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Organizational Life Aboard the Moving Bandwagons: A Network Analysis of Dropouts from a Swedish Temperance Organization, 1896–1937

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ABSTRACT
One consistent finding in research on social movement organizations is that new members are recruited along established lines of interaction. Drawing on these findings, I argue that an individual's decision to leave a social movement organization is the result of similar influences. Using information about membership turnover over time in a local Swedish temperance organization, I test whether the dropout propensity of existing members is related to prior members' dropout decisions. I find that existing members' dropout propensity increases when their socially relevant others drop out of the organization. Thus, the results suggest that the decision processes concerning leaving and joining an organization are mirror images. This should have implications for any analysis of social movement organizations because only when this duality of interpersonal influences is considered can we fully understand the social dynamics of social movement organizations.

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1. Introduction

Current research on collective behavior is almost entirely devoted to seeking explanations for the emergence of collective behavior. It has become almost a matter of course to study the process of joining collective action organizations (Udéhn 1993), and this one-sidedness has led to a negligence on the part of researchers of other types of decisions that are equally important for the existence of collective action organizations.[1] This is particularly true of the decision to leave a collective action organization.

Consequently, this paper deals with the issues of why and how individuals *leave* collective action organizations. The way in which I approach this problem is straightforward. Research that successfully addresses the problems of why individuals join such organizations has shown that new participants are recruited along established lines of interaction (Gould 1995; McAdam et al. 1988; Snow et al. 1980). In considering these findings, I explore the possibility that such interpersonal influences are equally important when individuals are deciding whether or not to leave a collective action organization.

I thus assume that the decision processes concerning leaving and joining an organization are to some extent mirror images. The consequences of such a relationship are twofold. If these decision processes are mirror images, this adds credence to the claim that interpersonal influences are of decisive importance when explaining collective behavior. The second implication is that it then becomes important

to consider these processes simultaneously, since the likelihood that an individual will participate in collective behavior is influenced both positively and negatively by the actions of other people.

I have organized the paper in the following way. The first section presents a general discussion of research on collective behavior and how individuals come to influence each other concerning the decision to join in collective behavior. I then present a more specific discussion of the mechanisms that I believe govern an individual's decision to leave an organization. Lastly, I perform an empirical test of the presence of these mechanisms by analyzing dropout propensities among members of a social movement organization.

2. Interpersonal influence in collective behavior decisions

One of the main concerns in recent sociological research on collective behavior has been how interpersonal influence assists or impedes the chances of recruiting new participants to social movement organizations (Udéhn 1993). Empirical work on recruitment to movement organizations suggests that the structure and density of network ties are potentially important causal factors influencing both the growth and the spread of a social movement (Hedström 1994; Chong 1991; Snow et al. 1980; McAdam 1988 and 1982; Gould 1991). Findings from such work often suggest that increased collective behavior is the result of contagious diffusion processes that flow through the individual's interpersonal networks in a fashion similar to when individuals come to adopt innovations (Brown 1981; Coleman et al. 1966; Hägerstrand 1967). Scholars who simulate and theorize about the emergence of collective action arrive at similar conclusions. For example, Marwell & Oliver (1993), Granovetter & Song (1983), Granovetter (1978) and Schelling (1978) have all explained emerging collective behavior as resulting from a contagious diffusion process in which collective behavior increases as more people join the organization.

These accounts have in common the notion that individuals to some extent 'pull' each other into collective action organizations (McAdam et al. 1988). To exemplify the effects of such interpersonal influence, consider Granovetter's work on threshold behavior:

> Imagine 100 people milling around in a square – a potential riot situation. Suppose the riot thresholds are distributed as follows: there is one individual with threshold 0, one with threshold 1, one with threshold 2, and so on up to the last with threshold 99 ... [T]he one with threshold 0, the 'instigator', engages in riot behavior – breaks a window say. This activates the person with threshold 1; the activity of these two people then activates the person with threshold 2, and so on, until all 100 have joined. (Granovetter 1978:1424)

Granovetter's analysis rests on the assumption that every individual has a specific threshold value that controls how many other participants there must be before that individual decides to participate (see Granovetter 1978; Granovetter & Song 1983 and 1986).[2] In social situations characterized by this type of interpersonal influence, behavioral patterns 'snowball' through a population, and for these reasons this sort of behavior has often been referred to as 'bandwagon' behavior. Granovetter offers many instances of situations in which these bandwagon effects are likely to exist, such as joining political parties or engaging in riots, all with the common notion that to do as everybody else does is a useful heuristic for arriving at better decisions when uncertainty prevails.

The analysis I am about to undertake does not question whether individual influence similar to that contained in Granovetter's example is of decisive importance for the emergence of collective behavior. On the contrary, I try to extend the current knowledge of interpersonal influence to encompass also decisions to leave a collective action organization by using these insights to provide a plausible explanation for dropout behavior.

Basing myself on Granovetter's example about threshold behavior, I argue that an 'instigating' defector may set a process in motion that fosters increased dropout tendencies in the same manner as the joining process described above. For example, imagine a party that has been going on for a while. The guests are 'milling around' and seem eager to leave, but no one wants to be the first. Finally, somebody decides to leave, and this single act sets in motion a 'negative bandwagon' that results in all the guests quickly leaving the party.

