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Abstract

This paper presents a model of consumer boycotts where the discrete choices of concerned consumers are represented as a stochastic processes.

We solve for the limiting distribution of the process and analyze its properties. We then discuss how the model relates to game-theoretic models of collective action and derive an equilibrium selection result. The type of equilibrium selected depends on the parameters of the model including the switching costs by boycott participants. We end by discussing the model's consequences for activist strategies and targeted firms.

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1 Introduction

Consumer boycotts are a widely used strategic tool of political activists to change corporate practice (Baron 2003, Friedman 1999, Shaw 1996). Yet, they represent a puzzling phenomenon to the modern theory of collective action (e.g. Granovetter 1978, Oliver and Marwell 1988, Oliver 1993, Olson 1965). Consumers are not part of an existing identifiable group or some other dense social network, nor do they share a common identity or other social activities. In addition, there are no readily available selective incentives, the social benefits of a boycott are not exclusionary, and there usually is no repeated interaction among participants. Thus, according to collective action theory, consumer boycotts should not occur.

Still boycotts do occur, and in many cases they are highly successful. In one of the few quantitative studies of boycott success, Wolman (1914) reports that 72% of the concluded labor-sponsored boycotts at the turn of the century were successful in attaining their stated objective. Indeed they were so successful that businesses began to devise political and legal strategies to effectively make them illegal. Their actions bore fruit in both Supreme Court decisions and Federal legislation that effectively outlawed "coercive" secondary boycotts in labor disputes (Friedman 1999).

Today, boycotts are the weapon of choice used by political activists with various agendas ranging from environmental concerns, global labor standards, to animal welfare or opposition to genetically modified food products. Boycotts critically rely on the participation of *concerned consumers* who are consumers that also care about the social dimension of a product such as its environmental impact or the way the product is manufactured or marketed. Concerned consumers are an increasingly important segment of the market. They may be willing to pay a higher price for a socially responsible product, or will switch to alternative products if their preferred products are considered socially unacceptable. In the oil industry, concerned consumers are estimated to represent up to 70% of all consumers.[1]

To fix ideas consider the famous example of the confrontation between Shell and Greenpeace over the decommissioning of the Brent Spar oil storage facility (e.g. Diermeier 1995, Jordan 2001). In 1991 Shell UK, the British operating company of multinational Royal Dutch/Shell Group, was

[1] Presentation by Steve Percy, former President of BP America. Kellogg School of Management. October 28, 2002.

facing the necessary disposal of the Brent Spar, an aging North Sea oil storage facility and tanker loading buoy. Regulatory guidelines (in this case by the UK. Ministry of Energy and Environmental Affairs) govern petroleum companies in the process of offshore facilities disposal; companies are required to rigorously evaluate disposal options and submit their preference, the Best Practical Environment Option (BPEO), for government approval. Two options survived Shell's screening process: on-shore dismantling and deep-water disposal. The former requires the transport of the buoy to shore for dismantling while the latter involves towing the structure to a deep-water disposal sight for sinking. Shell UK submitted deep-water disposal as their BPEO concluding that it was both less costly and less likely to result in mishaps that could be dangerous to the environment and the workers. In February of 1995, the British government accepted Shell's BPEO, deep-water disposal.

Meanwhile, one of the world's largest environmental groups, Greenpeace International, had become aware of Shell's plan and had commissioned their own study concluding that removal to shore was a better option than deep-water disposal. Greenpeace subsequently acquired satellite communications and video equipment, and on April 30, 2005, 14 activists and 9 journalists boarded the Brent Spar rig. After a three week occupation, the activists were expelled by Shell and local authorities using water cannons, an act that one Greenpeace official, Harold Zindler, characterized as having "portrayed Shell as unresponsive and inconsiderate big business." In response German motorists engaged in an informal boycott of Shell stations which led to a drop in sales of up to 40%.

On June 20, Shell announced that they would abandon the sinking of the Brent Spar rig. The Chairman stressed that while Shell still believed deep-water disposal to be the best environmental option, Shell UK was in an "untenable position" because of its failure to convince stakeholders in the North Sea. Shell also started an advertising campaign admitting mistakes and promising change, despite a University of London study arguing that deep-sea disposal would likely have been less dangerous to the environment than on-shore dismantling. Shell's additional costs were estimated at around $60 million.

Despite their practical importance, boycotts have not attracted much interest among political economists. This is particularly true of formal analyses.[2] In this paper we focus on the decision problem faced by concerned consumers. That is, we are interested in the dynamics of boycott participation where a large number of consumers needs to take coordinated and costly action.

2 The Basic Model

As our base-line model, we consider the interaction between (potentially) concerned consumers. These consumers have the usual consumption preferences but they also care about the social characteristics of a product. Interaction is modeled as a complete information non–cooperative game with simultaneous moves.

The decision of consumers whether to participate in a boycott can easily be modeled. First consider only concerned consumers. Assume that concerned Shell costumers need to decide whether to switch their consumption decision to BP in order to force Shell to abandon deep-water disposal of the Brent Spar. On the dimension of the private qualities of the product (quality, price, location of nearest gas station, etc.) these consumers have a preference for buying Shell. That is, if they switch to BP they will pay a private cost c. If the alternative product (here "BP") is a cheap substitute, c will be low. We also assume that on the social dimension, all concerned customers believe that on-shore disposal is better for the environment than deep-water disposal. This social benefit is denoted b, which we normalize at $b = 1$. This benefit has the features of a public good. If Shell decided to change its decommissioning strategy all concerned consumers would benefit from the decision whether they participated in the boycott or not. A boycott thus results in a drop of sales for Shell. We assume that if the drop is substantial enough, Shell will yield to pressure and choose on-shore disposal.

In the complete information case, the focus on Shell's concerned customers is without loss of generality. Concerned consumers with a strict private preference for BP, e.g. because of better gas station location, have a dominant strategy to buy from BP. On the other hand, Shell customers

[2] Recently, however, David Baron has proposed a series of formal models of private politics, i.e. actions by interest groups against private parties such as firms with the goal of changing a firm's behavior or industry standards (Baron 2002, 2003b, 2003c). His models focus predominantly on the interaction between activists and a firm, and the media, not the dynamics of boycott participation. For a recent model of strategic activism see Baron and Diermeier (2005).

that do not care about the Brent Spar or believe deep-water disposal is the preferred environmental option, have a dominant strategy to buy Shell. That is, the only customers who face a strategic dilemma are *concerned Shell* customers. For them it is only worthwhile to participate in the boycott if enough other consumers participate as well. That is, they face a collective action problem (Olson 1965).

The model thus corresponds to an N-player ($N \geq 2$) discrete public goods game as defined e.g. by Palfrey and Rosenthal's (1984) where c stands for the (net) opportunity cost of participating (e.g. the extra distance a driver has to drive to buy his gasoline from BP rather than Shell) while b ($0 < c < b$) stands for the (collective) benefit of stopping the Brent Spar from being sunk. This benefit constitutes a pure public good. If (and only if) a sufficient number of consumers k (with $1 < k \leq N$) boycott the bad product (Shell), the management of Royal Dutch/Shell will decide to dismantle to Brent Spar on-shore.

Formally, agents have two choices: they can either boycott (labeled choice 1) or decide not to participate in a boycott (choice 0). Let X denote the number of agents participating; similarly, let X_{-d} denote that number excluding agent d. Since an agent's payoff depends only on his action and on the number of other players participating, we can write an agent d's pay-off as $u(z; X_{-d})$, where $z \in \{0, 1\}$ represents the agent's choice. Agent d's payoffs can be summarized in the following matrix:

Payoffs $u(z; X_{-d})$	$X_{-d} < k-1$	$X_{-d} = k-1$	$X_{-d} \geq k$
$z = 0$	0	0	b
$z = 1$	$-c$	$b - c$	$b - c$

As Palfrey and Rosenthal have shown, the game has many equilibria. Specifically, there are $\binom{N}{k}$ pure strategy equilibria (each with exactly k boycotting consumers), and one pure strategy equilibrium where no boycott takes place. In addition, there are equilibria where some agents use mixed strategies. These agents must be indifferent between c and their pivot probability, i.e., the probability that their participation will lead to the provision of the collective good. Palfrey and Rosenthal show that as $N \to \infty$ mixed strategy equilibria disappear. That is, in large populations either the collective good is provided for sure or not at all.

