

Social Entrepreneurship effects on the Emergence of Cooperation in Networks.

ABSTRACT

Even in simple contexts, the dynamical interaction between agents creates complex features. The presence of agents of change affects dramatically the underlying social structure. Some agents seem to be important in shaping the evolution of interactions: traditionally, these agents have been referred to as leaders; nevertheless, recently scholarly interest has been attracted by social entrepreneurs. Do social leaders and social entrepreneurs act differently? Can a social entrepreneurship culture, one that aims for a large number of social entrepreneurs, be welcomed? This paper presents a model of interaction among agents in a community, and sheds light on the catalytic role that some individuals have on the social structure. The results provide some implications about the role of social entrepreneurs and the differences between social entrepreneurship and leadership.

Introduction

The language of social entrepreneurship may be new, but the phenomenon is not. The interest in it has been rising in recent years, and other forms of social entrepreneurship, beyond that occurring within the nonprofit sector, have also grown. The concept of social entrepreneurship is gaining popularity, but, at the same time, the term has undertaken several meanings, and many authors agree on the fact that this can be confusing (Dees, 2001; Austin *et al.*, 2006; Mair and Martí, 2006).

For this reason, social entrepreneurship is still an emerging area for academic inquiry. Theoretical supports have not been sufficiently explored, and contributions to theory and practice are necessary. In addition, boundaries of social entrepreneurship to other fields of study remain fuzzy. Several contributions have been proposed in order to clarify the topic. Among others, Austin (2006) presents studies of collaborations in social entrepreneurship, such as alliances and networks, hoping for interdisciplinary research. Empirical approaches examine the sociological aspects behind the exploitation of social entrepreneurial opportunities, deriving from the existing entrepreneurship theory of opportunity. Robinson (2006) considers the relationship among three factors: the decision to enter a particular market, the social networks in which entrepreneurs are embedded, and the existing types of institutions which can help the development of the initiative. Considering the integration of sustainability and the environment, Clifford *et al.* (2006) suggest that successes related to the mission-driven values and ideals and to creating networks of mutual benefiting stakeholders.

Following Austin *et al.* (2006), the social entrepreneur must focus on building a network of contacts, developing the skills to manage the different relationships in this network effectively. Furthermore, networking across organizational boundaries seems to be essential,

because the goals of creating social value do not imply that value can be captured within boundaries. An interesting case which emphasizes this aspect is studied in Rhodes and Donnelly-Cox (2008)

We do not intend to put much emphasis on social entrepreneurs as individuals, focusing on personality traits that may contribute to entrepreneurial success. Rather, we are interested in what social entrepreneurs do; in fact, it has been already observed that the right question to ask is not “who the entrepreneur is” (Gartner, 1988). Furthermore, as Light (2006: 50) underlines, the available evidence suggests that success depends less upon personality than on teachable skills. According to Light’s definition, social entrepreneurships “can also come from small groups or groups of individuals, organizations, networks, or even communities that band together to create pattern-breaking change”. Moving away from *who* becomes an entrepreneur to *what* they seek, the number of social entrepreneurs expands. The level and the intensity of social entrepreneurship can vary greatly: because of continuous changes in circumstances, this activity might pause, stop and restart. With this definition, social entrepreneurship can be found almost everywhere, aiming to include in the list of names for possible study also characters like “sometimes-entrepreneurs” or “on-hold entrepreneurs”.

In previous researches (Dal Forno and Merlone, 2007) social leaders were considered. They were characterized mainly by an assigned role which could not change; here we are interested in a more dynamical role. The aim of this paper is twofold. First we propose a model of interaction where the role of social entrepreneurs can be studied and assessed. This will allow us to propose answers to some questions: Do social leaders and social entrepreneurs act differently? Can a social entrepreneurship culture, one that aims for a large number of social entrepreneurs, be

welcomed? Moreover, we analyze how the role of social entrepreneurs differs from that of social leaders, allowing for the presence of “sometimes-entrepreneurs” or “on-hold entrepreneurs” as in Light (2006). In fact, in the model we present, it is possible to observe how their presence affects the dynamics of different linkages and interactions among agents. In this sense, *social entrepreneurs may be interpreted as facilitators in creating agreement on projects between individuals with different opinions*. Similar roles can be found when considering non-profit organizations, cross sector social partnerships, and NGOs (for a discussion, see Mohan, 2002, and Peredo and McLean, 2006). Finally, we shed light on the modifications each of the two roles, leader versus social entrepreneur make on the underlying social structure of the community in terms of emerging work groups.

The structure of the paper is as follows. In the next section we present the model of interaction. We will then explain the computational model and discuss the results. The article concludes by summarizing our implications and presenting further research.

The Model

Among the different scholarly contributions on social entrepreneurship, Waddock and Post (1991) considered the catalytic changes on complex social networks enabled by social entrepreneurs. In order to explore these aspects we consider a model of community where individuals may form groups to commit on projects. We are interested in shedding light on the emergence of groups when individuals do not act directly to the group formation process, rather they act on the social network which shapes the community structure. In particular, while in our

model all the agents exhibit the same simple behavior in order to form groups, some of them, acting on the social network, indirectly affect the emergence of groups.

Our purpose is to analyze, through a formal model, how group composition evolves as the result of the catalytic influence of the social entrepreneurs on the social network. While our model is general enough to consider also how the individual behavior, in terms of partner selection, and exerted effort may influence the social network and the group composition, in this paper we keep the first aspects simple and restrict our attention to the role of social entrepreneurs as summarized in Figure 1.

[Figure 1 about here]

To identify the role of social entrepreneurs in group formation, we introduce and compare different behavioral rules in the computational model of interaction among the artificial agents we consider. This way we are able to break down the agents' behavior in micro phases. This allows us to assess the relative importance of each of these individual aspects of behavior when leading towards the emergence of some macro behaviors in the artificial society we consider. In particular, the model enables us to study how the percentage of agents taking the role of social entrepreneur influences the emergence of groups.

Interaction Formalization

The community consists of n agents univocally identified by an index $i \in N = \{1, 2, \dots, n\}$. Agents interact forming groups to work on a project in which at most m members can participate. In the

artificial simulations, we fixed $m = 7$ (for an empirical motivation of this choice see chapter II in Miller and Rice, 1967).