Traditionally, when negative interpersonal influence has been analyzed the focus has usually been on what has come to be labeled 'snob' behavior (Granovetter & Song 1986),

which has been defined as the decreased demand for some good or commodity due to others' increased consumption of the same good or commodity (Libenstein 1950). Snob behavior, thus, clearly differs from the motives that underlie the above-described negative bandwagon. The reason for bandwagon behavior – positive as well as negative – is more rightly understood as a desire to associate with a certain group (Granovetter 1978; Libenstein 1950; see also Simmel on fashion 1971).

Although the snob effect is not the main concern here, it still remains important because 'snobs' may set a 'herd' in motion. Consider fashion, for example. When a new fashion spreads and becomes universally accepted, snob dissatisfaction will usually result. The snob will move away from the fashion (presumably in favor of a newer one), and ordinary people will follow the snob's example. However, contrary to the snob, ordinary people do not drop the 'old' style out of dissatisfaction: what motivates them is rather the urge to do the 'right' thing and to avoid becoming the object of attention by being out of fashion (Simmel 1971).

3. Bandwagons and collective behavior

Because analyses of collective action organizations rarely consider the above-described negative bandwagon effect or the possibility of a simultaneous positive and negative bandwagon effect, it is necessary to consider how such effects come into play. I take Granovetter's competent example as a theoretical device to elaborate what in this paper I label the positive and negative bandwagon effect.

To illustrate how these bandwagon effects can operate, consider a group of individuals who can be 'Non-participants', 'Participants', or 'Dropouts' in or from a collective action organization. Depending on their status, the individuals in this population face the options to join, not to join, remain in, or leave the organization.

Consider Granovetter's positive bandwagon effect first. The probability that a non-participant remains inactive or becomes a participant depends on the number of other individuals who are participating (the dotted line between Non-participants and Participants in Figure 1). If the number of Participants increases, this is likely to increase the flow of individuals from being Non-participants to becoming Participants (the solid line between Non-participants and Participants).

Next, consider the negative bandwagon effect. The probability that a Participant will remain in or leave the organization depends upon the negative bandwagon (the dotted line between Participants and Dropouts). If the number of Dropouts increases, this will increase the flow from Participants to Dropouts (the solid line between Participants and Dropouts).

In addition, an increase in the number of Dropouts is likely to send a signal to the Non-participants (the dotted line from Dropouts to Non-participants), reducing the propensity of

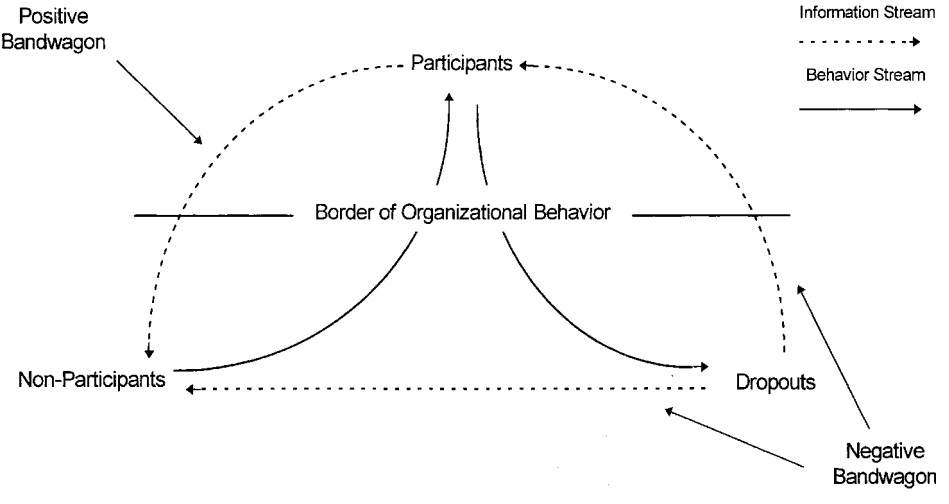

Figure 1. Bandwagon effects on individuals' choices of participation in collective action organizations.

the Non-participants to become Participants. Similarly, an increase in the number of Participants is likely to reduce the propensity of Participants to become Non-participants, since this signals that participation is to be preferred.[3]

As Figure 1 indicates, there are obvious parallels between the positive and negative bandwagons. However, there are reasons to suspect that the effect of the positive bandwagon is usually stronger than the negative bandwagon. One important reason is that the existence of bandwagon behavior is due to the uncertainty found in the decision process (Hedström & Swedberg 1998; Elster 1983; Sherif 1936). In uncertain situations, the choices of others may be the only information available to an actor on which to base his or her decisions. For example, the Non-participants in Figure 1 lack first-hand knowledge about the organization, this is likely to make them more prone to base their decisions about participation on other's behavior (i.e., the Participants). After joining the organization, they gain information that they previously lacked, and when they later consider leaving they can base their decision to leave on the experience of being Non-participants as well as Participants.[4] This removes to some extent the element of uncertainty from the exit decision, and thereby implies that the negative bandwagon may be less powerful than the positive. In addition, if the positive bandwagon is 'moving' in high phase, this is likely to dampen or even prevent the motion of a negative bandwagon, since the behavior of others in such situations strongly signals that participation is to be preferred.

