Understanding an Economic Dilemma:

Essays on Common Property Resources

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To my parents

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Abstract

There arc many economic environments in which individual incentives do not generate enough group cooperation. This dissertation investigates an instance of such a social dilemma – the use of a common property resource – and a special class of institutions that can promote the socially optimal outcome, namely self-governing institutions. Self-governance exists when the users themselves manage the common resource in a decentralized fashion through legal institutions.

The analysis is carried out from three distinct perspectives. The first perspective is an economic analysis of the property rights arrangements and an application of tools of game theory to a field case study. Between the 13th and the 19th centuries, many communities in the Italian Alps negotiated and enforced contracts (*Carte di Regola*) in order to efficiently manage their common pastures and forests. A comparison between two potential solutions to the Tragedy of the Commons, self-governance and informal cooperation through repeated interaction, leads to three conclusions. First, some legal arrangements were nccessary to support even a repeated game solution. Second, under certain conditions, the cost of building legal institutions was repaid by large gains in efficiency. Third, since the benefits of the institutions were a public good, and since the users themselves were in charge of creating and administering the institutions, there were insufficient individual incentives to build them. This induced collective action problem was overcome by repeated interaction among the users.

A simplified version of the monitoring and sanctioning mechanism devised historically to enforce the regulations on common resources is studied through a set of experiments. Individual users were allowed to inspect other users at their own cost, and impose a predetermined sanction (a fine) when a free rider was discovered. The fine was paid to the user who found a violator. This experimental economics study finds three classes of results. First, the mechanism is very effective in raising efficiency of resource use. Second, the classical model of identical, selfish agents does not describe the data as well as a model based on heterogeneous and other-regarding preferences, where altruism and spite play important roles. Third, this other-regarding agent model also explains important paradoxes that can be found in the existing literature.

Finally, an alternative explanation for the success of the monitoring and sanctioning institution as the result of the interaction with bounded rationality is examined. While keeping selfish preferences, limitations are put on the ability of decision makers to maximize and behave strategically by employing a genetic algorithm with memory sets. The simulations carried out replicate most aspects of the data with human agents. Interestingly, less sophisticated adaptive agents exhibit a higher degree of individual heterogeneity. In addition, the impact of the process that generates new ideas is explored by comparing uniform binary mutation with two other alternatives.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1. Introduction

How can institutions promote the socially optimal outcome when the unstructured interaction among a group of agents does not provide sufficient incentive to cooperate? This dissertation addresses this issue with reference to the use of a common property resource.

The general issue of promoting cooperation can be broken down into two related components. The first is the identification of the motivations for human behavior, and of the abilities of agents to achieve their goals. The second is an understanding of how institutions can modify the incentive structure of an initial situation. Although conceptually distinct, these two components might sometimes appear indistinguishable while reading the following chapters. The unfolding of each one of the components in the present work is now briefly illustrated, starting with models of human behavior.

Chapter 2 adopts the classical model, wherein agents are assumed to care purely about their personal income and are endowed with a high level of rationality, or "hyper-rationality," as Kreps (1998) puts it. Dealing with such simple agents is convenient because many reference results have been proven under those conditions. Moreover, the conclusions that can be drawn are important reference points even if the model is inaccurate.

The following chapters depart from the assumptions of the classical model in two different ways. Chapter 3 assumes that agents might consider the well being of others in their decisions and puts forward a specific model of other-regarding preferences. Recently, many models of other-regarding preferences have been suggested in response to otherwise unexplained experimental data (Krebs, 1970; Rabin, 1993; Ito et al., 1995; Chan et al., 1997; Levine, 1998; Bolton and Ockenfels, 2000; Saijo, 2000; Fehr and Schmidt, 1999). It is an attempt to develop a more accurate model of human behavior within the general framework of utility theory. The success of such attempts can be evaluated by considering the trade-off between improved accuracy in prediction and added complexity. The model adopted herein postulates that agents care about their own income and, to a different degree, about the income earned by all the other agents in the group. There might be both altruistic and spiteful agents.

Both the other-regarding preference models and the classical model assume hyper-rational agents. The last chapter explores the consequences of weakening the cognitive abilities of the agents to achieve their goal of personal income maximization. The approach employed modifies the decisional procedures of an agent by building into him limitations on his ability to maximize and to act strategically. In particular, a version of a genetic algorithm with a memory set is employed. Several adjustments were made to convert this algorithm into a model of human behavior.

The second component of the issue tackled in this dissertation concerns a type of institution introduced in order to foster cooperation among agents. The focus is on a form of common property resource management performed by the users themselves: the users both develop and enforce the rules. This class of institution will be called "self-governing," to stress the fact that the state does not directly administer the resource, but, on the contrary, the users themselves create the institution in an autonomous and decentralized manner.

Chapter 2 presents the rich texture of a group of historical and legal institutions that endured for more than six centuries in the Italian Alps. The aim of this work is to disentangle and explain the tasks accomplished by some of the norms toward the goal of promoting efficiency. This work studies the institutions that were set up in the field to foster cooperation and seeks to understand their logic through the lenses of the classical model.

While this part of the inquiry is a full spectrum economic analysis of the legal arrangements adopted to solve an instance of the common property dilemma, Chapters 3 and 4 isolate a specific element from the above institutions and study its performance in a more general context. The element chosen is a simplified version of the monitoring and sanctioning mechanism devised historically to enforce the regulations on the common resources.

Given that the mechanism is no longer in use, Chapter 3 examines the performance of a model based on it, under laboratory conditions. Chapter 4 investigates the same institution when the agents in the model have limited computational abilities.

The content of the dissertation is as follows: Chapter 2 is an economic analysis of the law that relies on the property rights approach (Barzel, 1997) and on game theory tools, and in particular on the theory of repeated games. We studied the contracts written by the communities in Northern Italy between the 13th and the 19th centuries (*Carte di Regola*) to manage pastures and forests, which were common property. This case study has never been analyzed from an economic point of view and presents the advantage of having a rich and detailed legal documentation. The originality of the contribution is in the analysis of the relationship between a repeated game cooperation and legal institutions, as potential solutions to the common property dilemma.

Chapter 3 is an experimental investigation involving one aspect of the *Carte di Regola* system, the peculiar monitoring and sanctioning mechanism employed to promote cooperation. This study shows the large improvements in efficiency induced by the mechanism, which cannot be measured in the field because the system is no longer in place. The experimental data provide a possible explanation for this mechanism's remarkable success. Individual heterogeneity is channeled into better group outcomes thanks to a beneficial set of incentives built into the *Carte di Regola* system.

Chapter 4 is a computational exploration of the same monitoring and sanctioning mechanism studied in the previous chapter. Simulations are conducted by modeling agents as adaptive learners with a sophisticated version of a genetic algorithm. The parameters of the model are calibrated using the experimental data of Chapter 3. This inquiry suggests an alternative explanation for the success of the *Carte di Regola* mechanism as a product of agents having bounded rationality.

Chapter 2

Emergence of Endogenous Legal Institutions:

The Rural Charters in Northern Italy

2.1 Introduction

In this chapter we are concerned with the use of a common property resource, which constitute an instance of social dilemma. Individual decisions to use the common resource lead to a sub-optimal outcome that is often called tragedy of the commons (Gordon, 1954; Hardin, 1968). In this situation economists have typically suggested two classes of solutions. One class is the intervention of a political authority, such as in the case of the Enclosure Acts in Britain or regulatory authorities. Another class of solutions relies on the results from the repeated game literature for the emergence of spontaneous cooperation among the users. In this paper we investigate a third class of solutions, self-governance, where a group of agents establishes a set of legal rules for their members and an organization to implement those rules.

When assuming that the central state was too weak or too costly to call into play, the investigation of possible solutions to the social dilemma is restricted to spontaneous cooperation versus self-governance. The comparison of efficiency between these two classes of solutions is particularly interesting when transaction costs are positive. Several questions arise. Can repeated interaction among agents overrule short-term temptations to free ride so that no regulations at all would be necessary? If not, can the group modify the conditions in a way to support such informal cooperation? Can self-governance be a better solution? What are the relations between the informal relationship of people in the group and the formal aspects of institutions (Greif, 1998a)? What are the incentives of agents to provide institutions for self-governance?

We examine these questions looking at the centuries–old organization of the management of common forests and pastures in the communities of the Trentino, in Northern Italy (Figure 2.1).

Figure 2.1: Italy During the Renaissance

Notes: the Principality of Trento was a mountain area on the Italian side of the Alps part of the Carolingian Empire. It was located North of the Republic of Venice. The current Trentino region covers a surface of 1,465 square miles and in 1754 had a population of 206,000 scattered in more than 300 villages (Cole and Wolf, 1974; Provincia Autonoma di Trento, 1995). Source of the map: Adapted from Muir's Historical Atlas: (1911), http://www.fordham.edu/halsall/sbookmap.html (checked on July 2001)

The commons were managed by the communities through self-governing institutions that were coded in formal documents called *Carte di Regola*, or rural Charters. A

Charter was a contract among the members of the community, on one hand, and between the community and the ruler, on the other, that allowed the community to establish and enforce local economic regulations. The rural Charters emerged in the Principality of Trento as a legal innovation in the 13th century and thrived for about six centuries.[1]

This paper presents a game theoretical and property rights[2] examination of this pre-modern institutional framework. While this contribution is about the management of communal resources, other studies have applied similar arguments to institutions facilitating private enforcement of rules (Hay and Shleifer, 1998) and trade (Greif, 1998b, Clay, 1997, Greif, Milgrom, and Weingast, 1994). In particular, Milgrom, North and Weingast (1990) explains how the merchant codes governing medieval commercial transactions in Europe promoted the trust necessary for efficient exchange when the individual traders had short-run temptations to cheat. Honest trade was promoted through a system of private judges who kept a centralized record of the reputation of individual merchants. Similarly, Greif (1993) describes an institution that surmounted a commitment problem intrinsic in the relations between Maghribis merchants operating in the Muslim Mediterranean area and their oversee agents in 11th century

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[1] The oldest known of such Charters dates back to 1202 and was drawn by the villagers of Civezzano, a small village nearby the administrative center of Trento. Most of the documents here quoted are from Giacomoni (1991), who copied 190 rural Charters of the Trentino area from the parchments that were found in the Biblioteca Comunale of Trento, Archivio di Stato of Trento, Archivio della Curia Arcivescovile of Trento, Biblioteca Civica of Rovereto, Ferdinandeum Museum of Innsbruck, Castel Bragher and several village archives. Nequirito (1988) surveyed the literature that published the text of Charters. Many Charters have not been published yet and new ones are discovered every year. For documents relative to some other regions in the Alps, see Batl (1951), Cortesi (1983), and Pototshing (1953).

[2] Allen (1998) defines property rights as "one's ability, without penalty, to exercise a choice over a good, a service, or person" and transaction costs as "the costs of establishing and maintaining property rights." See also Barzel (1997) and the classical article of Demsetz (1967). Besides trespassing, legal disputes over

trading contracts. The agency problem between merchants and agents was overcome through the use of coalitions: they were groups of traders whose member merchants were expected to hire only member agents and where cheating agents were subjected to the punishment of all member merchants in the coalition.

As the authors point out, the key to understand those pre-modern trading institutions is the theory of repeated games with imperfect monitoring. Provided that a continuing relationship is established and that agents can monitor each other to some degree, a repeated game solution can emerge without state enforcement of contracts (Rubinstein, 1979; Green and Porter, 1984; Fudenberg and Maskin, 1986; Kandori, 1992a; Fudenberg, Levin, and Maskin, 1994). In general, cooperation is less than full, and more accurate monitoring results in a higher level of cooperation (Abreu, Pearce and Stacchetti, 1986, 1990; Kandori, 1992b). The focus of Milgrom, North and Weingast (1990) is on such a monitoring institution, which takes the form of a third party – the judge - who collects and verifies information and then shares it with anyone needing it. The traders have an incentive to be honest because suspected cheaters are punished through a temporary ostracism from the community in the form of refusal to trade. In contrast, Greif (1993) devotes attention to illustrate how the Maghribis merchants punished dishonest oversea agents using informal mechanisms.

The present study applies the theory of repeated games with imperfect monitoring as well, and improves upon previous studies by taking up on three issues that have not yet been extensively examined. First, we are dealing not with long-distance trade but with land use, where the possibility of trespassing can undermine spontaneous cooperation.

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community borderlines were very common as it is testified by the incredible number of documents on the

The problem with trespassing is that if outsiders could easily enter the common resource, then they can reap the benefits of villagers' own cooperation efforts. The villages of Romeno, Don, and Amblar provide a colorful reminder of the importance of this matter. The peasants of the three villages owned in common a side valley mainly covered by forest. The valley was delimited on three sides by steep mountains and in the only side where the access was feasible, the entrance was so narrow that villagers built a gate on it and provided the gate with a lock. As the 1459 Charter states, the only key was kept in the church of the village of Romeno. In this way the community governor could have easily controlled everybody who went into the valley to log trees.[3] In other, less fortunate cases, the enforcement of property rights toward outsiders absorbed significant resources.

Secondly, because migration could undermine the nature of the continuing relationship within each village, institutions that promoted cooperation had to be robust to this threat. The issue of the incentives to maintain a long-term relationship will be extensively analyzed because of their crucial role in informal cooperation. Contrary to a common belief (Andreatta and Pace, 1981), the prohibition to trade communal land was not essential to ensure a long-term relationship among villagers. The Trentino communities could, and sometimes did, sell the commons. Instead, what guaranteed a long-term interaction was an elaborate form of village citizenship that discriminated between insiders and outsiders and granted selected rights to the insiders. A key feature was the cost associated with the choice to leave the village.

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matter that can still be found in the archives.

The third issue concerning the situation of the Northern Italian communities is actually a paradox. By establishing village citizenship rules, protecting property rights against outsiders, and by gathering information on users' actions, the communities created just the conditions sufficient to sustain informal cooperation among the users of the commons Yet, instead of relying on informal cooperation, they used legal regulations, which is a surprising paradox. Interestingly, most of the legal regulations concern the actions of insiders. Consider, for example, what happened in the community of Mezzolombardo. On July 18, 1589, the governor of the village recorded that a gentleman named Michel had been caught while illegally collecting firewood on common land. As a result he had to pay a fine for an amount of *troni* 4 and *carantani* 10. Like other neighboring communities, Mezzolombardo regulated villagers' use the community forests, pastures, and wastelands by restricting time and place of access or imposing quantity restrictions.[4] Mezzolombardo was hardly alone in enforcing these regulations via fines. Indeed, hundreds of other communities in the Trentino region of the Italian Alps did the same, as did villages throughout Europe. [5]

The description of many instances of self-governance can be found in the literature (Ostrom, 1990, Bromley, 1992, Netting, 1981, Stevenson, 1991, Casari, 1998), where

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[3] The reference is to the villages of Romeno, Don, and Amblar. Regulation of the gate is mentioned in the 1459 rural Charter (chapter 24: *Item che la chiave della porta di Vallavena sia tenutta et conservatta nella sacrestia della chiesa di santa Maria di Romeno*).

[4] Libretto di Amministrazione (1589): "*per una codanaza fatta per aver menado entro legna da le giare del nos,*" which literarily means "for a penalty inflicted for having removed firewood from the bank of the river *Nos.*"
For the rural Charters of Mezzolombardo see Devigili (1979).

[5] On the best of my knowledge at least three-quarters of the Trentino villages had a Charter by 1803 (284 villages out of 377). The count is approximate for two reasons: First, I took as total the number of villages the land register units, in which the province of Trento was divided, in 1897; secondly, I have counted only the Charters that I have collected, but some Charters might have been lost or not found by me. Both factors suggest that the actual ratio is above 75%.

legal rules for the use of the commons are in place but no authority external to the group of users has chosen the rules or enforces them. Ostrom (1990) in particular did a remarkable work in looking for general patterns that characterize long-enduring institutions to manage the commons. The purpose of this chapter is to go beyond empirical regularities and provide a theoretical framework to understand why self-governing institutions emerge.