Each agent can choose its partners from a subset $M \subseteq N$ of known people. Knowledge of agents in the community is described using a sociomatrix \mathbf{K} . Each element k_{ij} of the sociomatrix \mathbf{K} indicates whether agent i knows agent j : zero indicates that i does not know j ; conversely, value one indicates that i knows j . We assume that each agent knows itself; as a consequence, all diagonal entries are set to one. \mathbf{K} is not necessarily a symmetric $n \times n$ matrix.

Agents can participate in at most two projects; in each of them their decision is two-fold:

1. They must specify the designated members of the group.
2. They must specify the effort they will exert in each group.

When all participating agents agree on the group composition, this, together with their efforts, constitute an *implemented project* and is univocally determined.

The relation “ i works with j in an implemented project” defines a non-dichotomous symmetric matrix \mathbf{W} where element $w_{ij} \in \{0,1,2\}$ is defined by the number of projects in which agents i and j work together. Matrix \mathbf{W} defines the project network; when n agents work together on an n -member project, we say they form a *size n clique* since in the graphical representation of matrix \mathbf{W} , they are depicted as a clique with n nodes.

Within each implemented project, the agents play a public goods game. The efforts of the participants are aggregated and used to produce a collective benefit function f ; the output is shared among the members of the group. We denote c_i agent i 's cost of effort, and assume that

greater effort means greater cost to the agent and increasing marginal cost. The individual benefit of agent i in project p can be formalized as follows:

$$\beta_{i,p} = \frac{f\left(\sum_{j \in T_p(i)} e_j\right)}{n} - c_i(e_i) \quad (1)$$

where e_i is agent i 's effort and $T_p(i)$ is the set of partners of agent i in project p . We assume: 1) There exists a unique level of effort maximizing the agent's individual benefit; 2) when all the agents exert the same effort, the optimal collective benefit increases with the number of members participating in the project.

In order to keep the math simple we considered in our experiments the following individual benefit function:

$$\beta_{i,p} = \frac{\left(\sum_{j \in T_p(i)} e_j\right)^2}{n} - e_i^3 \quad (2)$$

In this case, it is easy to prove that the socially optimal effort for a n -member project is $e_n^S = 2n/3$. With this formulation, when everybody exerts the socially optimal effort, the individual benefit increases with the number of agents in the project.

In Dal Forno and Merlone (2005, 2007) human subjects behavior when interacting in the proposed model is analyzed; there was considerable evidence that free riding was limited in these situations, as the group members exerted optimal effort to the group and did not free ride. This evidence makes the proposed model quite appealing for analyzing social entrepreneurship in

artificial societies since, when agents do not free ride, the benefit to the social entrepreneur is the same as to other members in its group. This is consistent with Austin et al. (2006), who claim that “social entrepreneurs are seeking to attract resources for the social good, rather than for financial returns”.

The Computational Model

As in Dal Forno and Merlone (2007), each turn is divided in three phases. First, in the communication phase, the agents propose and discuss the group composition for projects. Then, some agents – the social entrepreneurs – under certain conditions, try to expand the sociomatrix in order to increase the probability of obtaining a larger consistent project. Finally, agents coordinate on the two best projects that emerged in the discussion and the game is played.

Communication and Discussion among Agents

In our model, we implemented the discussion and proposal of projects allowing each agent to propose up to 50 projects and having agents to choose the best feasible common project. This is a sort of brainstorming process (Osborn, 1991) in which agents propose whatever comes into their mind.

This brainstorming process is necessary since, when agents choose their project compositions randomly, the probability of obtaining a seven-member project is very low because they must know each other and the number of possible projects each subject may propose is very high. In fact, assume a population of n individuals knowing each other. We denote with r the number of group members. If $r \leq n$, then groups of different dimension can be formed, up to r -

member groups. For the sake of simplicity we call an r -member group a *size r clique*. Therefore, the number of projects that can be obtained with exactly r individuals (i.e., the number of r -cliques) is equal to the binomial coefficient $C_{n-1,r-1}$. In Table 1 we show how many size r cliques, with $r = 2, \dots, 7$, are possible in a population of n individuals.

[Table 1 about here]

Comparing the figures in Table 1 allows us to understand how the sociomatrix can play an important role. In fact, in a n -agent society, where all the agents know each other, the probability of obtaining size 7 cliques is very low: For example, in the case of a 7-agent society, the probability that the seven-agent project is implemented is $(1/64)^7 = 1/2^{42}$. This makes the coordination of several agents on a single project a complex task, due to the combinatorial explosion of the number of cliques. This factor is related to computational complexity (see Garey and Johnson, 1979). The agents rank their feasible projects assuming that they exert the socially optimal effort.

Individual Diversity in Social Interaction and Social Entrepreneurship

According to the feasible projects that emerged during the discussion among agents, some of them may decide to act on the sociomatrix. While in Dal Forno and Merlone (2007) only some agents were assigned this capability, in this research we assume that, under some conditions, all the agents may act on the sociomatrix. This assumption is consistent to Light (2006), since this author bases some of his arguments on the belief that several social entrepreneurs are either ready to emerge or are already working hard to make a difference.

At each round the density of matrix \mathbf{W} is computed through an appropriate measure; we recall that the density of a graph is the ratio of the number of lines present, to the maximum possible (Wasserman and Faust, 1999). Each agent has an individual density threshold which is assigned at the beginning of the simulation. The random individual threshold value is uniformly distributed in $[0,b]$ where $b \in [0,1]$. At each turn, when the individual threshold is greater than the current density, the agent assumes the role of a social entrepreneur with probability p . Vice versa, social entrepreneur quit their role whenever matrix \mathbf{W} density equals at least their individual threshold.

When acting as a social entrepreneur an agent may decide to introduce its acquaintances to others and/or expand the sociomatrix including all the agents known by its acquaintances. The social interactions have effect on the following turn. If we follow Mair and Martí (2006) and other researchers in defining social capital as actual and potential assets embedded in relationships among individuals, we can think of social entrepreneurs as agents who increase the social capital.

At the moment, we do not consider situations in which the entrepreneur may bargain with other agents on the group composition because, even with the simple kinds of social interaction so far implemented, the model is rather interesting.