Despite the negative bandwagon's relative weakness, its presence still alters the premises for how to account for collective behavior. If simultaneous bandwagon effects are present, it is feasible to account for both a positive and a negative effect on affiliation to an organization. One interesting future prospect would then be the possibility to predict the size of an organization by one mechanism, instead of two as, for example, the legitimacy and competition model suggested by organizational ecologists (McPhearson 1983).

4. Structural dependence and interpersonal influence

Up to this point, an implicit assumption has been that the action of one individual influences all other individuals to the same extent. However, Krackhardt & Porter (1986) have demonstrated that individuals' decisions to leave organizations snowball within clusters related to people's positions in a contact network. Considering these findings, it seems that a fruitful approach is to explicitly introduce structural heterogeneity into the analysis and allow for restrictions in contact possibilities (Hedström 1994; Heckathorn 1993; Strang & Tuma 1993; Burt 1987). This means that a given person's exit should affect only those who are structurally relevant to the actor who has dropped out.

However, it is not just the structural restrictions that must be considered if a misspecification is to be avoided. Distance in time is also important (Strang and Tuma 1993). In other words, if one individual drops out of an organization the effect of this event should decline rather sharply as time passes. It is unlikely, for example, that dropouts of some years ago would be as influential as last year's dropouts.

Given the above exemplification of how a negative and a positive bandwagon can coexist, I test two general hypotheses, both of which are based on Granovetter's (1978) threshold model. These are: (1) The negative bandwagon hypothesis: Past dropouts among an individual's structurally relevant others will positively affect that individual's propensity for dropping out of the organization, and (2) the positive bandwagon hypothesis: Past flows into the organization among an individual's relevant others will negatively affect that individual's propensity to drop out.

5. Data

The data that can provide a reasonable test for the presence of the above bandwagon effects require fairly extensive information on an organization's member activity. At the very least, the data need to be longitudinal, with information about the time when a person joins and leaves the organization. In my case I have access to information on one such organization. I use membership information from a lodge in the national temperance movement IOGT.[5]

The location of the lodge was in the parish of Husby-Rekarne, some 115 kilometers southwest of Stockholm. Most of the members lived and worked there. The size of the parish was roughly 90 square kilometers and the population varied between 1,900 and 2,500 inhabitants. In total, 569 individuals are included in

the database. The membership data available date from the founding of the lodge in 1896 until regular activity ceased in 1937 (Jansson 1981). The database contains membership information on an annual basis about every member's action in terms of joining and leaving the organization during that period. Besides data on the individual's affiliation with the organization, I also have information on where the members lived during their membership period, and demographics such as their age, sex and occupation. Supplementary information such as population size and income levels has been gathered from sources such as the census.

An additional requirement is that the organization can be regarded as a collective action organization. In the early 1900s, the temperance movement in Sweden included almost half of Sweden's organized population (Lundkvist 1977). Problems that resulted from drinking were seen as very important, and the question of whether alcohol should be prohibited was one of the most important social issues of the day. As far as this particular lodge's historical records tell, its primary aim was to produce a collective good. The lodge continued to elect representatives for joint activities with other temperance organizations throughout its existence. It also engaged in political activities at the local level, and tried to achieve the overall goal of total prohibition of alcohol (Jansson 1981). A law such as an alcohol prohibition act clearly constitutes a collective good, and an individual who favors prohibition faces the issue of whether or not to invest time and/or money in promoting the cause. The organization is, thus, suitable for analyses of collective behavior.

6. Measures

The implication of the above discussion of heterogeneity is that it is necessary to account for the group structure through which the information is channeled. In order to identify the group of relevant others, the preferred data are those on actual contacts between individuals. However, since I am unaware of any longitudinal data set that contains network information of such detail, I have adopted an alternative approach.

A range of earlier studies suggest that social and geographic distance between potential group members influences the composition of such groups. The reason appears to be that interpersonal distances structure communication and interaction probabilities (Gould 1995; Hedström 1994; Burt 1987; Hägerstrand 1967; Coleman et al. 1966) and that proximity, similarity and familiarity between individuals tend to increase the probability of face-to-face interaction (Marsden & Friedkin 1994; Friedkin 1983; Fischer 1982; Blau 1977; Gullahorn 1952; Festinger et al. 1950). Therefore, I expect that the probability of two individuals interacting with one another is inversely related to the distance between them. Hence, using information on individuals' positions in social and geographic space should make it possible to approximate the interpersonal networks that are likely to exist in the population.

Festinger et al. (1950) successfully demonstrated that the closer a group of people live to one another, the greater is the probability that friendship evolves and a group becomes established. According to Verbrugge's (1983) analysis of adult friendship contact, geographical distance indeed was the most important predictor of frequent interaction (see also Hägerstrand 1967). Therefore, it seems reasonable to assume that individuals who live close to former members of a social movement organization are more likely to interact with them and to have a group of relevant others composed of many former movement members.

Besides geographic proximity, Gans (1961) has argued that homogeneity in age and socioeconomic status increase the friendship potential. This is supported by Wright & Cho (1992), who found that social boundaries constitute obstacles to the formation of friendship ties, and by Boissevain (1974), who found age differences an important obstacle. For the same reasons, it seems reasonable to assume that individuals who are similar in age and social status to former members of a social movement organization are more likely to interact with them and to have a group of relevant others composed of many former movement members.

