COORDINATION PROBLEMS
AND THE ROLE OF INSTITUTIONS:
MULTI-AGENT SIMULATIONS WITH LEARNING

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**ABSTRACT**

The paper develops an agent-based coordination game in which agents seek, try out and maintain coordination in the presence of positive search and coordination costs. Agents are perfectly rational in the sense that they optimise their individual payoff through coordination. They are moreover perfectly loyal, since they do not abandon coordination unless it becomes collectively impossible to maintain it and they share equally both the net advantage of coordination and the net loss of failure.

Our findings appear to confirm that in context of ontological uncertainty, learning and coordination costs, cooperation often fails in terms of process and final outcome. The absence of opportunism thus do not ensure that agents will cooperate extensively.

Moreover learning on one hand optimises search costs and makes the artificial world of the experiment more realistic. On the other hand, it leads agents to more prudent and conservative behaviour.

Agents’ loyalty makes superfluous regulatory institutions preventing individual opportunism, but it gives them significant scope for intervention in context of coordination failure. As players involved in the game, rather than arbitrators or regulators, catalyst institutions accelerate coordination and induce cooperation equilibria higher than those single agents autonomously are able to reach.
1. Foreword

The failure of collective action is traditionally associated with uncertainty stemming from conflict between expected individual and collective benefit of cooperation. Individuals are hindered in pursuing common goals because it is rational to assume the behaviour of counterparts being affected by behavioural uncertainty. Behavioural uncertainty is caused by the difficulties in predicting the behaviour of agents when individual choices are affected by opportunism. Even if the benefits of reaching the common goals exceed the payoff of joint defection, joint defection may still be the outcome if the relationship is dominated by exploitation risk. Sub-optimal outcome is thus allowed if one cannot assure herself against defection. Implicitly it is assumed that if the agents’ behaviour were perfectly loyal, at least in the arena of economic transactions, the best possible outcome would be automatically guaranteed.

This paper discusses and tests by means of simulations the hypothesis that in most cases even a regime of perfect loyalty is not sufficient to remove the main barriers to collective action. When the result of cooperation is positive, but not measurable ex ante, since technology provides various alternatives and output is variable over time and strongly influenced by the nature of agent interaction, failure of collective action can be mainly attributed to coordination problems rather than to the seriousness of social dilemmas. High coordination costs in selecting one course of action out of multiple alternatives, the synchronisation of activities and the management of information over time can offset the benefit of cooperation and make collective action unaffordable even if a fair distribution of benefits is guaranteed.

Various solutions have been tried out to limit the difficulties of collective action by groups and individuals. Particularly relevant in this respect is the role of institutions (Schotter 1981). Currently, in the rational choice and new institutionalist approaches, institutions are seen as important in helping to resolve distributive conflict. Predefined procedures and stable laws and behavioural norms in social, economic and political fields regulate the interaction of agents and encourage collective action in that they lower the propensity to defect. The effect of institutional rules and the role of institutions that produce them is to provide a framework for relationships between agents by sanctions for noncompliance and by signalling likely courses of action for the groups (Shepsle and Weingast 1981, Knight 1992). Reconciliation of individual and collective rationality can, however, be interpreted in an alternative scheme. In this, collective action is influenced by the difficulty and cost of identifying an optimal equilibrium course of action, rather than the conflict between competing interests. According to

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1 We would like to thank Laura Leoni and Gabriele Manuguerra for their valuable assistance in developing this project and carrying out the simulations. We also thank Matteo Rossi, for his patient technical help in transforming our ideas into algorithms.

2 See Hardin (1982), North (1990), and Holt (2005).

3 See Arrighetti and Seravalli (2000) for a more detailed analysis. See also Lane and Maxfield (1997) and (2004) for recent discussion of the relationship between uncertainty and economic action.

4 See Eggerston (1990) for a survey of current literature.
this line of reasoning, the difficulties of collective action lie not only in defining the rules of the game but identifying what game is to be played, with whom and when. Actors’ interests may converge, but this does not lessen the problem of coordinating start up and running the process of coordination. Informational and organisational coordination costs are a serious obstacle and any instrument, institutional or otherwise, which allows the reduction of these costs may help the collective action in the start-up phase and in its evolving over time. From this point of view, institutions not only provide or constitute norms and rules, (Elster 1986, March and Olsen 1989, North 1990) but rather they are “catalyst” agents which facilitate collective action by centralising, selecting practicable courses of action from multiple alternatives and by lowering the organisational costs of cooperation.

An implicit corollary of this approach is that the assumption we make of perfect loyalty\(^5\) of agents, if makes unnecessary regulatory institutions (dedicated to contain opportunism), does not lessen the threat that coordination costs represents for collective action and thus does not weaken the role of catalyst institutions in solving coordination problems.

In sum this paper attempts to verify two main hypotheses:

a) the persistence of the risk of failure of collective action in contexts of perfect loyalty of agents and positive coordination costs;

b) the capability of institutions of reducing coordination costs and increasing the probability of cooperation between individuals

2. THE MODEL

In the present paper the hypotheses above are verified in a context of coordination game\(^6\) where two or more agents maximise their utility by identifying a unique common course of action. Generally, coordination games possess two specific characteristics: a) agents are averse to discordant solutions, which by definition are less (Pareto) efficient than concordant solutions; b) More than one (Nash) equilibrium is present so that agents do not automatically converge towards the same course of action. The combined effect of these characteristics exposes coordination games to a high structural risk of failure because the outcome of interaction between parties is affected by indeterminacy. In the simpler games, with symmetrical payoff, the failure of coordination derives from the difficulty in identifying the equilibrium ex ante. The problem becomes more serious when, in the absence of natural focal points, the outcome is affected by risk dominance (Van Huyck et al. 1990, Cooper et al. 1990, Carlsson and van Damme 1993) or by differences in effort costs (Goeree and Holt 1998). The risk of failure is mitigated, however, when agents take decisions in contexts where mechanisms, such as forward induction, favour the equilibrium selection (Adballa et al. 1989; Van Huyck

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\(^5\)Agents are perfectly loyal when they do not abandon coordination, even if better individual alternative are feasible, unless it becomes collectively impossible to maintain it. Moreover they share equally the net advantage of coordination, the cost to enter the game and the net loss of failure.

et al. 1993; Cachon and Camerer 1996) or they can communicate with each other (Cooper et al. 1989). Accordingly, information exchange, whether inexpensively implemented by loyal agents (cheap talk), guarantees the achievement of optimal solutions for all players involved.

This outcome is ensured only in the simplest configuration of the game. It is not generalised when collective action implies intense information exchange between agents on the multiplicity of possible technological, economic or organisational solutions, or on the heterogeneous nature of the physical, cognitive, and technical resources they own and are trying to coordinate. In this context, communication tends to change from cheap into expensive talk, as argued in the recent debate on long cheap talk (Aumann and Hart 2003) and the network formation models (Slikker and Van den Nouweland 2000; Goyal and Vega-Redondo 2000).

A previous work (Arrighetti and Curatolo 2004) was able to show that, in the presence of positive complementarity, the level and structure of coordination costs influence the duration of collective action, the process of coordination (number of attempts made, percentage of failure of coordination) as well as its morphology (size and stability of groups, variety of organisational configurations, etc.). In that model, a large number of heterogeneous agents comprise a network which allows each agent to have (costly) information relationships with its nearest neighbours. Each agent has a different initial set of characters, proxied by the following two variables: the first one is an ordered quantitative variable describing the dimension of the agent (for example firm size); the second is dichotomous and it represents one out of two types of technology or skill. Each agent receives in every phase of the process a partitionable monetary unit which can be invested to investigate whether her near neighbours are compatible in terms of size and technology for collective action towards a common goal.