Here we define institutions as "non-technologically determined constraints that influence social interaction and provide incentives to maintain regularities in behavior" (Greif, 1998). In particular, *legal institutions are defined as legal constraints that can be enforced in court.* In contrast, informal institutions are constraints that do not rely on a court of law neither for defining what constitute improper behavior nor for administering punishment. An important example of this kind of institutions is a *repeated game solution (or informal cooperation), that is the coordination on a strategy that supports an equilibrium yielding a better outcome than the "tragedy of the commons" outcome in a repeated game.*

The questions in reference to the rural Charters are, on one side, why wasn't a repeated game solution sustainable or effective? On the other side, as a repeated game solution was not the way the resource was managed most of the times, why was the community concerned about a long-term relationship among the users?

The next section (Section 2.2) applies the theory of repeated games to the situation of villagers using a common renewable resource, such as a forest or a pasture, and outlines the conditions under which a repeated game solution was possible and effective. Some of these conditions are then analyzed in more depth. Section 2.3 examines the role of membership rules in locking the villagers in a long-term relationship. Section 2.4 deals with legal sanctioning institutions to stop trespassers and immigrants. Section 2.5 discusses the role of information-gathering institutions to monitor individual actions. Section 2.6 suggests reasons why the Northern Italian communities adopted legal sanctioning institutions for insiders instead of relying on a repeated game solution while Section 2.7 provides an empirical test for some of the implications of the theory. Section 2.8 explains how building legal institutions induced another social dilemma and how that was solved. The conclusions discuss the broader implications of the paper, setting forth the relative advantages and disadvantages of formal and informal institutions.

2.2.Was a Repeated Game Solution Possible?

One might argue that the rural communities of Northern Italy offered the ideal situation for observing the Folk theorem in action: the villages were small and isolated in a mountain area, the villagers interacted with one another, and remained in the same village for generations. Upon closer inspection, however, it becomes unclear whether the Folk theorem actually applies. In fact, whether the Folk theorem operated turns out to depend on the presence of legal institutions purposively created to make it work. This section presents the collective action problem through a simple model, offers a taxonomy of institutions, and then outlines the conditions under which a repeated game solution was possible and effective.

A well-known body of the literature argues against unregulated common property of resources (Gordon, 1954; Clark, 1990). In the Trentino region a significant part of the land was owned in common on a village basis. Forests covered almost half of the surface while grazing land and meadows covered about one-third of it, and an overwhelming portion of both was owned in common.[6] For instance, in 1780 in a relatively large village 95% of the forests was common ownership and so was 66% of the meadows and pastures. The analogous shares in a high mountain village were 100% and 60%.[7]

The essence of the argument against common property is that it creates individual incentives that lead to a sub-optimal outcome, or to a "tragedy" in Hardin's words. The dilemma can be captured by the following simple model that is set in a zero transaction cost world.

Consider a renewable resource, such as a forest, that yields revenues according to a function $Y=a\cdot Q - b\cdot Q^2$, where $Q=\Sigma_{i=1,..N}\ q_i$ is the total quantity harvested by all the N users and a and b are positive technological parameters. Each user *i* independently takes the decision to harvest a quantity of timber $q_i \geq 0$. Harvesting involves a cost linearly increasing in the quantity appropriated, $C_i=c\cdot q_i$ and so the user is left with a profit (rent) given by the difference between the revenues appropriated and the costs borne, $\pi_i = \frac{q_i}{Q} Y - cq_i$. The user's revenues depend in a non-linear fashion on the user's appropriation level and on the appropriation of the others in the group. At the group

[6] The exact data are 48% and 31%. Source: 1897 land register data reported in Consiglio Provinciale d'Agricoltura, 1903.

[7] The two villages are, respectively, Levico and Predazzo. The data are from the *Catasti Teresiani of 1780-90*, manuscripted books recording ownership rights (*Archivio di Stato di Trento*). Goio (1978) reports the summary statistics for the village of Levico and Varesco (1981) for Predazzo. A more systematic study of the extent of common property could be carried on. In 1897 more than 76% of the forest in the region was municipal or State ownership. After 1803, both political and economic shocks reduced the extent of communal ownership. Part of the village estates were divided in individual plots or sold after the end of the Principality of Trento. An increasing population and more generally and increasing logging activity reduced the extension of the village forests (Perini, 1852, Monteleone, 1964).

level profits are simply $\Pi(Q)=Y-c\cdot Q$. This is a standard model of a renewable resource first formalized by Gordon (1954). For more details, see Appendix A. An exhaustive treatment can be also found in Clark (1990) and Baland and Platteau (1996). The maximum profit that the group can extract from the resource, Π^*, is obtained when the group harvests the resource at an optimal level Q^*. At the optimal level social marginal cost and social marginal benefit are equal, $N\cdot c=a-2\cdot b\cdot Q^*$.

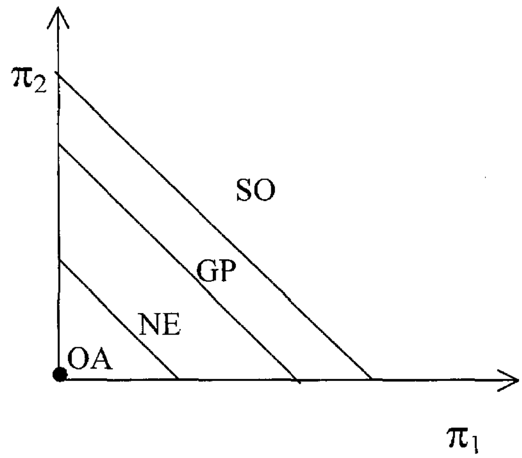
When there is common property of the resource and owners have unlimited rights to use the resource, the outcome is less than optimal. Group profits are a fraction of the potential level, $\Pi(Q)= E(Q)\cdot\Pi^*$, where E is the efficiency function, $E\in[0,1]$. In particular, the Nash equilibrium appropriation level $Q^{NE}(N)$ is sub-optimal for any group size N bigger than one, $E(Q^{NE}(N))<1$.[8]

When there are no property rights to the resource and anybody can harvest it, the arrangement is called open access (OA), and the outcome is less efficient than common property. In that case agents will access and use the resource as long as there is a positive profit to make out of it. Formally, such open access situation is studied computing the limit of the Nash equilibrium when the number of users goes to infinity. The result is a severe overexploitation of the resource, $Q^{OA}=2Q^*$, and a total destruction of the potential profits that could be made out of the resource, $E^{OA}=0$. Zero efficiency means that the revenues collected from the resource are just enough to cover the harvesting costs. This situation is called severe tragedy of the commons in order to distinguish it from the Nash equilibrium outcome that could result from an unregulated

[8] $E(Q^{NE}(N))=(4N/((N+1)^2))$

common property. Figure 2.2 offers a simple illustration of the various levels of rent that two users could extract from a resource.

Figure 2.2: Possible Rent Levels from the Use of a Common Resource



Notes: With a group of two users, N=2, the total rent is $\Pi = \pi_1 + \pi_2$.
SO = Social Optimum, NE = Nash Equilibrium, GP=Green-Porter, OA = Open Access.

To sum up, in a one-time interaction, the users of a common property resource in the absence of regulations earns less than what they potentially could if the resource was properly managed (NE versus SO in Figure 2.2). Earnings are even lower in an open access situation (NE versus OA).

When the interaction among the users of a commons is indefinitely repeated – as it was among the villagers in Trentino – the outcome does not have to be a 'tragedy' (NE) but might indeed be optimal (SO). This result has been proved under a variety of assumptions in the Folk theorems, or as Myerson calls it, the General Feasibility Theorems: "The general feasibility theorem can be interpreted as a statement about the power of social norms in small groups, such as families, partnerships, and cliques. According to the general feasibility theorem, if the individuals in a group know one another well, can observe one another's behaviors, and anticipate a continuing relationship with one another, then social norms can sustain any pattern of group behavior, provided it makes each individual better off than he would be without the group. When we go from small groups into larger social structures, however, the assumption that everyone can observe everyone else may cease to hold, and general *feasibility can fail*" (Myerson, 1991, p. 349-50). Such *imperfect monitoring* of individual actions turns out to have been a problem also for the Northern Italian communities. Moreover, the interaction among the villagers was not spontaneously repeated. Specific, legal institutions had to be established to bring the condition closer to the one needed to sustain cooperation according to the Folk theorem. To see why, let us first sketch a general typology of institutions. For our purposes, there are three types of institutions:

1. *Community-building institutions* aim at defining the borderlines of the common land and to identify a stable group of users (insiders) separated from the rest of the people (outsiders). They are legal institutions that define property rights.
2. *Information-gathering institutions* refer to the processes of collecting information about individual actions of insiders and outsiders and about the level of the physical stock of the common resource, evaluating the reliability of the information, and sharing it with all insiders.
3. *Sanctioning institutions* are the ways chosen to punish a perceived free-riding behavior of insiders and outsiders.

Each type of institution has a role in solving the collective action problem for both a repeated game solution and self-governance. The remaining of this section focuses on the central role of some legal institutions in promoting a repeated game solution, beginning with community-building institutions, which constitute a precondition for it. By a repeated game solution we mean any improvement of the outcome above the 'tragedy' level (NE) that is achieved without legal sanctioning of insiders. An agent is thus said to 'cooperate' when she reduces her use of the common resource to a level below her one-stage best response level and her action improves the group outcome.

A repeated game solution is not possible without community-building institutions. There are two components to such institutions. The first aims at ensuring exclusive access to the resource for the legitimate users. Without it, the outcome is a severe tragedy of the commons (OA in Figure 2.2). The second component has the purpose of inducing an expectation for long-term interaction among the users.

Historically, the first step that villages took to use their commons more effectively was to establish two community-building institutions: a legal title to the common land and a form of village citizenship. Those two legal institutions transformed the legal status of forests and pastures from open access to close access (common property). They were enforced through a court system that administered sanctions to violators. As the official courts of the state were too expensive to use, the communities set up a decentralized and self-administered system through the rural Charters.

In fact, without a legal sanctioning institution to enforce property rights toward outsiders – either state or village courts - a repeated game solution among the villagers themselves is doomed to fail because any effort to limit the over-use of the commons would be compensated by an increased harvesting activity by outsiders. Consider for example a situation where there are N users from the village itself (insiders) and M potential trespassers (outsiders). In the absence of legal property rights and of a court system to punish trespassers, the number of users is in practice N+M. Any cooperation agreement among insiders to limit resource use simply makes trespassing more profitable for outsiders and so more frequent. More outsiders could decide to use the common (increase in M). The only effective way to deter trespassing is through a system of legal sanctions. Folk theorem type strategies would succeed only when users are isolated from the outside world but not when trespassing is easy, because outsiders can easily escape community punishment. They might poach at the common and never show up again or they might free ride temporarily on other communities until the original one has reverted to a cooperative mode.

Protection from outside free riding ensures an improvement over the severe tragedy of the commons (namely a transition from OA to NE) but not the optimal outcome (SO) unless interaction among insiders is repeated. In the case of the Northern Italian communities, the expectation of a continuous interaction was guaranteed by a specific form of property rights on the common land that was in place to make it costly for insiders to leave the community. A description of this important feature will be given in the next section (Section 2.3).

Once proper community-building institutions were in place, a repeated game solution was possible provided that the agents were able to detect if the others cooperated: that way they could decide whether to keep cooperating or to switch to punishing. An insider had two ways to assess the cooperation level of the others. One way to detect cooperation levels was to monitor the individual actions directed at resource use of all the other insiders. A second option was to look at the physical stock of the resource and from it to infer the aggregate cooperation level of all the other agents.

In the Northern Italian communities both ways of assessing cooperation were imperfect. The situation could, however, have been improved employing information-gathering institutions. For a start, actions directed at resource use could be only partially observed (Section 2.5). Moreover, the physical stock of the resource could be observed with a degree of randomness.

By simply observing the physical stock of the common forest or pasture, a villager could have inferred what others had harvested and thus whether they were cooperating. In other words, instead of observing the people the villagers could have observed the land. The signal collected in this way, however, was not necessarily precise. The villagers had a good idea of the physical stock of the resource, but did not know exactly how many trees were in the forest or the exact quantity of grass that was on the ground in comparison with the level to be found if the harvesting was optimal.[9] Such a noisy signal might be enough to sustain some cooperation, although in general not full cooperation (GP, from Green-Porter, in Figure 2.2). The Green-Porter model - which explains oligopolistic collusion with imperfect monitoring – applies also to the

[9] A publicly observed signal is assumed. Cooperation is more problematic with private signals. A villager sampled the status of the common land in a given number of locations while doing his daily activities and did not usually cover the whole land and count every tree in order to find out the exact quantity of the leftover timber or grass. The signal was thus a random variable, which yielded different draws to different villagers because the sampled areas were in general different. This individual heterogeneity in the signal could easily make implicit cooperation unravel. If communication is allowed, however, the information will likely be aggregated into a public signal (Kandori and Matsushima, 1998; Compte, 1998).

exploitation of a common renewable resource[10] (Green and Porter, 1984 extended by Abreu, Pearce, and Stacchetti, 1986, 1990).

There are two types of costs associated with a repeated game solution with imperfect monitoring: one is due to the frequency with which the group reverts to punishment (α), which is in general positive and generates a low payoff (Π'); the other cost derives from the inability in general to support the socially optimal outcome during the cooperative periods ($\beta<1$).

$\Pi^{GP} = (1-\alpha)\, \beta\, \Pi^* + \alpha\, \Pi'$, $0< \alpha, \beta <1$, $\Pi^*>\Pi'$

The higher the noise level of the signal, the worse the outcome because of a higher chance of punishment α and/or a lower best attainable cooperation level β.

A similar reasoning can be done when cooperation is assessed looking at individual use levels of insiders. The information collected leads to an estimate of the cooperation level. Since the information is less than perfect, the estimate is uncertain and a repeated game solution will be able to support an outcome that is better than the 'tragedy' outcome (NE) but in general worse than the socially optimal outcome (SO). The poorer the information and the more uncertain the estimate will be, the worse the outcome will be. The adoption of legal information gathering institutions could reduce the uncertainty and improve the outcome.

Let's turn now to sanctioning institutions. It has already been mentioned that outsiders are punished through formal sanction. The essential difference between a repeated game solution and self-governance lies in the type of sanctioning mechanism

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[10] There is a perfect formal symmetry between firms competing on quantity in an oligopolistic market and users exploiting a common resource. See Appendix B.1 for a more extensive explanation.

for insiders. A repeated game solution, we know, relies on the threat of a punishment. The punishment is triggered by an aggregate use level that exceeds an established threshold, and it takes the form of a temporary overexploitation of the common resource. All the insiders are involved in the punishment and this behavior is self-enforcing in the sense that no external authority is needed to administer it. By contrast, legal regulations use individual punishment of insiders. If somebody violates one of the rules governing the villagers' behavior, she is subjected to an individual punishment. Such a system is self-governing in the sense that the insiders choose the rules and are responsible for their enforcement.

The rural Charter system was thus an instance of self-governing regulations with legal sanctioning institutions to punish insiders. A typical example from the Charters might be an individual quota and an associated monetary fine for violators of the quota. Other rules temporarily prohibited villagers from harvesting specific areas in the common forest and pasture. To enforce those rules, the community appointed guards to patrol the land and officials to try alleged violators. These legal institutions for information gathering and sanctioning were costly to build and maintain and those costs need to be subtracted when comparing the efficiency of different arrangements.