The importance of the Palfrey-Rosenthal model for our application lies in the fact that it demonstrates how boycotts can occur as equilibrium phenomena even if there is only a single interaction. Boycotts are thus consistent with rational action taken by concerned consumers. However, the game theoretic approach also faces some limitations. First, the Palfrey-Rosenthal game has many equilibria, some with a protest level of zero. Game-theoretic analysis, however, only specifies which outcomes are consistent with the incentives specified in the game. It does not indicate which one is more likely. Specifically, for large populations, the Palfrey-Rosenthal model implies that either boycotts will not occur with probability one, or (also with probability one) they will occur at exactly the efficient level. In the game-theoretic context we are thus left with an equilibrium multiplicity problem. Second, note that the two types of equilibria exist for all $k > 1$ and $0 < c < b$. Thus, the model cannot explain any of the following empirical phenomena: calls for boycotts are more likely to be successful if cheap substitute products are available (i.e. c is low), if the issue has high importance of salience (i.e. b is high), or if the company can ill afford to loose a large number of customers (i.e. k is high) (Friedman 1999). Third, for protests to occur, agents must be able to solve a complex coordination problem (especially in large populations) with no apparent coordination device because all equilibria where the collective good is provided are asymmetric if $k < N$. That is, although the game is symmetric in payoffs and actions, the predicted behavior is not: some agents participate while others free-ride. This leaves us with a puzzle: how do large populations manage to overcome a stark coordination problem, especially if there is no apparent coordination device like previous experience or existing social structures?

A common solution to the problem of equilibria is to invoke the theory of "focal points" (Schelling 1960) based on the observation that agents use salient features of a particular equilibrium to coordinate. However, many focal mechanisms such as prior experience or related conventions (e.g. Schelling's famous example of meeting in a foreign city at the train station at noon) are not available in the case of boycotts. Extensive media coverage may be interpreted as providing a focal point. However, the mechanism how coordination is achieved through the media remains unclear. Below we will suggest such a mechanism.

Theoretical sociologists have developed an alternative formal methodology to study collective action: so-called "threshold" or "critical mass" models (Granovetter 1978, Oliver and Marwell 1988, Schelling 1978).[3] Individuals in a population are assumed to vary in their willingness to participate in a collective action such as a boycott. These variations may stem from differences in costs and benefits (Oliver and Marwell 1988), or may be directly specified as propensities to act as a function of the number of others who are already acting (Granovetter 1978). Collective action will occur only if there is a sufficiently large critical mass of agents who are willing to take the first step and thus trigger mass participation. Whether collective action occurs thus depends on the distribution of individual participation thresholds in the populations. In contrast to game-theoretic approaches critical mass models explicitly model the dynamic nature of collective action. However, while there have been some informal attempts to explicitly model the implicit adjustment processes (e.g. Schelling 1978), a rigorous treatment of the their underlying dynamics is still lacking.[4] We propose a dynamic model to bridge this gap.

3 A Probabilistic Model

To explicitly analyze coordination in large populations we present a stochastic, dynamic model of collective action.[5] This approach differs from standard game-theory in two respects: (a) the behavioral assumptions, and (b) the predictive concept. In contrast to standard game-theoretic models, the model does not assume common knowledge of the game form or perfect foresight by voters. Rather, agents adjust their actions according to some behavioral rule. Moreover, the model's predictions are not given by an equilibrium, but by a probability distribution. Specifically, we use the game's normal form to define a Markov process and then use the process' limiting distribution as our solution concept.

The Markov process consists of an action rule and a selection rule. In classical game theory agent's are assumed to use best-response correspondences as their action rule. That is, behavior

[3] These models have experienced a recent renaissance as "tipping point" models (Gladwell 2000).

[4] Most of the theoretical development of tipping models relies exclusively on numerical examples and simulations (e.g. Granovetter 1978, Oliver 1993).

[5] There is a large related literature on the use of stochastic models in economics. See Blume (1997), Fudenberg and Levine (1998) or Young (1998) for detailed overviews,

is completely determined by the incentives specified in the game (unless the agent is exactly indifferent between two actions). We generalize this assumption to allow for random choice behavior.[6] Specifically, we use a random utility model (McFadden 1984). So, while each agent's mean utility is fixed, individual realizations may vary. This approach seems especially appropriate in models of boycotts where the perceived costs and benefits may well vary over time as a consequence of media coverage and other idiosyncratic sources of information.

Let $p^{\beta}(z|X^t_{-d})$ denote the conditional probability that in period $t+1$ agent d will play action z given that the current configuration of play is X^t. Under the standard extreme-value assumptions[7] for the error term each individual's choice for all $d \in N$ will be characterized by the probability distribution:

$$p^{\beta}(z|X^t_{-d}) = \frac{\exp[\beta u(z; X^t_{-d})]}{\sum\limits_{z' \in Z} \exp[\beta u(z'; X^t_{-d})]},$$

which is equivalent to the familiar log-linear choice rule. It captures the assumption that the pairwise probability ratios of choosing actions are proportional to the respective pay-off differences. The log-linear choice model is closely connected to the best-response correspondence. The parameter β formally captures the degree to which the deterministic component of utility (given by the payoff matrix) determines choice. A low β corresponds to the case where a participation decision is not much influenced by the incentives specified in the model. For $\beta = 0$ choice is completely random. That is, for all possible configurations, d will play each action with probability $1/2$. For $\beta \to \infty$, log-linear choice converges to a distribution that puts positive probability only on best-responses to X^t_{-d}.

In addition to an action rule we need to define a selection rule that specifies when agents act. In the Palfrey-Rosenthal game agents are assumed to act simultaneously. In our model they act sequentially: In each period t one specific agent out of N is randomly chosen with probability $1/N$. The agent then looks at the current configuration X^t of actions in the population and chooses an action according to $p^{\beta}(z|X^t_{-d})$. The next period, again a player is chosen at random, and so on. Given the current configuration, an actor will then probabilistically adjust her participation

[6] The case of (pure) best-response is discussed in detail in section 7.

[7] See McFadden (1973) for details.

behavior to improve her pay-off.

The model can now be summarized as follows. In each period one agent is randomly selected to change his behavior. That agent's action then is drawn from a log-linear behavioral rule given the current configuration of play. The realization of that action then determines the next period's configuration of play; again an agent is chosen (with replacement) and so forth. The key idea of our model is to "decompose" the simultaneous choice of classical game-theory (where agents form conjectures about each others beliefs) into a dynamic adjustment process. As in game-theoretic models, some features of the model are mainly technical, while others are of substantive importance.

One of the technical assumptions pertains to selecting exactly one agent in each period. This does not imply that agents cannot change their behavior "fast." After all, periods between revisions can be arbitrarily small.[8] .The *informational* implication of this assumption, however, is critical. That is, when revising their actions, agents have full information about the state of the dynamic system. This assumptions is a natural base-line, but it also models an informational environment where boycott activity is reported in the mass media [9]

Among the substantive assumptions perhaps the most important pertains to bounded rationality. Agents do respond to incentives, but not perfectly. For example, they optimize conditional on the current behavior in the population without anticipating the future strategic consequences of their actions. Agents need not believe that other actors reason in the same way as they do, or that they have the same payoff function. Indeed, they do not expect that their action may influence the future decisions of other participants. Agents simply adopt the action that maximizes their current pay-off given information about the global state of the system.

Our stochastic model defines a discrete time, discrete state Markov process (or Markov "chain"). Formally, we have a family of random variables $\{X^t : t \in \mathbb{N}\}$ where X^t assumes values on the state space $S = \{0, 1, 2, \ldots, N\}$. The value of X^t is updated at the beginning of each period t, such that, given the value of X^t, the values of X^s for $s > t$ do not depend on the values of X^u for $u < t$.

[8]While we adopt a discrete framewrok for simplicity, our analysis continues to hold for agents that adjust their actions in continuous time provided that the time between revisions is exponentially distributed.

[9]Alternative informational structures that could be investigates include agents observing a random sample of population behavior (e.g. Diermeier and Van Mieghem 2005) or only the actions in some local neighborhood (e.g. Blume 1993).

The probability of X^{t+1} being in state j (that is, $X^{t+1} = j$) given that X^t is in state i is called the transition probability P_{ij}^t. In our model, these transition probabilities are fully specified by the log-linear choice rule and the selection process. Since both stochastic components are independent of the time variable t, we have a Markov chain with stationary transition probabilities, denoted by the transition matrix P. A Markov process is completely defined once its transition matrix P and initial state X^0 (or, more generally, the initial probability distribution over X^0) are specified.

A Markov chain with transition matrix P is said to be *regular* if for some m the matrix P^m has only strictly positive elements. The following two conditions are jointly sufficient for regularity (Taylor and Karlin 1994; p.171):

1. For every pair of states i and j there is a path $l_1, ..., l_r$ for which $P_{il_1} P_{l_1 l_2} \cdots P_{l_r j} > 0$.