Game Interaction

According to the results emerged in the communication phase, each agent proposes the two best projects. Here the agents may decide whether to play the socially optimal effort as in the communication phase. Actually, as a consequence of the empirical evidence in human subjects

discussed in Dal Forno and Merlone (2005, 2007), we assume agents exerting the social optimal effort. Then benefits are computed and payoffs are given to agents.

Classes of Behavior and Structural Properties of the Sociomatrix

Given the complexity of the model, the behavior of artificial populations depends on four dimensions, namely: the *initial sociomatrix form*, the *group selection behavior*, the *effort determination behavior*, and the *social entrepreneurship behavior*.

The role of the Initial Sociomatrix

As discussed previously, the number of known agents is crucial in terms of the ability to select groups with several agents. This has been modeled using the dichotomous sociomatrix \mathbf{K} describing the knowledge relationship between agents. Our agents are assumed to be located on a circle graph where all nodes are interchangeable. At the beginning of each simulation the mutual knowledge between agents may assume different forms. Specifically, the following cases are relevant.

Total mutual knowledge. Every agent knows each other. In this case, sociomatrix \mathbf{K} is unitary. However, due to the combinatorial explosion mentioned above, this initial matrix configuration is not particularly interesting in terms of simulation results. In fact, a complete mutual knowledge affects the efficiency of the discussion phase, not allowing the emergence of clusters in a reasonable number of iterations.

n -neighbor knowledge. This graph generalizes the circle graph we discussed above. While in the circle graph each agent knows just one agent on each side, in the n -neighbor knowledge graph each agent knows n neighbors on each side. For 1-neighbor knowledge, that is the circle

graph, only size 2 cliques are possible, while, in order to have size 7 cliques, we need 6-neighbor knowledge. In this case, each agent knows 13 individuals.

Previously observed sociomatrix. Initial sociomatrix may be any previously saved one. For example, it is possible to start with one of the final sociomatrices that emerged during other simulations.

Group Selection Behavior

Since, as we saw previously, the combinatorial aspects of the group selection process must be carefully considered in order to have agents converging towards large projects, we developed different approaches in modeling this aspect of behavior. The most interesting were:

1. Considering the project with the largest number of members and expanding it by adding one more new agent.
2. Considering the two best projects and expanding the second one, either adding one more subject or proposing a new project with at least one more agent than the second best project.

The behavioral rules –allowing agents to keep their best projects and to expand them– proved to be extremely important in the simulations. These kinds of rules allowed, for example, the emergence of strong connections between agents.

Effort Selection Behavior

The behavior we implemented in terms of effort selection consists uniquely in playing the socially optimal effort. This behavior can be justified recalling the structure of the game the participants are called to play. In fact, since the game bears the structure of a public goods game, effort selections behavior can be interpreted as the strategy of a multiplayer Prisoner Dilemma, where playing the socially optimal effort stands for “cooperating”. In the experiments we

observed (Dal Forno and Merlone, 2007) the human subjects almost always exerted the socially optimal effort. This can be explained by assuming that players' behavior is driven by considerations of fairness and equity (e.g., Fehr and Schmidt, 1999).

Social Entrepreneurship Behavior

When modeling social entrepreneurship we are interested in considering quite simple behaviors. Assuming that agents are located on a circle graph, all the agents are interchangeable and know just their closest neighbors; in this case only size 2 clique projects are possible. As mentioned above, *social entrepreneurs* may wish to act on the social network in order to allow the selection of larger projects. Specifically, for these agents we considered several actions in order to expand the sociomatrix. The most interesting were:

- provided that the social entrepreneur knows less than thirteen agents, when the first best project is not a size 7 clique or, the first best project is a size 7 clique but the second project is not, then it introduces each other to all the agents it knows;
- when the social entrepreneur knows less than seven agents and the best project is not a size 7 clique or, the agent knows less than eight agents and the best project is a size 7 clique but the second best project is not, the social entrepreneur expands the vector of its known agents in order to include all the agents that in the sociomatrix have a geodesic distance smaller than three; in a friendship relation this would simply mean that “the friends of my friends become my friends”.

These combined procedures were the most effective for the emergence of connected clusters similar to those we observed in the human subjects experiment. In fact, the social entrepreneurs

expand the sociomatrix only when it is necessary to improve the size of projects. While the first procedure acts on the other agents, the second one increases the number of agents the social entrepreneur may contact. Given the combinatorial intractability of the project selection process, it is important to balance carefully the sociomatrix expansion with the number of members of implemented projects. Since in our model we do not consider explicitly communication, what we obtain seems to be a good approximation of these behaviors.

Results

The computational model has been implemented in C++; we obtained an interactive platform where the composition of the community can be chosen together with different parameters. We fixed a community of 63 agents and compared the results when considering different social entrepreneur distributions in the population. We assumed that agents, observing a density value for matrix \mathbf{W} smaller than their individual threshold, acted as social entrepreneurs with probability $p = 1$. Our interest was directed to analyze how the distribution of social entrepreneurs in the community could affect the cooperation among individuals.

With our approach we measure the effect of social entrepreneurship in terms of effective projects. In other words, social entrepreneurs act as catalysts on the social network in order to enable the formation of larger groups. To keep things simple, for the first set of simulations we considered the 1-neighbor knowledge as the initial sociomatrix; this choice allows at most size 2 cliques in the circle graph; when considering our assumption on the number of project to be implemented, this results in each agent implementing two 2-agent projects as depicted in Figure 2.

[Figure 2 about here]

We consider different series of simulations in a fixed size 63 agents population where agents play with socially optimal effort. The artificial population data are the mean of five independent replications; we decided not to consider many more replications since the results were quite stable and the time for each replication was quite long (about 5 hours on a Pentium 4 CPU 2.80 GHz, Ram 512 MB). Specifically, we observe evolution at turns 1, 2, 3, 4, 5, 6, 10, 20, 30, 40, 50, 60, 100, 200, 300, 400, 500, 600, 1000, 2000, 3000, 4000, 5000, 6000 and 10000. This time choice allows observation of both the short and long term evolution.