The comparison of legal institutions versus repeated game solutions is between two second-best outcomes, and the arrangement that can deliver a higher income stream to the owners of the resource is likely to vary according to environmental conditions such as informational conditions and enforcement technologies. The fact that both options, informal and formal, were available and that the Northern Italian communities chose *legal regulations through the rural Charters supports the conjecture that the latter option* was more efficient once transaction costs were taken into account.

To sum up, in a context of repeated interaction among insiders, the tragedy of the commons might be avoidable if the Folk theorem applies. For the Folk theorem to hold in the Northern Italian communities we need, first, legal sanctioning institutions to prevent free riding from outsiders, and, second, a property rights arrangement to promote long-term interaction among insiders. According to the theory of repeated games, though, the best attainable outcome would have still been sub-optimal because the cooperation level of insiders could be only imperfectly observed, either through the individual actions of the agents or through the condition of the common resource. The Trentino villages did not rely on a repeated game solution among insiders but adopted a legal regulation system.

Although not yet stated, there is an implicit assumption that if a property right arrangement is more efficient it is going to be chosen by the agents. Eggertsson (1990) calls this position the naïve theory of property rights. We will mention two possible ways in which this assumption can be satisfied, through voting or competition. Let us begin with voting.

A rural Charter had to pass two tests of consensus. First, the villager assembly needed to agree on a set of rules through a supra-majority voting procedure. Second, the local political authority, which in our case was the Prince of Trento, had the right to accept or reject the Charter[11]. It is well know from social choice theory that voting procedures often

[11] There are instances where a Charter was approved under the condition that some specific provisions had to be changed. As it is for private contracts today, there was also a general framework of rules that no Charter could contradict.

generate cycles and instability in the outcome or could have no core. How was this problem overcome in the case of the Northern Italian communities? If we assume that there was homogeneity of interest among the villagers of a community, in the sense that either preferences were identical or highly correlated then efficiency enhancing policies should have majority or supra-majority support.

The second incentive for efficient arrangements to emerge is due to competition among the communities. A better organization in exploiting a natural resource gives a community a higher income. Given that there were hundreds of communities in this region, an evolutionary-type of argument implies that the highest efficient groups will take over the lowest efficient ones. According to this position a competitive market selects those contracts that generate the highest profits because the agents that take the most successful actions are going to thrive while the others disappear. The first to suggest this line of reasoning in Economics was Alchian (1950). The fundamental theorem of natural selection states that evolutionary selection induces a monotonic increase over time in the average population fitness. This result is well-known in biology but it does not apply to any game (for instance not to the Prisoner's dilemma) (Weibull, 1995). When it does apply, there might be a short-term period of adjustment in the form of imitation of successful contracts or replacement of low-efficiency community by high-efficiency communities in the use of the natural resources (through rent or purchase, for instance) such that in the long-run we just observe efficient contract arrangements. These two considerations, about voting and competition respectively, corroborate the assumption that a switch will occur to a higher efficiency contractual arrangement if the alternative is available.

The following three sections cover in depth some crucial aspects of the rural Charter system that have been just mentioned here, namely the role of membership rules in locking the villagers in a long-term relationship and in controlling immigration, the legal sanctioning institutions to stop trespassers, and the information-gathering institutions to monitor individual actions.

2.3. Property Rights and Continuing Relationship

Without a long-term relationship among the legitimate users - the *vicini* – no repeated game solution could be achieved. In fact, there was a continuing interaction among the *vicini*. It was not, however, a 'natural' occurrence but the intended consequence of the type of chosen property rights arrangements on the commons. This section illustrates the specific content of those property rights in terms of freedom to leave the village, to sell and divide up the common land. Emigration - the individual decision of an insider to leave the village - was possible but costly. Selling or dividing the common land was possible only with the consent of a large majority of the owners. These details were vital in ensuring a continuing interaction and therefore the applicability of Folk theorems to this situation.

The peasants were not forced to live in the village. They used to migrate seasonally to the nearby Veneto and Lombardia areas (Figure 2.1). In the beginning of the Nineteenth century, every winter there was a flow of a few thousand workers going outside Trentino (Perini, 1852). This temporary emigration activity had been going on for a long time (Grosselli, 1999).

Emigration could also take place toward other villages within the Trentino, granted that the newcomers would be accepted. There were hundreds of separate communities and there is no obvious reason to assume that the person spent his whole life in the same community.

Despite this right to emigrate, few villagers decided to permanently leave the community. The same family names can be found in the same small village and nowhere else literally for centuries.[12] The fathers of the village owned and managed the commons and would transfer them one day to their sons, then to their grandchildren, and so on. The interaction among the *vicini* was a long-term one and the likelihood that the interaction took place the following year was so high that we are as close as we can get in a real world setting to the theoretical assumptions of infinite repetition.

Why did villagers not leave the original community? Because there was an individual right to exit the community, but exercising the right was costly. The crucial point is that everybody had the political freedom to leave the village, but no claim could be made of the community common resources. The emigrant could sell his individually owned house and fields but not his share in the community land. According to current property laws, if three persons own a piece of land in common and one of them wants to get out of the estate for no reason, she has the right either to sell her part to anybody or to be refunded by the other two. The arrangement in the North Italian villages was rather different. No Charter ever mentions the right of a *vicino* to be refunded of the value of his share of common land in case he leaves the community, let alone the procedures to

[12] Some Charters report at the opening the list of the heads of the families present at the meeting. Women usually moved to the man's village when they got married. The last name was transmitted through male lineage and only the pater familia was entitled with the right to use the common land.

satisfy that right. Moreover, there was a prohibition on trading membership rights. Indeed, there are indications that the decision to leave brought additional punishments. To begin with, if a community member no longer lived in the village (*non ha fuoco*), he could no longer use the common resources. In addition, if he returned to the village, he had to perform his chores (*obblighi* or *fattioni*) upon his return to the community, and sometimes could not use the common forest and pasture for one additional year.[13]

In practical terms, the villagers were locked into a long-term relationship one with another because the individual decision to leave the community in which a peasant was born involved losing the right to use the common land, at least while not presently living there, possibly for longer than that, and sometimes forever. Other features of the property right arrangement further support the view that it was an explicit intention of the community to set up a lock in mechanism.

The common land could be collectively sold or divided up among insiders. For instance, the villages of Nago and Torbole sold part of their common forest to an outsider and divided up another portion of their forest into individual assignments.[14] Tradability of the land was not an issue; the real concern was how that was done. The rights of alienation and division were specifically designed in a way to safeguard the lock-in mechanism that we have just described. Every detail in the property rights arrangement on the common land was aimed at promoting a long-term relationship.

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[13] From Statuti et Ordini della Spet. Communità di Nago e Torbole (1683): Nago and Torbole, 1647: "*Cittadini, che non habitaranno non possino goder beni communi*" (c.73: They cannot bring timber outside the village borders; they can use the common land only if they still have individually owned land in the village). "*Cittadini, che partono dal commune, et ritornano, che non possino goder beni communi, se non passato un anno*" (c.74). There is probably a relationship between the location of these two communities nearby the Garda lake – the biggest in Italy - and the very detailed regulations contained in their Charter for people who where leaving the community, temporary or definitely.
See also Tres, 1551 (the 1599 modifications regulates the *vicino* status) and Casez, 1632, c.45

As mentioned, parcels of the common forest and pasture were sometimes assigned to the members of the community in exclusive individual use. Such assignments were internal arrangements and the external legal property rights on the land always belonged to the community. In fact, when a member left the village, he also had to return his individual assignment to the community because it constituted a proper portion of the common resource. In addition, whenever the single villager could transfer his rights on the assignment, the buyer had to be a member of the community.[15]

What could have been a threat to a repeated game solution was an individual right to sell a share of common land to others. A *vicino* did not have this right. Otherwise, he could have taken advantage of the common resource by generously appropriating timber and overgraze the common pastures and then alienate his property right before the others would punish him using a Tit-for-tat strategy. That is why the right to sell the common land was always a collective right that belonged to the community as a whole. The rural Charters required the consent of a wide majority of the vicini for the alienation decision.[16]

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[14] See Dossi (1913) and Dossi (1927).

[15] Meadow assignments can be found in Pradibondo 1221, Condino 1340-3, Storo 1347, Nago-Torbole 1533, Caderzone 1591 (Papaleoni, 1891, Papaleoni, 1892, Valenti, 1911, Dossi, 1927). Forest assignments can be found in Storo 1347, Nago-Torbole 1541. Many other rural Charters mentioned temporary assignments of meadows (*sort*) (Mortaso, 1558, c.119-125), though sometimes the wording is ambiguous. Individual assignments were in fact family assignments. The individual assignments of common land have been interpreted as an early form of individual ownership (Papaleoni, 1892), but it remained in many ways closer to common than to individual ownership.

[16] For example, a qualified majority of at least 2/3 was required to sell the common land in Cles 1641, c.5 and in Cis 1587, c.80. Some authors interpret the absolute prohibition to sell the common land as a pivotal aspect of the traditional land management of the Trentino communities (Andreatta and Pace, 1981). In this paper we argue that this statement is not empirically correct and that it is not a requirement from a theoretical point of view to ensure a long-term relationship among users. Absolute inalienability and indivisibility of the commons were not cornerstones of the historical form of common property in Trentino, although selling the commons was sometimes subjected to the authorization of the feudal authorities (Cagnò 1587, c. 3, modification of 1693). An interesting discussion about the role of tradability of property rights in the commons can be found in Seabright (1993).

In conclusion, the property rights arrangement on the common land promoted a long-term interaction among the *vicini*, because the option to exit the community was costly. The individual *vicino* had the right to use the common resources according to the community rules and the right to participate in shaping those rules but no right to secession with compensation. Under these conditions, free riding was not profitable because avoiding the cost of the punishment involved facing the greater cost of leaving the community. Hence, the best behavior was not to exit the community but to cooperate and eventually voice complaints during the community gatherings (Hirshman, 1972).

2.4 Protecting the Community from Outsiders

Without restrictions to immigration and trespassing, the community land would be in practice available to everyone. As this section explains, the commons in Northern Italy were common property and not open access resources. First, there was a form of village citizenship or membership to govern the access to the commons by immigrants. The pillar of such system was the distinction between the group of legitimate users and regulators of the commons, called the *vicini* ("neighbors," insiders) and all the others, called the *forestieri* ("strangers," outsiders).[17] The second element that safeguarded the common property was a system of decentralized enforcement of property rights toward illegal trespassing. The rural Charters provided the legal tool for the delegation of jurisdictional powers from the Prince courts to village officers. Although it did not result

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[17] Examples of *forestieri* were the residents of neighboring villages, seasonal workers living in the village, occasional travelers. Similar systems were adopted in other regions of Europe (Popkin, 1979).

in a perfect enforcement of property rights, this institutional innovation decreased transactions cost of common property. We will begin with an analysis of the membership system.

The most rewarding free-riding action was probably to settle down in a village with a high per capita endowment of common resources and acquire full rights to use the commons. We might expect the members of the "poorest" communities to attempt moving into the "richest" communities. For persons without any memberships, acquiring any village membership would make them better off since they could access the commons for free. There were basically two tricks to acquire membership, through marriage with a *vicino* and through living long enough in a village.[18] Both the tricks and the correspondent countermeasures will be described.

The membership right entitled all the family members of the *vicino* to use the common resource and the *vicino* himself to participate and vote in the village assemblies that decided on various matters. The right was transmitted from father to son, but usually the son of a *vicino* would be recognized as a separate member only when moving out of his father's household with his wife. Since the membership right was usually inherited through a male lineage in all the villages, the wives would move to the husband's community and the system would be in balance.[19] There was however

[18] We are more likely to observe explicit immigration regulations where the per capita endowment of common forest and pasture was highest. Some rural Charters do not mention rules to accept newcomers and the reason might well have to do with the fact that nobody ever wanted to move into those "poor" communities. See lines 4 and 5 of Table 2.1 for the frequency of immigration regulations. I did not test this conjecture.

[19] For an example of male inheritance of the right to use the commons, see Tres 1551 (and modification of 1599, chapter 102 and 103). The *vicini* were men representing their families. In particular circumstances the family could be represented by a woman (in particular, the widow, if her male children were still too young). For a more detailed discussion on the recognition of the peculiar nature of these historical forms of collective properties in the Alps, see Grossi (1982) and Capuzzo (1985).

a legal loophole in the system and specifically in the remote valley of Fiemme. Up to 1582, in the Fiemme Valley the right to be a *vicino* was inherited by both sons and daughters of a *vicino*. Since the endowment of common forests and pastures was definitely richer in Fiemme than in many other communities, men from other villages tried to marry women from the Fiemme Valley. The practice became so widespread that the assembly of the *vicini* of Fiemme decided at one point to restrict the inheritance of commons' rights to sons only, as it generally was in most of the other Trentino communities. Asked from the Prince to give reasons, the community governor explained in a letter dated 16 November 1583 about the "mess and losses" caused by immigrants and argued in favor of the reform.[20]

Another possible way to gain access to the commons was to simply become a resident of the village and slowly work the way into a de facto user status. The *vicini* were well aware of this sort of behavior and as a result they usually put a number of obstacles in its way. First, the community needed to give explicit approval before an outsider could use the commons, or sometimes even before settling down in the village. Secondly, the newcomer had to pay an annual fee. Thirdly, in many cases newcomers could not transmit their right to their descendants.

The *vicini* wanted first of all to screen out people not worthy of trust (*degni di fede*) and would sometimes ask prospective residents, as in the Charter of Cles for

[20] A letter from the governor (*Scario*) to the Prince dated 16 November 1583: "*Et perché da uno tempo in qua molti forestieri se maridano in done de Fieme solamente per haver detta vicinanza, et questi tali forestieri continuamente hanno fato e fano assai desordeni et dani in li boschi de essa Comunità ...*" (Delugan and Visani, 1988, p. 54).

convincing proofs of an honest life and of decency.[21] In the Charters where the procedure is mentioned, the consensus of the *vicini* needed to be nearly unanimous.[22]

Admitting additional users on the common resource meant giving away a share of the claims on the resource profits, which is equivalent to alienate a portion of the property rights. The existing users wanted not only to have a say about the admission decision but also to be compensated for the reduction in their share of resources. In corporate law, this right is analogous to the right of shareholders to deliberate about the emission of new preferred shares and decide about their price. Interestingly enough, in 1671 the community assembly of the village of Cis stated - in the very same article of their Charter - that admitting a new member had to be deliberated with the same majority as the one adopted for selling the common land (any group of three or more *vicini* could veto the decision).[23] The annual fee was usually assessed on a case-by-case basis and in proportion to the expected use of the forest and pasture, looking at the size of the family or the number of animals owned.[24]

The acquired right to use the common land was tied to the designated person. It could not be sold or automatically passed on to descendants. Moreover, most of the times the

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[21] Cles 1641 (modification 1719, c.2, "*attestati autentici della sua buona vita et costumi*"). In addition from requiring the prospective member to give good references about his reputation, Nago and Torbole required some form of real warranty in case of misbehavior. For instance, see Nago and Torbole 1647, modified in 1670, c. 72: outsiders cannot stay in the village for more than 3 days unless they own a piece of land or a house (*stabili*) worth at least 200 fiorini. No outlaw could be accepted (*banditi* or *ricercati*). For a description of the situation in the Fiemme Valley, see Ciresa and Salvotti (1978) and Delugan and Visani (1988).

[22] Cis, 1587 (all but three dissenters), Cles,1641, Tres, 1551 (unanimity required in 1599)

[23] See the modification to Cis, 1587, chapter 80: "... *alienare beni comunali o ricevere alcuno forestiero per vicino se meno di 3 vicini son contrari*".

