-wise approach and a population analogy that recognizes changing distributions of traits and strategies minimizes much of this problem. The strategic consequences for the trajectory of the movement as a whole often arise from accumulations of smaller strategic events. Individual actors often do behave strategically in particular actions at particular moments in response to particular events, even if they generally lack perfect knowledge or perfect wisdom. Erratic intermittent government repression arises not from a concerted choice to be erratic, but from inconsistent

decisions by different actors in different situations. Social movements are not well-bounded phenomena. A coevolutionary perspective provides a clear way of talking about social movements as populations of actions without reifying them as coherent entities.

EVENT-ORIENTATION AND THEORETICAL SYNTHESIS

Resource mobilization, frame alignment, and political process theory are not competing theories, but rather focus on different aspects of a larger system. The evolving direction of social movement theory has always been towards synthesis, and these relationships are recognized by nearly all theorists writing today. Serious researchers know that it is not possible to study everything at once, that you have to draw boundaries around a problem to study it. At the same time, if you draw the boundaries too narrowly, you can mis-specify the problem and generate seriously erroneous conclusions about cause-effect relationships. We believe that the coevolution framework provides a general way of thinking about the "big picture" with a common set of concepts that can be applied to parts of the problem and will permit these partial results more readily to be integrated into a larger whole. In this section, we briefly sketch how important concepts can be captured in this framework, and how moving toward formal modeling reveals ambiguities in past treatments of the concepts.

Resources. A resource is not an event, but resources are important to events. Viewing social movements in a coevolutionary perspective forces a more rigorous approach to understanding resources. The term is often used loosely, to refer to anything which constrains the kinds of actions actors can perform or which affects the effectiveness of their actions in producing desired consequences. A full treatment of resource issues is beyond the scope of the present article, but we offer a few comments. First, there may be resource flows when some actors transfer consumable resources to others, e.g., when foundations give movement organizations money. In this case, the resource flow is an action or event engaged in by one actor which changes the properties of another actor. Relatedly, the size of a collective actor increases when more individuals join it; a change in the group's size is an event that may be affected by its actions or those of other actors. Sometimes the word "resource" is used for intangibles such as identities, discourses, culture, or influence. These intangibles do constrain action or affect the effectiveness of action; and it is in principle possible to include them in a coevolutionary perspective if the dimensions of such factors can be specified along with the ways in which they affect actions or change in response to other factors.

Political Opportunities. Although some scholars have tried to use the concept of political opportunity as a characteristic of regimes as actors, it is becoming increasingly clear that political opportunity is best understood as a multidimensional space in which some groups or actions are facilitated or responded to by political elites or institutions, while others are repressed or ignored. For this reason, it is best to think of political opportunity as a matrix of probabilities, where each element is the probability that a particular kind of action will meet with a particular kind of response or action from particular kinds of other actors. A general movement/regime interaction scheme would say that $m_t = f_1(r_{t-1})$ and $r_t = f_2(m_{t-1})$, where m and r are the actions of the movement and regime at times t and $t-1$, and the f's are specific functional relations giving the effect of past actions on subsequent actions. Thus, we might think of political opportunity as the f_2, the nature of the regime's response to the movement's actions. If it yields more policy concessions when there is more movement action, the political opportunity is high; it if yields more repression in response to more action, the political opportunity is low. Groups may differ in f_2, that is, in the ways regimes respond to their actions. Further, we may conceive of the m's (and r's) not as single actions which there is more or less of, but as vectors of alternative actions.

Frames and Discourses. Making a speech, writing a pamphlet, and publishing an article or book can all be treated as kinds of actions. Frame deployment is a form of action

(Bernstein 1997). Frame shifts and collective identity construction may be fruitfully analyzed in diffusion terms. It is possible to track the diffusion of particular terms through documents across time, for example the shift from "civil rights" to "black power" language, or the use of "Negro" to "Black" to "Afro-American" to "African American." Words, concepts, and frames diffuse in processes very similar to the diffusion of knowledge about actions. Beginning with the programmatic statement of frame theory (Snow, Rochford, Worden, and Benford 1986), a growing body of scholarship shows how frames interact with the kinds of actions groups pursue, the resources they attract, and the repression they receive. Thus, conceiving frame evolution in strategic interaction with other forms of action is certain to capture important elements of the dynamics of frame evolution. Similarly, identities develop in interactions with other actors (Dolgon 2001; Polletta and Jasper 2001). Just as with the actions and groups in a social movement, it is important to recognize that frames are always in competition with one another, and that there are always multiple frames available, even though one might be hegemonic in a particular period.

Decisions, Networks, and Communication. The mechanisms of "selection" are different for movement evolution than for biological evolution. Actions are chosen by actors through cognitive and emotional processes, in light of information they have about others' actions as it is filtered through interpretive frames. Communication is central to the diffusion of collective action, as actions do not diffuse directly but indirectly through the diffusion of information and influence. Different kinds of communication networks will produce different effects on collective action. Oliver and Myers (2002) elaborate the ways in which different kinds of network processes may generate different patterns of collective action. Chains of direct ties can indirectly link actors with others who are quite distant from them and lead to the widespread diffusion of information. The mass media are an important source of indirect ties, permitting the actions of one group affect another by way of media coverage. The influence can spread as far as the media are broadcast, without prior connection between the actors. Myers (1996; 2000) shows that large riots which received national media coverage increased riot propensities nationally, while smaller riots increased riot propensities within their local media catchment areas.

The media themselves are actors in the social movement field, adapting to the actions of others and also subject to diffusion processes. One outlet picks up a story and it may be picked up by other outlets. 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" (Cancian and Ross 1981; Downs 1972; McCarthy, McPhail, and Smith 1996). News coverage of protests is shaped by the cycle of institutional politics (Oliver and Maney 2000).

TOWARDS FORMAL MODELS: SOME INITIAL RESULTS

As McAdam, Tarrow and Tilly (2001) argue, our next direction in theorizing needs to move away from thinking of causes and effects as determinate inputs and outputs, and toward identifying mechanisms and processes that occur across many settings. A detailed exposition of modeling social movement cycles requires several separate more technical papers. In this article, we will demonstrate the potential of this approach with a few simple examples focusing on key mechanisms that influence the trajectory of movement cycles: stochastic probabilities, diffusion, adaptive learning, mutual adaptation, and competition. We conduct a dialogue between formal modeling and empirical data, using the logic of falsification. This dialogue's result is that external reinforcement and inter-movement competition are likely to be crucial for understanding the empirical patterns of movement cycles.

The first step involves specifying a mechanism or process. Verbal theorists may assert vaguely that one thing affects, or increases another, or that a given relationship may be