Following Arrighetti and Curatolo 2004, in the present paper, the role of coordination costs in contexts of perfect loyalty of agents can be modelled as a process of search, implementation of collective action, and accounting of its benefits and costs. Such a sequence (being completed in a time unit that we will call “step”) is iterated until a stable system equilibrium is achieved. In the search phase agents bear information investments aimed at identifying the optimal partner for collective action. In particular neighbours are evaluated under a twofold criterion of technological compatibility and size. The search procedure leads to a reciprocal selection of the subjects that best fulfil the requirements. The implementation phase encompasses a test of cooperative solution and the actual emergence of costs and benefits linked to common action. Finally, in the accounting phase, net benefit accrued by the parties is calculated.

The outcome of the test can be twofold: if the net payoff is positive, agents proceed to the following step as a group (or cooperating agents, i.e. strong coordination). Otherwise (negative net payoff) agents agree that the trial proved unsuccessful, agents regress symmetrically to the initial state of individual action characterizing the start-up of the game (weak coordination).

The implications are important. If we define $P_c =$ ex-ante payoff of collective action; $P_i < P_c =$ ex-ante payoff of individual (isolated) action and $C_c =$ individual information cost, in a game with two agents we have strong coordination (i.e. coordination and collective action) only if $(P_c - P_i) > C_c > 0.$
If instead $c_c \geq p_c$, other conditions being equal, coordination will be weak (agents reciprocally agree to turn away from collective action and to go back to individual action).

The analysis build upon a specific n-players coordination game DIT (Do It Together), characterized by high generality. In DIT, heterogeneous and loyal agents pursue the common objective of strong coordinating within increasingly large groups. The coordination and creation of groups leads to advantages in terms of efficiency, such as exploitation of scale economies, aggregation of output, enhancement of common sales channels, etc., which generate increasing profit margin. DIT may thus represent interactive situations where firms benefit from grouping into coalitions and consortia.

DIT assumes that each partner’s resources and technology are unknown to the others until the information is transferred. If players opt for individual action (weak coordination), they receive a fixed payoff $p_i > 0$ which is accumulated over the rounds of the game. But if they opt for strong coordination and the counterpart is suitable for collective action, the gross payoff is $p_c > p_i$. The actual value of net payoff ($p_c - \text{costs}$) is not known ex ante to the parties. It is in fact a direct function of the initial resources of grouping agents, and can only be acquired where agents are technologically compatible. In short, even with zero information costs, coordination ($A_1$ with $A_2$) does not occur when:

1. $A_1$ is technologically not compatible with $A_2$
2. $A_1$ has better alternatives for aggregation than those offered by $A_2$ (or vice versa)
3. $A_1$ opts for individual action

Introducing positive information costs radically modifies the game and exposes parties to a high risk of failure. Because even if $A_1$ were able to avoid facing the constraints described above, it may not converge to coordination with $A_2$ if information costs exceed the differential benefits between collective and individual action.

Realism requires coordination to be seen as a process, where repeated attempts at grouping with other players to reach stable group equilibriums are made. Furthermore agents are subject to mutation over time in their own size and technological capability, and they are able to learn.

Further realism requirements lead to evaluate benefits and costs of group management stemming from change in the size of the groups. This approach allows us to see coordination failure not only as the result of costs borne before the group formed, but also to take account of the costs resulting from "group hypertrophy", discordant evolution of preferences and the burden of group management. It follows that the relatively uninteresting classical coordination game with zero information costs may be replaced by the exponential complexity of dynamic relationships developing in real contexts, strongly influenced by positive information costs.

Briefly, in the DIT model coordination costs are made up of different features which affect coordination both in the phase of costly evaluation and search and in the subsequent phase of coordination maintenance. These elements are transfer and evaluation of information, comparing alternatives, realigning individual choices to collective purposes, etc.. In the presence of

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7 This may happen when learning agents choose such a solution as the most rational alternative (see further § 4).
positive and high coordination costs, any factor that can lower them leads to a significant impact on the coordination process and influences the outcome. As we have argued, however, agent loyalty does not remove the risk of coordination failure; these are in fact particularly marked where there is radical and irreducible uncertainty. It is in this context that institutions can play a significant role. In our model institutions are neither rules of the game, nor they play functions of arbitrating since agents have no incentive to defection. It can thus be hypothesised that institutions play a proactive role in terms of coordination catalysts as they have higher expectations and more efficient resources for computation and management than ordinary agents and can reduce coordination costs.

The extension of DIT to these requirements and the inclusion of institutions as catalyst agents do not allow us to resort to canonical game theory for testing the model. Alternatively it is necessary to adapt the traditional reasoning on coordination games by taking into account the more rich framework that can be analysed through agent-based simulations.

3. **Why Simulations?**

Software simulation of agent-based models can overcome some of the problems caused by lack of sound economic data and the difficulty of observing, constructing and replicating natural experiments on socio-economic groups. The hypothesis of agent heterogeneity and the fundamental importance of their interaction is increasingly recognised by social scientists and particularly economists (Tesfatsion, 2005; Delli Gatti and Gallegati, 2005; Kirman and Zimmerman, 2001; Axelrod, 1997). In an agent-based simulation model, rules of interaction can be specified in detail and can cover mechanically adaptive as well as chance behaviour. The nature of information, (free or expensive, global or local) and the way it is acquired by agents and spread through the system can be represented freely. Once the basic rules of interaction are fixed, the artificial world can be simulated, and we can observe both processes and final effects determined by the specific parameters chosen. The rapidity of application means that researchers can design and run ‘live’ experiments covering the whole range of theoretically significant initial states of the artificial world. The results often show many complex effects of exchange, feedback, contagion or diffusion characteristic of ‘systemic’ interaction which can be a priori unforeseen and unpredictable. In some cases, the complexity makes for completely unpredicted results, and frequently leads to improvements in agents’ behaviour rules and in a better understanding of how they interact.

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8 The context developed in this paper constitutes an attempt to apply the “context” hypothesis of pervasive ontological uncertainty (Lane and Maxfield, 2004) to the process of coordinating collective action in the absence of opportunism. Ontological uncertainty is defined as affecting the structure and dynamic process of interaction between agents resulting from the impossibility of knowing a priori the entities (groups, size, composition) which will be relevant for optimising the coordination since they will emerge only during the process itself. Ontological differs from epistemic uncertainty because it cannot be reduced simply in the cognitive sphere of the agents. It can be overcome only by effective individual or collective action which releases, step by step, the relevant ontology for each agent.
This circumstance should inspire caution in micro-founding theories based on the observed aggregate behaviour of social-economic groups. Aggregate behaviour is based not only on the nature of the agents [and their functional abilities, especially learning (Vriend, 2000)] but also on the emerging feature of micro and macro interaction between agents and groups. Provided aggregate outcomes can’t be determined in advance simply deducing it from the micro level behaviour of agents, simulations of agent-based models are well-suited to inductively define the range of micro behaviour which lead to “stylized” facts observed at macro level (See the pioneering work of Schelling, 1978). The DIT simulation software used here is an original code constructed at the Economics Department in Parma using SWARM library software\textsuperscript{9}.

The next section briefly describes the simulation model; a more detailed technical description is supplied in the appendix.

4. IMPLEMENTING THE MODEL

In the DIT model, collective action consists of the aggregation of adjacent agents or groups of agents. So opting for collective action is constantly affected for each agent by the heterogeneous nature of the relevant ontology she face: it basically corresponds to the geographical location, size and technological characteristics of agents or groups in the neighbourhood. Starting conditions being equal in terms of dimensional, technological and wealth endowments and geographical distribution, heterogeneity is substantially ontological in nature, as agents are characterized by random mutation of both size and technological characteristics over time. In this way the agent’s own ontology is not fixed a priori and the optimum strategy must be pursued through routine trial and error. Mutation thus places agents at a high level of uncertainty and it forces them to make numerous, lengthy and often vain attempts at collective action for the common good. But at the same time the environmental conditions surrounding each agent change continuously and this leads to the emergence of opportunities for collective action even for agents initially penalised by the geographical distribution of endowments. Mutation, moreover, acts directly on characteristics of the individual agent but through her interaction with other agents or groups, and within groups, it affects the whole system and how far collective action is spread in the configuration of system stability\textsuperscript{10}.