[24] For example Cles, 1641,c.57: "*Che li forestieri habitanti nella communità di Cles siino colettati dalla regola per l'honesto in loro arbitrio, considerando la loro qualità et animali che tengono sopra li comuni, et in più concorrino ad ogni cosa ordinaria et straordinaria come li vicini,...*". See also Tres, 1551 and following modifications.

new user could not participate or vote in the village assemblies and was considered an "outsider resident" but still *forestiero.*

Since sneaking into the community as a would-be new member hardly went unnoticed, outside free riders could only trespass. Such action was unanimously prohibited in the rural Charters (see Table 2.1). Outlawing trespassing, though, was not enough to eliminate it.

One might think that villagers could call in state courts to stop trespassing. But using the state court system to protect the property rights was often impractical because of the high costs involved. At the same time, enforcing the legal property rights on the common forests and pastures was essential to achieve an efficient management. The rural Charters emerged in the 13th century as a legal innovation to reduce the transaction costs involved in enforcing property rights on the land. The rural Charters (*Carte di Regola*) were formal documents drawn up by a notary in front of the village assembly and then sent to the Prince of Trento for official approval. An approved Charter awarded the villagers with the authority to enforce the rules listed in the Charter and in particular with the powers to appoint guards (*saltari*) and inflict monetary sanctions to trespassers.

But even though the Charters created a more efficient, decentralized enforcement of the property rights, not all trespassers were discouraged by the threat of a fine.[25] The enforcement of property rights was in fact likely to be incomplete because of the

[25] For example, the 1677-78 administration booklet of the community of Coredo lists at least ten fines extolled from outsiders, oftentimes for cutting trees in the village forest as is reported in the *Libri de Conti della Honoranda Comunità di Coredo*: "*ricevuto per condane fatte alli sottoscritti come forestieri*" (1677-78). This despite the fact that trespassers had to refund the market value of whatever they harvested and in addition pay a penalty. There are other reports of fines where it is not specified if the payment came from insiders or outsiders: "*per due larici taliati nel ingazato, e venduti a Sfruz*" (1672-73), "*per haver tagliato un pez dent in sas nella sorte*" (1673-74), "*per il valor di legni menati dal monte con buoi forestieri senza licenza*" (1677-78).

monitoring costs and the costs of collecting the fine. Detecting a trespasser, bringing her to court, and cashing the fine were time-consuming. If either the potential damage was small or the action was too difficult to detect, then the community would not profit by engaging in a stricter enforcement of property rights. For instance, detecting trespassing during the night required a higher effort. In order to discourage it, the community usually doubled the penalty. *Instead of increasing the probability of catching the person* p, *the* expected gain from trespassing can, in fact, be lowered by raising the amount of the fine s. A formal model of the decision is sketched in Appendix B.2.

The punishment level, however, was constrained by both economical and legal upper bounds. Under some conditions, there is a level of nominal amount of the fine that could ensure in theory a complete enforcement because the expected punishment $p \cdot s$ can be raised above the actual benefit of trespassing.[26] In practice, there was a ceiling to the maximum fine that could be imposed because of two constraints. The economic constraint comes from the fact that most peasants were poor and did not own much that could be taken away in order to pay the fine. Setting a fine higher than the value of their belongings did not necessarily increase the threat of the punishment. Besides these economic considerations, the rural communities in Trentino could not legally establish fines above a maximum amount set by the central political authority. A 1586 ordinance of the Prince of Trento called the *Moderatio Betta* set a limit of 5 *ragnesi* for any fine stated in the rural Charters. The Prince granted some self-governance powers to the local communities but did not want them to substitute the ordinary courts and laws on more

[26] Raising the level of the fine has two additional effects, a beneficial and a detrimental one. The benefit comes from the extra incentive in detecting trespasser (an increase in p). The extra cost is due to the

relevant issues. Physical punishments, for instance, were not allowed because criminal law was the exclusive realm of feudal authorities. The rule was binding on the communities as it is evident by the attempts to include higher fines and from the subsequent censoring from the Prince bureaucrats when approving the Charters.[27]

In conclusion, there were membership rules and a deterrence mechanism for trespassing that effectively restricted the access to the community land to a well-defined group of users. The enforcement against trespassers was imperfect and – as it will be discussed later on - this made the signal about insiders' cooperation level more uncertain. Moreover, the rural Charters were convenient legal tools to lower the transaction costs of fighting trespassing but they might have been - and actually were - employed also for other tasks.

2.5 Monitoring Insiders

Although less difficult to monitor than outsiders' actions, insiders' usage levels of the common resource were not fully known by the other insiders. As already discussed, imperfect monitoring of insiders might undermine a repeated game solution. Once property rights on the common resources are legally well defined and enforced and once insiders face a continuing relationship, a repeated game solution can be sustained provided that each insider can assess the cooperation level of the others, so that she could decide whether to keep cooperating or to switch to punishing. This section

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increasing effort necessary to collect the fine from the trespasser, since he could for instance appeal to the landlord and Prince courts.

[27] For the text of the *Moderatio Betta* see for instance Salter e Malgolo, 1586. For a comment on the *Moderatio Betta* see Welber (1992).

discusses one way to detect free riding, simply by observing the actions to appropriate the common resource of all the other insiders.

Several cues suggest that monitoring individual actions of insiders was problematic. Consider, for instance, the common prohibition of harvesting grapes in individually owned vineyards before a date designated by the village assembly (Table 2.1). This apparently odd rule is quite sensible when monitoring is imperfect or costly. If all peasants were in the vineyards to harvest on the same day, they could have checked one another's behavior at no additional cost. Without this regulation, instead, it would have been easy for a peasant to pick the grapes of his neighbors without being noticed.[28] In addition, during the weeks before harvesting day, the community paid a guard to police the vineyards all day long - and sometimes all night, too. The existence of guards indicates that the benefit of additional monitoring was above its cost.[29]

More generally, there was a widespread fear of thefts from the fields. There were frequent complaints of robberies of fruits and vegetables. In order to reduce this risk, the peasants adopted inefficient agricultural practices, such as tiny vegetable gardens

[28] This rule was almost always there if there were vineyards in the village (see Table 2.1). For an example see Tassullo, Rallo, Pavillo and Sanzenone, 1586, c.30, 52, 60. One reason was to collect the *decima* (tax on the harvest) but fear of thefts were relevant as Sanzeno (villa), 1586, c.27 makes clear: in case somebody needs to harvest a day before "*che ogn'uno sia obligato lasciar da vendemar appresso li suoi confinanti: che non debba integralmente vendemare in un luogo, havendo confinanti, et questo si apparerà alli regolani; et che quello il quale vendemerà sia obligato avisar li decimani che vengino pigliar la sua decima*".

[29] For an example Vigolo Vattaro, 1496, c.22

Table 2.1: Organizational Features of Legal Institutions

	Feature	*Number of doc. (tot.of 23)*	*% of relevant doc.*	*Relevant documents*
	TRESPASSING AND IMMIGRATION			
1	• Monetary sanction imposed on outsiders who trespassed on the common land	23	100%	All (= 23)
2	• Non-member residents had to pay an annual fee to use the common land	10	43%	All
3	• Explicit consent of village members (*vicini*) was required to use the common land	5	22%	All
	OBSERVABILITY OF INDIVIDUAL ACTIONS			
4	• Higher sanction for violations at night	12	52%	All
5	• Higher sanction for violations committed by outsiders	16	70%	All
6	• Guards for vineyards	15	100%	Where vineyards were mentioned
7	• Prohibition against harvesting grapes before a publicly announced day	13	87%	Where vineyards were mentioned
8	• Guards for high mountain meadows and forests	15	-	
9	• Prohibition against mowing hay before a publicly announced day	12	80%	(10)
	OTHERS			
10	• Participation at meetings was compulsory for all village members	19	83%	All
11	• A share of the monetary sanctions had to be given to the Prince or to the Landlord	8	35%	All
12	• Only witnesses with a good reputation can be accepted in the village court	9	39%	All

Notes: Sub-sample: rural Charters from Valley of Non, 1581-1644. The 23 Charters analyzed are all the documents published in Giacomoni (1991) concerning the Valley of Non (current administrative district of the Val di Non) in the years 1560-1660 with the exclusion of three Charters that were in Latin (Sarnonico and Ronzone, 1586; Mechel, 1587; Bresimo, 1603). Subsequent modifications to the original Charters up to the year 1800 have not been counted in the Table. That would add 3 to line (2), 2 to (3), and 1 to (8) and (9).

located nearby houses and shrunken areas devoted to orchards (Monteleone, 1964).[30] Sanctions for thieves were doubled when monitoring was particularly difficult such as at night or if the thief was an outsider (Table 2.1).[31]

A further example of imperfect monitoring was the prohibition against staying overnight or spending religious holidays in the high mountain meadows and forests. The 1586 Charter of Sanzeno explains that the aim of the rule was to avoid free riding on the common resource or thefts in individual plots. Given that everybody else was in the village or observing the no-work custom, the free rider would have been difficult to catch.[32]

In conclusion, individual appropriation actions of insiders were not public information. On the contrary their knowledge required in general costly monitoring activities. The examples given above show, however, how appropriate information-

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[30] For references from rural Charters, see for instance Malosco 1593, c.25, 26 and Tres 1551, c.53, 54, and 55.

Monteleone (1964), pages 34-37, provides clear evidence for the years 1810s when the rural Charters were abolished. He writes about the thefts in the vegetable gardens: "*L'istituzione dell'orto nel Trentino era ritenuta particolarmente rischiosa per la facilità e la frequenza dei furti che sconsigliavano l'agricoltore non solo dal dargli il desiderabile respiro superficiale ma anche dall'erigerlo in aperta campagna e distante dagli abitati.*" and again about fear of thefts on fruit trees: "*Un altro ramo redditizio della produzione era costituito dal frutteto, la cui diffusione, in generale notevole, trovava però una limitazione comprensibile in non poche regioni caratterizzate da alti indici di delinquenza, che inibiva col timore dei furti l'iniziativa del contadino*". Another colorful example is the theft of the wooden supports from the vineyards: "*... il timore dei furti, a tal punto incruditi negli ultimi anni, da convincere il contadino di non poche regioni che pali e tronconi 'sarebbero rubati, se non il primo, certamente il secondo inverno seguente'*".

[31] For two among many: Salter and Malgolo, 1586, c.26 (fines doubled at night); Sanzeno (villa), 1586, c.13 (fines doubled for outsiders), c.6 (differential treatment of outsiders from insiders: need to leave timber in the village for three days).

[32] Pieve di Sanzeno, 1586, ch.23: "*Item per tor via molti abusi et cative usanze et cativi costumi che per alcuni che per il passato si ha fatto, si statuisce che niuno della pieve non debba, né anco forestiero ardisca, di stare di notte, né dì di festa, eccetto che il gazaro, uno over più, in la montagna predetta ed massime nel tempo della segagion ed mentre è ancor il fieno nelli pradi: sotto penna de lire cinque per cadauna persona; ed se fosse rubato fieno ad alcuno over legnami over anco taiato legnami (...) che si imputi tal furto ed contrafacion a quello over quelli che si trovarono esser stati la note over il giorno di festa sul monte*", see Cagnò, 1587, c.43 for a more generic rule against working during holidays.

gathering institutions could bring a community closer to an ideal situation of perfect monitoring.

In order to gather additional information about insiders' behavior, the Charters adopted three kinds of methods: a direct one - through guards hired to patrol the land - and two indirect ones – through an imposed re-organization of production to make actions more readily observable and through a monetary incentive for whoever would discover the violation of a rule. All three ways involved costs for the community, which is evidence that a positive benefit was expected from it.

Some guards were hired to patrol the high mountain pastures and forests (*saltari del monte*) while others were in charge of patrolling the meadows nearby the village (*saltari di campagna*).[33] The *saltaro* received a share, usually one-third, of the fine collected by anybody that he caught breaking one of the Charter's regulations. If an ordinary *vicino* reported a violation to the governor's officials and the report was recognized to be grounded, he - instead of the *saltaro* - would receive a share of the cashed fine.

The monitoring and sanctioning mechanism set up by the rural Charters contained elements to minimize the chances of bribery. A risk of any legal sanctioning system is that the discovered violator could attempt to bribe the officer who discovered him. Two countermeasures built into the Charters decreased the probability of this course of actions. First, a share of the sanction was paid to the inspector, and, second, any villager had the right to bring the free rider in front of the village court. Consider a free

[33] There were also guards for the vineyards (*saltari delle vigne*). Vineyards were nearly all in individual hands but there still was a need to enforce the property rights toward trespassers. This activity was

rider j who is caught by inspector k and should pay a fine s_j. A bribe B_k might be accepted by the inspector only if it is at least as large as the legal reward, $B_k > \beta s_j$, where $\beta \in (0,1)$. On the other hand, the free rider faces the threat of multiple inspectors for the same violation. Hence, he might need to bribe more than one inspector in order to get away from the legal sanction. When the expected number of inspectors and the share of the fine that is paid to the inspector are sufficiently high, $\beta\ E[N]>1$, the best choice for the free rider is to pay the bigger sanction and not to bribe. For instance, when $\beta=1/3$ bribing is profitable only when the violator expects two or less agents to discover him. Moreover, the bribed inspector could help others to extract more rent out of the free rider by sharing the information about the wrongdoing with other agents.

Gathering information about insiders was costly but the same guards could be employed to report both trespassing by outsiders and insiders' behavior. The economies of scope of the two activities were likely to be very high. Moreover, for reasons similar to the ones put forward for trespassing in the previous section, it was unlikely that knowledge about insiders' actions would be perfect. The interested reader can look at the model in Appendix B.2.

It is worth remembering that much information about other villagers' actions was acquired as a byproduct of daily activities. It thus could be gathered at zero or near zero cost, especially in small villages. Most villages were in fact small, with populations on the order of few hundred people (Figure 2.3).

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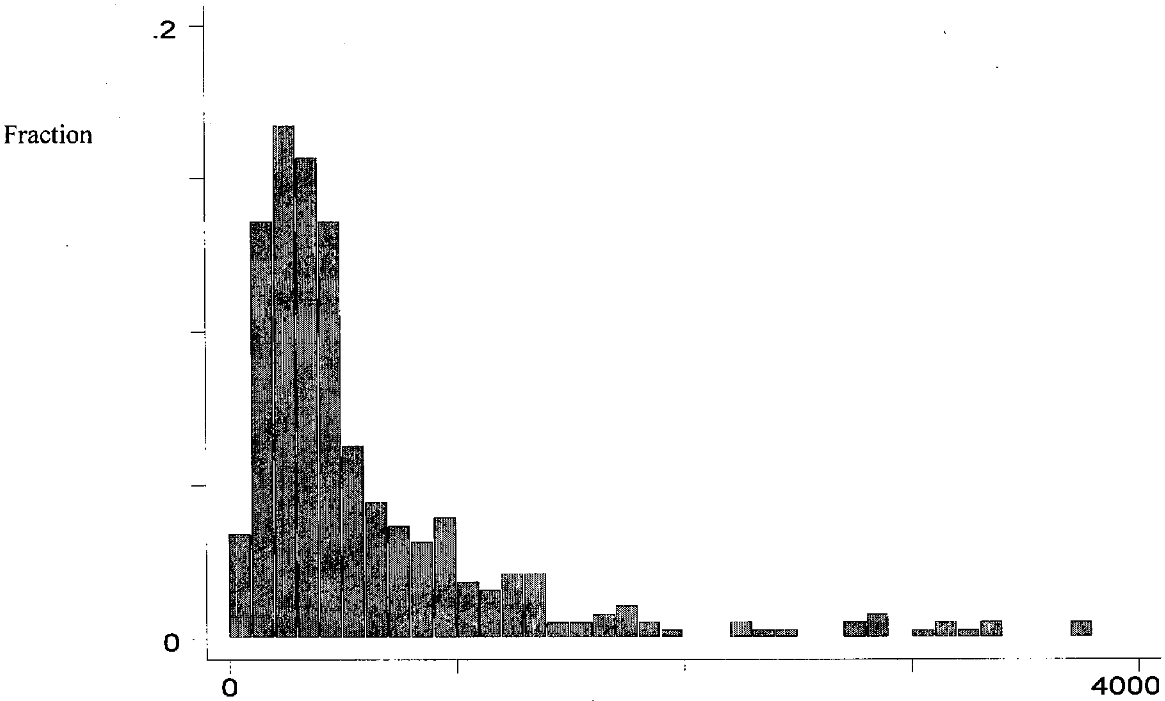
organized collectively and regulated in the rural Charters (see Table 2.1). Switching from village to individual ownership would not exempt from the need for external enforcement of property rights.