Figure 1. 1960s riots by month (top panel) and week (bottom panel). (Source: Gregg Carter's compilation from multiple official and news sources)
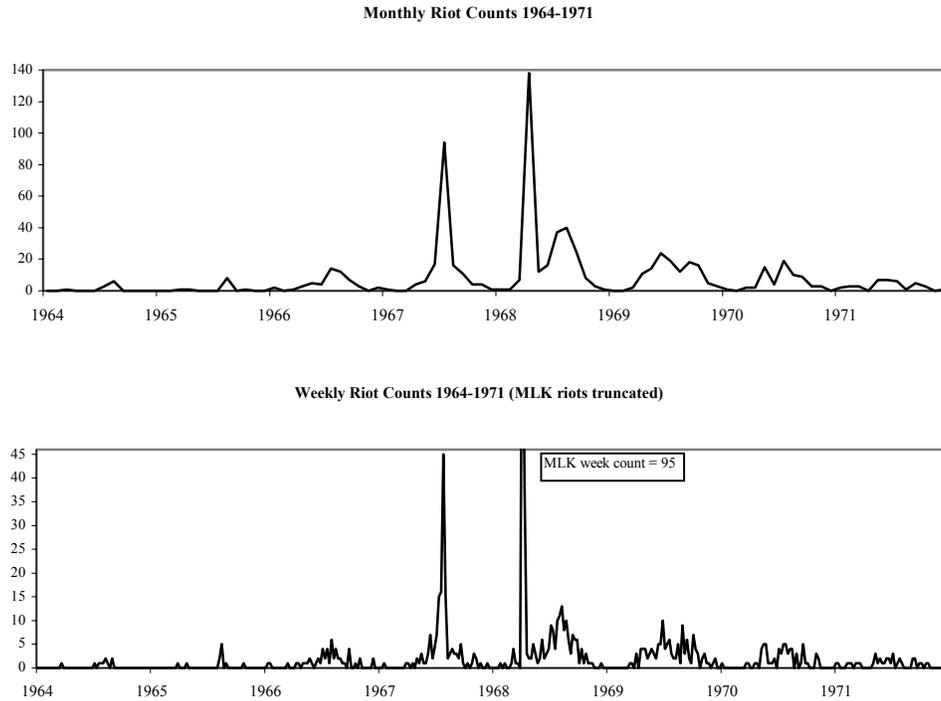
Monthly Riot Counts 1964-1971

Weekly Riot Counts 1964-1971 (MLK riots truncated)

Figure 2.   German new social movements protests, 1975-1989, monthly counts. (Source: Ruud Koopmans)

German Protests Monthly Counts

curvilinear, but formal theorists must spell out exactly how they think a relationship works. What exactly is the mechanism? How specifically does this affect the outcome? What exactly is the mathematical relationship? The simple act of formalizing a theory immediately exposes the ambiguity in much verbal theorizing. The second step involves determining whether the postulated mechanism can, in fact, produce the kinds of patterns observed empirically. Being able to reproduce empirical patterns does not, of course, prove that the postulated mechanism is the correct one. But many plausible mechanisms can be rejected at this point because they

simply cannot reproduce empirical patterns. In this article, we exhibit a few models that pass the first test. That is, they have basic theoretical plausibility and can account mathematically for the empirical patterns. Subsequent work is required to investigate them more thoroughly, and make comparisons among plausible models to determine which fit the data the best.

FORMAL MODELS AND THE REALITIES OF COLLECTIVE ACTION

Our goal in theorizing is to be closely linked to empirical data. We are not fitting models to data, but we want models that could generate real data. Figure 1 shows plots of riot counts across time for the 1960s black riots from data compiled from a wide variety of sources by Gregg Carter (1983; 1986) and figure 2 the "new social movements" protests in Germany 1975-1989.[1] McAdam's (1983) plot of activity in the civil rights movement (figure 1 on page 739 of his article) is also readily available to most readers. (Other important sources of quantitative data include Hocke 1998; Jenkins and Eckert 1986; Kriesi, Koopmans, Duyvendak, and Giugni 1995; McAdam 1982; Olzak 1990; Olzak 1992; Olzak and Olivier 1994; Olzak, Shanahan, and McEneaney 1996; Olzak, Shanahan, and West 1994; Rucht 1992; Rucht and Neidhardt 1998). It should be noted that data from news sources is not "pure" but is affected by the selection processes in newsgathering and, again, in data gathering from newspapers. As work proceeds, we will need to investigate the ways in which these selection processes affect the data we see, but we begin with the assumption that event series we observe in news sources exhibit at least some of the properties of actual event series.

The plots in these figures exhibit several important characteristics of empirical protest waves. There are cycles: protest goes down after it goes up, especially in the riot series. More generally, the overall rate of protest changes across years. However, the plots do not exhibit the long smooth rise and fall that the phrase "cycle of protest" evokes. They are jagged, irregular, and spiky (highly peaked). The plots also exhibit smaller waves within waves, and waves within those waves, and waves within those waves. These smaller waves are substantively and theoretically important. Myers (1997a) finds nested diffusion processes in the riot series, Koopmans (1995) discusses the issue- and locale-specific protest waves that build into the larger waves, McAdam (1983) shows that the bursts of activity in the civil rights movement followed tactical innovations, and Kriesi (1995) shows that a general wave of international mobilization was coupled with nation-specific waves. In addition to these nested diffusion processes, protest cycles are affected by what we may call the "rhythms" of protest. These include regular variations across time (e.g., season, day of the week), variations linked to external cycles (e.g., electoral cycles), and variations intrinsic to particular forms of protest (e.g., mourning periods or organizing mechanics). In fact, these "rhythms" are closer to what the term "cycles" generally means. These rhythms interact with diffusion processes. Myers (1996), for example, found clear evidence of localized riot diffusion after seasonal rhythms were controlled.

SIMPLE STOCHASTIC PROCESSES

Stochastic (random or probabilistic) processes appear to be at the core of protest event data and can produce the jagged cycles characteristic of protest series. Figure 3 was generated by simulating 200 iterations for 50 actors, each of whom has a probability of .02 of acting on each iteration, and displaying the moving sum of actions across 10 iterations.[2] Although this sum averages 10, in this series it ranges between 4 and 18 and has low phases and high phases. Purely random processes produce event series which exhibit apparent cycles and the spikiness characteristic of plots of empirical event series. In fact, Francisco and Lichbach (2001) argue that the cycles in many protest event series can be accounted for by simple random processes. In our work, only models that have some such random process at their core can generate event series which look like empirical series. To us, this means that random or

stochastic processes need to be understood as a central factor in protest cycles. This is entirely consistent with theorizing that recognizes the importance of contingency and uncertainty in actors' choices and the unfolding of events.

In this and other models, an "actor" is conceived as a group or population emitting protests about a particular issue. A random process does not mean that actors are acting without purpose or meaning. Accumulating across time, a random process occurs when actors have a long-term rate of emitting action at a certain number of acts per unit of time (e.g., an average of once a week or once a month) but the timing of their actions is random across time, rather than being at fixed intervals, so there is variability in the amount of action across aggregated time periods. Accumulating across actors, a random process occurs when each actor has a given probability of acting, but the actions of different actors are not coordinated, so that the number of actors acting at a given time varies.

A shift from deterministic to stochastic (probabilistic) thinking is crucial to the advance of social movement theory. Structural conditions constrain action, but do not determine it. Strategic actors often analyze their situations, seeking to identify the course of action which will lead to the best outcome, but their choices are made under conditions of partial information and uncertainty, and constrained or affected by a variety of goals, moral constraints, and emotions. Over the course of a series of actions and reactions, the trajectory of strategic interaction can go in a direction unintended and unpredicted by any of the participants. Innovation, creativity, and strategic genius can play crucial roles in strategic interactions, as do pure luck in external conditions and events outside the control of any actor. If we are following the course of action of any one actor, what we will see is contingency, unpredictability, and path dependence. It is important not to make the error of reasoning backward from the outcome to the cause: the fact that a particular outcome arose from a particular interaction does not imply that it "had" to have happened that way.

But the reality of uncertainty should not lead us to the error of believing that there are no general patterns. The weak occasionally vanquish the strong, but usually the strong win. Structural constraints exert powerful influences and put strong boundaries around the possibilities for luck and genius. Stochastic thinking lets us accommodate both the general tendencies and the occasional exception. An event with probability .99 is extremely likely, but the .01 probability of an exception is a real possibility. To find the structure in probabilistic processes, we have to get away from case studies and instead study the accumulation of many sequences of action and examine the range of possible outcomes that would have been possible from a set of initial conditions. When we do this, we find that some sets of initial conditions produce highly predictable results—despite the influence of chance events, while other sets of initial conditions create extremely volatile situations that can flow in dramatically different directions depending on luck.