The aim of pairs of agents or of larger groups is to keep coordination stable or to increase it, through investigating the characters of other neighbour agents and/or groups. The aggregation (strong coordination) of new agents is advantageous in terms of collective goods in two ways. First of all, agents forming a group have their neighbourhood in common so that the larger the

\textsuperscript{9} SWARM software was originally developed at Santa Fe Institute (http://www.santafe.edu). It was designed specifically to study agent-based models. It comprises libraries of codes written in objective-C and Java which allow a large variety of agent based models showing interaction by large groups of more or less heterogeneous agents to be built. It is available for use by researchers with the sole constraint of the GNU General Public Licence (see http://www.gnu.org). See the SWARM community website for the technical characteristics (See www.swarm.org). Copies of the DIT model software used in this work are available from the authors on request.

\textsuperscript{10} See footnote 17 below.
group, the lower are individual costs for finding out for new group members. Secondly, there is also a gross payoff of aggregation which is the overall advantage of obtaining the common good which grows as the size of the group increases. On the other hand, there are two types of coordination costs; one type increasing as group size increases and the other type is the cost of realigning the group, in presence of mutation, to be paid by the group as agents’ characteristics are modified. So mutation does not act only through changes in the geographical distribution of attributes of isolated agents, but also on agents taking part in groups, by forcing groups to pay costs of realigning attributes.

Aggregation becomes unsustainable when the payoff is negative for the group members. This happens because the costs of search, coordination and intra-group realignment to mutation are higher than advantages of grouping. Consequently the group splits and individuals go back to their initial isolation (weak coordination). This usually happens after a group has joined a group or another individual, leading to the “group-hypertrophy” already mentioned. After group failure, individual agents are left with a negative individual payoff which lowers their dedicated resources for search and thus limits the residual number of possible attempts.

The initial distribution of characteristics assigns ‘institutional label’ to a random subset of agents and henceforth defined as ‘institutional agent’. An institutional agent acts in the same way as other agents except that it has zero search costs, these being entirely financed through fees paid by ordinary agents. An institutional agent carries out search and coordination exactly like all other agents. If the coordination of ordinary agents with an institutional agent is successful, the whole group is labelled as institutional and shares the learning structure but not the advantage of information costs with its founding institutional agent.

A feature of the DIT model is in fact learning. In general, learning is the function by which the system and its agents face heterogeneity and thus their adaptability to a changing environment. Agents and groups, facing an inherently unstable surrounding context, try to single out behavioural routines to optimise coordination payoff out of their finite amount of resources. It is important to note that agents cannot determine their optimum course through learning except by chance. Ontological uncertainty cannot by definition be reduced in the cognitive sphere of agents. But learning enables agents to reduce the effects of uncertainty by simply searching for the best course of action: the action (and interaction) chosen step by step reduces to one all the infinite possible ontological outcomes of the system.

Learning has two levels of functionality in DIT. Both are present in each agent but the effects are shown under different conditions: The two types

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11 Percentage of total agents labelled as “institutional” can be fixed a priori by researcher.
12 There is a wide range of literature on learning, especially in the field of evolutionary games. (Erev and Roth, 1995; Blume and Easley, 1993; Fudenberg and Kreps, 1993; Ellison and Fudenberg, 1993; Levine and Pesendorfer, 2002; Vriend, 1996; Vriend, 2000). This literature often emphasises the difference between individual and collective learning. See Garland and Altermann, 1998 for an interesting analysis learning in a multi-agent model with uncertainty. But the cost of learning is less frequently discussed, although see Sugawara and Lesser, 1998 for an exception to this. The DIT model allows for individual and collective learning, and the shift from individual to collective learning and back to individual is governed by the limited amount of resources and positive search costs.
are 1) learning from imitation of others (hetero-imitative learning, EIL) and 2) learning from self-imitation (auto-imitative learning, AIL). EIL occurs when each agent or group tries to optimise coordination on the basis of the best results obtained by the system as a whole. This form of learning is informationally expensive and is supported by a dedicated budget. When this sum is spent without the agent having reached a stable group configuration, AIL takes over. This means that each agent or group tries to optimise the search for coordination on the basis of its own previous best results. If even this does not lead to forming a stable group, the agent remains permanently isolated. From subsequent failures the agent learns that it is economically impossible to emulate system best practice, and that it is not even able to repeat past successes; given the changed circumstances it is forced to individual action. These failures can lead to local or systemic negative externality\(^{13}\) that are unintentional; scaling down collective action to weak coordination means agents not only harm themselves but other agents or groups also have less chance of finding valid partners for grouping.

Institutional groups and agents also differ from ordinary ones in learning. EIL in institutional groups can only take place above a certain threshold of maintained or stable strong coordination. In other words, institutions can be imagined to have previous similar experience of coordination and put forward their vision of outcome, putting it into practice by interacting with other agents or groups in the system. Only when the system can offer better results than that envisioned by the institutional agent will they learn from the system.

The simulation strategy used to analyse the role of institutions in agent coordinating process in DIT is based on three experimental contexts:

\(^{13}\) A failure harms the agent from the point of view of its aims but harms also the other agents in the system. In DIT, this can be an agent who attempts to form a group and fails, thus depriving neighbours of a possible member. This type of effect is completely unintentional given our starting hypothesis of perfectly loyal agents. The complexity of systemic interaction may make contagion of these negative externalities for agents or groups more harmful than the failures which originally caused it.

\(^{14}\) Note that this first scenario, where coordination costs are positive but agents have unlimited resources to spend on searching for coordination solutions, makes learning as an attempt to optimise the use of available resources conceptually useless. In a sense it also removes the scenario from the field of economic interest. It remains however useful grounds for comparison between contexts with only ordinary agents and those with institutions.
uncertainty through learning (firstly resorting to EIL procedure, then, eventually, to AIL);
III threshold parameters with learning
Mutation and costs parameters are such that agents interact on the ultimate feasible frontier of coordination. Collective action is still affordable but information and organisational costs are almost prohibitive\textsuperscript{15}.

The DIT model allows for a variable network size and this makes simulations more flexible, although it also means that coordination processes can vary with sizes and number of agents. Our simulation took account of this variability and tested the robustness of the results for different sizes of the artificial world. All the simulations were replicated (with and without learning and institutions) for the following configurations:
A) network 35x35 (1225 agents)
B) network 40x40 (1600 agents)
C) network 45x45 (2025 agents)
The analysis of variance of the main variables was conducted in all contexts, to check for robustness of the differences between the averages that represent outcomes and dynamics of coordination processes.

5. Results of the simulations

For ease of discussion, this analysis is limited to simulations of the intermediate matrix (network 40x40 with 1600 agents)\textsuperscript{16}. For each scenario the main variables describing the coordination process, morphology and diffusion are detailed as follows: the diffusion, measured by the percentage of agents aggregated in systemic stability (henceforth SS)\textsuperscript{17}; the morphology of coordination, measured by the number and size of SS groups and lastly the process of coordination shown through the time needed for two thirds of the agents to join stable groups, or for the entire system to get SS (see Table 1).
The extent and state of coordination, mutation and learning, resources, costs and profits, group size and number of members etc., is updated at every step.