Figure 2.3: Communities Sorted by Populations Levels



Note: Two towns with more than 4000 inhabitants were Trento (11,989) and Rovereto (7,069). Eight supra-village entities had also a population above 4000.

Still, information-gathering institutions had two important roles to play: to validate knowledge, and to disseminate it among all insiders. Uncontrolled rumors of a free riding action that quickly spread among insiders could trigger a collective punishment, even if the claim is wrong. To avoid such an inefficient outcome, an established procedure can be followed to investigate alleged violations in order to come up with corroborated and unbiased conclusions. Efficiency might also suffer from lack of coordination. Consider a situation where insiders receive private signals about the actual level of cooperation of the other insiders. Suppose, for instance, that just one user believes that a violation occurred and switches to a punishing mode. The following period the increase in aggregate resource use could trigger everybody else's to punishing. A perturbation of any of the private signals could provoke a cascade that drags the whole group into the punishment mode. Appropriate institutions could help to promote coordination among agents in the choice between cooperation and punishment (Kandori and Matsushima, 1998; Compte, 1998; see note 9).

Village courts and periodic meetings of the *vicini* did precisely this: they helped to accomplish both goals of validating and disseminating information about free riding actions. A village court would hear witnesses, read the Charter, and come up with an 'official truth' about the alleged violation. The court would also eventually inflict a monetary fine to the insider, since there were legal sanctioning institutions for insiders. In principle, however, the two functions of validating knowledge and punishing the agent are distinct and the former one is relevant also for a repeated game solution. There are in fact parallels elsewhere in the world. For example, in some Bolivian communities that rely on informal sanctioning institutions, the leader of the village publicly announces when somebody has violated a norm governing the use of the common resource. The announcement thus works as a coordination device to trigger the punishment by all the villagers.[34]

To sum up, monitoring of insiders' actions was imperfect but proper institutions could improve the efficiency of a repeated game solution through the gathering, validation, and sharing of information. Moreover, there were economies of scope between institutions to monitor insiders and to detect illegal trespassers. Having information about individual actions' of all insiders is one way to assess the cooperation level of insiders but there is the alternative to look at the level of physical stock of the resource. Nevertheless, knowledge of individual actions has the advantage of enabling the community to inflict individual punishments, either using social sanctions or legal sanctioning institutions.

2.6 Institutions to Sanction Insiders

Up to this point, we have shown that community-building institutions and legal sanctions for outsiders are needed if the Folk theorem is to apply. We have also mentioned the possibility that information-gathering institutions can improve the efficiency of the outcome. This section goes one step further by comparing the advantages and disadvantages of legal over informal sanctioning institutions in charge of punishing free-riding behavior of insiders. Most of the Northern Italian communities adopted legal sanctioning institutions for insiders.

When monitoring is imperfect, a repeated game solution involves sizable losses for the insiders. The reason is that informal sanctions in the form of a temporary overuse of the common resource by all the insiders inflict a cost on both free riders and cooperators, a cost that is a deadweight loss for the group. Under perfect information conditions, a self-interested agent never free rides in equilibrium because she knows that the group will surely revert to a punishment mode and the expected individual cost from the punishment outweighs the expected benefit of free-riding. But with imperfect monitoring the group is not able to assess with certainty if somebody free rode. For instance a signal, S, of bad condition of the resource could be the result of insufficient

[34] Oral communication by Marco Boscolo, June 2000.

cooperation or of some external shock, such as unfavorable weather conditions. There were at least two sources of uncertainty on the signal S about the condition of the common forests and pastures: first, an imperfect survey of the current condition of the resource; second, because of chances of thefts from outsiders. Since the enforcement of property rights toward outsiders was not absolute, the theft of an outsider could have been mistakenly interpreted as free riding behavior of an insider and triggered a punishment. In other words, the undetected appropriation by outsiders was an additional and independent source of bias because the same stock of resource could have been the results of various combinations of insider and outsider appropriation levels.

The optimal strategy with imperfect monitoring is to tolerate some degree of apparent overuse of the common resource but revert to a punishment mode whenever the signal is below a given threshold. The implication is that in equilibrium there are recurrent, costly collective punishments of insiders; even when there is no punishment the outcome is still less than optimal.

The mechanism is very different with legal sanctioning institutions. The main advantage of legal over informal sanctions was that the legal sanctions were mostly a transfer of resources within the community and not a deadweight loss. In the Trentino communities, revenues from fines were divided between the officers, the person who brought the violator in front of the court, and the community treasury. Sometimes a share of the fine - usually one-third but sometimes half - was paid to the Prince or to the local feudal lord. In the sample of Charters surveyed in Table 2.1, such payment was required from 35% of the communities. This transfer from the community to the

Prince was not a cost but rather a rent extraction. Since legal regulations were successful compared to the alternative of a repeated game solution and since the Prince had the power to approve or revoke a Charter, he claimed part of the surplus for himself.[35]

The only real variable cost of inflicting a fine came from assessing the violation and eventually having to force the payment, so that a fraction ϑ of the revenue R was wasted in the process of collecting it. This cost includes the resources employed to monitor the individual actions of insiders. While a repeated game solution can rely on aggregate knowledge of resource use, legal sanctioning is based on information about individual actions. This last point brings us to the second advantage of legal sanctions, namely the punishment is directed toward the free rider only and not to the whole group. A mistake in detecting a violation is therefore less costly with legal sanctioning institutions.

On the other hand, the main disadvantage of legal sanctions was the sunk cost of creating and maintaining additional legal institutions. The *vicini* had to agree upon a set of regulations and to finance the monitoring activity and the court system. Writing an official document such as a rural Charter involved non-recoverable costs and so was spending time in the community meetings to listen and vote on an endless list of small issues. There were however strong complementarities between building institutions to legally punish insiders and institutions for the enforcement of property rights toward outsiders. Both required appointing guards to monitor individual actions and once a

[35] The fact that we do not often observe formal regulations also in oligopolistic markets is because cartels are illegal contracts. In order to overcome the unavailability of the otherwise convenient way of enforcing the agreement through courts, the oligopolistic firms use Folk-theorem type strategies.

guard was patrolling the forest looking for outsiders, it took little extra effort to report the actions of insiders as well. Prosecuting outsiders required courts and officials in charge of cashing the fine. The same machinery could be used for insiders. Notwithstanding these considerations, the extra monitoring efforts and the creation of legal regulations for insiders were a cost for the community.

From the fact that the Trentino communities chose legal sanctioning institutions for insiders even though informal sanctioning was available, I conclude that legal sanctions were more efficient in the sense that the payoff of legal institutions was greater than the payoff of a repeated game solution:

$$\Pi^* - C - \vartheta R - TC \quad > \quad (1-\alpha)\,\beta\,\Pi^* + \alpha\,\Pi' - TC, \quad 0 < \alpha, \beta < 1, \quad \Pi^* > \Pi'$$

Where TC are the transaction costs common to legal and informal sanctioning for establishing community-building institutions and legal sanctioning institutions for outsiders, C is the additional sunk cost of legal regulations of insiders and information-gathering institutions, and Π^* is the maximum group profits in an ideal zero transaction cost world.

The greater efficiency of legal sanctioning institutions is not a general conclusion but depends upon informational and technological conditions. For instance, the efficiency of a repeated game solution depends from the quality of the signal about the condition of the resource. The more erratic was the pattern of trespassing by outsiders and the worse was the signal. A legal regulation of insiders was likely to be more efficient for villages nearby a main road or in a heavily inhabited valley than in isolated villages. Another central variable was the wage level. Institution-building is a labor-intensive activity, so the lower the salary relative to the value of timber or milk, the more likely that a community would choose legal sanctioning for insiders. These and other implications will be tested in Section 2.7.

To sum up, legal sanctioning institutions exhibit advantages and disadvantages in comparison with informal sanctioning institutions. The advantages are that the punishment is not a deadweight loss for the group and is directed only toward the free rider instead of the whole group. The disadvantages of legal regulations include the need to build additional legal institutions to prosecute insiders and to monitor individual actions of insiders. Social sanctions have been briefly discussed. In the specific conditions of the Northern Italian communities, legal sanctioning institutions for insiders were chosen probably because they were more efficient than a repeated game solution. Still, we need to explain how those institutions came to place.

2.7 A Choice between Two Sub-optimal Alternatives

In a world without transaction costs, where property rights can be enforced without effort, and where information is freely available, a repeated game solution delivers full efficiency and so does a legal institution. When those conditions are not present, both solutions are to some degree sub-optimal, and their relative efficiency is affected by the external environment. Given the assumption that the better of the two institutions is chosen, an empirical investigation can be carried out.

About three quarters of the communities in the region under analysis had had a rural Charter by 1800. The others either lost the Charter or managed their common resources without legal institutions. Moreover, the number of Charters written over time varied considerably between the 13th and the 19th centuries. If the analysis conducted in the previous sections is correct, then a repeated game solution was more likely to be chosen by communities that were small and remote, and under conditions of high salaries.

Implication 2.1

The remoteness of a community increases the efficiency of a repeated game solution because there are lower chances of trespassing by outsiders.

The effect of remoteness is two-fold: on one side, it is less beneficial to build local legal institutions to enforce property rights toward outsiders and, on the other side, monitoring insider cooperation levels is easier (Section 2.5).

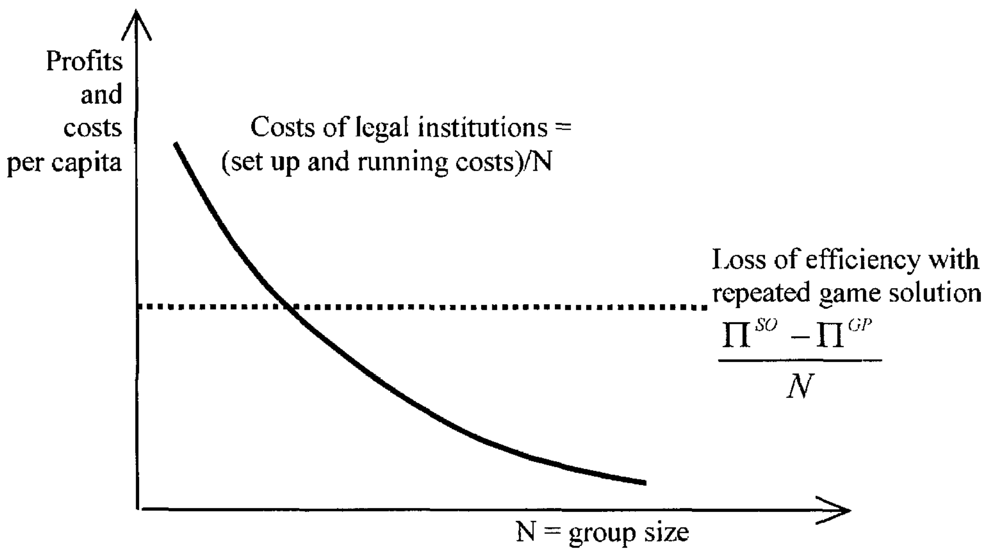
The level of remoteness is measured by the distance in kilometers of a community from the local town, which was generally the reference place in the valley.[36] Given the mountain landscape, an alternative measure of remoteness can be constructed as an attempt to include also the steepness of the connecting road by combining with various weights distance and altitude difference.

Implication 2.2

The smaller a community, the less efficient are legal institutions because of the fixed costs of setting up and running legal regulations.

Writing a Charter is a fixed cost, which is basically independent from the community size. Paying community officers and guards was also more costly per capita if the group of users was smaller (Figure 2.4). The implication is that small villages will either group together to form a larger community or they will turn to the repeated game solution, since it will be a better choice. In either case, the communities administered by a Charter are likely to be bigger than the ones who are not. Community size is here measured by their population in 1810.

Figure 2.4: Community Size and Efficiency of Legal Institutions



The results of the empirical tests about the effect of remoteness and community size on the probability of having adopted a charter are shown in Table 2.2. Both Implications 2.1 and 2.2 are supported by the sign of the coefficients in the logit regression. Larger communities are more likely to have had a Charter by 1800 than smaller communities, and more remote communities are less likely to have had a

[36] Seventeen centers were selected: Borgo, Canal S.Bovo, Canazei, Cavalese, Cles, Condino, Fondo, Levico, Malè, Mezzolombardo, Pergine, Riva del Garda, Rovereto, Stenico, Tione, Trento.

Charter than less remote communities. This last result is robust when alternative proxies for remoteness are adopted.[37]

Table 2.2: Effects of Remoteness and Community Size on the Probability of having Adopted a Charter by 1810

Logit regression	Coefficient	p-value
Dependent variable: The community does (1) or doesn't (0) have a Charter in the year 1810		
Independent variables:		
Community size (inhabitants)	0.00089	0.001
Remoteness (distance in km from local town)	- 0.08241	0.000
Constant	0.87348	0.001
Sample size:	295	
Pseudo R2	0.087	

While the two implications above are relative to the situation at a given point in time[38], the third implication concerns the emergence of legal institutions over time.

[37] Some communities included more than one village. There might have been a general community Charter, and eventually a village Charter in addition to it. The region was divided into 392 geographical units and the regression presented in Table 2.2 excluded the units that were in the above condition.
[38] The point in time chosen was 1800, but similar tests could be performed for any year as long as reliable data about population at the village level could be collected.

Implication 2.3

As building legal institutions was a labor-intensive activity, a decrease in real wage increased the likelihood that a Charter was written.

This consideration can shed some light on the temporal distribution of new Charters. The period 1200-1800 has been divided into either 50-year, 25-year, or 10-year intervals, and the number of new or rewritten Charters has been counted. These time intervals were dictated by the availability of data about real salaries (Allen, 1998, Wilson and Parker, 1977). The results neither support nor reject Implication 2.3. The sign of the coefficients are correct (negative), but the values are largely insignificant. Given the limited sample size and the distance between Trentino and the places from where data about real salaries of building laborers are available (Milan, Vienna, Genoa), the test cannot be considered conclusive.

To sum up, this section has formulated and tested three implications of the analysis done so far about the relative efficiency of a repeated game solution versus a legal institution. Two implications are supported by the data, while a third is not rejected. A legal institution is more likely to emerge when the community is large and not remote.

2.8 Second Order Social Dilemma: Who Builds the Institutions?

We know for a fact that the most Trentino communities – instead of relying on a repeated game solution among their members - adopted legal sanctioning institutions for insiders. If they made this choice because it was more efficient, we still have to explain how those institutions were established. The point in question is that legal institutions are similar in nature to public goods, they supply valuable services to the whole group but they are costly to provide and each member of the group has too little incentives to contribute to them. As a result, a beneficial institution might never be created. A possible way around it is the one chosen by the Trentino communities.

Compliance with the regulations benefited everybody because it promoted efficient use of the common resource. Regulations were enacted through a legal sanctioning system toward insiders. In the Northern Italian villages, the community officials exacted a monetary payment when an insider appropriated timber or grazed on the commons in violation of a Charter rule. Inducing compliance with the regulations, on the other hand, constituted another social dilemma. Crafting, updating, and enforcing legal regulations involved costly activities and it was not in the best self-interest of any individual to voluntarily bear those costs. In other words, regulations solved the social dilemma of the use of a common resource but generated a second-order social dilemma of institution building.