I thus assume that the probability of two individuals interacting with each other is a function of the geographic, age and social distances between them. The most practical way to handle distance measures like these is to create square matrices, the entries of which are the distances between pairs of individuals.

To obtain a square matrix of the geographic distances, I measured the distances between the 161,569 pairs of individuals in the database. This resulted in a [569 $\times$ 569] matrix (**G**), with the entries giving information on distances in kilometers between pairs of individuals. I then

inverted the cell entries in this matrix since I assume that contact is a decaying function of distance.

I obtained the matrices of distances in social space in a similar fashion. First, I ranked the occupational categories to which the 569 individuals belonged on the basis of average income.[6] I then used this information to obtain the desired [569 × 569] matrix (**S**) of inverted occupational distances. Finally, in a parallel fashion, I obtained a matrix (**A**) of inverted age differences.

Since information is available on the individuals' mobility, I estimate a new distance matrix every time an individual changed profession or geographical location. Finally, I set the matrix diagonal to equal 0 for all matrices, which prevents the individual from being included in his/her own group of relevant others.

To approximate the negative bandwagon effect, I post-multiplied the three distance matrices with a [N × 1] column vector, $\mathbf{D_t}$. The cell entries in this column vector are 0 if the individual was a member and then takes the value 1 if the individual left the organization during the year. I account for temporal heterogeneity by letting the magnitude of an event decrease exponentially as time passes (Strang & Tuma 1993). Thus, after the departure, the value declines exponentially by 50 per cent for each subsequent year.[7] Consequently, the value is 1 the year the individual leaves the organization. The year after it is 0.5, followed by 0.25 the next year, and so on. The measures are obtained from the following equations:

$$\mathbf{X_t} = \mathbf{G_t D_t} \ (1) \qquad \mathbf{Y_t} = \mathbf{S_t D_t} \ (2) \qquad \mathbf{Z_t} = \mathbf{A D_t} \ (3)$$

where: $\mathbf{G_t}$ is a [N × N] matrix of inverted distances in kilometers between i and j at time t, $\mathbf{S_t}$ is a [N × N] matrix of inverted distances in status between i and j at time t, and **A** is a [N × N] matrix of inverted distances in age between i and j. The entries of the column vectors resulting from these operations – $\mathbf{X_t}$, $\mathbf{Y_t}$, and $\mathbf{Z_t}$ – can be interpreted as proxy measures of the proportion of movement defectors in individual i's group of relevant others at time t.

To obtain a measure for the positive bandwagon effect, I used a method similar to the above. The difference is that I now post-multiply the distance matrices in equations 1–3 above by a different [N × 1] column vector $\mathbf{M_t}$. The i:th cell entry in $\mathbf{M_t}$ takes the value 1 if individual i is a member at time t and 0 otherwise. This operation generates three new column vectors – $\mathbf{x_t}$, $\mathbf{y_t}$, and $\mathbf{z_t}$, – the cell entries for which can be interpreted as proxy measures of the proportion of former movement members included in individual i's group of relevant others at time t.

Other control variables included in the analysis are the individual's, age, gender (dummy variable), status/class (dummy variables), and time as member. I also control for calendar time, the number of residents in the municipality, the effects of the Swedish referendum for or against prohibition of alcohol (dummy coded 0 before the referendum and 1 after Prohibition was voted down in 1923).

7. Method

As suggested by Strang (1991) and Hedström (1994), event history methods are appropriate for analyzing mobilization processes. I use a complementary log-log equation to estimate the probability of dropping out of the organization after the observations have been changed from individuals to individual-years.[8] Each individual then contributes one observation for every year they are at risk of dropping out of the organization.[9] I focus on the time at which the individual departs and how the timing of that event relates to a set of covariates, including other individuals' departures. Thus, the parameters of the following equation are estimated as follows:

$$\ln(-\ln(1 - p_{it})) = \alpha + \sum \gamma_k \, n_{ikt} + \beta_1 \, X_{it} + \beta_2 \, Y_{it} + \beta_3 \, Z_{it} + \beta_4 \, x_{it} + \beta_5 \, y_{it} + \beta_6 \, z_{it} \ (4)$$

where p_{it} = the probability that individual i will drop out at time t; n_{ikt} = values at time t on the k factors likely to influence the probability that i will drop out; X_{it} = number of Dropouts adjacent to i — weighted by distance in kilometers; Y_{it} = number of Dropouts adjacent to i — weighted by distance in status; Z_{it} = number of Dropouts adjacent to i — weighted by distance in age; x_{it} = number of Members adjacent to i — weighted by distance in kilometers; y_{it} = number of Members adjacent to i — weighted by distance in status; z_{it} = number of Members adjacent to i — weighted by distance in age; and α, γ_k, β_{1-6} are logistic coefficients to be estimated.

8. Results

Figure 2 illustrates the membership development over the organization's life course. It is evident from Figure 2 that there is no obvious

Figure 2. Yearly membership development.

pattern of growth or decline. Apart from a brief period from 1904 to 1907, the organization had a fairly stable membership of about 75 members until the last few years, when interest in the organization appears to have waned (see Table 1).