\textsuperscript{15} Threshold levels were fixed through preliminary simulations to find the parameter of search costs above which no collective action is possible.
\textsuperscript{16} Results for the smaller and larger networks were statistically in line with the middle case scenario. A copy of the calculations may be obtained from the authors.
\textsuperscript{17} Systemic stability in this context differs from the equilibrium concept typical of economic models and from the meta-stable equilibrium of physics. Agents are subject to ontological uncertainty about the systemic constraints on their target functions so that they have to decide intuitively on the basis of individual or collective experience rather than deductively, which is normally taken to be the case in economic models. On the other hand, DIT SS has in common with meta-stable equilibrium the fact that it emerges from several concurrent actions which reciprocally neutralise in a meta-stable state (mutation, learning and action persist in this state too, so that stability is generally only a probability). DIT SS is different from meta-stable equilibrium in that it is determined by systemic properties emerging from action based on learning in the presence of ontological uncertainty and scarce resources; it is thus characteristic of socio-economic interaction (see Lane and Mansfield, 1997 and 2004; Delli Gatti and Gallegati, 2005).
Table 1
Proxy variables of coordination diffusion, morphology and process

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Illustrates</th>
</tr>
</thead>
<tbody>
<tr>
<td>STEP66</td>
<td>Number of steps needed to reach 66% aggregation</td>
<td>Dynamics of coordination process</td>
</tr>
<tr>
<td>PERAGGRST</td>
<td>Percentage of SS aggregation</td>
<td>Diffusion of coordination process</td>
</tr>
<tr>
<td>NGRST</td>
<td>Number of groups in SS</td>
<td>SS morphology</td>
</tr>
<tr>
<td>DIMST</td>
<td>Average size of groups in SS</td>
<td>SS morphology</td>
</tr>
<tr>
<td>STEPST</td>
<td>Number of steps needed to reach SS</td>
<td>Dynamics of coordination process</td>
</tr>
</tbody>
</table>

5.1 Benchmark Parameters (Context I)

Graph 1 shows the ‘typical’ or average evolution\(^{18}\) of DIT in a context where there is mutation but no learning. The graph shows time on the horizontal axis, in steps, and the percentage of aggregated agents on the vertical axis. (All subsequent graphs have this design).

The agents, subject to high mutation, are forced into a long period of failures in the grouping process. In the first phase, the coordination affects a small share of agents and it evolves in a cyclical pattern where collective action alternately fails and succeeds. Thanks to mutation, favourable conditions for some groups emerge; aggregation in some cases yields benefits which exceed the joint costs of search, coordination and intra-group realignment of the mutating agents. A limited number of groups consolidate and grow thanks to the opportunity of incorporating new agents made compatible by mutation. About two thirds of the agents are in groups around step number 200. Finally SS is reached with the system saturated by one or two large groups which aggregates all agents.

Graph 2 shows the evolution of DIT in context I, augmented with institutional agents\(^{19}\).

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\(^{18}\) The randomness of the distribution of effects of heterogeneity (mutation) and the complex effects of interaction and feedback which it produces makes it impossible for agents to know the outcome of system evolution in advance. Unfortunately, the same limitations affects the present writers in selecting a “representative” simulation to be presented here. Hence, we opted to show as ‘typical’ just one of the fifty different simulations carried out, all different one from the other but all using the same parameters. We selected one simulation which we felt exemplified the average outcome, composition and process, and that shown in the graph is thus an example rather than representative. But the statistical analysis of average results and the robustness of the differences between averages discussed below make it possible to distinguish in a statistically significant manner the coordination with and without institutional agents.

\(^{19}\) The ratio of institutional agents to ordinary agents in this and subsequent cases is 1 to 30. It is beyond the scope of this paper to examine the effects of different ratios.
Graph 1
Evolution of the proportion of grouped agents in a simulation without institutions in Context I (Network 40x40)

Legend: dark line = overall percentage of aggregated agents; light line = percentage of groups with ten or more members.

Graph 2
Evolution of the proportion of grouped agents in a simulation including institutions in Context I (Network 40x40)

Legend: see Graph 1.
The final outcome in terms of stable groups in this case too is complete coordination, but a very different pattern emerges in terms of dynamics. The phase of initial selection and failures lasts for a much shorter time than in the scenario without institutions. Lower is also the duration, and thus cost, of the coordination process: the proportion of two thirds is reached in half the length of time needed in the previous scenario. The final morphology is different in terms of numbers of group members in SS rather than in terms of size.

Table 2
Descriptive statistics of proxy variables of the coordination process in Context I (Network 40x40; 100 simulations)

<table>
<thead>
<tr>
<th>Institutions</th>
<th>STEP66</th>
<th>PERAGGRST</th>
<th>STEPST</th>
<th>NGRST</th>
<th>DIMST</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO Mean</td>
<td>174.40</td>
<td>100.00</td>
<td>352.34</td>
<td>1.26</td>
<td>1392.00</td>
</tr>
<tr>
<td>N</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>std.dev.</td>
<td>67.38</td>
<td>.00</td>
<td>81.27</td>
<td>.44</td>
<td>354.47</td>
</tr>
<tr>
<td>YES Mean</td>
<td>83.72</td>
<td>100.00</td>
<td>261.32</td>
<td>11.40</td>
<td>152.93</td>
</tr>
<tr>
<td>N</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>std.dev.</td>
<td>13.25</td>
<td>.00</td>
<td>27.49</td>
<td>3.39</td>
<td>47.60</td>
</tr>
<tr>
<td>Totale Mean</td>
<td>129.06</td>
<td>100.00</td>
<td>306.83</td>
<td>6.33</td>
<td>772.47</td>
</tr>
<tr>
<td>N</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>std.dev.</td>
<td>66.41</td>
<td>.00</td>
<td>75.73</td>
<td>5.63</td>
<td>671.57</td>
</tr>
</tbody>
</table>

Coordination in SS involves all the agents in the network, but the average speed of the process with institutions is clearly faster than that without institutions both for STEP66 and STEPST. The morphology of systemic stability is different, too; where institutions are present, the average number of groups is more than 11 while the context without institutions shows an average of 1.26 groups in SS, which means that outcomes with only one group prevail.

In order to test the significance of the differences between averages with and without institutions presented above, we also carried out analysis of variance (See Table 3) and robust tests of the differences between averages. These tests confirm our results and are not included here\(^{20}\).

\(^{20}\) They may be obtained from the authors on request.
Table 3
ANOVA of averages of proxy variables in coordination process in context I (network 40x40)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Sum of squares</th>
<th>df</th>
<th>Mean squares</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>STEP66 * ISTI</td>
<td>Between groups</td>
<td>205609</td>
<td>1</td>
<td>205609</td>
<td>87.21</td>
</tr>
<tr>
<td></td>
<td>Within groups</td>
<td>231058</td>
<td>98</td>
<td>2357.7</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>436667</td>
<td>99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STEP ST * ISTI</td>
<td>Between groups</td>
<td>207116</td>
<td>1</td>
<td>207116</td>
<td>56.28</td>
</tr>
<tr>
<td></td>
<td>Within groups</td>
<td>360656</td>
<td>98</td>
<td>3680.2</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>567772</td>
<td>99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NGRST * ISTI</td>
<td>Between groups</td>
<td>2570.5</td>
<td>1</td>
<td>2570.5</td>
<td>439.15</td>
</tr>
<tr>
<td></td>
<td>Within groups</td>
<td>573.62</td>
<td>98</td>
<td>5.85</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>3144.1</td>
<td>99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DIMST * ISTI</td>
<td>Between groups</td>
<td>38382134</td>
<td>1</td>
<td>38382134</td>
<td>600.12</td>
</tr>
<tr>
<td></td>
<td>Within groups</td>
<td>6267835</td>
<td>98</td>
<td>63957.5</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>44649968</td>
<td>99</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Institutional agents thus appear to catalyse coordination and speed up the time it takes. Arrighetti and Curatolo (2004) found that the increase in search costs for ordinary agents tends to be associated with a slowing of the grouping process, although in a non linear and variable way. Here however higher costs of financing institutional agents are more than offset by the catalyst effect. Hence institutional set up, while boosting coordination, also pays for itself. The solution is thus clearly superior with respect to a system of overall incentives for all agents.\(^{21}\)

In context I agents have unlimited resources available for search. A more realistic approach requires the agents to be subject to a budget constraint about search expenses. In a framework of ontological uncertainty and limited resources, both EIL behaviour (imitation of best practices observed in the system, for example ‘patience’ or at the opposite, “enthusiasm”) and

\(^{21}\) Arrighetti and Curatolo (2004) also found it was necessary to reduce search costs by 30-40% to obtain significant advantage in time needed for grouping.
AIL behaviour (trial to replicate one’s own best stable coordination results of her past history), become main instruments in optimisation choices.