Before discussing how the new dilemma was solved, we have to consider the costs associated with legal regulations of insiders. There were at least three types of costs: first, resource use rules and prosecution procedures had to be negotiated in meetings among villagers, recorded by a notary, and then submitted to the political authority for approval. For instance, participation at the community meetings was time consuming and the discussions frequently raised animosities.[39] Some villagers would have preferred to avoid them. Second, once the legal rules and procedures were agreed upon,

[39] Bringing weapons to the meetings, even a knife or a farming tool, was prohibited. Sometimes the guard (*Saltaro*) could bring the *roncola*, a special cutting tool used for chopping wood. Many charters explicitly punish the use of insulting words during meetings.

a specific effort had to be devoted to information-gathering activities in order to monitor the individual actions of insiders. That could have taken the form of additional guards, constraints on actions – such as a rule outlawing going out at night in the woods -, and voluntary monitoring efforts by ordinary *vicini*. Third, enforcing regulations entailed other significant costs. A transgressor sometimes had to be brought in front of the governor and an estimation of the damage that was done to the resource assessed. Sometimes dedicated officials (*stimadori*) were in charge of suggesting a fair compensation to be paid on top of the penalty indicated in the Charter. The convicted transgressor could then appeal to the community assembly and after that to the Prince courts. These activities of determining the amount of punishment and actually exacting the payment were costly. For instance, the office of governor (*regolano*) was oftentimes taken on unwillingly by a *vicino* because it was more of a burden than a form of employment. The option of relinquishing the office after being elected was frequently considered unacceptable. To avoid an uneven distribution of these labor contributions among the insiders, some communities rotated the office among all the *vicini* while others set limits to the number of consecutive terms in office. [40]

To sum up, legal regulations were costly to provide but the *vicini* did not have the individual incentive to voluntarily provide efforts to build and run them. As mentioned, there is evidence in least two instances - participation in assemblies and acceptance of some offices - that the *vicini* were quite reluctant to contribute to the village institutions.

[40] Seio, 1616, c.1: The refusal to take on the governor office when elected is punished. *Vicini* are appointed guards by rotation. See also Casez, 1632, c.5. The Charter of Romallo,1598, c.81 mentions the need in general of the *vicini* to perform their duties, "*fare tutte le foncioni ordinarie et straordinarie.*"

Surprisingly, this second order social dilemma of providing legal institutions was surmounted through a repeated game solution. According to the theory of repeated games, provided that some conditions are met, an optimal level of contributions to the creation of legal institutions could be sustained. In this case there was no difficulty in observing individual actions because everybody knew who was participating in meetings, involved in court actions, or holding offices. Eventual free riding could have been punished with social sanctions or other means. The community of Romallo provides an example: it explicitly used ostracism. A *vicino* who refused to perform the required tasks was deprived of his status of insider and considered an outsider. As such he would have to pay rent for using the communal resources.[41]

The role of a repeated game solution here helps to resolve the paradox that we began with: namely, that although the Trentino communities satisfied the conditions of the Folk theorem to sustain a repeated game solution, they apparently turned to legal regulations to manage the commons. The paradox was only apparent. The seemingly redundant institutions, in fact, served different purposes. The legal regulations aimed at limiting the appropriation of resources from the common forests and pastures, while the repeated game solution supported the provision of the necessary legal institutions. The paradox is thus resolved.

In a sense, both the informal and especially legal institutions can be thought as social capital (Coleman, 1990, chapter 12). They were part of a set of valuable assets in the form of community organizations, social networks, and customary coordination cues that were useful for the efficient conduct of economic activities. Such social capital is

[41] Romallo, 1598, c.46 "... *et se alcuno vicino dicessero e non volessero far per fuogo, sia astretto et*

subjected to depletion and needs constant replenishment in order to allow the same level of efficiency. A portion of this capital was inherited from previous generations. A member of the community benefited not only for the availability of a physical capital in the form of communal forests and pastures but also from the social capital that protected the property rights and made possible the efficient use of the resources. With a weak central state, it might well be that physical resources would be worthless without social capital. [42]

In conclusion, the contributions to institution building activities from insiders were provided thanks to the repeated nature of the interaction among insiders. The Folk theorem helped here but it did not directly solve the social dilemma of limiting the use of the communal resources. Rather, its role was only indirect in that it supported the creation and maintenance of the legal institutions, which prevented the 'tragedy of the commons'.

2.9 Conclusions

This paper discusses the interrelations between legal institutions and repeated game solutions in solving a well-known social dilemma, the management of a common property resource. The issue is examined in reference to the alpine communities of the

sottoposto a perdere e renunciare la sua parte di commun et sia obligato pagar l'affitto come forestiero."

[42] The services provided by the community organization were valuable. Since insiders contributed to building the social capital, they were asked to pay less than outsiders for such services. An example are the payments requested to outsiders for the services of protection of property rights inVion, 1620, c.45, "*Item hanno statuito et ordinato che se alcun forestiero che haverà o possederà beni nelle pertinenze di Vion sia tenuto ong'anno dar al saltaro, qual haverà avuto custodire delli suoi beni, una quarta di segalla.*" See also Pieve di Vigo di Ton, 1644, c.2 (outsiders pay more than insiders for the services of the guard). Another example is about the service of damage estimation from village officers Sanzeno (villa), 1586 (modification 1694, c.5) "*Che li regolani per stimare danni habbino per loro mercede carentani sei a*

Trentino, a region of Northern Italy. The commons were managed by the communities through self-governing institutions that were coded in formal documents called *Carte di Regola*, or rural Charters. A Charter was a contract among the members of the community, on one hand, and between the community and the ruler, on the other, that allowed the community to establish and enforce local economic regulations.

Legal institutions existed side by side with the sort of repeated interaction that would breed a repeated game solution generating a paradoxical redundancy of institutions. The contribution of the paper is a game theoretical and property rights examination of the emergence of this pre-modern institutional framework. Other studies have highlighted the complementarities between legal institutions and repeated game solutions to facilitate private enforcement of rules (Hay and Shleifer, 1998) and trade (Greif, 1998b; Clay, 1997; Greif, Milgrom, and Weingast, 1994; Greif, 1993; Milgrom, North, and Weingast, 1990). Here the focus is the relative advantages and disadvantages of one over the other and on the conditions that make self-governance possible.

One might think that the rural communities of Northern Italy in the period from the 13th to the 19th century offered the ideal situation for observing the Folk theorem in action: the villages were small and isolated in a mountain area, the villagers interacted with one another, and remained in the same village for generations. Upon closer inspection, however, it becomes unclear whether the Folk theorem actually applies. In fact, whether the standard Folk theorem operated turns out to depend on the presence of legal institutions purposively created to make it work. Property rights were aimed at excluding outsiders from the use of the commons and promoting a long-term

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ciascheduno di loro, et il medemo al saltaro denuntiante; et se il pretendente l'estimo del danno fosse interaction among the users (Rubinstein, 1979; Green and Porter, 1984; Fudenberg and Maskin, 1986; Abreu, Pearce and Stacchetti, 1986, 1990; Kandori, 1992a, 1992b; Fudenberg, Levin, and Maskin, 1994). The two goals were achieved by prosecuting trespassing and by an elaborate set of membership rules. In particular, as leaving the community meant renouncing the benefits of the common resource, villagers had an incentive to stay.

Despite having created the conditions to support a repeated game solution, the rural communities adopted legal institutions to manage the commons, where users who exceeded quotas or violated time or place restrictions were subject to monetary fines. Here the legal institutions were legal constraints to behavior that could be enforced in court. The rural Charters established self-governing legal institutions, which means that the insiders chose themselves the set of rules and were responsible for the enforcement of those rules.

Limiting the overuse of the common forests and pastures with legal institutions was probably more efficient than with a repeated game solution. Both alternatives were available yet at least three quarters of the communities relied on legal institutions, not on a repeated game solution to the problem. The rural Charters were the solution: a legal innovation that decreased transaction costs of defining property rights and enacting legal regulations. They made it possible to replace the expensive state courts with village officers.

Legal regulations like the rural Charters have the advantage of a more efficient sanctioning system but they require the development of additional legal institutions that

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forestiere, haverano li regolani et saltaro il dopio" are costly to create and maintain. As for the repeated game solution, it entails significant deadweight losses because imperfect monitoring leads to the recurrent collective punishment of users. In order to sustain cooperation, the users must know the cooperation level of the others, so that they can decide whether to keep cooperating or to switch to punishing. As the users receive only a noisy signal about other players' cooperation, there will be periodic overuse of the resource that will harm both free riders and cooperators. A legal sanctioning system, by contrast, targets only free riders and punishment merely transfers resources within the community and is hence not a deadweight loss. Exacting monetary fines does involve some effort but most of the money ultimately flows to either the community officials or treasure.

The chance of a repeated game solution over a legal institution reflects the relative efficiency of the two solutions, which varies according to informational and environmental conditions. Three implications of the theory here outlined are formulated and tested. Two implications are supported by the data while a third is not rejected. The results are that the legal institution is more likely to emerge when a community is large and not remote. The effect of the wage level on the institutional choice was not conclusive.

On the other hand, creating and maintaining additional legal institutions was costly. The users had to agree upon a set of regulations, engage in extra monitoring activity, and run the court system. Those activities absorbed real resources and such costs should be taken into account when comparing efficiencies of different arrangements.

The choice of legal regulations for the management of the commons raises two related questions. On one side, stating their superiority in terms of efficiency does not explain how legal institutions themselves were established. Since the legal regulations were self-governing, the users themselves had to bear the costs of creating and maintaining them. Legal institutions are public goods, in the sense that they supply valuable services to an entire group, but are costly to provide and individual members of the group have too little incentives to furnish them on their own. As a result, a beneficial institution might never be created. On the other side, there is the paradox of redundancy because legal institutions existed side by side with the sort of repeated interaction that would support a repeated game solution.

To resolve the paradox, we have to consider the two layers of social dilemmas. The first layer concerns the efficient use of the commons, and it was surmounted through legal regulations of insiders. In turn, that arrangement generated a second order social dilemma of provision of such legal institutions. This second-order dilemma was solved thanks to the repeated interaction among insiders, which supported a repeated game solution. In other words, there was no redundancy of institutions. The theory of repeated games did not help directly with the first-order social dilemma, but rather indirectly with the problem of providing legal regulations. Self-governance was possible because there was a sustainable way to promote institution-building efforts.

Chapter 3

Decentralized Management of Common Property Resources: Experiments With a Centuries-old Institution

3.1 Introduction

For six centuries a special institution for managing common property resources was long and enduringly employed by villages in the Italian Alps. It began to emerge at the beginning of the thirteenth century for application to common forests and pastures and remained in place until it was forcefully removed by Napoleon in 1805 (Casari, 2000). The experiments and theory reported here reflect an attempt to pinpoint the reasons for the success of this particular system when compared to other systems with similar institutional features. Part of the research involves the study of experiments reported by others and the paradoxes one can see in their data.

The decentralized management system negotiated by the Italian villages had a very simple structure. The population of a village developed a contract among themselves, subject to the approval of the regional government, called *Carte di Regola*, where they describe a system for monitoring and sanctioning those who are discovered violating or exceeding patterns of use that the villagers agreed upon in the contract. The *Carte di Regola* specified in advance the conditions under which a sanction could be inflicted on a person found in violation of the contract and the amount of the fine. The village court would sentence people who used the common resource above an established limit to pay a fine proportional to the severity of the damage inflicted to the community. Any villager could report a violation but he usually incurred a cost in the form of a monitoring effort to discover the violator and additional costs to bring him to court. A share of such a fine usually went to the person who discovered the violator in order to give an incentive to monitor. The questions posed for study here are related to how this particular management system performs and why.

Experimental results have demonstrated that unregulated use of a common-pool resource such as a common pasture or fishery generates inefficient levels of use. However, the experimental literature contains a fundamental paradox, which we will call the spite/altruist paradox, which is in need of replication and explanation. On the one hand, Walker, Gardner and Ostrom (WGO, 1990) report group over-use of the resource at levels that go beyond what a pure free-riding Nash equilibrium model would predict. That is, the individuals choose to exploit the resource beyond what the self-interested Nash model would predict, as if individuals actually wanted to harm the group in a manifestation of spitefulness. On the other hand, in a public goods environment, which is essentially a transposition of a common-pool environment, Andreoni (1995) and Isaac, Walker and Williams (1994) report behavior of an opposite nature. They report cooperation levels above the Nash equilibrium in public goods environments while WGO report cooperation levels below the Nash equilibrium in the common-pool environments. It is as if people are altruistic when faced with public goods provision and the opposite ("spiteful") when using common-pool resources. The spite/altruist paradox is the suggestion that cooperative behavior is the opposite within two institutions that are theoretically similar.

The experimental results reported in this paper are first that the *Carte di Regola* institution is surprisingly successful in raising efficiency in the use of a common-pool resource. In addition, the patterns of results previously reported in the literature are replicated. As it turns out, spite/altruist paradox can be explained by a model where agents have heterogeneous, other-regarding preferences. Such model allows for selfish, altruistic, and also spiteful agents. The interaction among these different types of agents -

and in particular the presence of spiteful individuals - can explain a wide array of regularities related to these and other similar experiments. In addition, the model provides insights about how the institution relies on the heterogeneity of preferences that exist in the population to efficiently coordinate decisions into the enforcement of management plans.

The structure of the paper is as follows. Section 3.2 outlines aspects of the institutions under consideration. The basic common-pool resource environment is introduced in Section 3.3. The classical game theoretic model is outlined in Section 3.4. The stylized version of the *Carte di Regola* monitoring and sanctioning institution is described in Section 3.5. These two sections also present the Nash equilibrium according to the classical model, where all agents are selfish and this fact is common knowledge. The other-regarding agent model is outlined in Section 3.6 along with the predictions for the various treatments with and without sanctions. The experimental procedures are described in some detail in Section 3.7. Baseline experiments without sanctions are reported in Section 3.8. Here the results of WGO are replicated and extended. The results of experiments with sanctions can be found in Section 3.9 and Section 3.10. Two treatments of the sanctioning mechanism are studied: a weak sanction institution that should have no effect on the outcome according to the classical model and instead greatly improves efficiency; a strong sanction institution that has the goal of bringing the group to the socially optimal outcome and turns out to fall slightly short from the target. A discussion in Section 3.11 demonstrates how the models extend themselves to related issues and data. Section 3.12 contains reflections about the nature of the institution and speculates about why it had such remarkable success. Section 3.13 is a summary of conclusions.

Table 3.1: Monitoring and Sanctioning Institutions

	CASARI and PLOTT (2001) [This study]	**MOIR (1999)**	**OSTROM et al. (1994)**	**FEHR and GäTCHER (2000)**
Environment:	**Common-pool Resource**	Common-pool Resource	Common-pool Resource	Public Goods Provision
MONITORING (SEARCH)				
• *Monitoring Fee*	**Fixed fee for each request**	Variable fee for each request	None	None
• *Are all individual use levels (investment levels) revealed?*	**No, only if somebody in the group requests it**	No, only if the agent requests it	All use levels are public; all agent histories are public	All use levels are public; no individual history is available
SANCTIONING				
Targeted agent:				
• *Amount of the fine*	**In a fixed proportion of over-use**	*Subjective choice* of inspector (variable upper bound)	*Subjective choice* of inspector (fixed upper bound)	*Subjective choice* of inspector (up to 100% of period earnings)
• *Condition for inflicting the fine*	**If over-use occurred**	If over-use occurred	Subjective	Subjective
• *Multiple fines on the same action*	**No**	Yes	Yes	Yes
• *Identity of targeted agent*	**Publicly known after fine**	Publicly know after fine	Unclear*	Known only to targeted and inspecting agent
Inspecting agent:				
• *Fee (cost of administering the fine)*	**Included in monitoring fee**	*Proportional to* the amount of the sanction	*Proportional to* the amount of the sanction	*More than* proportional to the amount of the sanction
• *Who receives the fine*	**Inspector**	Experimenter	Experimenter	Experimenter
• *Limits to requests of sanctions per period*	**None**	Limited to the budget of the inspector	Each agent is limited to a single request	Unclear*
• *Identity of requesting agent*	**Not revealed**	Not revealed	Not revealed	Not revealed*

Notes: (*) This feature was not explicitly described in the papers. Monitoring is always perfect (i.e., there is truthful revelation of the action). In Ostrom (1992) and Fehr and Gächter (2000) agents can sanction each other but there is really no monitoring device, since the individual actions are automatically revealed to everybody at the end of each period. Moir (1999) introduces two distinct decisions, first to monitor an agent and then to eventually sanction her. We have compacted them in a single decision: to inspect an agent or not. An inspection uncovers another agent's action and automatically inflicts a sanction if some conditions are met.