2. There is at least one state i for which $P_{ii} > 0$.

The most important fact concerning a finite, regular Markov chain is the existence of a unique limiting distribution, denoted by the column vector π, where

$$\pi_j = \lim_{t \to \infty} \Pr\{X^t = j | X^0 = i\},$$

and $\pi_j > 0$ for all $j \in S$ (Taylor and Karlin 1994). Thus, π_j is the long-run ($t \to \infty$) probability of finding the process in state j, irrespective of the initial state. A second interpretation of the limiting distribution is that π_j also gives the long-run mean fraction of time that the process is in state j.

It can easily be shown that π is the unique distribution that solves $\pi = \pi P$.[10] These equations are called the *global balance equations* because, rearranging $\pi_i = \sum_j \pi_j P_{ji}$, yields

$$(1 - P_{ii})\, \pi_i = \sum_{j \neq i} \pi_j P_{ji},$$

which can be interpreted as saying that the probability "flow" out of state i must equal the probability flow into state i.

[10] To see this, let $P_{ij}^{(t)} = \Pr\{X^t = j | X^0 = i\}$ denote the "t-step" transition probabilities. We have that $P^{(t+1)} = P^{(t)} P$. Now letting $t \to \infty$ and using the definition that $\pi_j = \lim_{t \to \infty} P_{ij}^{(k)}$, yields $\pi = \pi P$.

Because at most one individual can change his behavior in any period, X^t can change by at most 1 at a time. That is, we have $P_{ij} = 0$ if $|i - j| > 1$. Such Markov process is called a *birth-death process*. To simplify notation, denote $P_{i,i+1}$ by the "birth" probability λ_i (i.e., the probability that the number of participants increases by one) and $P_{i,i-1}$ by the "death" probability μ_i (i.e., the probability that the number of participants decreases by one). Hence, $P_{ii} = 1 - \lambda_i - \mu_i$. For a birth-death process, the balance of probability flow satisfies a stronger property:

$$\lambda_{i-1}\pi_{i-1} = \mu_i \pi_i \Leftrightarrow \frac{\pi_i}{\pi_{i-1}} = \frac{\lambda_{i-1}}{\mu_i}. \tag{1}$$

These equations are called *detailed balance equations.* It is easy to verify that they indeed also solve the global balance equations, which now read

$$(\lambda_n + \mu_n)\pi_n = \lambda_{n-1}\pi_{n-1} + \mu_{n+1}\pi_{n+1}.$$

Since in a birth-death process the limiting probability ratio equals the transition probability ratio, we easily can derive a closed form solution of the limiting distribution in our probabilistic model.

4 Results

To analyze the limiting behavior of the participation model, we must first specify the transition matrix P. Given that only direct-neighbor transitions are possible, we only need to specify the birth and death parameters $\lambda_n = P_{n,n+1} = \Pr\{X^t = n + 1 | X^t = n\}$ and $\mu_n = P_{n,n-1}$. The transition probabilities have two components. First, we have the probability that any one agent is selected to make a decision, which we call the "selection probability." Second, there is the probability that a given action is chosen, which we call the "action probability." The probability that any action is taken depends on the current configuration, i.e., the configuration X^t just before the revision time. If actor d did not participate, we characterize him as being of sub-type $(d, 0)$; otherwise he is of sub-type $(d, 1)$. Given that $X^t = n$, the probability that the randomly picked actor d is of a subtype $(d, 0)$ or $(d, 1)$ is, respectively,

$$p_0(n) = \frac{N - n}{N} \qquad \text{and} \qquad p_1(n) = \frac{n}{N}.$$

This characterizes the selection probabilities.

Action probabilities are determined by the individual choice rule. It is useful to rewrite our pay-off matrix by sub-type. For example, the second row captures the next period pay-off of an agent that switches from non-participation to participation, conditional on the configuration of play (expressed by the columns).

Payoffs $u(z\|X)$	$X < k-1$	$X = k-1$	$X = k$	$X > k$
Type $(d,0)$: $z=0$	0	0	1	1
Type $(d,0)$: $z=1$	$-c$	$1-c$	$1-c$	$1-c$
Type $(d,1)$: $z=0$	0	0	0	1
Type $(d,1)$: $z=1$	$-c$	$-c$	$1-c$	$1-c$

Given log-logistic choice, actor d selects payoff action z with probability $p^{\beta}(z|X^{t}_{-d})$. This allows us to specify the action probability matrix as:

Action Probabilities	$X < k-1$	$X = k-1$	$X = k$	$X > k$
Type $(d,0)$: $z=0$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{\beta(1-c)}}$	$\frac{e^{\beta}}{e^{\beta}+e^{\beta(1-c)}}$	$\frac{e^{\beta}}{e^{\beta}+e^{\beta(1-c)}}$
Type $(d,0)$: $z=1$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{\beta(1-c)}}{1+e^{\beta(1-c)}}$	$\frac{e^{\beta(1-c)}}{e^{\beta}+e^{\beta(1-c)}}$	$\frac{e^{\beta(1-c)}}{e^{\beta}+e^{\beta(1-c)}}$
Type $(d,1)$: $z=0$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{\beta(1-c)}}$	$\frac{e^{\beta}}{e^{\beta}+e^{\beta(1-c)}}$
Type $(d,1)$: $z=1$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{\beta(1-c)}}{1+e^{\beta(1-c)}}$	$\frac{e^{\beta(1-c)}}{e^{\beta}+e^{\beta(1-c)}}$

which simplifies to:

Action Probabilities	$X < k-1$	$X = k-1$	$X = k$	$X > k$
Type $(d,0)$: $z=0$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{\beta(1-c)}}$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{-\beta c}}$
Type $(d,0)$: $z=1$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{\beta(1-c)}}{1+e^{\beta(1-c)}}$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$
Type $(d,1)$: $z=0$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{-\beta c}}$	$\frac{1}{1+e^{\beta(1-c)}}$	$\frac{1}{1+e^{-\beta c}}$
Type $(d,1)$: $z=1$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$	$\frac{e^{\beta(1-c)}}{1+e^{\beta(1-c)}}$	$\frac{e^{-\beta c}}{1+e^{-\beta c}}$

The birth probabilities stem from a sub-type $(d,0)$ changing his action to "participate" $(z=1)$, while death probabilities derive from a demonstrating sub-type $(d,1)$ changing his action to "not demonstrate" $(z=0)$. We can then calculate the total transition probability by de-conditioning on subtype as:

$$\lambda_n = \begin{cases} \frac{e^{-\beta c}}{1+e^{-\beta c}} p_0(n) & \text{if } n \neq k-1, \\ \frac{e^{\beta(1-c)}}{1+e^{\beta(1-c)}} p_0(n) & \text{if } n = k-1. \end{cases}$$

$$\mu_n = \begin{cases} \frac{1}{1+e^{-\beta c}} p_1(n) & \text{if } n \neq k, \\ \frac{1}{1+e^{\beta(1-c)}} p_1(n) & \text{if } n = k. \end{cases}$$

Notice that our Markov chain is regular. Hence, it has a limiting distribution π that solves the detailed balance equations:

$$\forall n \neq k-1 : \frac{\pi_{n+1}}{\pi_n} = \frac{p_0(n)}{p_1(n+1)} e^{-\beta c} = \frac{N-n}{n+1} e^{-\beta c}. \tag{2}$$

$$\text{for } n = k-1 : \frac{\pi_k}{\pi_{k-1}} = \frac{e^{\beta(1-c)} p_0(k-1)}{p_1(k)} = \frac{N-k+1}{k} e^{\beta(1-c)}. \tag{3}$$

We can solve this recursive system of equations to characterize the limiting distribution. Intuitively, to calculate any π_n we will define an arbitrary reference state, in our case 0, and then "chain" the detailed balance conditions together along a path from 0 to n. This allows us to derive each π_n as a function of π_0. The probability of the reference state (and thus the probability of every state) can then be derived using the normalization condition $\sum_{n=0}^{N} \pi_n = 1$.

Proposition 1 *The limiting distribution for the participation model is:*

$$\pi_n = \begin{cases} \binom{N}{n} e^{-\beta n c} \pi_0 & \textit{if } n < k, \\ \\ \binom{N}{n} e^{-\beta n c} \pi_0 e^{\beta} & \textit{if } n \geq k, \end{cases}$$

where π_0 is a normalization factor with $(1+e^{-\beta c})^N \leq \pi_0^{-1} \leq e^{\beta}(1+e^{-\beta c})^N$ such that $\sum_{n=0}^{N} \pi_n = 1$.