5.2 BENCHMARK PARAMETERS WITH LEARNING (CONTEXT II)

The introduction of learning characterizes this second context: Firstly, agents try, for a budgeted number of attempts, to emulate (or exceed) the size of those groups in the system which proved successful and stable. If all the budgeted attempts at grouping by EIL fail, the agent is forced to change objective and she aims towards a group size which she has already successfully reached (AIL, auto-imitative learning). Changed environmental-neighbourhood conditions may imply that group sizes which were feasible in the past are now no longer feasible. Hence it is not certain that AIL will lead to success. If an agent is unable to reach a stable grouping, it is forced to remain permanently in isolation. Accordingly, learning leads to scale down recursively failing attempts.

On the same line, institutions differ from ordinary agents not only in that their search costs are shared equally among ordinary agents, but also in a different learning process. Institutional agents work with their own high objective, a mission initially independent from best practice in the system, which they pursue using the same budgeted attempts as ordinary agents. Only when the system shows that a better solution in terms of size will institutional agents and groups resort to EIL. Once the they run out of budgeted trials, they will resort to AIL exactly like all ordinary agents.

Graph 3 shows the dynamics of the diffusion process in the simulation with learning and benchmark-level costs’ parameters without institutions.

Graph 3  
Evolution of the proportion of grouped agents in a simulation without institutions in Context II (Network 40x40)

Legend: see Graph 1.
The more realistic hypothesis that agents learn to save on costs of doomed attempts at grouping in fact increases systemic coordination failure also in contexts of perfect loyalty (stable collective action covers only 82% of the agents in the final SS phase. See Graph. 4). Since EIL entails diffusion of success but also contagion of failures, in an initial experimental phase success of collective action rapidly alternates with failure. However, EIL both facilitates coordination and puts agents at risk at the same time. It helps because the emergence of best practices encourages other agents and groups to try. Best practice tends to spread rapidly through the system. But when costs of coordination are higher than advantages, there is a contagion effect which slows down or prevents attempts at grouping until a new attracting best-performer group appears. Moreover, mutation continues to exert its positive and negative effects. As they are affected by the waves of diffusion and contagion, agents build up an individual memory of their own attempts at grouping and their degree of success. Once their maximum number of attempts is spent up, agents try to replicate their own best past results. This happens more frequently in a relatively early phase and slows down the effect of contagion. Agents or groups having less capacity for coordination cease to become attractors and fall back on AIL, so implying a sort of selection at system level. Consequently the effects of negative contagion weaken over time.

While learning is intended to save on coordination failures, it does not remove agents from uncertainty caused by mutation and its effects on interaction. Even in its most prudent form, AIL, it has to take account of mutation in local grouping conditions which can lead to permanent individual action.

In addition, even if not all agents are stabilised in groups, learning optimising routines for search results in sort of active adaptation, which significantly shortens the time the system takes to stabilise.

Simulations conducted with institutional agents modify outcomes in at least three aspects:

1) Group coordination failure doesn’t entail generalized system failure. In facts institutional agents push ordinary agents to a high level of aggregation and thus act as ‘institutional attractors’ even where ordinary attractors fail. In other words, institutional actors are important not so much because they lead other agents towards final objectives of high coordination, but because they act as stable catalysts in the early and intermediate phases of evolution, which is precisely where ordinary groups frequently fail.

2) Absence of generalised failures allows search to extend on a longer period. There are consequently fewer agents in isolation (weak coordination) in the final SS phase (about 92% of agents are grouped

---

22 Negative in the sense of greater variability and uncertainty exerted by mutation on the possibilities for grouping locally and on the higher costs faced by groups to realign within themselves. Positive in the sense that the mutation of agents’ individual characteristics tends to overcome possible disadvantages of localisation, giving new opportunities for grouping between agents and groups previously incompatible.
in the final SS phase of a “typical” simulation$^{23}$ presented in graph 4).

3) On average, SS is reached more quickly. Time that in the system without institutions is consumed in selecting new best practice or attractors, is now freed to be used for searching optimal solutions for collective action.

**Graph 4**

*Evolution of the proportion of grouped agents in a simulation with institutions in Framework II (network 40x40)*

On average, institutions make the diffusion of coordination faster (see Tables 4 and 5); where institutions are present, two thirds of agents are grouped by step 116, but in their absence this result is reached in almost 165 steps. The greater speed of coordination where institutions are present is confirmed by the time taken to get to SS (292 steps are required on average when they are present vs. 330 when they are not). The extent of coordination is greater with institutions present (on average it covers 87% of agents compared to 82% with ordinary agents only). Lastly the average morphology is also different: SS with institutions has an average of 23 groups, each aggregating 81 agents; SS without institutions has an average of 45 groups with 47 agents.

---

$^{23}$ The simulation is typical in the sense that it is only one selected to roughly “represent” the average results.
Table 4
Descriptive statistics of proxy variables of the coordination process in Context II (Network 40x40; 100 simulations)

<table>
<thead>
<tr>
<th>Institutions</th>
<th>step66</th>
<th>peraggrst</th>
<th>Stepst</th>
<th>Ngrst</th>
<th>Dimst</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO Mean</td>
<td>164.83</td>
<td>.8197</td>
<td>330.50</td>
<td>45.02</td>
<td>46.65</td>
</tr>
<tr>
<td>N</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>69.62</td>
<td>.060</td>
<td>111.92</td>
<td>73.94</td>
<td>26.32</td>
</tr>
<tr>
<td>YES Mean</td>
<td>116.12</td>
<td>.8706</td>
<td>291.72</td>
<td>21.94</td>
<td>81.08</td>
</tr>
<tr>
<td>N</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>42.26</td>
<td>.072</td>
<td>113.59</td>
<td>10.56</td>
<td>39.71</td>
</tr>
<tr>
<td>Total Mean</td>
<td>140.47</td>
<td>.8452</td>
<td>311.11</td>
<td>33.48</td>
<td>63.86</td>
</tr>
<tr>
<td>N</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>62.30</td>
<td>.07</td>
<td>113.87</td>
<td>53.81</td>
<td>37.72</td>
</tr>
</tbody>
</table>

Table 5
ANOVA of the averages of proxy variables of the coordination process in Context II (network 40x40)

<table>
<thead>
<tr>
<th></th>
<th>Sum of squares</th>
<th>Df</th>
<th>Mean squares</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>step66 * isti</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>59306.6</td>
<td>1</td>
<td>59306.6</td>
<td>17.88</td>
<td>.000</td>
</tr>
<tr>
<td>Within groups</td>
<td>324990</td>
<td>98</td>
<td>3316.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>384296</td>
<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>peraggrst * isti</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>.065</td>
<td>1</td>
<td>.07</td>
<td>14.88</td>
<td>.000</td>
</tr>
<tr>
<td>Within groups</td>
<td>.43</td>
<td>98</td>
<td>.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>.49</td>
<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stepst * isti</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>37597.2</td>
<td>1</td>
<td>37597.2</td>
<td>2.96</td>
<td>.090</td>
</tr>
<tr>
<td>Within groups</td>
<td>1245989</td>
<td>98</td>
<td>12714.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1283586</td>
<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ngrst * isti</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>13317.2</td>
<td>1</td>
<td>13317.2</td>
<td>4.78</td>
<td>.030</td>
</tr>
<tr>
<td>Within groups</td>
<td>273320</td>
<td>98</td>
<td>2788.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>286637</td>
<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dimst * isti</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>29635.7</td>
<td>1</td>
<td>29635.7</td>
<td>26.12</td>
<td>.000</td>
</tr>
<tr>
<td>Within groups</td>
<td>111208.1</td>
<td>98</td>
<td>1134.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>140844</td>
<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The averages of the two different contexts are significantly different: with a statistical error probability lower than 10% for the STEPST variable. The percentage of probability is lower than 5% for the NGRST and lower than 0.1% for all other variables.