Figure 3. Sample plot of random events. 50 actors, p=.02, moving sum of 10 time periods.

Random Events
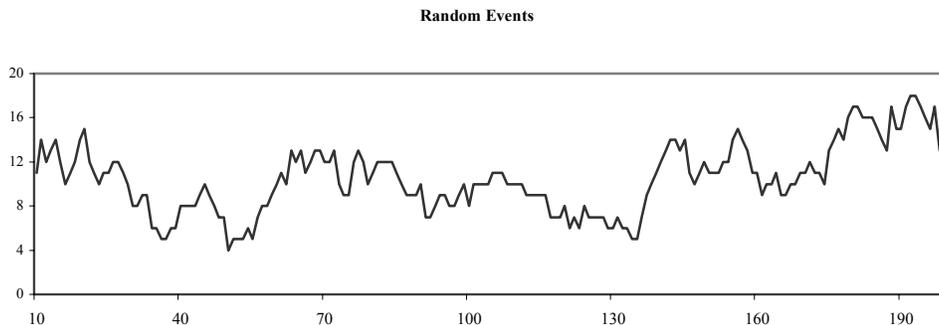
PROCESSES THAT CHANGE PROBABILITIES:
DIFFUSION AND ADAPTIVE LEARNING

Random fluctuations around a given probability are, of course, not the only factor affecting protest cycles. The probabilities of acting change. Cumulative distributions reveal what may be hidden in the event plots. As figure 4 shows, random processes produce linear cumulative distributions, while empirical plots show changes in slopes. We see small waves-within-waves from short-lived bursts of activity, especially in the riot series, but also in the German protests. There are even modest ripples in the random series. We also see longer-term shifts in the overall slopes of the cumulative distribution toward the S-shape characteristic of diffusion processes, especially in the riot series. The German protest distribution appears essentially random prior to 1981, and has a higher but modestly declining probability thereafter.

Adaptive learning and diffusion are two mechanisms that can account for waves-within-waves and longer-term probability shifts. An adaptive learning process is one in which actors change their behavior depending on its outcomes. A diffusion process is one in which people change their behavior depending on what others are doing. The exact mathematical details of how adaptive learning or diffusion processes are postulated to work will affect trajectories of action, and exploration of these details is beyond the scope of the present discussion. Here, we will just present some examples of how each kind of process can work.

However, before giving examples of each, we consider some issues common to both. Standard models of both learning and diffusion are unidirectional. That is, they are designed to account for movement from one steady-state probability to another, but not for cycles or oscillations in behavior. By contrast, the one certain thing we know about protest is that it always goes down after it goes up. Accounting theoretically for the universal decline in protest is actually one of the most difficult and most controversial problems in formal modeling of protest cycles. Basically, the question is whether there is an endogenous source of the decline (often called an exhaustion effect), or whether the decline arises because protest is always responded to from outside (a repression effect). Repression obviously plays a role at least sometimes, but our work in progress suggests that mechanisms of repression cannot easily fully account for observed empirical patterns. In addition, many peaceful forms of action are never repressed, but still decline. Olzak (1987) and Myers (1997b) suggest that some sort of "exhaustion" effect is at work, in which actors use up their stocks of resources and/or literally become tired and give up. Different kinds of actions doubtless vary in the extent to which they exhibit forms of exhaustion effects.

We cannot resolve this debate here, but we can provide a plausible account by using an adaptive learning framework that incorporates both endogenous and exogenous considerations. This approach assumes that protest inherently disrupts the normal rhythms of people's lives, and therefore is always costly to maintain over a long duration. Thus, protest is not a self-reinforcing behavior, but will persist only if it receives some kind of positive response. We may assume that people protest periodically on a stochastic basis with a given probability. This occasional protest can be understood as experimental behavior when baseline conditions are undesirable. But the probability of protesting will increase if and only if it is met with some sort of positive reinforcement (i.e., "success"), and the probability will decrease if there is no positive response (i.e., "failure"). In this approach, the success (or failure) may be postulated either to come from "outcomes" in an adaptive learning model, or from others' actions in a diffusion model.

DIFFUSION PROCESSES

In a diffusion process, actors are inspired to act by the example of others. A variety of psychological or social mechanisms may underlie diffusion. Actions of others may generate

Figure 4. Cumulative distributions for random series (top panel), 1960s riots (middle panel), and German new social movement protests (bottom panel)

Random Series: Cumulative

Cumulative Riot Counts 1964-1971

German Protests, Cumulative Counts
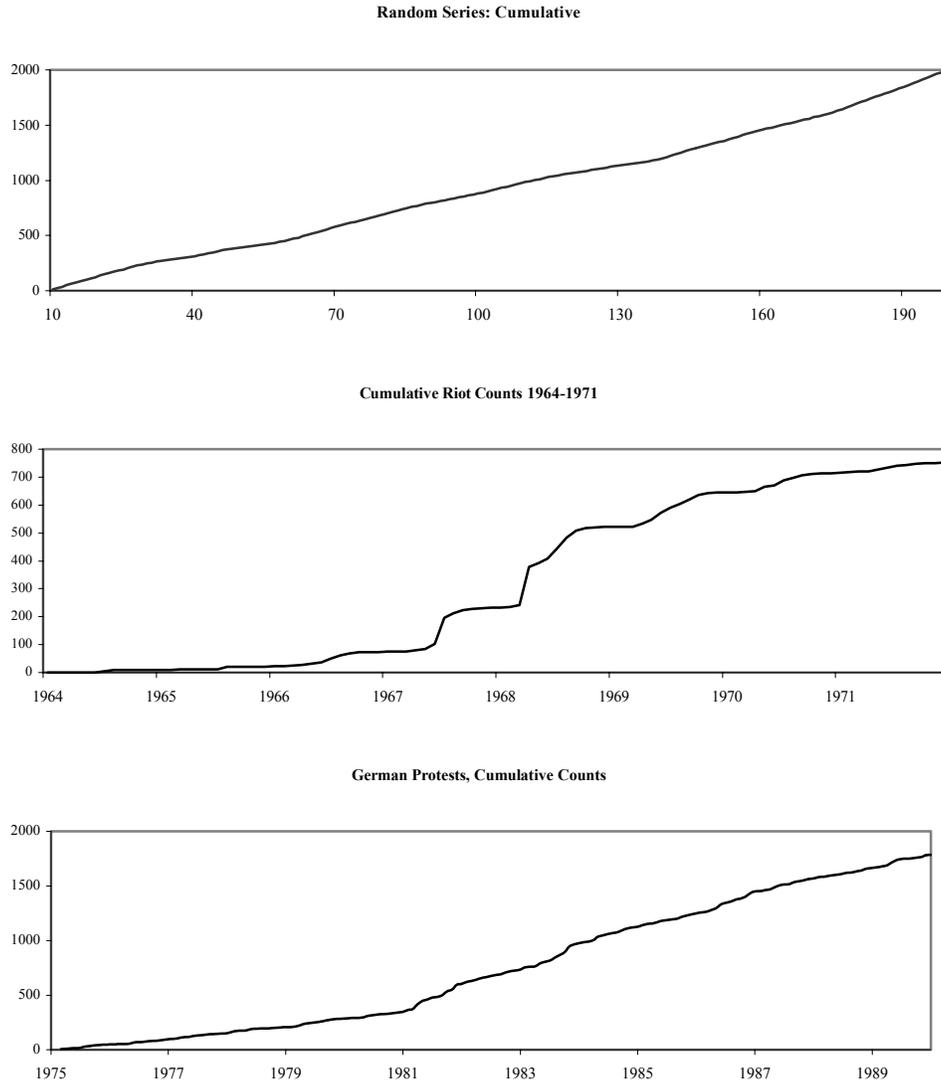
social influence and normative pressure to conform. They may act as an implicit signal that a particular form of action has been efficacious in producing results. They may create an "occasion" for considering whether to act (Collins 1981; Oliver 1989). Mathematically, the key is that the probability of action is a function of the amount of prior action. A standard diffusion model is a one-way process: the number of prior "adopters" increases non-adopters' probabilities of acting until everyone has acted. The action is assumed to be either permanent adoption (once you start using email you continue) or non-repeatable (after you catch the measles you are immune), so action declines after everyone has acted once. But protest is not permanent and is repeatable, so its decline requires explanation. Myers and Oliver (2000) have developed an "opposing forces" diffusion model that can account for the long-haul rise and fall in action probabilities as the net effect of the diffusion of two ideas, one promoting

protest and the other promoting non-protest. This model fits many single protest cycles quite well, but provides no account for cycles-within-cycles or the initial rise in protest.