Proof: From (2), we have that $\forall n \leq k-1$:

$$\pi_n = \left(\prod_{i=0}^{n-1} \frac{p_0(i)}{p_1(i+1)} \right) e^{-n\beta c} \pi_0 = \frac{N(N-1)...(N-(n-1))}{1 \cdot 2 \cdot \ldots \cdot n} e^{-n\beta c} \pi_0 = \frac{N!}{n!(N-n)!} e^{-n\beta c} \pi_0.$$

From (3) and (1) it follows that:

$$\pi_k = \frac{\lambda_{k-1}}{\mu_k} \pi_{k-1} = \frac{e^{\beta(1-c)}(N-(k-1))}{k} \frac{N!}{(k-1)!(N-(k-1))!} e^{-(k-1)\beta c} \pi_0 = \frac{N!}{k!(N-k)!} e^{-k\beta c} e^{\beta} \pi_0.$$

Finally, reapplying (2) yields that $\forall n > k$:

$$\begin{aligned}\pi_n &= \left(\prod_{i=k}^{n-1} \frac{p_0(i)}{p_1(i+1)}\right) e^{-(n-k)\beta c}\pi_k = \frac{(N-(n-1))(N-(n-2))...(N-k)}{(k+1)\cdot(k+2)\cdot\ldots\cdot n} e^{-(n-k)\beta c}\pi_k \\ &= \frac{(N-(n-1))(N-(n-2))...(N-k)}{(k+1)\cdot(k+2)\cdot\ldots\cdot n} e^{-(n-k)\beta c} \frac{N!}{k!(N-k)!} e^{-k\beta c} e^{\beta}\pi_0 \\ &= \frac{N!}{n!(N-n)!} e^{-n\beta c} e^{\beta}\pi_0.\end{aligned}$$

Applying the binomial theorem $\sum_n \binom{N}{n} x^n = (1+x)^N$ directly yields the bounds for π_0. That is given (2), we have

$$1 = \sum_{n=0}^{N} \pi_n = \pi_0 \left[\sum_{n=0}^{k-1} \binom{N}{n} e^{-\beta nc} + \sum_{n=k}^{N} \binom{N}{n} e^{-\beta nc} e^{\beta}\right].$$

Hence

$$\sum_{n=0}^{N} \binom{N}{n} e^{-\beta nc} e^{\beta} \geq \pi_0^{-1} \geq \sum_{n=0}^{N} \binom{N}{n} e^{-\beta nc}.$$

■

Notice that the limiting distribution π_n combines the results of the selection process, as represented by the combinatorial $\binom{N}{n}$, and the results of the action process, represented by $e^{-\beta nc}$ or $e^{\beta} e^{-\beta nc}$. To characterize the long-run behavior of the probabilistic model we now need to identify the maxima of π_n. These are characterized in the next proposition. First, we need a definition:

Definition *For any $x \in \mathbb{R}$ define $\lfloor x \rfloor$ as the largest integer z with $z \leq x$ and $\lceil x \rceil$ as the smallest integer z with $z \geq x$ and let*

$$[x] := \begin{cases} \lfloor x \rfloor & \text{if } \pi_{\lfloor x \rfloor} \geq \pi_{\lceil x \rceil}, \\ \lceil x \rceil & \text{if } \pi_{\lfloor x \rfloor} \leq \pi_{\lceil x \rceil}. \end{cases}$$

Proposition 2 *There exist two critical numbers n^* and k^**

$$n^* = \max\left\{0, \frac{Ne^{-\beta c} - 1}{1 + e^{-\beta c}}\right\} \quad \textit{and} \quad k^* = \frac{N+1}{1 + e^{-\beta(1-c)}}, \tag{4}$$

with $n^* < \frac{N}{2} < k^*$ such that the following holds:

(i) If $k = 1$, then π_n has a unique maximum at

$$\begin{cases} n = k = 1 & \textit{if } \frac{N-1}{2} e^{-\beta c} \leq 1, \\ [n^*] > 1 & \textit{if } \frac{N-1}{2} e^{-\beta c} > 1. \end{cases}$$

(ii) If $k > 1$ and $k \notin (n^*, k^*)$, then π has a unique maximum at $[n^*]$.

(iii) If $k > 1$ and $k \in (n^*, k^*)$, then π has two maxima, one at $[n^*]$ and another at k, of which k is the most-likely long-run state if

$$\pi_{[n^*]} < \pi_k \Leftrightarrow g(k) := (1 - (k - [n^*])\, c)\, \beta + \sum_{i=[n^*]}^{k-1} \ln \frac{N-i}{i+1} > 0. \tag{5}$$

Otherwise the most likely long-run state is $[n^*]$.

Proof: Define $f : [0, N] \to \mathbb{R} : x \to f(x) = \frac{N-x}{1+x} e^{-\beta c}$. Note that f is continuous and strictly decreasing over its domain $[0, N]$ with $f(0) = Ne^{-\beta c}$ and $f(N) = 0$. From (2), it follows that the odds ratio $\pi_{n+1}/\pi_n = f(n)$ is strictly decreasing in n (with a possible jump at $n = k - 1$). Notice that if n were extended to a continuous variable x, π_x would reach an interior maximum at $x^* \in (0, N)$ where $f(x^*) = 1$ or at $x = 0$ otherwise. If $Ne^{-\beta c} > 1$, then f is continuous and monotone decreasing with $f(0) > 1$ and $f(N) = 0$, so that there exists a unique x^* and solving $f(x^*) = 1$ for x^* yields $x^* = \frac{Ne^{-\beta c} - 1}{1 + e^{-\beta c}}$. We now must consider the implications of the integer constraints on n and the possible jump at $n = k - 1$.

First consider the case where $k = 1$. For π_n to have a maximum at $n = k = 1$, we need $\pi_1/\pi_0 = Ne^{\beta(1-c)} > 1$, which always holds because $N \geq 2$ and $\beta(1 - c) \geq 0$, and $\pi_2/\pi_1 = \frac{N-1}{2} e^{-\beta c} \leq 1$, which is also sufficient for a unique maximum at $n = k = 1$ because π_{n+1}/π_n is strictly decreasing in $n \geq 1$. If $\frac{N-1}{2} e^{-\beta c} > 1$, then also $f(0) = Ne^{-\beta c} > 1$ so that $n^* := x^*$ and $[n^*]$ constitutes the unique maximum for π_n.

Now consider $k > 1$. If $Ne^{-\beta c} \leq 1$, then $\pi_1/\pi_0 \leq 1$ so that π reaches a maximum at $[n^*] = 0$. If $Ne^{-\beta c} > 1$, then as before $[n^*]$ constitutes a maximum for π_n. We now need to check for other (possible) maxima, which can only occur around the "jump" at $n = k - 1$, namely at $n = k - 1$ or at $n = k$.

Suppose $k < n^*$. For two maxima we need $k < [n^*]$. But since π_{n+1}/π_n is increasing below n^*, we have $\pi_{[n^*]}/\pi_k > 1$ so that $n = k$ cannot be a maximum. For $n = k - 1$ to be a maximum, we need

$$\pi_{k-1} > \pi_k \Leftrightarrow \frac{N - k + 1}{k} e^{\beta(1-c)} < 1 \Leftrightarrow k > k^*.$$

Notice, however, that $n^* < \frac{N}{2} < k^*$ (because $0 \leq e^{-\beta(1-c)} \leq 1$ and $0 \leq e^{-\beta c} \leq 1$, given that $\beta \geq 0$

and $0 < c < 1$). Therefore, there cannot be a second maximum if $k < n^*$.

Suppose $k > n^*$. If $k-1 = \lfloor n^* \rfloor = [n^*]$ then, since π_{n+1}/π_n is decreasing above n^*, k cannot be a maximum, and since $k-1 = [n^*]$ there cannot be a second maximum. If $k-1 > [n^*]$, then, since π_{n+1}/π_n is decreasing above n^*, there can only be a second maximum at k. For a second maximum at k we need $\pi_{k-1} < \pi_k \Leftrightarrow k < k^*$.

To characterize the most likely long-run state note that (2) and (3) imply

$$\pi_{[n^*]} < \pi_k \Leftrightarrow \frac{k!(N-k)!}{[n^*]!(N-[n^*])!} < e^{-\beta((k-[n^*])c-1)}. \tag{6}$$

Condition (5) then follows immediately.■

The proposition states that the most likely state is either $[n^*]$ or k. Notice that k is the state where an efficient number of people participates, while state $[n^*]$, on the other hand, represents random participation. That is, $[n^*]$ is entirely driven by the error component in the log-logistic choice rule; it is independent of the threshold k and depends only on N, c, and β. Indeed, as we reduce randomness at the individual level so that $\beta \to \infty$ (and approach best-response in the limit), $[n^*]$ approaches 0.