5.3 \textit{Threshold parameters with learning (context III)}

This last section discusses the results of simulations in the third context, where learning takes place and where costs are fixed at ‘threshold level’. This means that the process of acquiring information by her nearest neighbours is very expensive so that the agent consumes, at each step, all the monetary unit received\(^{24}\). This is an extreme environment for survival by single (not aggregated) agent and even the smallest increase in cost would lead to the economic impossibility of stable strong coordination.

Analysis of the typical simulation for this context (Graph 5) shows three important differences compared to the previous Context II. Firstly, there is a lower diffusion of coordination, with only 45.2\% of agents grouped in SS vs. 82\% in the benchmark context, due to a long phase of more than 75 steps where agents repeatedly attempt and fail in coordinating. This is partly explained by costs of maintaining coordination and partly because attraction is exerted, through EIL, only by the few groups able to reach as well as maintain a large size.

Secondly, provided costs are so high, groups result to be highly unstable and hence they record few successes, usually in small size groups. During the process, some groups stabilise, but then many agents have spent all their budgeted trials and are forced to seeking AIL solutions or going back to individual action.

Thirdly, even if the systemic diffusion of coordination is actually poor, yet SS is reached fairly rapidly, around step 150. When institutional agents are introduced, the typical simulation changes as shown in Graph 6.

---

\(^{24}\) The unit cost of investigating the neighbourhood was increased by 9\% (from 0.115 to 0.125 for each question). The mutation was more than doubled; the mutation of technology and size characteristics in the previous context of high mutation was 0.125 per step. In each step, one third of the agents, chosen randomly, increase their size, one third downsize and only one third remain the same size. As size can be increased by only 0.125 per step, eight steps of continuous increase or reduction are needed for a unitary change and thus to modify technology. This mutation is now modified to 0.251 per step so that only four steps are needed for an agent to change her technology.
Graph 5
*Evolution of the proportion of agents aggregated in a simulation (without institutions) in context III (network 40x40)*

Legend: see Graph 1.

Graph 6
*Evolution of proportion of aggregated agents in a simulation with institutions in context III (network 40x40)*

Legend: see Graph 1.
An higher diffusion of aggregation is achieved. The initial phase of selection is much shorter, due to larger and more stable attractors. As already mentioned, not all the institutional groups acting as attractors in early phases necessarily survive in the final SS. But their function as catalyser of collective action induces, through EIL, many ordinary agents to seek coordination solutions in quite large groups and a significantly high percentage of these succeed. Accordingly, there are fewer and larger groups in the final SS. It is important to emphasise that, in order to finance institutions, ordinary agents are forced to pay costs above the threshold level; these costs would be largely too high for collective action to take place if the institutions didn’t act as attractors.

Table 6 shows that the diffusion of coordination is on average higher where there are institutions present: 59% compared to 45.2%. The dynamics of the process show that the context without institutions never sees a proportion of two thirds of agents in groups, while in the context with institutions twelve out of fifty cases reach this proportion in an average number of 108 steps. SS is reached more quickly by the context without institutions, only 166 steps on average compared to 256 on average where institutional agents are present. Looking at morphology, simulations without institutions show a large number of smaller groups, on average 90 groups containing 14 agents vs. 38 groups with 53 agents with institutional agents.

Table 7 shows that the averages of the four relevant variables describing diffusion, dynamics, and morphology of the system in Context III without institutions are statistically different from those in the context with institutions (Sig. F < 0.1%).

25 Differently from the previous contexts, variable step66 is not relevant here, because the system only in very few cases can reach a diffusion of aggregation higher than 66% of agents.
Table 7
ANOVA of the averages of proxy variables of coordination in Framework III (network 40x40)

<table>
<thead>
<tr>
<th></th>
<th>Sum of squares</th>
<th>Df</th>
<th>Mean squares</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>step66 * isti</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>.00</td>
<td>1</td>
<td>.00</td>
<td>.00</td>
<td>1.000</td>
</tr>
<tr>
<td>Within groups</td>
<td>6508.01</td>
<td>10</td>
<td>650.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
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</tr>
<tr>
<td><strong>peraggrst * isi</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>.46</td>
<td>1</td>
<td>.46</td>
<td>50.94</td>
<td>.000</td>
</tr>
<tr>
<td>Within groups</td>
<td>.89</td>
<td>98</td>
<td>.01</td>
<td></td>
<td></td>
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<tr>
<td>Total</td>
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<td>99</td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Stepst * isi</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
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<td>1</td>
<td>201332</td>
<td>54.33</td>
<td>.000</td>
</tr>
<tr>
<td>Within groups</td>
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<td>98</td>
<td>3705.45</td>
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<td>Total</td>
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<td></td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Between groups</td>
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<td>1</td>
<td>68225.4</td>
<td>17.05</td>
<td>.000</td>
</tr>
<tr>
<td>Within groups</td>
<td>392120</td>
<td>98</td>
<td>4001.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
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<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Dimst * isi</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between groups</td>
<td>38734.9</td>
<td>1</td>
<td>38734.9</td>
<td>12.26</td>
<td>.001</td>
</tr>
<tr>
<td>Within groups</td>
<td>309685</td>
<td>98</td>
<td>3160.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>348420</td>
<td>99</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6. CONCLUSIONS

The paper develops an agent-based coordination game in which agents seek, try out and maintain coordination in the presence of positive search and coordination costs. Agents are perfectly rational in the sense that they optimise their individual payoff through coordination. They are moreover perfectly loyal, since they do not abandon coordination unless it becomes collectively impossible to maintain it and they share equally both the net advantage of coordination and the net loss of failure. Our findings appear to confirm our starting hypotheses. In context of ontological uncertainty, learning and coordination costs, cooperation often fails in terms of process and final outcome. The absence of opportunism thus do not ensure that agents will cooperate extensively.
Moreover learning on one hand optimises search costs and makes the artificial world of the experiment more realistic. On the other hand, it leads agents to more prudent and conservative behaviour. Agents’ loyalty makes superfluous regulatory institutions preventing individual opportunism, but it gives them significant scope for intervention in context of coordination failure. As players involved in the game, rather than arbitrators or regulators, catalyst institutions accelerate coordination and induce cooperation equilibria higher than those single agents autonomously are able to reach.

Institutions here are characterised by high commitment to coordination targets for the whole system. However better performances are reached not because ordinary agents are led to more ambitious objectives known only to institutional agents, but because institutions attract or catalyse agents towards collective action in the starting and intermediate phases of the process when endogenous cooperation achievements are too uncommon or unstable to back the coordination of ordinary agents.