An approach to explaining short-haul cycles is to assume actors respond to the change in others' actions: actors increase their probability of action when others' action rises, and decrease their probability when others' action declines. The specification we use follows suggestions in Bush and Mosteller (1955) for learning models, and weights rising action more when the probability is low and falling action more when the probability is high:

(1) $p_{t+1} = p_t + u_t \; {}^\star)_t \; (1 - p_t) + d_t \; {}^\star <) \; p_t$

where p_t is an actor's probability of acting at time t, $)_t$ is the relative change in the total number of actions (calculated as the current number of actions minus the previous number, divided by 1 plus the previous number), * is a coefficient for the strength of the diffusion effect for rising action, u_t is a dummy variable which is 1 if the difference is positive and 0 otherwise, d_t is a dummy variable which is 1 if the difference is negative, and $<$ is the ratio of the negative diffusion effect for declining action to the positive effect. In the example output shown in figure 5, * and $<$ are both 1, the initial probability of action is .02, there are 50 actors, and event counts are aggregated across 2 time periods. The net effect of this kind of process is an initial rise in the probability of action until an equilibrium is reached, and then oscillations around that equilibrium. The equilibrium is determined by the ratio of positive to negative effects, while the speed with which the equilibrium is obtained and the magnitude of the oscillations around that equilibrium is determined by the absolute magnitude of the effects. The cumulative distribution after the initial rise is linear, however, indicating that these short-haul fluctuations in the probabilities balance out quickly. This kind of simple single diffusion process, even one which responds to changes in others' actions and not just the total, cannot alone account for the patterns characteristic of protest cycles. Diffusion of protest has been documented empirically, but this exercise suggests that either the mechanics of how diffusion works must be more complex than modeled here, or diffusion must operate in conjunction with other mechanisms in affecting the trajectory of a protest cycle.

Figure 5. Acts and cumulative acts for a simple diffusion process. Process produces oscillations around an equilibrium; cumulative distribution is linear after equilibrium is reached. (50 actors, initial probability .02, diffusion effect=1, negative ratio=1, summed across 30 time periods)
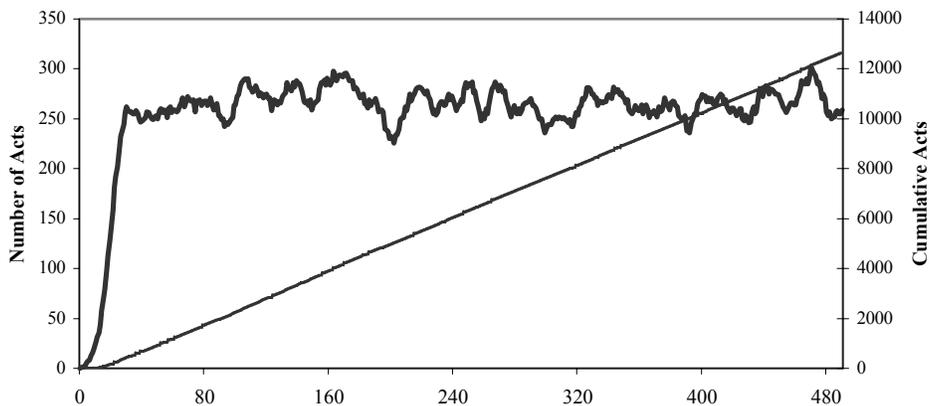
ADAPTIVE LEARNING PROCESSES IN RESPONSE TO EXOGENOUS
SUCCESS/FAILURE

Protest is often purposive in that it aims to affect policy or public opinion, or gain news coverage. Adaptive learning models are designed to capture the way in which actors adapt their behavior to produce desired outcomes (Macy 1990). We work with a simple learning model in which the increase in probability p from having action be reinforced is proportional to *1-p* (i.e., to the amount of change possible), while the decrease in probability from having action not be reinforced is proportional to *p*. The equation for this model is given by:

(2) $p_{t+1} = p_t + " S_t A_t (1-p_t) + " < (1-S_t) A_t p_t$

where S_t is a dummy variable equal 1 if "success" occurred at time *t* and *0* otherwise, A_t is a dummy variable equal 1 if the actor acted at time *t* and *0* otherwise, $"$ is the coefficient on positive reinforcement of action when success occurs and $<$ is the ratio of the coefficient on negative reinforcement of non-success to $"$. This model assumes that reinforcement is only relevant when the actor "acts." We treat non-action and its reinforcement as irrelevant in this model. If the only effect is a positive reinforcement of protest (i.e.,$<$ is 0), protest will increase to the maximum possible. Even if the probability of reinforcement is low, each time action is reinforced it will increase until it is constant. But if "failure" also affects probabilities ($< > 0$), this model can produce cycles, in which the probability of action rises temporarily, and then falls again.[3]

We begin with "success" being entirely exogenous: it is randomly determined and not actually affected by action. Even though the reinforcement is random, actors respond to "success" with increased probabilities of action. The learning coefficients determine both how rapidly the probability rises with success and how rapidly it dies down again with failure. In our example, the probability of action and the probability of "success" are each set at .02 and the learning coefficients favor a rapid rise and slower decline after reinforcement. Since they are independent, the probability that an actor's action is reinforced by success is .0004, or 1 in 2500. Figure 6 presents event series and cumulative totals resulting from one run of this condition for 1000 iterations for five independent actors who have independent probabilities of reinforcement and no effect on each other. The top plot sums across the five actors, and the smaller five plots show the individual actors. Three were never reinforced. One actor happened to be reinforced three times, including twice in close succession. The other was reinforced once. When there is only one actor, this model produces highly volatile outcomes: most of the time, the probability is low and little action occurs, but occasionally there will be a burst of repeated action arising from the (random) repeated positive reinforcement of action.

This model of high response to random external reinforcement and low baseline probabilities generates the erratic spiky plots and waves within waves often characteristic of event data. The underlying probabilities are random and, in the very long run, the cumulative distribution must be linear, but when the probabilities are low, this model produces S-shaped cumulative distributions for actors who happen to be reinforced. Non-random but exogenous intermittent low-probability events which reinforce action would generate similar patterns of event plots. Data which aggregates a small number of independent actors experiencing independent reinforcement exhibits sharp spikes when individual actors are acting. This is consistent with empirical studies showing that peaks of mobilization are around distinct tactics or issues (e.g., Markoff 1997; McAdam 1983).

The patterns for larger number of actors depends on whether they experience exogenous success together or independently. If success either occurs or not for all actors on a given iteration (an assumption appropriate for aggregation across similar kinds of actors) and if actors respond to the (random) reinforcement of any of them with a response proportional to

Figure 6. Rare random external reinforcement and high responsiveness produces bursts of activity. Each graph shows acts and cumulative acts. Top panel is the sum across five actors. Plots for individual actors show that two were reinforced and three were not. This mechanism produces spiky event distributions with waves and S-shaped cumulative distributions.