In order to measure the role of social entrepreneurs we considered different values for the upper bound b of the uniform distribution which determines the individual threshold. The following values of b were considered: .25, .50, .75, and 1.00. As it concerns the value .25 some comments are in order. In fact, observe that when considering a number of agents which is a multiple of m , the density of the initial projects depicted in Figure 2 is greater than .25; this means that having agent with individual threshold level distributed in $[0, .25]$ results in no agent assuming the social entrepreneur role. The consequence is that in a circle graph population, agents keep on proposing and playing size 2 cliques forever, since no one acts on the sociomatrix.

A first series of simulations analyzes the optimal distribution of social entrepreneurs and compare their effect to the role of social leader described in Dal Forno and Merlone (2007). The results of this comparison may help to understand how social entrepreneurs differ from social

leaders. In fact, while both social entrepreneurs and social leaders expand the sociomatrix when it is necessary to improve the size of projects, the latter are placed every six agents, and keep their role throughout the simulation since they do not have any internal threshold.

The results of these first series are depicted in Figure 3.

[Figure 3 about here]

We can observe that, among social entrepreneurs the most effective threshold upper bound seems to be .50; with higher values, the number of social entrepreneurs makes sociomatrix **K** expansion too fast, and the combinatorial complexity mentioned above hampers the formation of groups. Finally, when the threshold upper bound value equals .25 no agent acts as a social entrepreneur.

The comparison with social leader provides several insights. In fact, it must be observed that, while in terms of number of links, social leaders are more effective, their role is exogenously assigned and they are strategically positioned every other 6 agents. This, on one hand would suggest that having agents with assigned role would be more effective, but on the other would steer away from the motivations of social entrepreneurs.

In order to better understand what makes the social entrepreneurs peculiar, we performed a second series of simulations where we took as initial sociomatrix, instead of the circle graph, the final sociomatrix obtained at the end of the previous simulations. These series were run with neither social leaders, nor social entrepreneurs, and considering the final sociomatrices obtained in the previous simulations; the results are presented in Figure 4. In this figure we can observe

the evolution of sociomatrix \mathbf{W} when the initial knowledge matrix \mathbf{K} is the same as the one obtained at the end of the 7-leader and at the end of the .50 threshold social entrepreneurs simulations depicted in Figure 3

[Figure 4 about here]

This approach allows for incorporating one of the effects of having social entrepreneurs and leaders in the population: in fact, the sociomatrix is already expanded. While theoretically these sociomatrices are necessary to have the same simulation outcomes we obtained when social entrepreneurs and social leaders were present, the results are quite different. In fact, when considering social entrepreneurs the two kinds of sociomatrices allows for the emergence of a different number of links, what really matters is that, when considering social entrepreneurship, the evolution in terms of links is quite similar. On the contrary, when considering social leaders this difference remains wide for a large number of iterations. This may indicate that social entrepreneurs differ starkly from social leaders on their actions on the sociomatrix. While for social leaders the results are similar only on the long run, as it concerns social entrepreneurs, the results become closer earlier. This may be interpreted in the sense that social entrepreneurs' actions are absorbed more deeply in the sociomatrix when compared to actions performed by social leaders.

The results we have presented so far are in aggregate form; in the following we present the same comparison when considering one single simulation for each kind of the simulations depicted in Figure 4.

[Figure 5 about here]

[Figure 6 about here]

Comparing Figures 5 and 6, we can see that, on the first turns, the situation is completely different as the result of the initial sociomatrix. While with a circle initial sociomatrix, the agents start implementing projects with their neighbors; in the other case some agents in the very first iterations remain isolated due to the large number of agents they already know. Furthermore, it can be observed that later on, in both cases, the same group structures emerge even if in the case of no social entrepreneurs the network evolution is slightly slower.

By contrast, when comparing Figures 7 and 8, we can see that differences are not limited to the first iterations. In fact, in case of no social leader the network evolution is much slower: in fact, in Figure 8 the working projects are much sparser and densely connected working groups emerge later on in the evolution.

[Figure 7 about here]

[Figure 8 about here]

Finally, comparing Figures 6 and 8, we can observe that the change the social entrepreneurs induced on the sociomatrix allowed for a faster emergence of clusters. This confirms the differences between social entrepreneurs and social leaders, in terms of effects on

the sociomatrixes; also in this case, we could say that changes inducted by social entrepreneurs on the sociomatrix are more deeply embedded and retained.

Conclusions and Further Research

In this paper we presented a model of interaction among individuals in a community, where the network of interactions may allow for the emergence of cooperative projects. The model consists of two coupled networks modeling respectively knowledge and cooperation among individuals. We showed how the combinatorial explosion of the number of possibilities on which agents may cooperate makes the coordination a complex process. Our model sheds light on the role of leadership in complex systems by examining two different roles: the first one –the social entrepreneur– shared and mediating internal drive with community needs and the second one – the social leader (Dal Forno and Merlone, 2007)–more individualistic and intrinsic.

Two aspects of complexity are intrinsic in the model: the large number of group combinations, and the dynamical interactions among agents. In order to have the best outcome – i.e., the largest number of wide groups which, as illustrated in Figures 2 and 3, is measured in terms of number of links in the network – the action of agents of change is needed. These particular agents must be able to help the realization of effective groups enriching the net by exploiting old connections and looking for new ones between members of the community. But, at the same time, they must be able to state the pace of a balanced expansion of the social matrix. In other words, they tame the combinatorial explosion while fostering mutual knowledge among agents, making possible projects otherwise impossible. In fact, as we saw when discussing Table 1, as the number of connections increases the probability of agreeing on 7-agent projects

decreases exponentially. Social entrepreneurs, by acting on the knowledge matrix, catalytically allow the emergence of cooperation projects. In our model, social entrepreneurs do not suggest projects; rather they act on the social network and may help the emergence of projects in the discussion phase. Any member of the community can be a social entrepreneur, as long as they believe it is appropriate.

We compared the effectiveness of social entrepreneurs in terms of number of links in the community. According to our findings the number of social entrepreneurs and their relative location is extremely important. In this sense, the social entrepreneurship role is necessary for a sort of implicit coordination of agents. Different levels of social entrepreneurship diffusion in the community may have different effects on the emergence of projects; when the level is low the coordination remains limited, while a too high level of social entrepreneurship, on the contrary, hampers coordination. Only a moderate level of social entrepreneurship is effective to approach the complexity of coordinating on larger projects. This suggests that a culture for a moderate social entrepreneurship would be effective in promoting projects; deciding who should act as a social entrepreneur can be considered a coordination game.