3.2 Management Systems and Sanctioning Institutions

A variety of systems for the management of common property resources and public goods provision can be found in the literature. All systems are structured around the assumption that unless guided by specially crafted institutions the users of the resource hold the potential for over-exploitation and sub-optimal use or, in the case of public goods, a failure to pay for the provision of the public good. To an untrained eye, the differences among the different systems might seem insignificant, but through the lens provided by economic theory and by game theory, the differences are substantial. This paper is concerned only with provisions of sanctions that are associated with the more decentralized systems. Table 3.1 lists major variables and the papers in which investigations have been reported.[1]

The variables fall into two major classes. The first is related to the cost of monitoring and what might be revealed as a result of monitoring. The presumption is that the actions of individual users are not necessarily freely observable and that management institutions might differ accordingly. The *Carte di Regola* system studied here was crafted to address common property resources and the assumption is that for any one agent there is a cost of observing the levels at which various other agents use the resource.

The second class of variables is related to the nature of rewards and punishments involved in detecting an agent who over-uses the resource, the sanctioning institution. Some variables are related to whether or not a sanction/fine is levied on the targeted agent, including the amount of the sanction or sanctions and whether the sanction was

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[1] Some studies have not been included in the review either because they have an external sanctioning authority (Beckenkamp and Ostmann, 1999, Cardenas et al., 2000) or because the experimental design is for other reasons too different from ours (Yamagishi, 1988; McCusker and Carnevale, 1995). See Ostrom (1990) for field examples.

public. Other variables are related to the position of the inspecting agent including the financial costs and benefits of conducting an inspection. In particular, the amount of the sanction and indeed whether a sanction is levied or not is determined according to a known rule as opposed to being determined by the inspector.

A study of the Table 3.1 will reveal that the *Carte di Regola* differs from other systems in two important ways. First, the fines resulting from social sanctions involve a transfer of income from the inspected to the inspector as opposed to a loss of system wealth. Of course, the cost of inspections is a loss to the system. By contrast, successful fines in the other systems are a dead weight loss to participants. Second, the punishment level cannot be changed by the inspector and is set to fit the crime. In particular, the targeted agent pays a fine only if use of the resource is more than a publicly known level and the fine is proportional to the excessive use.

The theory and experiments reported below are focused on the *Carte di Regola.* The focus is on the efficiency properties of the system and on models that are put forward to help explain the behavior of the systems. Experiments with no sanctions establish an important baseline for comparison with other studies and for measuring the impact of the *Carte di Regola.* Then by varying the level of sanctions the model with heterogeneous agents can be explored and compared to the classical model that has been used to capture the performance of other institutional arrangements.

3.3 The Laboratory Common Property Resource Environment

The environment studied here is similar to common pool resource environments studied elsewhere in the literature (See Appendix A). A group of N agents interacts in the use of a common pool resource. In general, agents have preferences for any benefits they receive from the availability of the common pool resource as well as the cost to them of their efforts to harvest it. However, for purposes of developing the models in terms of preferences that will be found later in experimental environments, each agent, i, is characterized by preferences of a special form where π_i can be interpreted as a personal monetary value of resource use net, of any per unit cost, α, resulting from a level of effort, x_i:

(1) Ui (π_i) where:

(2) $\pi_i = \frac{x_i}{X} \cdot f(X) + \alpha \cdot (\omega - x_i)$;

x_i, $\in [0,\ \hat{x}]$ is interpreted as the level of "effort" expended by agent i in the use or harvesting of the common pool resource, $X = \sum_1^N x_i$ is the total use levels of the group of N agents.

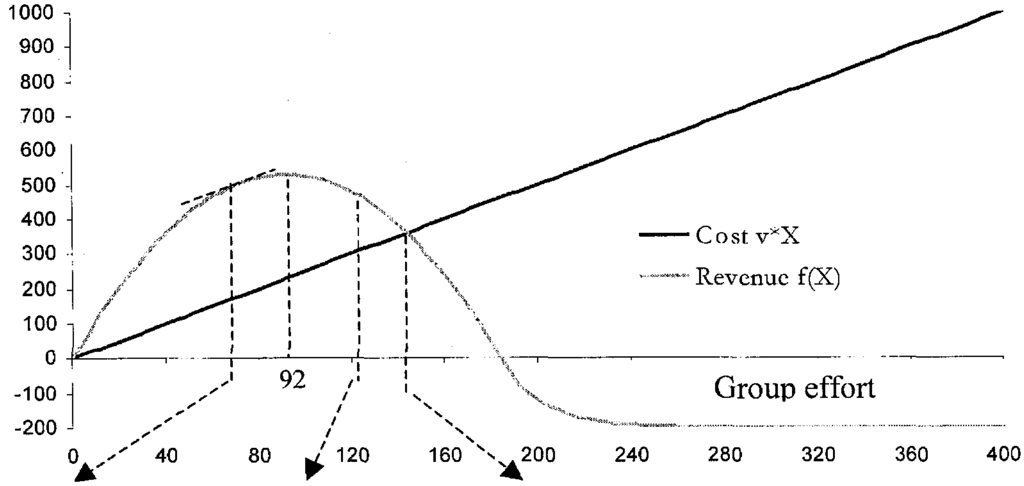
$f(X)$ is the quantity of a common pool resource, interpreted as a group revenue,

$\frac{x_i}{X}$ is the fraction of total the group effort that is expended by agent i. If $x_i = 0$ then the agent gets none of the common pool resource. ω is a parameter indicating the "initial endowment" of agent i and it is the fraction of revenue that is returned to i. If x_i =0 the agent gets $\alpha \cdot \omega$.

The group revenues $f(X)$ are nonlinear in the group effort and first increase in X up to a maximal point and then decrease as illustrated in Figure 3.1 and defined by (3).

(3) $$f(X) = \begin{cases} aX - bX^2, & if\, X \leq 184 \\ 200 \cdot [e^{-0.0575(X-184)} - 1], & if\, X > 184 \end{cases}$$

Figure 3.1: Technology of the Common Pool Resource



OPTIMAL USE	*NASH EQUILIBRIUM*	OPEN ACCESS	
72	128	144	Group use X
9	16	18	Symmetric individual use
100%	39.5	0%	Efficiency level *(% of maximum rent)*

The dynamic of renewable resources is generally modeled with a parabola (Clark, 1976, Gordon, 1954) as it is done in the first piece of *f(X)*. For high level of efforts *f(X)* has a lower bound at –200.

The parameters used throughout the experiments are N= 8, $\hat{x}$=50, α = 5/2, a = 23/2, b=1/16. The parameter ω has no effect on the incentive structure of the game theoretic models and in the experiment can be viewed as a fixed bonus to subjects for participation.

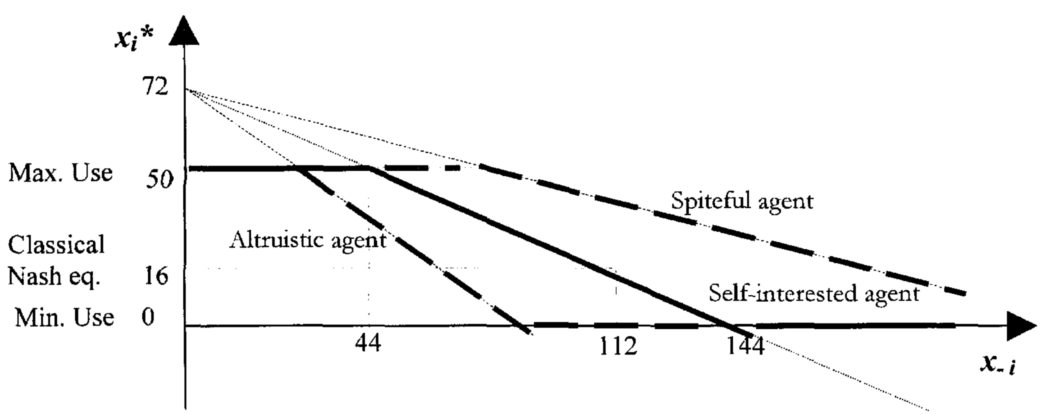
The resource environment can be viewed as the physical environment, including preferences and the relationships among effort and the magnitude of the resource pool. How those interact depends on institutional arrangements and the behavior that takes place within those institutions. The following sections address models of those relationships.

3.4 The Classical Model

Behavior within the context of a common pool resource environment can be understood in the context of principles of game theory. The structure of the environment *in the absence of any intervening institutions leads to a game theory model that we will* call the *Classical Model.* That is, a description of the physical environment is simultaneously a description of the institutional environment. Individuals are assumed to maximize $U_i(\pi_i)$ as defined in (1) and (2) subject to the strategy set, $x_i, \in [0, \hat{x}]$ and the relationships found in (3).

It is important to notice that the utility function defined by (1) has no parameters related to the income of others or risk aversion. Furthermore, it is assumed in the classical model that all agents have the same utility function.

Figure 3.2: Best Response Functions, No-Sanction Treatment



Notes: In the no-sanction design (N=8, a=23/2, α=2.5, b=1/16) the classical best response function (selfish agent) is x_i*= 72 - ½ x_{-i} (solid bold line).

The Nash equilibrium of the game is easy to compute. From the first-order conditions to maximize earnings $\frac{\partial \pi_i}{\partial x_i} = 0$ we derive the best response functions $x_i{}^* = \frac{a-\alpha}{2b} - \frac{1}{2}X_{-i}$, where $X_{-i} = \sum_{j \neq i}^{N} x_j$, which is a linear function of the use level of everybody else (Figure 3.2). As all agents have identical incentives and preferences, at the Nash equilibrium the group outcome is $X^* = \frac{N}{(N+1)} \cdot \frac{a-\alpha}{b}$, when Na-184(N+1)b > Nα. In this game the Nash equilibrium is unique and symmetric.

Given the parameter values N=8, a=23/2, α=5/2, and b=1/16, the Nash equilibrium outcome is X=128, which corresponds to an individual effort level of x_i=16 ∀i.

The efficiency of an outcome is defined in reference to the group earnings minus the endowment money Π'=Π - Nαω. A group outcome is normalized using the maximum earnings that the group could reach ($\overline{\Pi}$'=324). This efficiency index scores 100% when the resource is used at the socially optimal level and 39.5% at Nash equilibrium. The efficiency of the Nash equilibrium goes down as group size goes up because there is less incentive to take into account the strategic interaction among the agents.

The last observation is of particular interest because it leads to another model that we shall call *open access*. When the number of users goes to infinity, agents completely ignore the strategic interactions among them. If the number of agents is finite but agents are poorly informed about the consequences of the actions they take (in the sense that agents believe that $\frac{\partial}{\partial x_i}[\frac{x_i}{X} f(X)] = 1$), then the model leads to exactly the same behavior. The solution at the open *access* equilibrium has efficiency at 0%, which implies a complete destruction (Π'=0) of the potentially positive incomes that the group could have made out of the common-pool resource. The efficiency is 0% because agents use the resource up to a point where average costs equal average benefits.[2] Given the parameters adopted, the socially optimal outcome is at X=72 and could be obtained if all the eight agents in the group choose x_i = 9 while the open access outcome is at X=144 (x_i=18, Figure 3.1). If the group uses the resource above the open access level, group earnings are negative and efficiency can be as negative as –321% (for X=400).

Proposition 3.1A (*RESOURCE USE WITHOUT SANCTIONS*) Without a sanctioning institution, the classical Nash equilibrium outcome has an efficiency of 39.5% [group appropriation X=128]. All the agents use the resource at an identical rate of x_i = 16.

3.5 The "Carte di Regola" System under the Classical Model

The basic features of the "Carte di Regola" mechanism for monitoring and sanctioning are captured by a simple game where any agent i in the group has the option of selecting other individuals $j \neq i$ for inspection after he has privately decided his own exploitation level of the common-pool resource. At a unitary cost k, the inspector can view the decision of any individual. If the inspected individual has exploited the resource excessively, relative to a publicly known amount λ, a fine s_j is imposed and paid to the inspector:

$$s_i = \begin{cases} 0, & if\ x_j \leq \lambda \\ h(x_j - \lambda), & x_j > \lambda \end{cases}$$

The parameter h is the unitary fine for each extra unit of effort and measures the stiffness of the punishment. Agent i makes a profit when the fee k paid to carry out the inspection is more than compensated by the transfer s_j from agent j to agent i, namely when r_{ij} = (s_j

[2] To use a market analogy, the three situations correspond to a monopoly, Cournot oligopoly, and perfect

$- k) > 0$. As the transfer s_j is proportional to the use of agent j in excess of the "legal" threshold λ, a profit is made when agent j uses the resource more than $\tilde{x} \equiv \frac{k}{h} + \lambda$.

Considering both the use and the inspection decisions, the payoff of agent i is:

$\pi_i = \frac{x_i}{X} \cdot f(X) + \alpha \cdot (\omega - x_i) - I_i s_i + \Sigma_{j \neq i} I_{ij} r_{ij}$, where $I_{ij} = 1$ indicates that agent i inspected agent j and $I_{ij} = 0$ indicates otherwise, while $I_i = 1$ if $\Sigma_{j \neq i} I_{ji} \geq 1$.

The game model takes place sequentially into two steps. In step one agents decide the use of the common-pool resource. In step two agents take inspection decisions. An inspection involves at the same time information discovery as well as punishment. Before requesting an inspection, agents know only the total group use. After the inspection phase, the appropriation actions of the inspected individuals become public information. Another feature of the mechanism is that there is no accumulation of sanctions when more than one agent request to inspect the same action. When such cases arise, one inspector is randomly selected out of the requesting agents.

The threat of sanctions reduces the incentives for high use levels of the common-pool resource because they increase the cost of any effort above the "legal" limit, $x_i > \lambda$. The consequence is a downward shift in the best response function of a targeted agent (Figure 3.2). The degree of the shift depends on the perceived probability p_i that an agent has of being inspected. If such probability is positive, the agent's best response is to use the resource less than in the corresponding no inspection case.

The symmetric Nash equilibrium outcome is a pair (X^*, p^*) that jointly satisfies the following two conditions, one for each of the steps of the game model:

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competition situation.

(X*, p*) that solves
$$\begin{cases} X^* = \dfrac{N}{N+1}\left(\dfrac{a-(\alpha+h\cdot p^*)}{b}\right) \\ p^* = \begin{cases} 0, & if\ E[X^*] \le N\tilde{x} \\ 1, & if\ E[X^*] > N\tilde{x} \end{cases} \end{cases}$$

Notice the crucial role that is played in the inspection decisions by the assumption that agents are identical and by the assumption that it is common knowledge (so in equilibrium x_i=x^* and p_i=p^* $\forall i$).

As will be explained in the later sections, experiments will be performed with two levels of sanctions – a weak sanction and a strong sanction design. Both will be analyzed under the assumptions of the classical model. In the strong sanction design, the unitary fine h is four times higher than in the weak sanction treatment and the definition of excessive resource use λ is stricter (lower).