Sum of Five Independent Actors
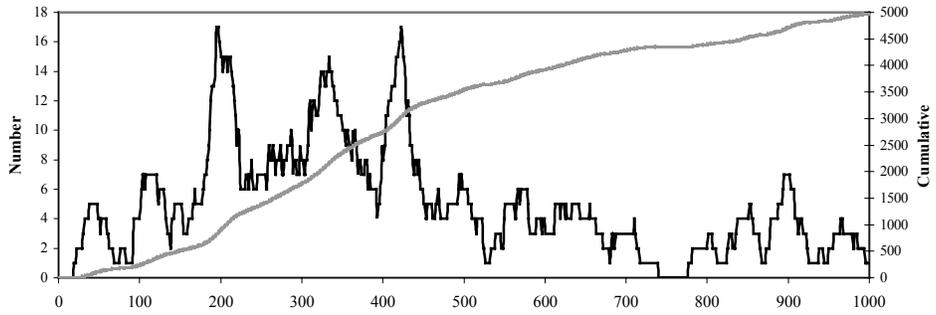
Reinforced Actors   Unreinforced Actors
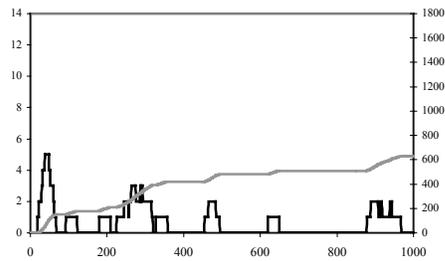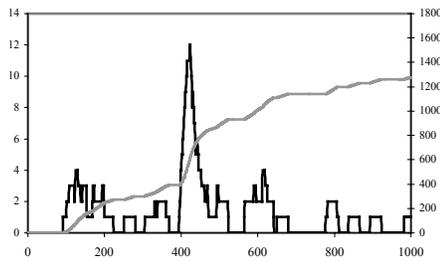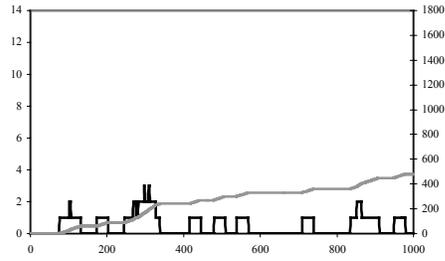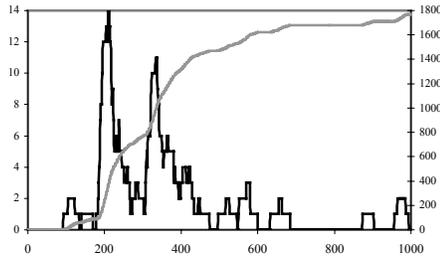
Top actor was reinforced three times, twice in close succession. Bottom actor was reinforced once.
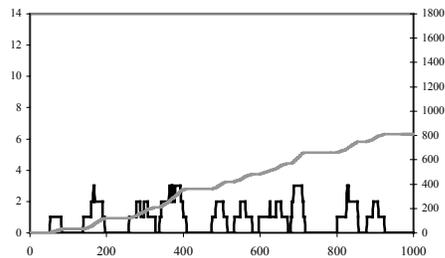
Figure 7. Total acts and cumulative acts for fifty actors experiencing exogenous random reinforcement. Upper panel gives two examples of reinforcement in common and response to reinforcement proportionate to the number who acted. Lower panel gives two examples of independent reinforcement. Independent reinforcement yields higher cumulative totals and a smaller range of variation in the level of action. Initial probabilities of action and success are .02 in all cases, and response to reinforcement is high.

Reinforcement in Common

Independent Reinforcement
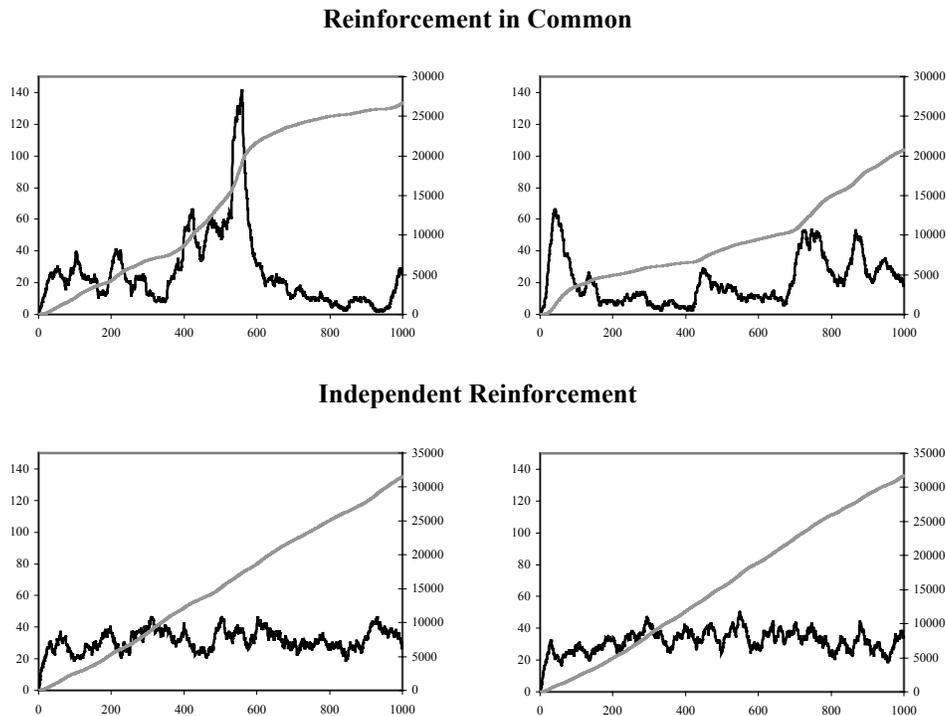
the number who acted, the result is a spiky volatile wave. Two examples are shown in the upper half of figure 7. Again, the model of exogenous reinforcement produces S-shaped cumulative distributions and waves within waves. By contrast, aggregation across a large number of actors experiencing independent reinforcement (i.e., where one actor's reinforcement on an iteration is independent of another's) generates a plot that is usually visually indistinguishable from a simple random probability of acting, except for slightly more pronounced waves, as in the examples in the lower half of figure 7. This is a model appropriate for the aggregation of data across diverse kinds of actors.

These examples show the importance of considering the type of data being modeled, including the number of "actors" whose actions are being tallied, and the extent to which those actors are similar to each other. Event series aggregated across issues would be expected to look more like data from simple random processes, while event series focusing on only one issue would look more like the "one actor" or "reinforcement in common" series. The "one actor" series would be similar to data accumulated on one issue in one locale, while the series for multiple actors with reinforcement in common would be similar to data accumulated on one issue across multiple locales. Taken together, they suggest that occasional exogenous reinforcement is a plausible account of many of the patterns in empirical event series.