Finally, social entrepreneurs were compared to social leaders. As a matter of fact in our model they do not act differently; rather the differences among the two roles are in terms of strategic position, persistence in acting on the knowledge matrix and the fact that, while the level and intensity of social entrepreneurs' action can vary greatly, social leaders are more constant in their actions. This turns to the consequences of Light's (2006) definition of social entrepreneurs, which is more directed to what they do instead of considering their personality traits. While social leaders outperform social entrepreneurs in terms of number of links, their actions on the

knowledge matrix are retained at a different level. While the action of social entrepreneurs seems to be more delicate, it seems to be embedded in the knowledge sociomatrix as it can be replicated when active social leaders are removed. On the contrary, while the action of social leaders is more effective, when they are removed the community cannot replicate the evolution in the short run.

In further research it would be interesting to find the most effective threshold in fostering effective cooperation links among agents. Another aspect which would be interesting might be introducing a sort of decay in the knowledge matrix, i.e., to consider the tendency for relationships to weaken and, eventually, disappear (Burt, 2000). This would help to keep effective the knowledge sociomatrix and would be more realistic in how human networks evolve over time. Finally, since our results showed that too many social entrepreneurs could be counterproductive it would be interesting to model the coordination game implicit in this.

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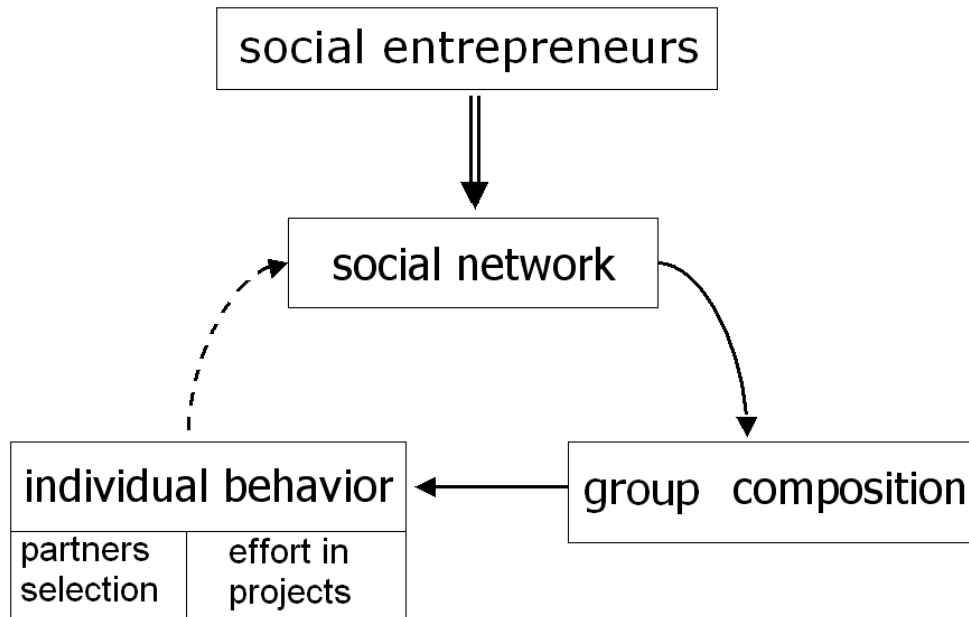


Figure 1

Group Composition as the Result of Social Network and Social Entrepreneurs

N	size 2 cliques	size 3 cliques	size 4 cliques	size 5 cliques	size 6 cliques	size 7 cliques	Total
7	6	15	20	15	6	1	64
8	7	21	35	35	21	7	127
9	8	28	56	70	56	28	247
10	9	36	84	126	126	84	466
11	10	45	120	210	252	210	848
12	11	55	165	330	462	462	1486
13	12	66	220	495	792	924	2510
14	13	78	286	715	1287	1716	4096
15	14	91	364	1001	2002	3003	6476
16	15	105	455	1365	3003	5005	9949
17	16	120	560	1820	4368	8008	14893
18	17	136	680	2380	6188	12376	21778
19	18	153	816	3060	8568	18564	31180
20	19	171	969	3876	11628	27132	43796

Table 1

The Number of Possible Projects in a Population Consisting of n Individuals

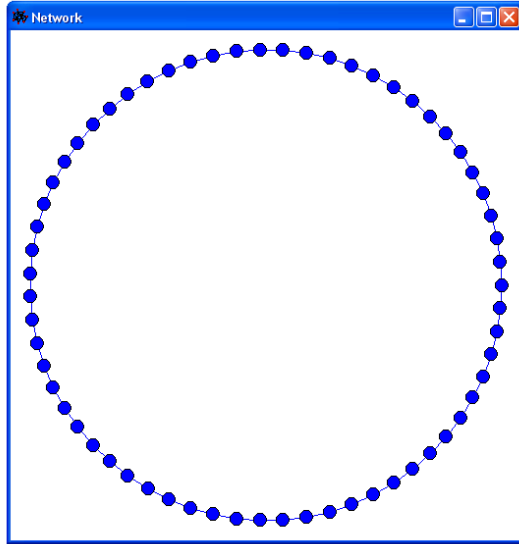


Figure 2

Project Emergence with 1-neighbor Knowledge Initial Sociomatrix.