While the integer restriction on n complicates Proposition 1, the basic intuition can be conveyed informally. From Proposition 1, it follows that the limiting distribution π has two components. At $n = k-1$ the probability distribution π_n "jumps" from one component to the other. It thus suffices to characterize the maxima of the components and then identify possible maxima at the "jump" from $n = k-1$ to $n = k$. The detailed balance equations (2) immediately imply that the probability ratio π_{n+1}/π_n is strictly decreasing in n. So either, there is a corner solution at $n = 0$ or one interior maximum where the probability ratios are approximately equal to one. Hence, for k smaller than the interior maximum, a maximum would have to be at $k-1$. But, as we show, in the proof of Proposition 2, in this case the jump is too small. So, there can only be a second maximum at k larger than the interior maximum. The conditions for such a maximum are given by (5). Ignoring the knife-edge case of $k = 1$ we thus have four possible cases displayed in Figure 1.

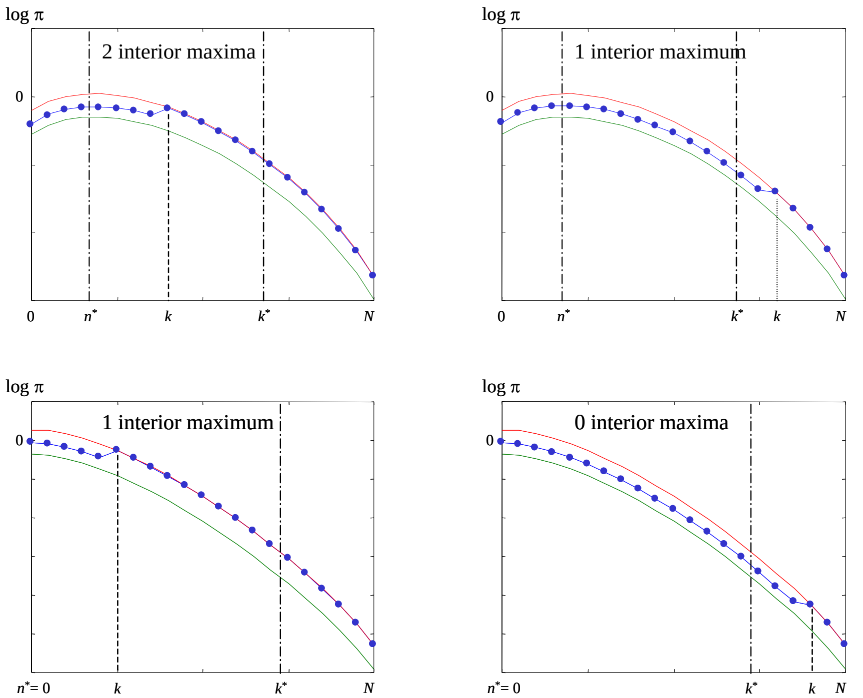

Figure 1: The limiting distribution π assumes one of four possible cases, depending on the parameters n^*, k^* and k.

5 Discussion

Proposition 2 now allows us to derive our model's predictions concerning mass collective behavior. Note that the qualitative features of the limiting distribution change as a function of the cost c, the threshold k, the responsiveness β and the size of the population N. We need to distinguish three cases:

1. There is one maximum at $[n^*]$, perhaps at 0.
2. There are two (local) maxima, one at $[n^*]$, the other at k, with k the most likely long-run state (global maximum).
3. There are two (local) maxima, one at $[n^*]$, the other at k, with $[n^*]$ the most likely long-run state (global maximum).

To see the effect of changes in k consider an example at $N = 50$, $c = 0.5$, and $\beta = 2.5$, for which $n^* = 10.4$, $k^* = 39.6$ and $[n^*] = 11$. Figure 2 illustrates how the qualitative features of the limiting

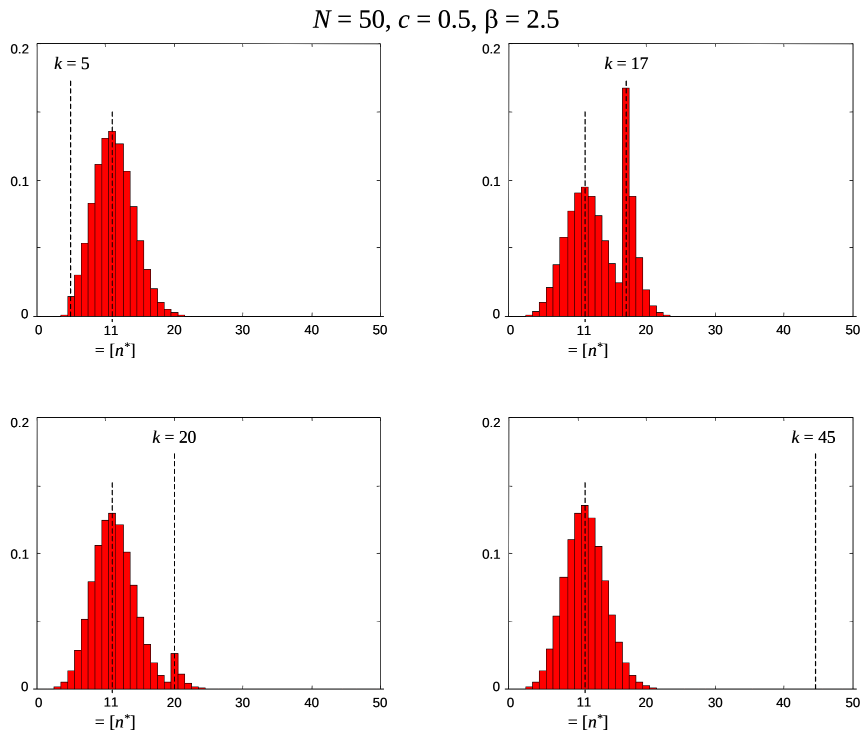

Figure 2: Four cases for the distribution π_n depending on the threshold level k. Other parameters are fixed at $N = 50$, $\beta = 2.5$, and $c = 0.5$.

distribution change in response to changes in k.

At low $k < n^*$ (here $k < 10.4$) there is a unique maximum at $[n^*]$, which thus must be the most likely long-run state. This corresponds to the case with permanent (very) low participation. Any participation is solely driven by randomness at the individual level. For example, using the random utility interpretation, on average there are some individuals that have an incentive to participate on their own. Note that as individual choice approaches best response behavior ($\beta \rightarrow \infty$) n^* converges to 0.

For higher k (here $k = 17$) there are two maxima with k the most likely long-run state. This captures the case of an unstable polity with frequent demonstrations and sustained levels of political protest.

At even higher k ($k = 20$), $[n^*]$ becomes the most likely long-run state, but k is still a local maximum. This case most closely corresponds to the empirical regularities outlined in the introduction.

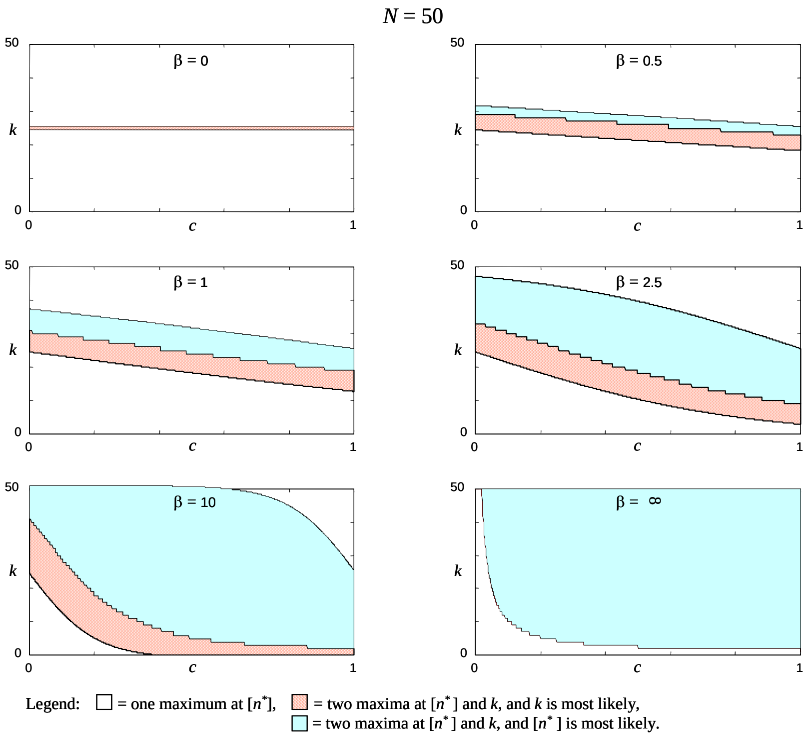

Figure 3: Strategy regions in (k, c)-space for different values of β for $N = 50$.