The social composition of the membership was to a large extent proportionate with that of the parish (Jansson 1981), i.e., the highest percentage of members consisted of factory workers, farm hand-maids, farm laborers-cotters, and craftsmen-teachers. The ratio of members belonging to each category was fairly stable over time with a slight increase in factory workers and a decrease in farm hand-maids over time, which was most likely related to the effects of ongoing industrialization. While the organization attracted members of all ages, young people in their twenties formed the largest segment. Gender distribution was surprisingly equal over time, with slightly more men than women.

To test for the presence of a general negative and positive bandwagon effects, I first model individuals' dropout propensity without structural constraints. For this I use the cumulative number of dropouts and the actual participation level in the organization (see Model 1 in Table 2). In Models 2 to 4, I test for the presence of negative and positive bandwagon effects when the action of relevant others depends on each of the structural constraints

Table 1. *Yearly membership development.*

Year	1896	1897	1898	1899	1900	1901	1902	1903	1904	1905	1906	1907	1908	1909
Members	52	55	86	81	70	69	61	60	50	37	31	41	58	83
New members	52	18	45	14	16	13	12	12	5	3	1	10	17	34
Dropouts	0	15	14	19	27	14	20	13	15	16	7	0	0	9
Year	1910	1911	1912	1913	1914	1915	1916	1917	1918	1919	1920	1921	1922	1923
Members	84	108	114	89	94	88	73	69	72	89	81	98	103	92
New members	23	31	21	5	20	4	1	5	12	33	2	31	18	7
Dropouts	22	7	15	30	15	10	16	9	9	16	10	14	13	18
Year	1924	1925	1926	1927	1928	1929	1930	1931	1932	1933	1934	1935	1936	1937
Members	92	102	98	101	103	96	84	79	86	71	62	56	46	36
New members	16	20	8	16	14	7	1	8	14	0	0	0	0	0
Dropouts	16	10	12	13	12	14	13	13	7	15	9	6	10	10

Table 2. *Estimates for complementary log-log models* (*) (Z-values in parentheses).

Model	1	2	3	4	5	6
Constant	−7.666**	−3.081	−3.423	−3.007	−3.282	−3.987**
	−(3.033)	−(1.499)	−(1.665)	−(1.455)	−(1.587)	−(1.584)
Time	−0.052**	−0.016	−0.006	−0.016	−0.007	−0.013
	−(3.575)	−(1.513)	−(0.540)	−(1.432)	−(0.679)	−(0.854)
$Time^2$	0.002*	0.000	0.001	0.000	0.001	0.001
	(2.088)	(0.563)	(1.453)	(0.582)	(0.984)	(1.005)
Time as member	0.339**	0.334**	0.285**	0.347**	0.279**	0.277**
	(7.375)	(7.339)	(6.322)	(7.573)	(6.243)	(6.171)
Time as $member^2$	−0.018**	−0.018**	−0.015**	−0.019**	−0.015**	−0.015**
	−(6.359)	−(6.276)	−(5.603)	−(6.456)	−(5.480)	−(5.445)
Population	0.001	0.000	0.000	0.000	0.000	0.001
	(1.150)	(0.467)	(0.248)	(0.465)	(0.500)	(0.610)
Referendum 1923	−0.332	−0.161	−0.275	−0.197	−0.227	−0.246
	−(1.313)	−(0.652)	−(1.124)	−(0.800)	−(0.921)	−(0.988)
Cat1: Yeomen-Tenants	−0.499	−0.360	−0.433	−0.259	−0.168	−0.176
	−(1.549)	−(1.104)	−(1.334)	−(0.772)	−(0.482)	−(0.504)
Cat2: Craftsmen-Teachers	−0.333	−0.236	−0.276	−0.032	0.124	0.111
	−(1.153)	−(0.808)	−(0.949)	−(0.093)	(0.334)	(0.290)
Cat3: Soldiers	−0.025	0.013	0.061	0.132	0.186	0.175
	−(0.068)	(0.034)	(0.163)	(0.348)	(0.480)	(0.450)
Cat4: Crofters	0.190	0.265	0.236	0.373	0.440	0.431
	(0.632)	(0.862)	(0.782)	(1.173)	(1.308)	(1.268)
Cat5: Farm laborers-Cotters	0.280	0.364	0.390	0.433	0.586	0.578
	(0.929)	(1.193)	(1.284)	(1.378)	(1.788)	(1.752)
Cat6: Farm hand-Maid	0.711**	0.775**	0.641*	0.683*	0.900**	0.902**
	(2.492)	(2.688)	(2.233)	(2.136)	(2.699)	(2.654)
Cat7: Day laborers (Farming)	0.347	0.397	0.363	0.368	0.457	0.457
	(0.964)	(1.093)	(1.004)	(1.018)	(1.245)	(1.243)
Cat8: Factory workers	0.024	0.136	0.030	0.242	0.420	0.412
	(0.084)	(0.467)	(0.103)	(0.717)	(1.169)	(1.122)
Age	0.057	0.047	0.034	0.050	0.041	0.043
	(1.794)	(1.522)	(1.165)	(1.587)	(1.341)	(1.376)
Age^2	−0.001**	−0.001**	−0.001*	−0.001**	−0.001*	−0.001
	−(2.908)	−(2.667)	−(1.971)	−(2.744)	−(1.952)	−(1.982)
Gender	−0.133	−0.143	−0.168	−0.158	−0.182	−0.179
	−(1.416)	−(1.521)	−(1.783)	−(1.672)	−(1.891)	−(1.858)
Number of Members	−0.173					−0.050
	−(0.912)					−(0.151)
Number of Dropouts	0.455**					0.076
	(3.032)					(0.514)
X_t (Positive Bandwagon – Geographic)		−0.352**			−0.272**	−0.268**
		−(5.268)			−(3.652)	−(3.522)
x_t (Negative Bandwagon – Geographic)		0.012**			0.009**	0.009**
		(6.132)			(4.036)	(3.974)