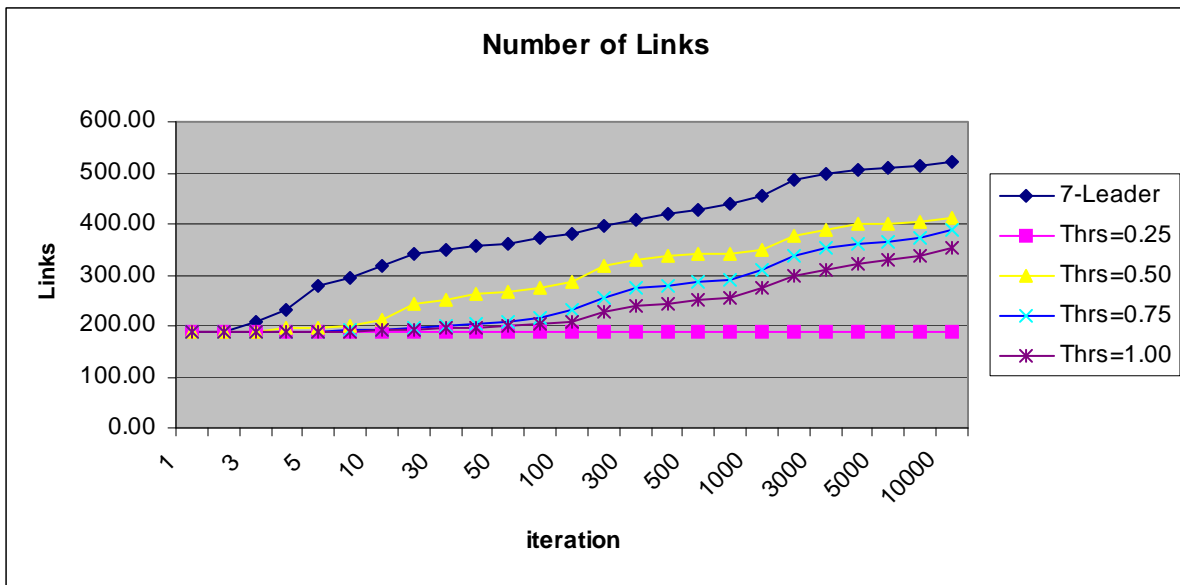


Figure 3

Number of Links in Different Populations

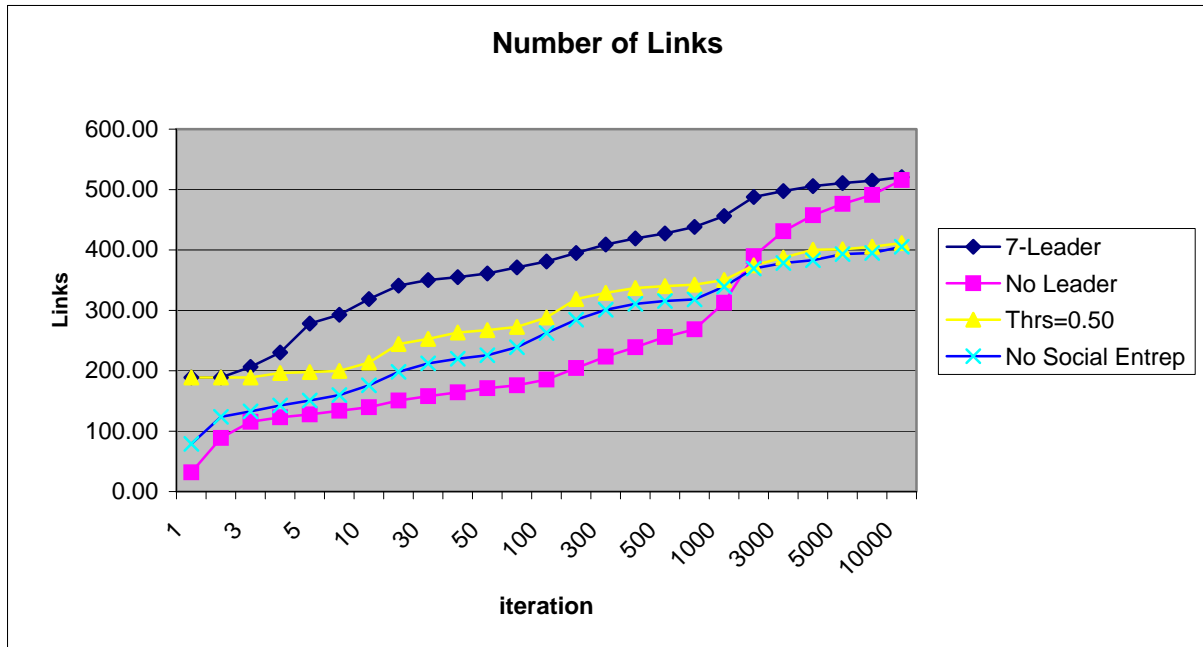


Figure 4

Number of links when comparing the Differences between Social Entrepreneurs and Social Leaders