7. REFERENCES


Blume, L.E. and D. Easley, (1993), What has the learning literature taught us?, in Kirman, A.P. and M. Salmon (eds), Learning and Rationality in Economics, Blackwell, Oxford;


Cooper, R., D.V. DeJong, R. Forsythe and T.W. Ross (1990), Selection Criteria in Coordination Games: Some Experimental Results, American Economic Review, 80, 218-233;

Delli Gatti, D. and M. Gallegati, (a cura di), (2005), Eterogeneità degli agenti economici e interazione sociale: teorie e verifiche empiriche, Il Mulino, Bologna;


Goeree, J. K. and C. A. Holt (1998), An Experimental Study of Costly Coordination, working paper, University of Virginia;


Holt, C.A., (2007), Markets, Games, and Strategic Behavior: Recipes for Interactive Learning, Addison-Wesley;

Kirman, A. e J.B. Zimmermann, (eds), (2001), Economies with Heterogeneous Interacting Agents, Springer;


Schelling, T.C. (1978), Micromotives and Macrobehavior, Norton, New York, NY;


Van Huyck, J., R. Battalio, and R. Beil, (1990), Tacit Coordination Games, Strategic Uncertainty and Coordination Failure, American Economic Review, 80, 234-248;

Vriend, N.J., (1996), Rational behavior and economic theory, Journal of Economic Behavior and Organization 29 (2);

Appendix: The DIT model

1 Firm (agent) variables

A generic firm $i$ on the network has the following attributes:

- A pair of coordinates $(x, y)$ giving its position in the network
- A coordinate $i$ identifying it
- A physical coordinate $c_i(t)$ initialised with integer numbers from 1 ... 6;
- A colour according to its state;
  - Red – institution
  - Black . not an institution, not grouped with other firms
  - Brown, green, yellow, light blue, purple, dark red, light turquoise, white or orange – not institution, grouped with other firms. (colour of group)
- A coordinate $N_i^{PV}(t)$ showing number of close neighbours questioned
- A coordinate $j$ identifying the group it is a member of ($j$ equal to 0 for isolated agent)
- A coordinate $d_i$ identifying the size of the group it is a member of ($d_i = 1$ for isolated agent)
- A coordinate $N_i^I$ (initialized at 1) showing number agents in groups for AIL
- A coordinate $N_i^E$ showing number of agents in groups for EIL
- A coordinate $b_i$ showing budget available for EIL
- A coordinate $p_i(t)$ showing instant payoff at time $t$
- A coordinate $g_i(t)$ showing immediate profit at time $t$
- A coordinate $s_i(t)$ showing immediate expenditure at time $t$
- A coordinate $P_i(t)$ showing cumulated payoff at time $t$
- A Boolean coordinate $isIst$: true for institutions and false otherwise

2 Group variables

A generic group is an entity generated by
- the union of two isolated firms
- the fusion of a group and an isolated firm
- the fusion of two groups

A group is characterised by the following:

- A coordinate $k^G$ identifying the group
A colour variable for group on the graph
- Time $t_l$ showing the lifespan of the group
- A coordinate $p(t)$ showing immediate payoff at time $t$
- A coordinate $g(t)$ showing immediate profit at time $t$
- A coordinate $s(t)$ showing immediate expenditure at time $t$
- A coordinate $P_T(t)$ showing accumulated payoff at time $t$
- A set of parameters $\Sigma_+, \Sigma_-, \Sigma_0$ needed to calculate costs of updating
- A variable $N_{stab}^k$ giving maximum group size and all $N^l_i$ of the member companies
- A set of average parameters of typical company size;
  - $\overline{N}^{PV}$ average number of close neighbours of member company
  - $\overline{C}$ average coordinate of member company
  - $\overline{CD}$ equal to $c_D$ average of member company. (The average is necessary given the existence of $c_D$ and $c_{Dist}$
  - A coordinate $\overline{b}$ showing average budget of grouped agents for EIL

- A Boolean coordinate $haveIst$: true for groups containing institutions and false otherwise.

### 3 Simulation Parameters

The following parameters are used in the simulation. They can be personalised by the user.

- $CST\_WORLD\_X\_SIZE$, $CST\_WORLD\_Y\_SIZE$: size of network (whole positive numbers)
- $CST\_END\_TIME$ $[T]$ duration of the simulation (whole positive number)
- $CST\_MUTATION$ $[c_M]$: mutation of coordinate of individual company (real number)
- $CST\_QUERY$ $[c_D]$, $CST\_QUERY\_IST$ $[c_{Dist}]$ determines cost of questioning close neighbours (positive or negative, real numbers)
- $CST\_TIME\_LEARNING$ $[t_X]$: time in which global learning starts (this may be positive numbers or zero even though for $t_X < 2$, learning starts at $t = 2$);
- $CST\_ORGANIZATION$ $[c_O]$: determines organisation costs for a group of companies (positive or negative, real number)
- $CST\_GAIN$ $[c_A]$: determines profit after group formation (positive or negative, real number)
• \( CST\_ALPHA \ [\alpha], \ CST\_BETA \ [\beta] \): correction factor to check positive and negative term of group payoff (positive real number)
• \( CST\_N\_FIRM\_IST \): defines the number of institutions randomly chosen at the start of the simulation
• \( CST\_N\_G\_IST \): defines starting value of \( N^g_t \) for institutions
• \( CST\_BUDGET\_IST \): defines starting budget for institutions
• \( CST\_DUMP\_SWITCH \): if it has value 1 it saves graphic data in the file \texttt{data_dump.txt}.

These parameters can be varied by changing their value in the ModelSwar window and pressing ‘enter’ or by modifying the file \texttt{firmParameter.scm} with a text editor.

When using \( CST\_DUMP\_SWITCH = 1 \) in order to save \texttt{data_dump.txt} on exiting the simulation the simulation itself needs to be closed down properly (Stop + Quit + Quit or Quit + Quit) and not simply by brute force (CTRL-C) on the cygwyn. The simulation may be slightly slower than usual.

Once the file is saved it can be opened with \textit{Microsoft Excel} in the following way:

• Open Excel
• File Open (Type of file: All files)
• Go to folder containing \texttt{data_dump.txt} (typically: C:cygwin\home\Administrator\firms) click on it select: Open
• Follow on screen guidance, continue
• Comma, continue
• Set advanced, decimal separator, thousand separator.

Using Matlab the following scripts can be used to upload data and create graphics. \texttt{LoadData.m}, \texttt{plotGraph1.m}, \texttt{plotGraph2.m}, \texttt{plotGraph3.m}, \texttt{plotGraph4.m}. This is the procedure:

Open Matlab
\textbf{Key in loadData enter} (saves all column vectors)
\textbf{Key in plotGraph1 enter} (creates graph 1)
\textbf{Key in plotGraph2 enter} (creates graph 2)
\textbf{Key in plotGraph3 enter} (creates graph 3)
\textbf{Key in plotGraph4 enter} (creates graph 4)

Graphs can be modified, saved or exported in the most common forms, for example \texttt{bmp, eps, jpg, tif and png}.

The ModelSwar window also shows two other variables \textit{learningSwitch} and \textit{dump_file} which must not be modified. These are public variables of the model and they may not be hidden. In order to avoid error they appear in lower case letters at the bottom of the window.

4 Evolution of the simulation
The following operations are carried out at every time step of the simulation:

- **Mutation update**: the coordinates of a firm are modified: 
  \[ c_i(t) = c_i(t-1) + \delta \cdot c_M \] 
  with \( \delta \) equal to -1, 0 or 1 selected randomly.

- **Questioning of close neighbours**: Firms question their closest neighbours in order to form a group. Two new Boolean variables are introduced to clarify the criteria on which this questioning is carried out.
  - \( \text{isLearningTime}() \) yields true if \( t \geq 2 \) and \( t \geq T_x \), otherwise false,
  - \( \text{hasParityChanged}(i) \) yields true if the parity of any close neighbour has changed compared to the previous step, otherwise and if \( b_i < 0 \) (it’s a typical dimension of the \( i \) firm to which it belongs) it yields false.