Political protest is possible, but it will be rare and comparatively short-lived.

For very high $k > k^*$ (here $k = 45 > 39.6$), we are back at the case where $[n^*]$ is the most likely long-run state without a local maximum at k.

A similar pattern can be observed for c. For general k and c we characterize maxima and long run states in Figures 3 to 5.

Note that for $\beta \to 0$, the critical numbers $n^* \to (N-1)/2$ and $k^* \to (N+1)/2$. Hence, π has a single maximum at $N/2$. In this case individual behavior is not at all governed by the incentives given in the model, it is purely random. This randomness at the individual level corresponds to a collective process with a binomial distribution. As β increases, however, the white areas (unique maximum at $[n^*]$) are shrinking. Even for moderately high β ($\beta = 10$) the largest region is the grey area (global maximum at $[n^*]$, local maximum at k). This effect is present independent of the size of the population N.[11] It becomes, however, more pronounced as N increases. For very large N we

[11] Note that even in the case of $N = 500,000$ there exists a small region where k is the most likely long-run state (case 2), but this region is too small to be picked up by the figure.

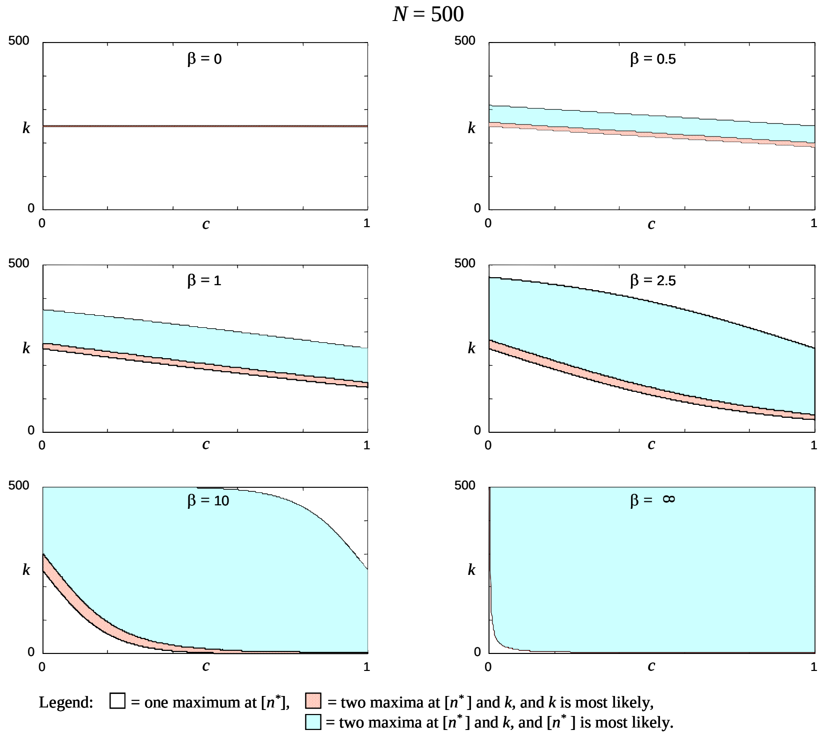

Figure 4: Strategy regions in (k, c)-space for different values of β for $N = 500$.

virtually only have two regions: If individual randomness is high (low β), we have larger regions with $[n^*]$ as the most likely long-run state, but as individual behavior is better characterized by our normal form, we also have a local maximum at k.[12]

The existence of a local maximum at k even for very large N is one key insight from our model. It implies that at least some times agents are able to spontaneously coordinate on collective action. Note that these states are efficient and asymmetric (i.e. k agents participate, while $n-k$ agents stay home). Nevertheless, mass collective action may occur in the absence of any apparent coordination device.

[12] This result may surprise readers familiar with Olson's (1965) seminal work on collective action. Olson's central thesis was that large groups are much less likely than small groups to solve the free-rider problem. Subsequent work, however, has challenged Olson's thesis (e.g. Marwell and Oliver 1988, Oliver 1993). In her comprehensive survey of the literature Oliver (1993; p.275) concludes: "Put simply, in some situations the group size effect will be negative, in others positive. You have to know the details of a particular situation before you can know how group size will affect the prospects for collective action."

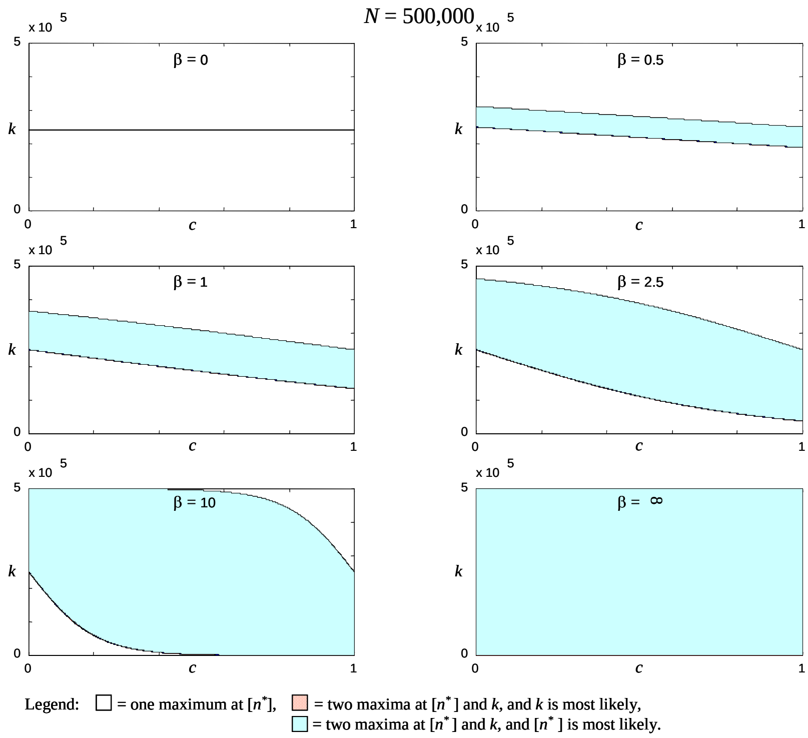

Figure 5: Strategy regions in (k, c)-space for different values of β for $N = 500,000$.

6 Equilibrium Selection and Activist Strategies

As discussed in section 3, the parameter β indicates how closely individual choice behavior approaches best response correspondences. For example, as $\beta \to \infty$, log-linear choice converges to a distribution that puts positive probability only on best-responses to X_{-d}. We can use therefore use our analysis to select among the strict Nash-equilibria in Palfrey and Rosenthal's participation game. If $\beta \to \infty$, then $n^* \to 0$ and $k^* \to N$, so that there exist two maxima for large, but finite β, corresponding to either zero turnout or minimal critical turnout k. These maxima thus are analogues to the pure Nash equilibria in the Palfrey and Rosenthal model. Note that in the limit of $\beta \to \infty$, the probabilistic model approaches the best-response model with the noted exception that at most one of the maxima corresponds to a stochastically stable state. This can be interpreted as the selection of one of the pure Nash equilibria in an environment with arbitrarily small (but persistent!) perturbations.

From (5), it follows that the selection depends on the sign of $g(k)$, which, for $\beta \to \infty$, is positive if $kc < 1$ and negative if $kc > 1$. Hence, the key factor that drives the selection is the sign of $1 - kc$. If $kc < 1$, then the unique long-run prediction is collective action at $n = k$ (almost surely); otherwise, the unique long-run prediction is $n = 0$ (almost surely). Note that the selection does not depend on N. That is, once we control for k the absolute group size plays no explanatory role.

As we demonstrated in Figures 3-5, the case where $kc < 1$ is rare, especially if N is large. Intuitively it captures the case where even if the benefit of unit 1 was private (not public as assumed in our model), it could be redistributed among the minimum k participants needed for a revolt to cover their show-up cost c. That is, form the point of view of concerned consumers the selected equilibrium satisfies an efficiency property. However, the analysis in Figures 3-5, of course, presupposes that each parameter configuration is "equally likely." But it follows from the model that strategic activists will try to lower costs, increase collective benefits, or decrease the threshold k. According to the model once the threshold of $kc < 1$ is crossed, we will switch to a regime where high participation in a boycott is very likely. Such a switch, technically a phase transition in kc-space, formally captures the fact that this particular phenomenon "has legs."