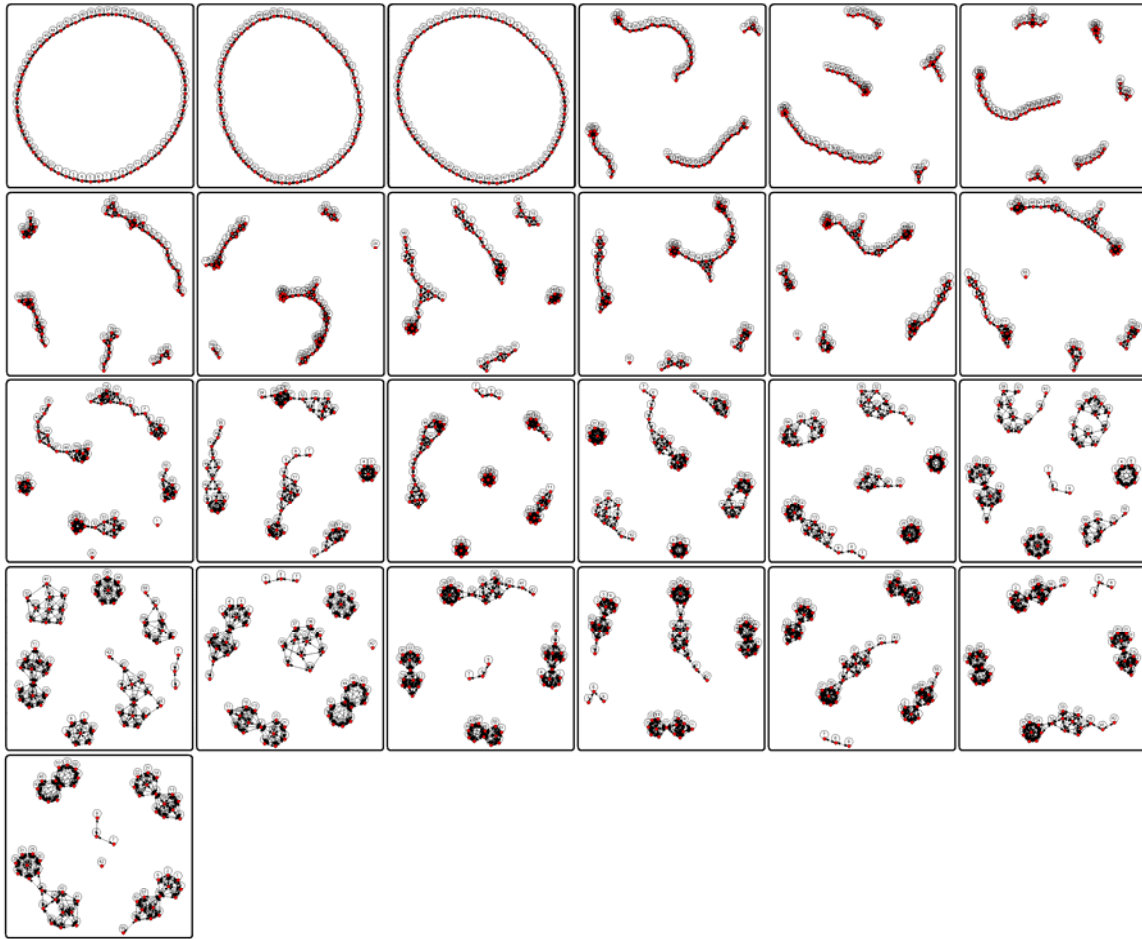


Figure 5

Project Network Evolution in Populations with Threshold .50 Social Entrepreneurs and Circle Graph Initial Sociomatrix, at Iterations 1 – 6, 10 – 60, 100 – 600, 1000 – 6000, 10000

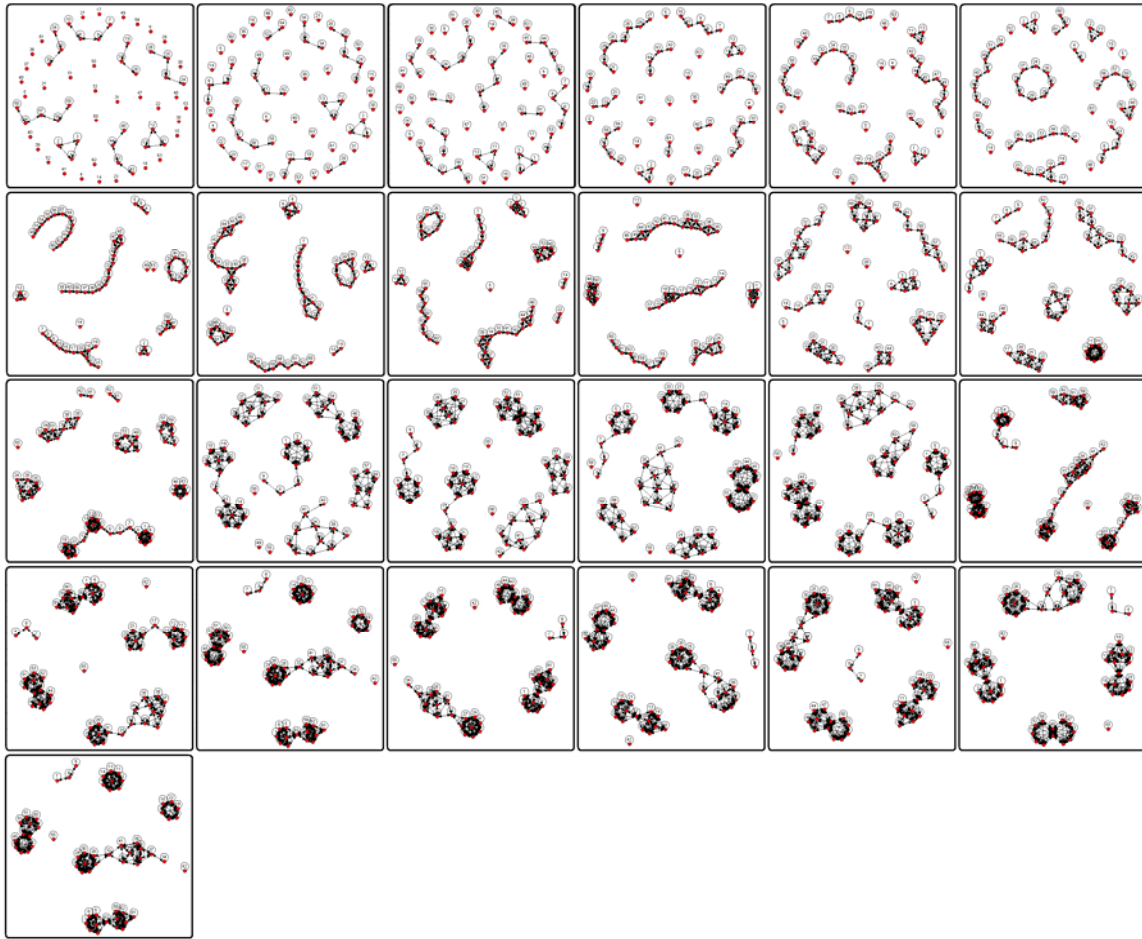


Figure 6

Project Network Evolution in Populations with no Social Entrepreneurs and Previous Case Final Sociomatrix as the Initial One