If either of these conditions hold:

\[
(b_i \leq 0 \land N_i^l \leq d_i) \lor \\
(b_i \geq 0 \land \text{isLearningTime}() \land \neg \text{learningSwitch} \land \neg \text{hasparityChanged}(i))
\]

the firm does not question its nearest neighbours.

But otherwise it runs through neighbouring firms one after the other. It omits questioning of those firms which
- show negative cumulative payoff;
- belong to the same group
and also those for which one of the following conditions holds:

\[
(b_j \leq 0 \land N_j^l \leq d_j) \lor \\
(b_j \geq 0 \land \text{isLearningTime}() \land \neg \text{learningSwitch} \land \neg \text{hasparityChanged}(j))
\]

Firms not omitted are investigated in order to find the best neighbour to group with. First of all it is basic that the following condition be met:

\[
(b_i \leq 0 \land N_i^l \geq (d_i + d_j)) \lor \\
(b_i \geq 0 \land \text{isLearningTime}() \land ((N_i^g \geq (d_i + d_j) \land \neg lS) \lor lS)) \lor \\
(b_i \geq 0 \land \neg \text{isLearningTime}())
\]

In this case a comparison is made between the coordinates of the asking and the answering firms. The best firm has the highest coordinate among those with the same parity (disparity) as the asking firm. The same parity (disparity) means pairs of coordinates which rounded up or down to the nearest whole number are equal. The firms with negative payoff ask questions too even if they are never asked or chosen as best neighbour themselves, sort of punishment for having negative payoff.

All firms questioned increase \( N_i^{PV} \) by one unit.
The formulae always give the questioning firm as \( i \) and the questioned firm as \( j \).

- **Group formation**: when all firms have found their best close neighbour, groups can form. If firm A finds its best close neighbour is B and vice versa, a group is formed. The following cases can be distinguished:
  - If both firms are isolated, a new group containing them is formed;
  - If only one of the two is grouped, the isolated one joins the group. In practice the existing group enlarges to enclose the new firm.
  - If both firms are already in groups, one group takes over the other.

- **Updating of group variables**: each new member of a group adds \( t_i \), calculates \( \bar{c}_D, N_{\text{tot,k}} \) and determined average levels of \( N_i^{PV}, c_i, b_i \), stored in \( N^{PV}, \bar{c}, \bar{b} \) respectively.

- **Updating group payoff**: new members update their own payoff using these equations:
  \[
  p(t) = g(t) - s(t) \\
  g(t) = \alpha \cdot (g_C + g_A) \\
  s(t) = \beta \cdot (s_D + s_A + s_O) 
  \]
  where
  \[
  g_C = \bar{c} \\
  g_A = c_A \cdot N \\
  s_D = \frac{c_D}{\bar{c}_D} \cdot N^{PV} \\
  s_A = \begin{cases} 
  0 & \Sigma_+ = d \lor \Sigma_- = d \lor N_0 = N \\
  c_M & \text{otherwise} 
  \end{cases} \\
  s_O = c_O \cdot N 
  \]
  where \( d \) is the size of the group, \( t \) is the time of evolution of the system, \( \Sigma_+, \Sigma_- \), \( \Sigma_0 \) are respectively the sum of positive mutations (\( \delta = 1 \)), negative mutations (\( \delta = -1 \)) and zero mutations (\( \delta = 0 \)) mutations inside the group.

- **Updating group members**: the typical sizes of a firm in a group are updated like this:
  \[
  P_i(T) = \sum_{t=0}^{T} p_i(t) \\
  p_i(t) = p(t) = g_i(t) - s_i(t) \\
  g_i(t) = g(t) \\
  s_i(t) = s(t). 
  \]
the budget $b_i(t)$ of the firms is equal to $\overline{b}$ if $p \geq 0$, and equal to $b_i(t-1) - |p|$ if $p < 0$, $b_i \geq 0$ and \textit{isLearningTime()} is true.

- \textit{Updating payoff for isolated agents}: the typical measurements for isolated firms are updated like this:
  \begin{align*}
  P_i(T) &= \sum_{t=0}^{T} p_i(t) \\
  p_i(t) &= g_i(t) - s_i(t) \\
  g_i(t) &= 1 \\
  s_i(t) &= (c_D \lor c_{Dist}) \cdot N_i^{PV}(t).
  \end{align*}
  These firms are shown in \textit{black}, except for institutions which stay \textit{red} for the whole simulation.

- \textit{Updating AIL}: groups update the variables $N_i^l$ of their members as follows:
  \begin{align*}
  N_i^l = \begin{cases}
    N_{i_{\text{stab}}}^k & \text{for } \overline{b} \geq 0 \land p \geq 0 \land t_i \geq 3 \\
    N_{i_{\text{stab}}}^k - 1 & \text{for } \overline{b} \geq 0 \land p < 0 \land t_i \geq 3 \\
    N_{i_{\text{stab}}}^k - 1 & \text{for } \overline{b} < 0 \land p < 0
  \end{cases}
  \end{align*}

- \textit{Checking group member payoff}: groups with $p < 0$ are destroyed and their members go back to being isolated. Firms go back to being \textit{black}, except for institutions, and have $d_i$ equal to 1.

- \textit{Updating EIL}: variables of EIL are updated as follows: a vector of size three having three elements remembers the maximum group size over the last three periods for three consecutive steps. The vector is updated by replacing the oldest time value with the maximum size at the instant of updating.

- \textit{Updating firms’ EIL} if \textit{isLearningTime()} yields true and the three values recorded in the EIL vector are equal and greater than zero, each firm in the network updates its $N_i^g$ to maximum, unless the value of $N_i^g$ in the previous step were higher. It can happen that for institution firms $N_i^g$ a value higher than one is initialised. These firms will not update $N_i^g$ until the maximum measurement is higher than $CST.N_G.IST$. In the definition of \textit{isLearningTime()} it is required that $t \geq 2$ precisely because the AIL vector has to record at least three time instants. Time starts from zero.
- **Firm’s EIL in groups with institutions**
  firms that are members of a group containing at least one institution adapt their $N^g_i$ to the maximum level of $N^g_i$ among group members.

  - **Updating variables of the model:** the levels needed for the various graphs are calculated.
  
  - **Updating company coordinates:** if a firm is a group member its coordinate is rounded up or down to an integer number. Groups pay to adapt themselves, and cancel out any possible mutation. If the updated coordinate is higher than 7 it is reduced by 2. But if it is lower than 0 it is increased by 2.
  
  Isolated firms do not erase mutations. So their coordinate can over time change parity.

  - **Saving data:** If variable `CST_DUMP_SWITCH` is equal to one the graphic data is saved in the file `data_dump.txt`. The file is closed at the end of the simulation by closing the programme with Quit+Quit.

5 Carrying out the Simulation

To start the application:

- Create a folder in `C:/cygwin/my_name_user/`,
- save all files `*.class`;
- open Cygwin shell
- use the `cd` command to enter the folder
- execute command: `javaswarm StartFirm`

It is possible to modify the various parameters of the simulation inside the `ModelSwarm` window, pressing ‘enter’ to confirm each change. Parameters can also be modified in the `FirmParameter.scm` with a text editor.

The files are kept online on the web server of the Economics Library site. All files in `class`, `scm` and `m` used in the simulation as well as this guide (in italian) for the latest version can be found at [http://swrwebeco.econ.unipr.it/Swarm/](http://swrwebeco.econ.unipr.it/Swarm/). The folder `/src` contains the sources and copies of old versions of the sources and cannot be accessed externally. The folder `/oldVer` contains old versions of compiled sources.