Table 2. *Continued.*

Model	1	2	3	4	5	6
Y_t (Positive Bandwagon – Age)			−0.212		0.028	0.055
			−(1.813)		(0.203)	(0.311)
y_t (Negative Bandwagon – Age)			0.056**		0.043**	0.041**
			(7.034)		(4.669)	(4.394)
Z_t (Positive Bandwagon – Status)				−0.321**	−0.174	−0.157
				−(2.987)	−(1.354)	−(1.112)
z_t (Negative Bandwagon – Status)				0.005**	0.000	0.000
				(3.975)	−(0.026)	−(0.179)
N	3622	3622	3622	3622	3622	3622
Deviance	2665	2622	2631	2661	2609	2609
Chi-square	56*	13*	22**	52**	0	–
Df	6	6	6	6	2	–

* Significant at less than the 0.05 level.

** Significant at less than the 0.01 level. The omitted category when controlling for the individual's own status is 'Estate owners-Manufacturers-Priests'. The omitted category when controlling for gender is women. Chi-square is obtained by comparing models 1–5 with model 6 in order to see if they are significantly worse than model 6 (significant levels as above). An individual's own exit or participation is never included in the variable measuring the total number of dropouts and the participation level. Further, the variables are the natural logarithm of the actual number of participants and dropouts.

along the lines discussed above. Model 5, then, tests how each of the structurally constrained measures in Models 2 to 4 behaves when they are introduced together. Finally, Model 6 contains all the previous measures in establishing a reference point to determine which of the prior models provides the best fit. The control variables, time, length of time as member, and age are all squared to control for possible non-linearity.

Model 1 demonstrates a negative bandwagon effect, where prior dropouts from the organization contribute to an increased probability that others will drop out. An increased number of members does not, however, contribute significantly to the outcome. Hence, the expected positive bandwagon is lacking, but the sign of the relationship is the expected. Since the analysis concerns the probability of leaving and not that of joining, the expectation for this variable is that an increased inflow of members should decrease the probability of dropping out. With only a negative bandwagon effect present, I lack the statistical evidence for the counterbalancing negative and positive bandwagon on the decision to leave this organization. However, the presence of the negative bandwagon agrees with the hypothesis that decisions to leave the organization are governed by the same mechanism as decisions to join it.

However, one of the main arguments of this paper has been that bandwagon behavior is likely to be structurally channeled. In Models 2 to 4, I therefore substitute the above measure for the variables that control for the hypothesized heterogeneity. The results in these models reveal that all the alternative measures behave according to my theoretical anticipation. The variables representing positive bandwagon effects all have a significant negative effect on the probability of dropping out, except for the non-significant estimate on the age-constrained variable. Similarly, the variables representing negative bandwagon effects all have a significant positive effect on the probability of dropping out of the organization.

These results, thus, indicate that there is a counterbalancing bandwagon effect on an individual's decision to drop out of the organization. In terms of deviance, the models also agree with the hypothesized effect – that structurally channeled bandwagons influence the individuals. Models 2 and 3 each provide a better fit than does Model 1, when comparing deviance with Model 6, although all three models perform less well than the full Model 6.

The non-significant estimate for the age-constrained variable, measuring the positive bandwagon effect, is most likely due to the problem of discriminating non-relevant others

from relevant others using only similarity in age as a criterion. Just because individuals who enter the organization are similar in age to the participants does not mean that they are acquainted with the participants. New members can come from all over the municipality, which makes spatial distance an obstacle for interaction. On the other hand, individuals similar in age to participants who leave the organization are most likely acquainted with the remaining individuals, since the organization provides a much smaller frame for contacts than the society at large. Hence, the much stronger observed effects that the remaining individuals will drop out after age-similar others have dropped out.

Model 4 does not noticeably deviate from the first model, since both models perform equally badly compared to Model 6. Nevertheless, the expected pattern of the simultaneous bandwagons is more salient in Model 4 than in Model 1. Proximity in class/status therefore seems less efficient as an approximation of who the relevant others are than does geographical proximity or similarity in age, probably in part for reasons similar to the age case above.

To come to terms with the independent result of each of the structurally constrained measures in Models 2 to 4, it is necessary to consider them together. In that way, some of the spatial effects experienced above are controlled for. In Model 5, I introduce all three measures from Models 2, 3 and 4 at once. The significant effects now remaining are the effect of the negative bandwagon in the age and geographically constrained variables and the effect of the positive bandwagon constrained by geographical proximity. The effect of the status/class constrained bandwagons in Model 4 has disappeared. The estimates are also smaller. One likely interpretation is that geographic proximity appears to be the measure that works best as a proxy for who the relevant others are, when holding constant the effects of the age and status/class constrained measures. It should be noted that the negative bandwagon weighted by similarity in age is still strongly significant and has the highest estimate when the effects of geographic and status/class constrained measures are held constant. Apparently, age is an important criterion for the approximation of who the relevant others are for dropout decisions. It seems reasonable to conclude that similarity in age and geographic proximity modeled together in this way give a fairly good account of the structurally constrained negative and positive bandwagon effects.