7 Some Implications for Activists

The incentive to lower costs, increase benefits, or decrease the threshold k can shed some light on common activist strategies. Here we discuss a few examples. Baron and Diermeier (2005) provide an game-theoretic model for activist strategies and counter-strategies by firms.

7.1 Target Selection

The goal of many boycotts is to change industry practice. According to the model, activists should select industries where consumers have cheap substitutes, and, within the targeted industry, should target companies (or company units) with lowest switching costs. The Shell-Greenpeace controversy illustrates both point. First, vertically integrated oil companies are good targets since consumers have low costs of switching; filling up one's car at a BP instead is enough. Second, activists that seek to change industry-practice should target a *single* firm in the same industry. In the case of the Brent Spar, Shell was targeted because of its strong global brand recognition. Third, activists may target unrelated business units of the same company if this lowers switching costs for consumers or increases perceived benefits. In the Brent Spar case Greenpeace targeted Shell Germany (not Shell UK, the truly responsible party) even though Shell Germany had nothing to do with the initial decision to seek approval for deep-water disposal (Diermeier 1995). The reason? Greenpeace expected a better strategic environment in Germany where global environmentalism has wide appeal and recycling is a national passion. The fact that the targeted business unit may have nothing to do with the practice, indeed may not even know about it, makes it much more difficult to anticipate and prepare for proactive boycotts.

7.2 Secondary Boycotts

An important tactic by activists is the use of secondary targets. Secondary boycotts focus their activity not on the business entity that engages in the offensive practice, but on some other entity in the value chain, frequently a retailer. For example, in the early 1980s environmental activists who wanted to reduce the use of Styrofoam containers boycotted McDonald. Another example is the recent boycott of Home Depot over the use of wood products from tropical rain forests. Based on our model, the key advantage of secondary targeting is the reduction of switching costs by consumers *and* for the targeted business.

Sometimes secondary targeting is necessary because only the secondary target is a consumer goods company and/or will provide the necessary media coverage to provide information to concerned consumers, such as in the McDonald's example discussed above. Secondary targeting, however, is frequently the key to success, even in the case of a consumer goods company and high media coverage. A well-known example is the Calvin Klein boycott over its controversial advertising, in which apparently under-age models were depicted in sexually suggestive scenarios. Accusing Calvin Klein of soft-core child pornography, boycott organizers did not limit their boycott to Calvin Klein products, but targeted over 50 department stores where Calvin Klein jeans were sold, as well as various magazines that traditionally ran Calvin Klein advertising such as *Seventeen*. The strategic insight provided by this strategy is that while switching costs to Calvin Klein customers may be high[13] switching costs to department store customers or magazines (and their advertisers) are much

[13] The controversy surrounding the jeans may indeed make them more attractive to teenagers.

lower.

Of course, targeting may not stop at secondary targets. This is already obvious in the Calvin Klein example. If a magazine (secondary target) refuses to participate in the boycott, *its* advertising customers can be targeted (tertiary target) and so forth. This targeting chains can have an astonishing length. Consider the example of Huntingdon Life Sciences (HLS), one of the leaders in animal testing for pre-clinical drug testing (Diermeier et al. 2003). In 1999 HLS was targeted by an aggressive animal rights activist group called "Stop Huntingdon Animal Cruelty" (SHAC). Predictably SHAC targeted HLS' customers such as large pharmaceutical companies, Glaxo-Smith-Kline, Eli Lilly, and Bayer. However, due to the heavy reliance of pharmaceutical companies on contract research organizations such as HLS, these boycott calls were unsuccessful. HLS subsequently targeted every aspect of HLS' value chain, including the Royal Bank of Scotland, which eventually cut HLS' credit line. SHAC also targeted providers of services to HLS, such as its insurance brokers Marsh, Inc., a subsidiary of Marsh McLennan Companies. To put pressure on its secondary target, Marsh, SHAC then took aim at Marsh value chain, including its employees and directors. To force action by one of March's directors Hamish Ritchie (tertiary target), SHAC targeted other organizations where Mr. Ritchie served as a board member such as English National Ballet (quarternary target). In addition to Mr. Ritchie's board membership Marsh was a major sponsor of the ballet company. The ballet subsequently forced Halma Ritchie's resignation, and the Marsh sponsorship was terminated. In December, 2002, Marsh terminated its relationship with HLS.

Targeting chains constitute sophisticated strategies that exploit multiplier effect. That is, the effect on the ultimate target, e.g. HLS, is entirely driven by the weakest link in the chain, i.e. the link with the lowest switching costs (here the cost of replacing directors of the English National Ballet). Once one link gives in, the multiplier effect can be devastating. In the case of HLS, the company was unable to secure any privately supplied insurance coverage and was subsequently (and only after heavy lobbying by the British biotech and pharmaceutical industry) effectively insured by the British government.

7.3 Boycotts and Strikes

An illustrative example of the strategic incentives indicated by the model is provided by the late 19th century consumer boycotts organized by the Knights of Labor union (Friedman 1999, Fusfeld 1980, Wolman 1914). The Knights of Labor were founded in 1869 as a secret organization. After a spontaneous strike by unskilled workers in 1877, they became an open nationwide organization that represented skilled and unskilled workers from all industries. The Knights' importance for our context lies in the fact that the organization used as its main tool boycotts instead of strikes. Such boycotts included both primary and, overwhelmingly, secondary boycotts. For example, in the Danburry Hatters' boycott in 1902, labor activists targeted primarily retail outlets including well-know department stores such as Macy's (Friedman 1999).

The Knights' boycotts in the later 19th century were spectacularly successful. Based on historical sources, Friedman (1999) reports that 72% of the concluded boycotts were successful in attaining the stated objective like a change in labor practice. The Knights were subsequently replaced by the better-organized American Federation of Labor that continued the Knights tradition by publishing a "We do not patronize" list. The success of this new tactic predictably led to counter-action by the employers who founded the American Anti-Boycott Association in 1902. Increasingly, employers also used legal strategies to defend themselves against boycotts, especially if there were secondary targets. Mostly, employers tried to obtain legal injunctions against picketing etc. When one of the founders of the American Anti-Boycott Association, the non-union hat manufacturer, Dietrich Loewe, was boycotted , he sued the union in an attempt to recover damages. The suit went all the way to the Supreme Court who, in 1908 in *Danburry vs. Lawlor,* found the hatter's unions boycott tactics to be illegal. In a later decision the Supreme Court permitted the collection of treble damages from the union. These decisions in conjunction with Federal legislation such as the *Taft-Haltrey Act* (1947) or the *Landrum-Griffin Act* (1959), which outlawed "coercive" secondary boycotts, created significant legal obstacles and has led to a significant decrease in labor-organized boycotts (Friedman 1999).

Labor-organized boycotts are an important test case for our model since they allow us to compare the use of boycotts with another, closely related, form of collective action: the strike.

Like boycotts, strikes can be modeled as collective action problems with some significant structural differences, such as a clearly identified group of actors, the ability of repeated interaction, and selective incentives such as strike funds or linkage of strike participation to other social activities.[14] On the other hand, strike participation is a high-cost activity, and strike participation usually needs to be very high to have an effect. Thus, in terms of our simple model, strikes are characterized by high c and high k. Unions try to compensate for these problems by creating selective incentives and punishments, such as social ostracism of strike-breakers. They also critically rely on frequent, repeated interaction.[15] However, in the historic circumstances of the Knights of Labor, none of these mitigating circumstances were present. In addition to a significant unemployment, a large segment of The Knights's constituency represented unskilled labor with high turnover. This had two effects. First, workers were not unionized locally, which would facilitate the strategic use of repeated interaction, selective incentives etc. Second, striking workers, especially when they were unskilled, could easily be replaced at low cost by unemployed workers. These circumstances made consumer boycotts an attractive alternative. The strategic trade-off here is between a comparatively small group of striking workers with high cost of participation and a high threshold versus a very large group of consumers with low cost of participation and a low threshold.