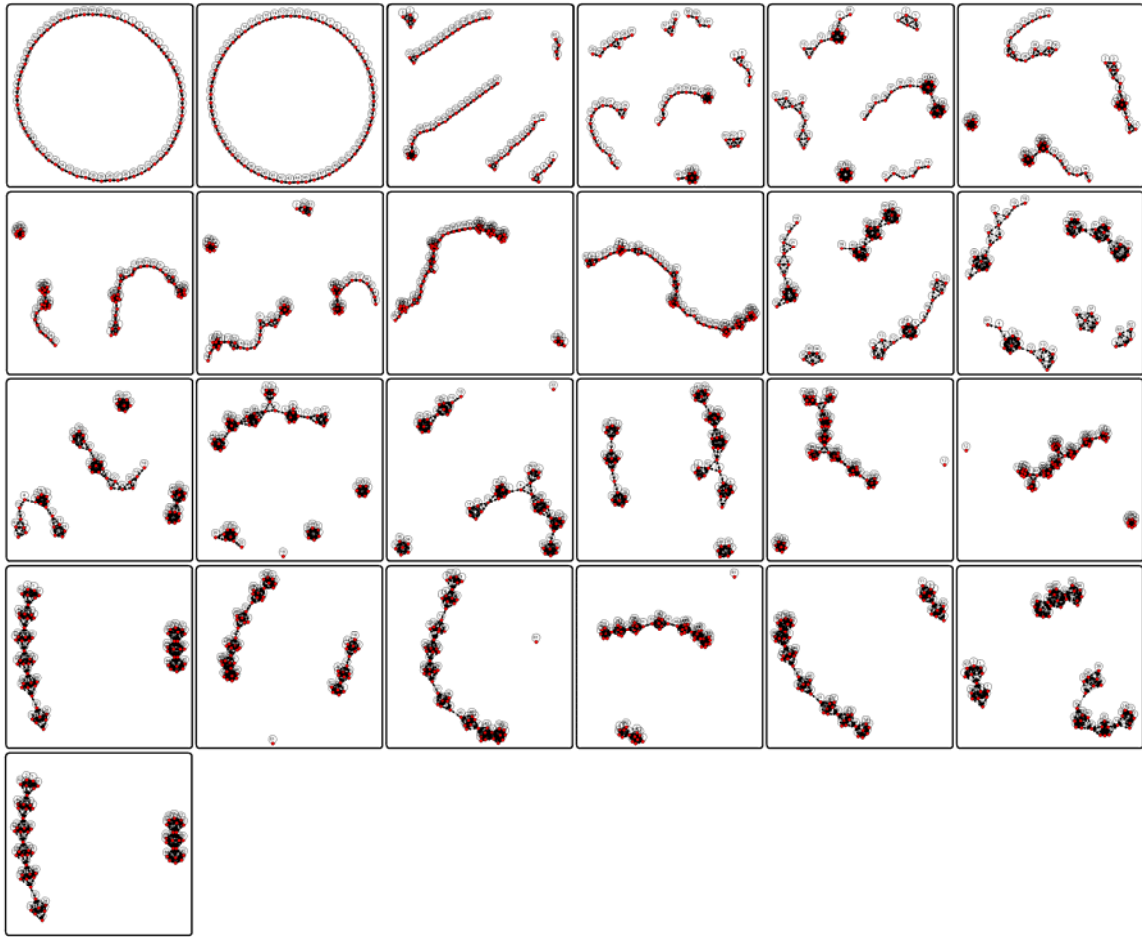


Figure 7

Project Network Evolution in Populations with 7-interval Social Leader and Circle Graph Initial Sociomatrix

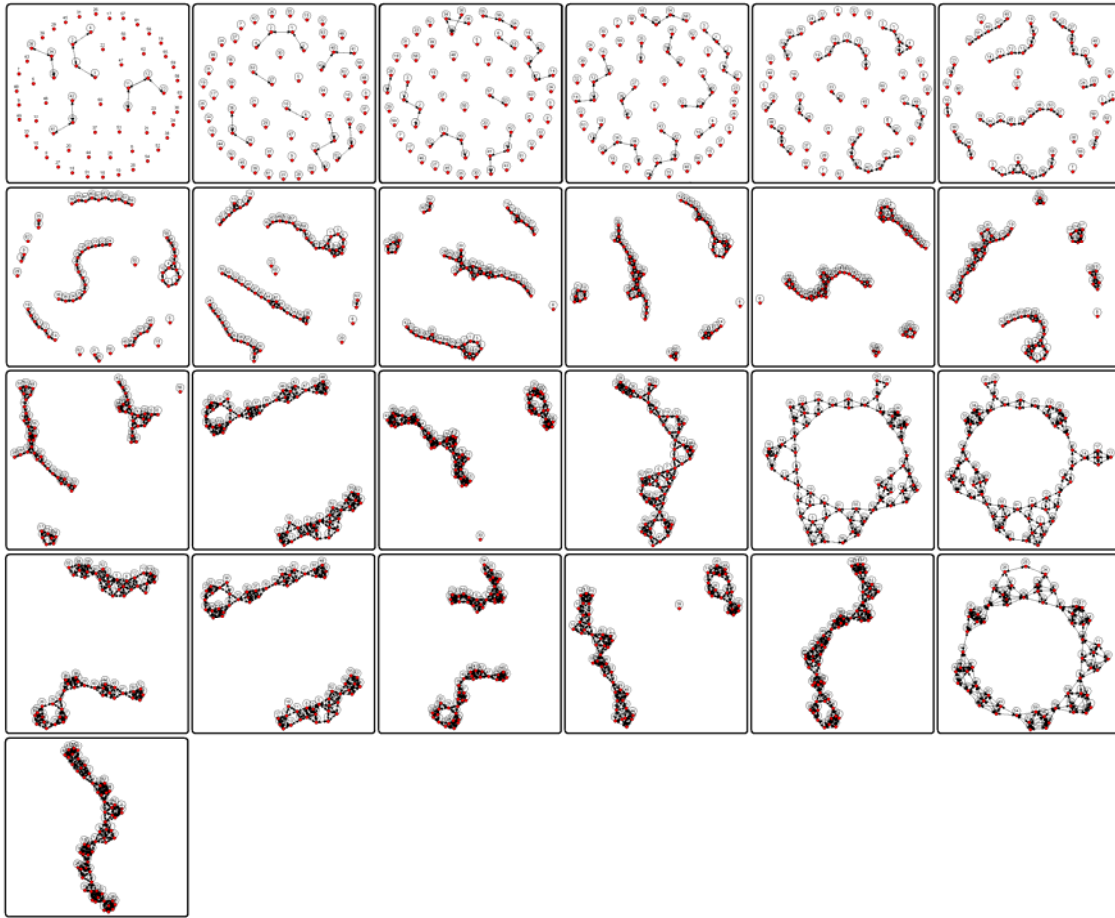


Figure 8

Project Network Evolution in Populations with no Social Leaders and Previous Case Final Sociomatrix as the Initial One