To establish a meaningful comparison between the relative effects of the geographic and age-constrained bandwagons, I estimate the effect of each of the four bandwagons on people's dropout propensity with all the other covariates held constant at their mean. I then graph these predictions against the independent variable. The result is four so-called conditional effect graphs (see Figure 3) with identical y-scales; these provide a visual comparison of how each bandwagon affects the propensity of people to drop out (Hamilton 1998). As we can see, the graphs reveal that the age and the geographically constrained negative bandwagons are relatively equal in strength. Evident also from Figure 3 is the strong counterbalancing effect of the geographically constrained positive bandwagon. The relative effect of this bandwagon is about as strong as its negative counterpart. The effect of the age-constrained positive bandwagon is close to zero, as expected.[10]

On comparing the deviance in Model 5 with that in Model 6, one finds that Model 5 provides just as good a fit as Model 6. Compared with the previous models, Model 5 shows a significantly better fit than all the other models. It is worth noting that in Model 6 the earlier observed significant effects of the cumulative number of dropouts are no longer significant, implying that the propensity to drop out is not affected by dropouts among structurally irrelevant others.

Lastly, some comments on the significance of the other variables. Individuals exhibit a higher probability of dropping out of the organization up to around 20 years of age. After that point, the probability decreases with increased age. This effect is fairly similar across models. The most significant variable in all models is the individual's time as a member. Evidently, the longer individuals remain as members the less likely they are to drop out. However, the effect of membership duration is non-linear, i.e., the probability of dropping out increases up to around nine years of membership, and decreases thereafter. The preference to remain a member, thus, seems to be reinforced by prior behavior (Elster 1983). The influence of calendar time is only significant in Model 1 and it seems that the probability to drop out increases with increased rate over time. This agrees with the history of the temperance movement in Sweden, which shows a dying interest in such organizations over time (Lund-

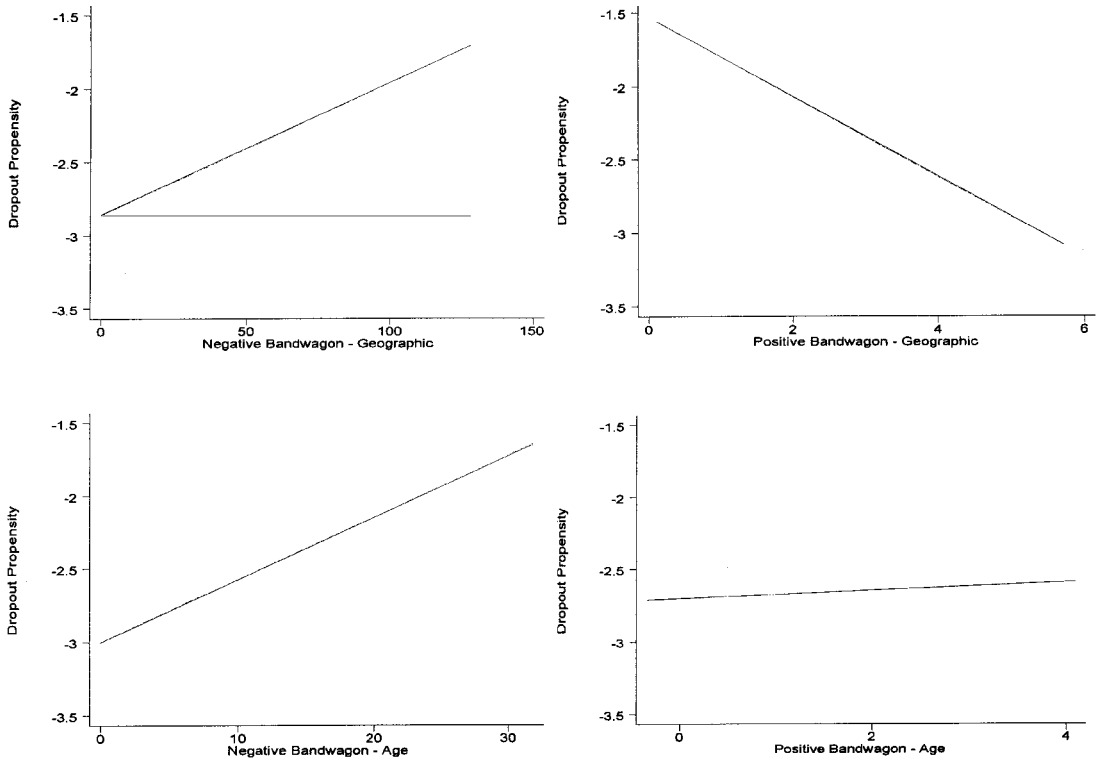

Figure 3. Conditional effects graphs for the age and geographically constrained bandwagons.

kvist 1977). The effect of individuals' class/status membership does not seem to vary across categories, with one exception, Category 6, which implies that all the categories are reasonably equally prone to drop out.