MUTUAL REINFORCEMENT PROCESSES

Most often, "success" is not random, but is at least partly affected by how much action there has been. In fact, most protesters and most protest researchers assume that there is at least a moderate positive effect of protest on success. In this case, there is a two-actor system in which the actor emitting success and the protest actors are in a coevolutionary relationship in which each modifies their behavior in response to the other. However, a simple model of mutual responsiveness is less good than random reinforcement at generating event series that look like empirical plots. If success is dependent upon the total amount of prior action, action and success are in a positive feedback loop in which the system must evolve to a limit in which both action and success have probability 1, as shown in the top panel in figure 8. Thus, we assume that declining protest reduces the probability of success. We model this by assuming that the change in the probability of the second actor emitting "success" at time t, s_t, is a function of the change in the amount of prior protest action by the original actor. The equation for the probability that this second actor generates a "success" for our first actor is:

$$(1) \quad s_{t+1} = s_t + u_t \text{ "}_s \text{)}_t (1\text{-}s_t) + d_t \text{ "}_s <_s \text{)}_t s_t$$

where (as for the diffusion model) $)_t$ is the change in the amount of action by the original actor, u_t and d_t are dummy variables marking increasing and decreasing action, respectively, and $"_s$ and $<_s$ are the positive effect of rising action by the first actor on the second actor's probability of generating a "success" for the first actor, and the ratio of the negative effect of declining action to the positive effect. This model can produce cycles. If positive reinforcement is stronger than negative, the system rises to an equilibrium determined by the ratio of positive to negative effects, and then oscillates widely around that equilibrium, as in the bottom of figure 8.

If mutual negative reinforcement from failure or non-action is as strong as the positive reinforcement and the initial probabilities are low, no overall rise in the probabilities occurs but, instead, actors experience occasional bursts of action and reinforcement, followed by declines back to the baseline. This condition produces spiky volatile event plots as shown in figure 9. The processes are stochastic and highly variable. Given the same initial conditions, some actors never rise above the low baseline probability of action, while others experience one or more bursts of activity of various sizes. As with exogenous reinforcement, summing across five actors produces plots with spiky irregular oscillations whose cumulative distributions are essentially linear although markedly scalloped by small waves, while summing across a large number of actors produces less spiky random oscillations. Thus, if mutual adaption is an important process explaining empirical data, it appears that factors pulling action and regime responses down must be as strong as those driving them up.

COMPETITION AND DIFFERENTIAL SELECTION PROCESSES

One of the important insights we may gain from adapting evolutionary models is that the mix of action types is affected by the differential response to them by a regime (e.g., Lichbach 1987). A full consideration of these issues is beyond the scope of this article. However, we can provide a simple example of how stochastic processes and differential reinforcement can randomly promote some forms of action and reduce others. We demonstrate this by putting five actors together in the mutual reinforcement scenario defined above with only one further restriction: the regime can give success to only one of the five actors at a time. The probabilities of success are determined independently for each actor and the Monte Carlo process generates tentative successes independently for each actor as a function of that probability. But if two or more tentative successes are generated on an iteration, only one can win.

Figure 8. Mutual reinforcement. Acts and cumulative acts when actor and reinforcing agent affect each other. Top panel: If there is only positive reinforcement, the first success quickly creates a mutual spiral toward constant action and constant success. Bottom panel: If there is both positive and negative reinforcement but a low negative to positive ratio, the system oscillates around equilibrium probabilities of action and success.

Positive Reinforcement Only

Positive Reinforcement Greater Than Negative
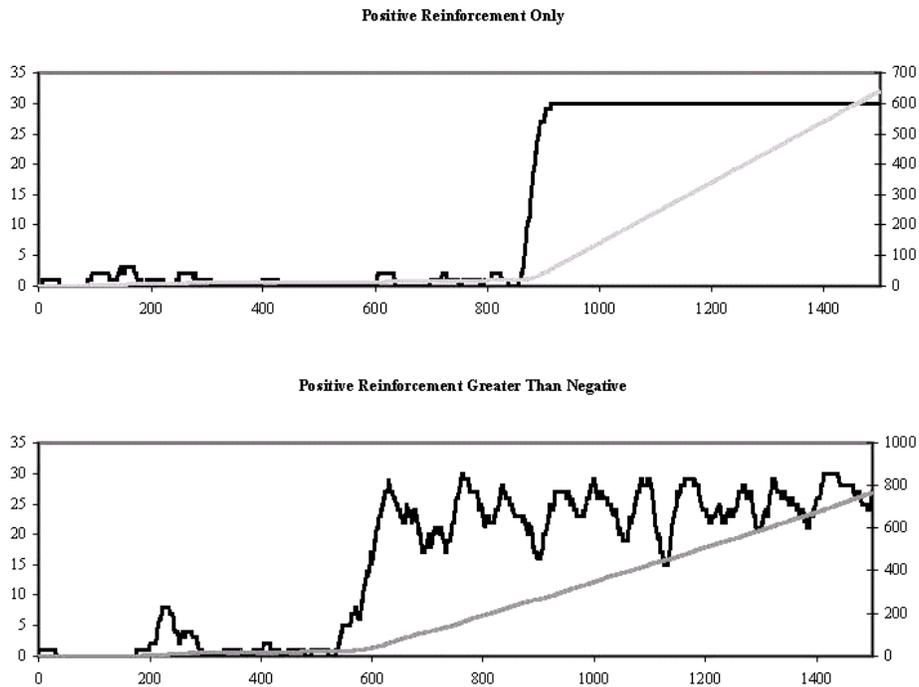
The trajectory of this system is determined by how ties are broken when two or more actors tentatively achieve success on a given trial. If the choice is entirely random, then the actors evolve together toward a state in which all are continuously acting, the regime is tentatively generating success for all of them, and they randomly "take turns" obtaining success. However, if the choice rule favors the actor which is already ahead by some criterion, i.e., who already has the highest probability of success or who has the greatest total of recent actions, the system leads one actor at a time to become dominant: its probability of action and success go to 1, while the others' action probabilities decline. However, the system is not stable. Over a long-enough series, the dominant actor will "slip" and another will take its place as dominant. These dynamics can produce alternations among several actors in periods of dominance, or sequences of competition in which two actors alternate dominance several times, in what looks like a movement-countermovement cycle. Across a modest number of iterations (even as high as 10,000), there are usually some actors which never have a turn at dominance. Figure 10 shows one sequence in which every actor gets a turn to dominate. Considering one actor at a time, this competition pattern generates a long-term cycle in which action starts low, rises and stays high for a while, and then falls, perhaps to rise again later.

The competition among actors for external "success" seems to be a plausible mechanism to account for some of the ebbs and flows of collective action. Movements rise and fall not just because of their own logics or their own relationships to the state, or to media cycles, but because of the competition from other movements for attention. Although this suggestion needs to be explored further, it seems like a very promising lead, and one that arose from carefully considering what possible mechanisms could account for observable patterns in collective action.