The model suggests that in the absence of repeated interaction or selective incentives, consumer boycotts would be very attractive indeed. Note also that once we control for k, the actual size of the participant group plays no role. Once the goal is a consumer boycott, it is essential that both k and c need to be low. This explains the strategic focus on secondary boycotts. It also accounts for the second successful use of consumer boycotts in labor disputes: the United Farm Workers Organizing Committee (UFWOC) lead by Cesar Chavez in the late 1960s (Friedman 1999).[16] The UFWOC was formed to organize migrant farm workers. As in the case of the Knights of Labor, this constituency was characterized by high turnover and mobility, the ease of hiring strike breakers and

[14] That is, strike-breakers can be ostracized in the community and excluded from all social contact and cooperation. The more valuable this interaction for the potential strike-breaker, the more severe the punishment. Thus, ceteris paribus, closely knit communities should be more successful in organizing strikes.

[15] Unions not only play a role in wage-bargaining, but also labor conditions, the administration of workers' grievances, and day-to-day management practices.

[16] The actions led to the historic Table Grape Agreement in 1970 that officially established the UFW.

replacements, and the absence of strike funds. The key to the successful strategy devised by Chavez was to use consumer boycotts of table grapes, a highly appropriate choice, because at the time it constituted a discretionary purchase for most consumers,[17] reducing c. As we may now expect, action exclusively focused on retailers such as A&P supermarkets in New York, where UFWOC activists picketed less than 30 stores. After store managers complained to their division heads, A&P pulled table grapes from all its 430 stores (Smith 1990).

Both the Knights of Labor and the UFWOC indicate another key requirement of successful union-boycotts. They critically depend on the existence of concerned consumers, i.e. a sufficiently high b. Thus, union causes need to appeal to the social conscience of consumers, such as the perceived violation of rights (like the right to be organized as a union)[18] or deplorable living and working conditions. Union-led consumer boycotts are less likely to work in wage disputes.

8 The Role of the Media

It is widely understood that the media plays a critical role in consumer boycotts.[19] In his handbook for activists, San Francisco low-rent housing activists Randy Shaw puts it succinctly as follows:

> Ideally, tactical activists should use the media both to generate a scandal and then to demand a specific, concrete result. (Shaw 1996; p. 155)

Most successful boycotts involve heavy media coverage (Friedman 1999) and activists shrewdly design their activities to maximize media coverage. As an example, consider the media strategy used by San Francisco tenant activists (Shaw 1996; 154-155)

> To keep the media, especially television, pushing for stronger heat laws, tenant advocates had to make the legislative process unusually interesting. We accomplished this by attracting a large turnout of hotel residents to the first Board of Supervisors hearing on the proposed legislation and stationing a person dressed in a polar bear

[17] About half of all table grape purchases occurred in the 10 major cities (Friedman 1999).

[18] In the case of the UFWOC, the National Labor Act had prohibited organizing of farm workers, the result of lobbying by agricultural employers.

[19] See Baron (2003c) for a recent paper that provides a formal model of the media and their role in boycotts.

> costume to hand out flyers demanding heat. Costumed protesters at hearings garner so much press attention that it's a wonder activists do not use this tactic more frequently. The polar bear gave television cameras some eye-catching footage, something other than the typical clips of speeches. (...) We followed up our polar bear appearance at a subsequent hearing by distributing badges that showed penguins marching to demand heat. Our emphasis on visuals, combined with the media's sudden interest in running "day in the life" profiles of elderly hotel residents, kept the heat legislation on the media's front burner for over a month.

Media coverage can have at least four distinctive advantages:

1. Media coverage provides a cheap means of communicating the activists' message and related information to the public.
2. Coverage by respected media outlets gives the covered issue some *prima facie* credibility and puts it on the public agenda.
3. Visual coverage may provide a cognitive and emotional frame for viewers. The use of water canons in the Greenpeace-Shell confrontation, for example, evoked memories of the 1989 Eastern European uprisings among German viewers.
4. Coverage by the mass media provides information about current participation rates.

In this paper we have focused mainly on 4. The key point is that media reports about boycott participation may lead to more participation. That is, the media are not only important in the sense that they provide inexpensive ways to share information and political views with the public, but the coverage itself is a necessary component of enabling collective action. The media does not just cover events, it brings them about. It is therefore not surprising that activists increasingly rely on actions that are attractive to the media such as occupations, costumes etc.

9 Conclusion

This paper provides a formal model of consumer boycotts as a collective action problem between concerned consumers. We show that in this model a unique equilibrium is selected. The type of equilibrium depends on the switching costs, the threshold for success, and the importance of the social dimension of the boycott to concerned consumers. If switching costs are sufficiently low, an optimal number of agents will join the boycott, leading to mass participation.

We then discuss the model's consequences for activists' strategies. The following empirical phenomena are consistent with the model:

1. Activists should frequently rely on secondary boycotts, i.e. boycotts where the target is not the business entity engaged in the offensive practice. Secondary targeting should also occur in cases where the primary target is a well-known consumer brand. Targeting is predominantly driven by switching costs and multiplier effects. This can lead to complicated targeting chains.

2. In cases where activists try to change industry practice, they will not target the firm that caused the most egregious offense, but the most vulnerable. Activists should also limit their actions to a single target.

3. Union-sponsored boycotts should occur predominantly in cases of rights violations or exploitative working conditions, not in wage disputes.

The model provides a general, flexible model, that can be incorporated into more comprehensive models of strategic activism and counter-strategies by firms and industries (e.g. Baron and Diermeier 2005). However, the formal and empirical analysis of such interactions is still in its infancy. We hope that our approach can serve as a "work-horse" model to facilitate such analyses.

References

[1] Baron, David.P. 2002. "Private Politics and Private Policies: A Theory of Boycotts." Working paper, Stanford University.

[2] Baron, David P. 2003a. Business and Its Environment, 4th ed. Upper Saddle River, NJ: Prentice Hall.

[3] Baron, David P. 2003b. "Private Politics." Journal of Economics and Management Strategy. 12 (Spring): 31-66.

[4] Baron, David P. 2003c. "Competing for the Public through the News Media." Working paper, Stanford University.Blume, Lawrence E. 1993. "The Statistical Mechanics of Strategic Interaction." *Games and Economic Behavior* 4:387-424.

[5] Baron, David P. and Daniel Diermeier. 2005. "Strategic Activism and NonMarket Strategy." Working paper. Stanford University.

[6] Blume, Lawrence E. 1997. "Population Games." In W. Brian Arthur, Steven N. Durlauf, and David A. Lane, eds. *The Economy as an Evolving Complex System II.* Reading: Addison-Wesley.

[7] Diermeier, D. 1995. "Shell, Greenpeace, and Brent Spar." Teaching case. Stanford University Graduate School of Business.

[8] Diermeier, D. and J. A. Van Mieghem. 2005. Coordination and Turnout in Large Elections. Working paper. Northwestern University.

[9] Friedman, Monroe. 1999. Consumer Boycotts. New York: Routledge.

[10] Fusfeld, D.R. 1980. The Rise and Repression of Radical Labor in the United States, 1877-1918. Chicago, Charles H. Kerr Publishing Company.

[11] Fudenberg, Drew, and David Levine. 1998. *The Theory of Learning in Games.* Cambridge: MIT Press.

[12] Granovetter. Mark. 1978. "Threshold Models of Collective Behavior." *American Journal of Sociology* 83:1420-43.

[13] Jordan, Grant. 2001. *Shell, Greenpeace. and the Brent Spar*. New York: Palgrave.

[14] McFadden, David. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior." in P. Zarembka, ed., *Frontiers in Econometrics*. New York: Academic Press.

[15] Oliver, Pamela E. 1993. "Formal Models of Collective Action." *Annual Reviews of Sociology* 19:271-300.

[16] Oliver, Pamela E., and Gerald Marwell. 1988. "The Paradox of Group Size in Collective Action: A Theory of the Critical Mass II." *American Sociological Review* 53 (February):1-8.

[17] Olson. Mancur. 1965. *The Logic of Collective Action*. Cambridge: Harvard University Press.

[18] Palfrey, Thomas R., and Howard Rosenthal. 1984. "Participation and the Provision of Discrete Public Goods: A Strategic Analysis." *Journal of Public Economics* 24:171-193.

[19] Schelling, Thomas C. 1978. *Micro-Motives and Macro-Behavior*. New York: W. W. Norton

[20] Shaw, R. 1996. *The Activist's Handbook*. Berkeley: University of California Press.

[21] Taylor, Howard M., and Samuel Karlin. 1994. *An Introduction to Stochastic Modeling*. Second Edition. Boston et al.:Academic Press

[22] Young, H. Peyton. 1993. "The Evolution of Conventions." *Econometrica* 61:57-84.

[23] Young, H. Peyton. 1998. *Individual Strategy and Social Structure*. Princeton: Princeton University Press.

[24] Wolman, L. 1914. The Boycott in American Trade Unions. Baltimore: John's Hopkins Press.