9. Conclusions

In using Granovetter's (1978) idea of bandwagon behavior, I have argued that individuals' collective behavior, aside from being influenced by a positive bandwagon that pulls them into an organization, is also influenced by a negative bandwagon that pulls them out of organizations. This theoretical expectation is supported by my empirical findings that strongly suggest the presence of a negative bandwagon effect. These findings also support the expectation that there is a simultaneous positive and negative bandwagon effect. In this case, the positive bandwagon decreased people's propensity to leave the organization at the same time as the negative bandwagon increased their propensity to leave the organization.

Analyses focusing only on the effect of recruitment to collective action organizations have established that the structure and the density of network ties can promote bandwagon effects that favor the growth of organizations. Given current knowledge of negative bandwagons, this kind of inference appears somewhat premature, since dropout behavior appears to be conditioned in much the same way. Therefore, not considering both negative and positive bandwagons when attempting to account for the conditions that favor organizational growth is likely to render a misspecified model with empirical results that are likely to be misleading. Despite these implications, the findings here add credence to prior research claims that interpersonal influences are of decisive importance for collective behavior, since not only decisions to join collective action organizations but also decisions to drop out of these organizations depend on interpersonal influences.

An additional argument in this paper has been that the information about others' behavior is likely to be structurally constrained. For this, I adopted a theoretical approach that emphasized the importance of social structure

and individual decision-making. I argued that people deciding whether or not to leave an organization were more likely to be influenced by individuals with whom they were also likely to interact. The empirical result confirmed this expectation. People in the organization tended to leave in clusters related to where they lived and how old they were. This renders important insights on how the effect of explanatory factors such as dropout decisions can differ across groups and levels of aggregation. In terms of the results I have presented here, the effect of the number of past members belonging to one's own group of relevant others increased the likelihood of dropping out, while the number of past members belonging to groups other than the relevant group of others had no effect on the likelihood of dropping out.

The findings in this paper are grounded in one case, which strongly suggests that more theoretical as well as empirical work is necessary before we will fully understand the importance of these positive and negative bandwagons. If consistent evidence for these effects becomes available, it will open up interesting possibilities for modeling organizational size more extensively, since it would then become possible to estimate people's thresholds for both entering and leaving an organization. Such a model should be appealing, since it would enable us to explain organizational size by one mechanism, instead of, for example, the legitimacy – competition model used by organization ecologists.

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Notes

[1] Throughout this paper I use the expressions 'Collective Action Organization' and 'Social Movement Organization' interchangeably.

[2] The analysis conducted by Granovetter & Song is formalized to a great extent by Thomas Schelling (1978), who developed a tipping model for individuals' actions. This type of belief-formation mechanism was also at the core of Robert K. Merton's (1968) work on self-fulfilling prophecies, James Coleman et al.'s (1966) work on network diffusion processes. The bandwagon concept derives from the economic theory of consumer demand, where the utility of a commodity is influenced by the number of others that have also consumed the commodity: 'By the bandwagon effect we refer to the extent to which the demand for a commodity is increased due to the fact that others are also consuming the same commodity. It represents the desire of people to purchase a commodity in order to get into the swim of things; in order to conform with the people they wish to be associated with; in order to be fashionable or stylish; or in order to appear to be one of the boys' (Libenstein 1950:189).

[3] For simplicity's sake, I ignore the possibility of re-entering after dropping out. However, in the following analysis re-entry is considered.

[4] Elster (1983) defines this as informed preference. According to Elster, informed preferences are grounded in experience, and differ from other preferences in their stability.

[5] These data were collected by Professor Torkel Jansson of the Department of History, University of Uppsala (see Jansson 1981). IOGT stands for 'Independent Order of Good Templars'. The organization is divided into lodges, where every lodge is an independent organization with its own administration.

[6] The occupational coding is based on the nine categories that Jansson (1981) originally coded the individuals into: 'Estate owners–Manufacturers–Priests', 'Yeomen-Tenants', 'Craftsmen –Teachers', 'Soldiers', 'Crofters', 'Farm laborers–Cotters', 'Farm hand-maids,' 'Day laborers', and finally 'Factory workers'.

[7] I have no theoretical reasons for choosing the value of this decline in influence. I tried several different values that all gave similar results; 0.50 proved to give the best overall fit.

[8] See Allison (1982) on the procedure for converting observations from individuals to individual-years in event-history analysis. The appropriateness of using a complementary log-log equation instead of a logit equation was suggested by David Firth. The advantage of a log-log estimation is that the model has a higher generalizability regarding the time-unit in the analysis. The log-log approach I apply is equivalent to Cox's proportional hazard model (see Blossfeld et al. (1989) and Roystone (1994) for a technical elaboration of complementary log-log models).

[9] Cases considered as dropouts are active departures only. Hence, individuals who die or move to a different society are not considered as active dropouts.

[10] It is reasonable to assume that the age and geographically constrained bandwagon effects are interdependent. To check for interaction effects I run an additional model in which interaction terms for the age and the geographical constrained bandwagon effect are included. While none of the interaction effects was significant, there were indications that, for example, high values on the age constrained bandwagon had less effect on people's dropout propensities if the value of the geographically constrained bandwagon at the same time was low. However, since the effects were insignificant I chose not to report them in Table 1.

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