Figure 9. Mutual reinforcement. When initial probabilities of action and success are low and the ratio of negative to positive reinforcement is high, mutual reinforcement between an actor and a reinforcing agent produces occasional bursts of activity and success off a low baseline. These five example action series are independent.
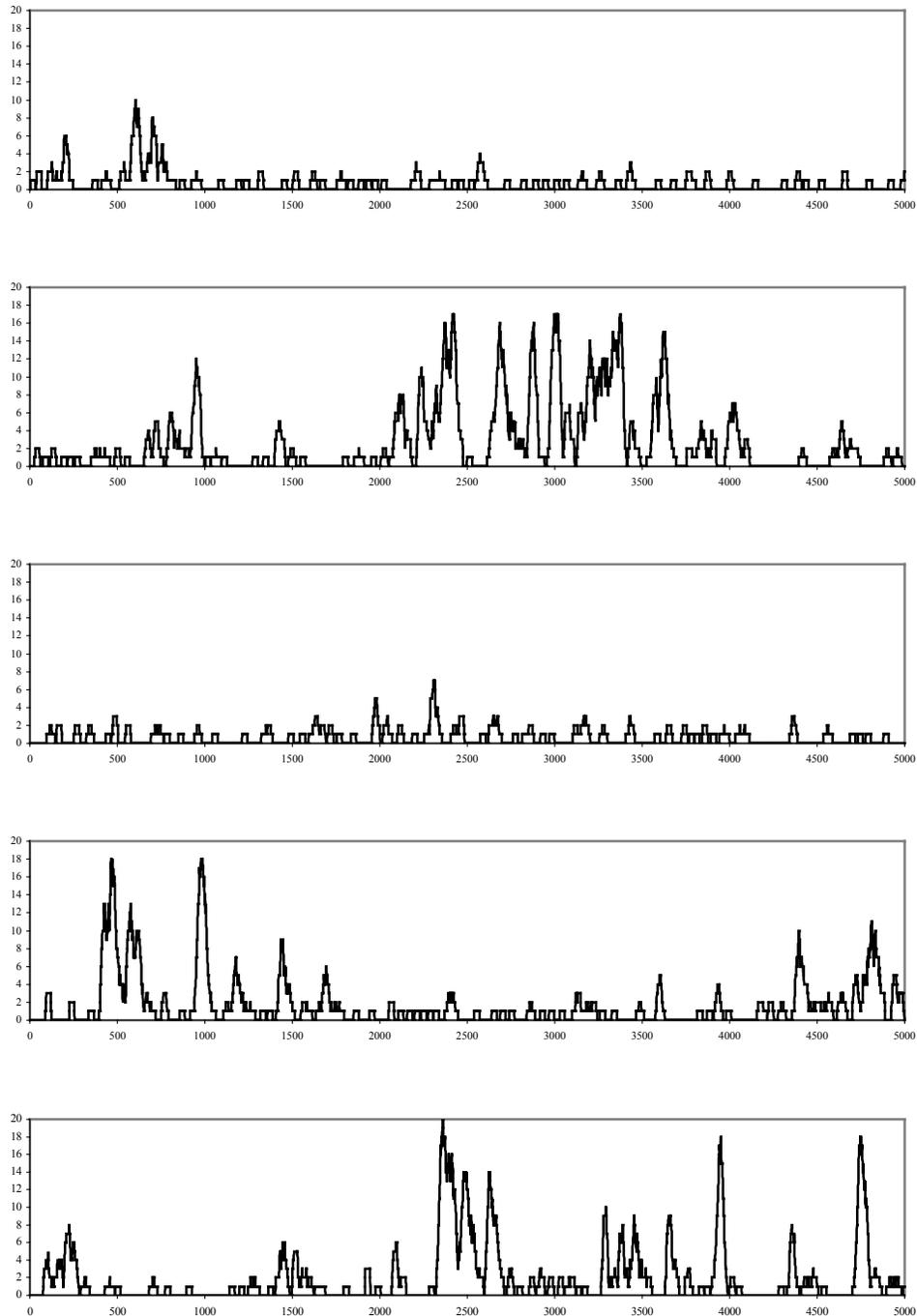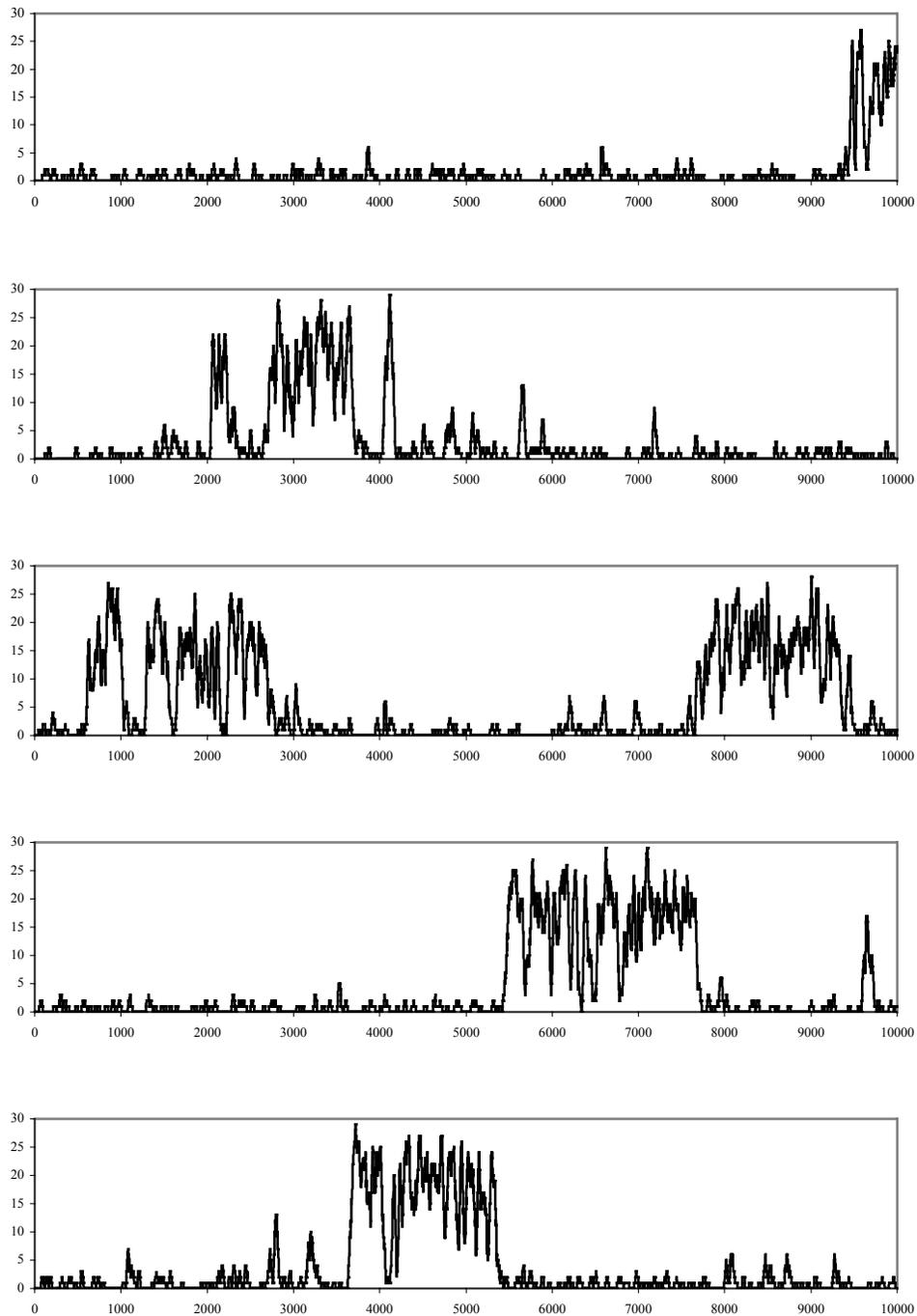
Figure 10. Five actors in mutual reinforcement relation with an external reinforcing agent compete with one another for success under conditions in which each would otherwise maintain high levels of action and success for all actors. Only one actor at a time can be reinforced.

CONCLUSIONS AND FURTHER DIRECTIONS

In this article, we are calling for a paradigm shift that builds upon prior understandings but positions our theorizing to take the next step. We have argued that we need to change the metaphorical underpinnings of social movement theory, viewing social movements as coevolving populations of actions rather than as coherent organisms. Central to this metaphorical shift is a move away from deterministic to stochastic thinking, and a move toward investigating mechanisms and processes that occur in many movements, rather than the grand inputs and outputs or historical details of one movement at a time.

Only an action or event-based perspective captures the complexity, fluidity, and strategic interaction that characterize social movements. Qualitative as well as quantitative research can be informed by focusing on the interrelations among events (Sewell 1996a; Sewell 1996b). Case studies repeatedly show us the ways in which actors within social movement organizations actively choose how to respond to the prior actions of others in the context of their particular political, economic, and organizational situations. Beyond this, coevolution theory is the best way to understand the wealth of new data that are being collected by protest events researchers. These researchers are increasingly studying the joint coevolution of protest forms, social control responses, and political structures and practices. We have argued that this approach is a new way of organizing old ideas, and that prior theoretical approaches can be understood within a broader coevolutionary approach.

As formal models go, the examples we have presented in this article are very simple, even simplistic. Systems analysts and evolutionary biologists have identified more complex models that better fit particular empirical cases, such as predator-prey and niche competition relations. This article does not pretend to present what will prove to be the best formal models for protest cycles. Rather, our goal has been to give simple examples to show the payoff that is possible when modeling is used as part of a rigorous dialogue between theory and data. We believe that formal mathematical modeling needs to play a role alongside empirical research as a basis for theory development. We have argued that the very act of formalization forces theorists to address vagueness and imprecision in verbal theory. A formalization is one way to nail down exactly what is meant by a particular process or mechanism. Carefully working through the deductive implications of assumptions about mechanisms is the only way to find out whether they can, in fact, do what it is thought they do. At a bare minimum, a proposed mechanism ought to be able to produce event trajectories that look like empirical data. Critics who fault a particular formalization as unrealistic should refer to data and offer specific alternatives, not retreat into unfalsifiable ambiguity. Regression-based analyses of quantitative data are obviously important, as well, but are better for determining whether an independent variable has a relatively monotonic effect on a dependent variable than for uncovering the ways in which the stochastic interactions between two or more strategic actors shape the trajectories of protest cycles.

We have shown that stochastic models capture both the volatility and path dependence of collective action and its underlying structural constraints, and we believe that the next "big step" that all theorists (formal or not) must take is to understand how to think stochastically when reasoning about collective action. We have suggested that reinforcement from the environment, adaptive learning, and competition are important processes which underlie protest cycles. Exogenous reinforcement, and mutual adaptation with high levels of negative reinforcement for failure or non-action can produce the spiky, volatile trajectories, which characterize much of collective action. By contrast, diffusion processes alone cannot produce such trajectories, nor can mutual adaptation with low levels of negative reinforcement.

We draw two tentative conclusions from our work so far. First, the dynamics of collective action cannot be understood apart from its interaction with external actors. Theories of protest and social movements must be theories of interaction and relationship. Second, the

factors which generate discouragement and failure are at least as important for understanding protest cycles as those which generate enthusiasm and success. We have to stop focusing so much on grand mobilizations and sweeping reforms, and get more information about all of the little events that go nowhere and the forces producing disillusionment and despair.

Although our models have investigated the effects of adaptive learning and a logic of consequences, nothing in the broader coevolutionary framework restricts attention to such logic. People often behave instead according to what is often called a logic of appropriateness, in which they seek to do what seems right. The question is what this insight implies about observable patterns of protest. It is possible to build formal models of norm or identity construction: Gould (1993) and Kim and Bearman (1997) have each developed models of collective action premised on the assumption of a moral calculus or influence process. The next step is to ask how such processes would shape a trajectory of action in interaction with other actors.

We have noted that one of the most difficult problems is to provide a theoretical account for the mechanisms driving the long-term changes in protest rates, and especially the decline of a protest cycle. Our analysis has suggested two mechanisms for this. One is that declines are the natural product of protest-regime interactions and adaptive learning in which the failure to be reinforced is as important as the occasional success. The other is that competition between movement actors inherently forces alternation among them in their chances for success in interaction with their environments. In stochastic processes, it is basically a matter of luck who gets reinforced when, and under some conditions there is a high level of indeterminacy and volatility in outcome trajectories. Of course, much of external reinforcement and the differential competitiveness of movement actors are not random, but are structured by other factors that change over time. Understanding how these external "biases" affect stochastic processes will move us closer to a full account of the interplay of structure, agency, and luck in the interactions between protest and regimes.

We have also shown that the predicted trajectory of a stochastic protest cycle is strongly affected by the number of actors. In general, the effects of "success" (external reinforcement) on action produce volatile trajectories when there are few actors, reinforcement effects of failure are strong relative to those for success, and the baseline probabilities are low. We have argued that this should be understood in relation to the character of the data we are examining. Event series tallying the actions around one issue for one action form or one locale are more likely to look like the one actor or few actors cases. Data tallying the actions around one issue across many locales or groups or types of action are likely to fit models which assume that actors experience success or failure in common. The trajectories for one issue at a time, then, are likely to be volatile and sporadic and quite different from each other. But when data are aggregated across issues and multiple locales, they are much more likely to look like simple random variations around a common probability, perhaps altered periodically by some long-term probability shift. These considerations should feed directly into the ways empirical analysts approach event data.

Thinking in terms of the interaction between protest events and external "success" will help us to resolve some of the important methodological questions we face in analyzing protest events data. Most protest data must be obtained from newspaper records, as they are the most readily available data source that spans times and places. But the media do not perfectly capture all events that occur, nor are the events covered an unbiased sample of all events. In fact, one of the most important forms of "success" that reinforces protesters is receiving news coverage. This means that the mechanism we use for data collection is, itself, part of the system producing protest. Much recent research is focused on understanding how newspapers select which events to cover (e.g., Franzosi 1987; Hocke 1998; McCarthy, McPhail, and Smith 1996; McCarthy, Titarenko, McPhail, and Augustyn 1998; Mueller 1997a; Mueller 1997b; Myers and Caniglia 2000; Oliver and Maney 2000; Oliver and Myers 1999). If we think of the media as another actor in the coevolution of protest, we have a way

of theorizing and potentially integrating these methodological results into our general theory of social movements.

For example, we know that larger and more intense forms of action receive more news coverage. If the news media are the main communication network that drives a diffusion wave and the main source of reinforcement for protest, we should be able to make predictions about the "infectiousness" of individual events and the overall trajectory of the protest wave on the basis of the size or severity of events. When this kind of distortion is produced by the media, it advantages movements with large events and disadvantages those who can only produce small events. Armed with this understanding of how a communication network reacts to different events, we can come closer to a correct model of the effect of discontinuous "shocks" to a system that come from large, dramatic events or tactical innovations. It could also lead toward formal models that incorporate stochastic production of such innovations as action in general is accelerating.

The theoretical shift toward what we are calling coevolution theory is already under way in the political process synthesis, the move toward an event-oriented theory, and the shift toward examining mechanisms and processes rather than inputs and outputs. These moves need to be accompanied by a shift to stochastic thinking, which recognizes both unpredictability and path dependence on the one hand and the power of structural constraints and high probabilities on the other. The search for processes and mechanisms should begin with fundamental general processes such as diffusion, adaptive learning, mutual reinforcement, and competition. Formal models cannot stand alone in theorizing and must always be constructed in close dialogue with both quantitative and qualitative empirical data. But formal models are an essential component of theory development, for only the discipline of formalization forces verbal theory out of its ambiguity and vagueness and into specific claims which can be assessed against empirical data. Only translating vague references to the "effects" of diffusion or regime responsiveness into specific processes revealed their limitations as accounts of empirical patterns and pointed toward failure and inter-actor competition as an important processes in movement dynamics.

ENDNOTES

[1] Thanks to Ruud Koopmans for supplying the data from his book (1995).

[2] All the models in this article were generated using the Stella computer simulation package. A Monte Carlo function generates 0's and 1's randomly for a given probability.

[3] It should be noted that "success" can sometimes reduce the probability of action if it removes the grievance or supplies the benefit toward which protest is directed. A model which takes account of this process in interaction with a reinforcement process must necessarily be more complex, and is beyond the scope of the simple exposition we offer here. An assumption of the present analysis, then, is that the "success" does not eliminate the underlying grievance or goal which provides a baseline propensity to act.

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