The weak sanctions (k=7, λ=9, h=1) are designed to have no effect on the Nash equilibrium of the group outcome of the classical model. The weak sanction parameters are set so that no inspection is strictly profitable when the individual use of resource is at or is lower than $\tilde{x}$=128/N=16.[3] Thus, in classical Nash equilibrium the total group use does not change from the no sanction design level and there are no inspections, (X*, p*)=(128, 0). As explained, even without the threat of sanctions, selfish agents have no incentive to use the resource more than X=128. Instead, when X>128 the inspection of each one of the agents will be profitable. If all the agents expect to be inspected with probability one, though, the group resource use drops to X=113.7 (66.4% efficiency).

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[3] The equilibrium X*=128, p*=0 is slightly altered when the agents have a "trembling hand" in their inspecting decisions. If a subject inspects "by accident" and this kind of events is common knowledge, the

Proposition 3.2A (*RESOURCE USE WITH WEAK SANCTIONS*)

The introduction of weak sanctions does not change the classical Nash equilibrium level [X=128].

Proposition 3.3A (*INSPECTIONS UNDER WEAK SANCTIONS*)

When weak sanctions are introduced, at the classical Nash equilibrium inspections pay zero. However, if a slight psychological cost exists, no inspections are requested. Strong sanctions (k=7, λ=7, h=4) are designed to move the equilibrium away from the inefficient outcome of the no sanction treatment to a fully efficient outcome (X=72).[4] The following properties are immediate.

Proposition 3.4A (*RESOURCE USE WITH STRONG SANCTIONS*)

The introduction of strong sanctions moves the classical Nash equilibrium outcome very close to the socially optimal level [above 99% efficiency, X=71.1].

Proposition 3.5A (*INSPECTIONS UNDER STRONG SANCTIONS*)

When strong sanctions are introduced, at the classical Nash equilibrium all agents inspect everybody.

In the symmetric Nash equilibrium under strong sanctions, (X*, p*)=(71.1, 1), all the agents are inspected and the group efficiency is at 99.97%. Inspecting an agent is profitable when x_i> 70/N=8.75. A slight discrepancy between the total group use X* in equilibrium and the social optimal value was preferred to assigning non-integer numbers to the parameter values. The difference in terms of efficiency is, however, negligible.

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equilibrium will be below X=128. We believe that this point affects neither our basic results nor our conclusions.

[4] The inspection fee k was not changed because it relates to the difficulty of observing other people's actions, which is a technological parameter generally outside the control of the mechanism designer.

3.6 A Model With Heterogeneous, Other-regarding Agents

This section outlines a simple other-regarding model where an agent's utility depends not only on personal earnings but also on the earnings of the other people in the group and computes the Nash equilibrium for appropriate parameters. Many other-regarding models can be found in the literature (Krebs, 1970; Rabin, 1993; Ito et al., 1995; Chan et al., 1997; Levine, 1998; Bolton and Ockenfels, 2000; Saijo, 2000; Fehr and Schmidt, 1999).

The version of heterogeneous, other-regarding model adopted here intends to capture in a parsimonious way a specific motivation for economic behavior. Let π_i be defined as in equation (2) and let $\Pi_{-i} = \Sigma_{j \neq i}\, \pi_j$. Then the assumptions of the heterogeneous, other-regarding model are:

(4) Other-regarding preferences $\quad U_i(\pi_i, \Pi_{-i}) = \pi_i + \gamma_i\, \Pi_{-i}$

(5) Range of preferences $\quad \gamma_i \in [-1,+1]$

(6) Heterogeneity $\quad \exists i,k \text{ with } i \neq k : \gamma_i \neq \gamma_k$

In this model, agent *i* is willing to give up \$1 of personal earnings (π_i) in order to see the other people's earnings (Π_{-i}) changed by $1/\gamma_i$ dollars. The classical model is a special case when all agents are selfish ($\gamma_i = 0, \forall i$). Agent i is called altruistic if other-regarding parameter of agent i is $\gamma_i > 0$ and if $\gamma_i < 0$ then agent i is called spiteful. A spiteful agent finds enjoyment in decreasing the earnings of others and is therefore willing to pay in order for that to happen. Although not crucial for the conclusions, we fix by assumption boundaries to the degree of altruism and spite, $\gamma_i \in [-1, +1]$, such that nobody chooses to pay more than \$1 to modify the group earnings by less than \$1.[5] The definition of spite adopted is similar to Levine (1998) and Saijo (2000) but different to the concept of envy suggested by Mui (1995). The model does not incorporate any reciprocity nor equity nor fairness considerations. As in the classical model, agents are assumed to be risk neutral and the preferences of all the agents, common knowledge.

The rest of this section is devoted to the computation of the Nash equilibrium of the heterogeneous, other regarding model in the three levels of sanctions, no sanctions, weak sanctions and strong sanctions.

When there are no sanctions, the best response function with other-regarding preferences is $x_i{*} = \frac{a-v}{2b} - \frac{(1+\gamma_i)}{2} x_{-i}$. There are both symmetric and asymmetric equilibria but all outcomes are within the values of the two "extreme" equilibria computed assuming $\gamma_i = -1, \forall i$ or $\gamma_i = 1, \forall i$.[6] For instance, if all agents are fully altruistic ($\gamma_i = 1$) the equilibrium is at the socially optimal outcome $X^{*}=72$. If all agents are moderately altruistic ($\gamma_i = 1/7$) then $X^{*}=115.2$, while if they are moderately spiteful ($\gamma_i = -1/7$) then $X^{*}=144$.[7]

With heterogeneous preferences, the individual use levels are heterogeneous. In particular, the lower the other-regarding parameter γ_i, the higher the individual use x_i is.

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[5] We assume that the vector of other-regarding parameters γ is such that the *individual* response function is within the interval $x_i \in [0,50]$. This assumption might further restrict the range of γ to a subset of the [-1, −1] interval.

[6] The same outcome X* can be the equilibrium result of more than one vector of agent preferences but given a vector of preferences, an individual shift in preferences has a predictable change on the outcome, $\partial X^{*}/\partial \gamma_i < 0$.

[7] An interesting case is when the preferences in the group are symmetrically heterogeneous or, in other words, when for every altruistic agent *i* with $\gamma_i > 0$ there is a spiteful agent *k* with $\gamma_k = -\gamma_i$. The Nash equilibrium with symmetrically heterogeneous agents is in general more efficient than the classical Nash equilibrium. For instance, when half of the agents $\gamma_i = 1/7$ and the other half $\gamma_k = -1/7$ the outcome is $X^{*}=126$, $x_i = 0$, and $x_{k\,i} = 31.5$.

In other words, spiteful agents use the resource more than selfish agents and selfish agents use it more than altruistic ones.

Proposition 3.1B (*RESOURCE USE WITHOUT SANCTIONS*)

Without a sanctioning institution the Nash equilibrium outcome with heterogeneous, other-regarding agents has an efficiency ranging in [-321%, 100%] - or use levels in [72,400] - depending from the preference structure of the agents.

In general, individual agents use the resource at different rates, with spiteful agents using it more than altruistic agents.

When preferences in a group are heterogeneous, there are two consequences for inspecting decisions. First, because agents use the resource at different rates (Proposition 3.1B) some actions could be inspected for profit even in the weak sanction treatment. In particular, if there are at least two types of agents and at least one agent is altruistic, then there exists an agent that uses the resource above x_i=16. Second, the decision to inspect depends on the preferences of the inspector. In particular, spiteful agents are willing to request also non-profitable inspections. The utility of agent i from inspecting agent j is $V_i = U_i(\pi_i, \Pi_{-i}) + (s_j - k) - \gamma_i \cdot s_j$. A spiteful agent finds enjoyment not only from the cash flow $(s_j - k)$ but also from decreasing the income of agent j by s_j. On the other hand, an altruistic agent does not consider all the money $(s_j - k)$ as a gain since the sanction s_j has been subtracted from somebody else that he cares about. A completely altruistic agent (γ_i =1) never inspects, while a complete spiteful one inspects when x_j>12.5 in the weak sanction treatment and when x_j>7.9 in the strong sanction treatment. When facing the same use pattern, spiteful agents are more aggressive inspectors than altruistic agents because they inspect for lower values of x_j. This propensity is captured by the fact that an agent of type γ_i inspects the actions of j if $\gamma_i < -\frac{k - s_j}{s_j}$.

Sanctions also affect level of use decisions. When a sanction is imposed, agents of every type lower the resource use because the sanction increases the unitary cost of an appropriation effort. Under the threat of sanctions, the best response function of an agent i with other-regarding preferences is $x_i^* = \frac{a - v - p(1+\gamma_i)h}{2b} - \frac{(1+\gamma_i)}{2} x_{-i}$, if $x_j > \lambda$. The utility of agent i when inspected is $V_i = U_i(\pi_i, \Pi_{-i}) - s_j + \gamma_i(s_j - k)$ and, given the nature of the *Carte di Regola* institution, sanctions induce a spiteful agent to lower his appropriation level proportionally more than any other type. In fact, spiteful types are doubly troubled while paying a sanction: for a start, they earn less money and in addition, somebody else is going to be better off. Altruistic types are the least affected because a portion of the sanction is transferred to other people in the group they care about. Only fully altruistic agents, though, are not affected by sanctions in their appropriation decisions.

How do sanctions change the relative appropriation levels of altruistic versus spiteful agents? When there are no sanctions, altruistic agents use the resource less than spiteful agents. As explained above, sanctions induce a more than proportional reduction in the level of use by spiteful people than altruistic people (Proposition 3.1B). The effect of relatively light sanctions - as it is the case of the weak sanction treatment - is to reduce inequalities in use levels within the group, although spiteful agents still use the resource more than altruistic agents (Proposition 3.3B). When sanctions are sufficiently heavy – as in the strong sanction design - spiteful agents' concern for the transfers of money induced by the sanction dominates the incentives coming from their own earnings. The reduction in the use levels across the different types is such that altruistic agents use the resource more than spiteful agents. This reversal of the solution can be verified by substituting the parameter values into the best response function (Proposition 3.5B). In a strong sanction environment, when all agents are fully spiteful the Nash equilibrium outcome is $X^*=64$ while is $X^*=72$ when all agents are fully altruistic, which corresponds to an efficiency range [98.77%, 100%].

Finally, the predictions of the model with heterogeneous, other-regarding preferences – which hold under some mild regularity conditions on preferences[8] - are listed below.

Proposition 3.2B (*RESOURCE USE WITH WEAK SANCTIONS*)

When agents are heterogeneous and other-regarding, the introduction of weak sanctions improves efficiency upon the Nash equilibrium level without sanctions.

If two or more agents are selfish or spiteful (sufficient condition), the improvement is strict.

Proposition 3.3B (*INSPECTIONS UNDER WEAK SANCTIONS*)

With weak sanctions and agents with heterogeneous, other-regarding preferences,

(i) There are inspections when two or more agents are not altruistic (sufficient condition)

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[8] Because of the reversal in behavior of spiteful agents from the weak to the strong sanction treatment, a stringent condition on preferences is required to obtain the prediction that in equilibrium all agents are inspected with probability one. In order to have inspections with weak sanctions it is sufficient if two or more agents are not altruistic. A sufficient condition for all agents to be inspected in the strong sanction treatment is that in addition to the above, the most spiteful agent is "not too far apart" from the next. More formally, when agents are ranked low to high other-regarding parameters $\gamma_{(1)}, \gamma_{(2)},\ldots, \gamma_{(8)}$, then $\gamma_{(1)}, \gamma_{(2)} \leq 0$ and $|\gamma_{(1)} - \gamma_{(2)}| < 0.25$. This condition is satisfied in three of the four no sanction experiments. The April 7 experiment satisfies a different sufficient condition: No agent is very spiteful ($\gamma_i > 0.45\ \forall i$) and at least two agents are not altruistic ($\exists\ i,j : \gamma_i, \gamma_i \leq 0$). The above statements are based on the estimation described in Section 3.8 point (e).

(ii) The heaviest users (the most spiteful agents) are more aggressive inspectors than lightest users (the most altruistic agents) and purposively request non-profitable inspections.

Proposition 3.4B *(RESOURCE USE WITH STRONG SANCTIONS)*

When agents are heterogeneous and other-regarding, the Nash equilibrium outcome with strong sanctions has an efficiency above 98.5% ($X^* \in [64, 72]$) under some regularity conditions on preferences.

Proposition 3.5B (*INSPECTIONS UNDER STRONG SANCTIONS*)

With strong sanctions and agents with heterogeneous, other-regarding preferences,

(i) All agents are inspected under some regularity conditions on preferences

(ii) Lightest users (the most spiteful agents) are more aggressive inspectors than heaviest users (the most altruistic agents).

3.7 Experimental Procedures

A total of 56 subjects were recruited from the campus of the California Institute of Technology for a total of 10 experimental sessions. The different treatments are outlined in Table 3.2. There are three different sanctioning designs: No Sanction, Weak Sanction, and Strong Sanction. Within each treatment, half of the experiments were conducted with inexperienced subjects and the other half with experienced subjects.

There is a much milder condition that ensures that at least 87.5% (i.e., 7/8) of the action is inspected (It suffices that at least one agent is not strongly altruistic, $\gamma_{(1)} < 0.08$).

Table 3.2: Summary Table for Use Decisions

	NO SANCTION				WEAK SANCTION				STRONG SANCTION	
Experiments	1	2	3	4	5	6	7	8	9	10
Date	021298	090898	040798	090998	022598	082498	040898	082598	083198	090198
Sanctions	No	No	No	No	Yes	Yes	Yes	Yes	Yes*	Yes*
Experience	No	No	Yes	Yes+	No	No	Yes	Yes+	No	Yes+
Number of rounds	32^	32	33	32	27	27	27	27	27	27
Period endowment (tokens)	4	4	4	0	4	4	4	0	0	0
Conversion rate ($ per franc)	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03
GROUP USE										
Average	124.7	134.2	133.1	133.3	125.6	115.4	110.8	110.0	91.8	79.1
Classical Nash equilibrium	*128*	*128*	*128*	*128*	*128*	*128*	*128*	*128*	*71.11*	*71.11*
Minimum	100	85.5	121.5	87	87.3	87	92.5	90	74	69
Maximum	154	161	149.5	167	186.8	160	154.7	137	126	95.5
Standard deviation (Sd)	14.84	15.49	6.01	15.46	23.13	20.57	12.15	10.20	13.22	6.50
First half Sd/Second half Sd	4.52	1.68	2.59	0.79	0.92	0.83	2.57	1.46	2.18	0.85
GROUP EFFICIENCY			**(% of maximum rent)**							
Average Rent (1)	42.29	20.97	27.36	23.00	34.67	55.74	68.20	70.15	89.73	98.24
First 25 periods	*42.48*	*23.74*	*27.13*	*22.27*	*32.43*	*52.71*	*68.94*	*70.75*	*89.29*	*98.14*
Last 2 periods (after announce.)	*54.23*	*1.28*	*28.21*	*41.06*	*62.68*	*93.58*	*58.95*	*62.62*	*95.29*	*99.47*
Fees (2)	-	-	-	-	13.04	8.24	6.64	7.68	17.20	17.04
Fines	-	-	-	-	14.01	8.90	6.49	6.19	43.39	28.44
Net Average Rent (1)- (2)	-	-	-	-	21.63	47.49	61.56	62.47	72.53	81.20
INDIVIDUAL AVERAGE USE LEVELS										
Lowest average user	8.8	10.6	9.9	9.0	11.7	10.2	11.0	11.1	8.9	7.1
Highest average user	32.5	39.2	44.8	35.2	20.0	17.3	18.4	15.3	14.1	13.0
Rank correlation 1st/2nd half	0.917	0.902	0.961	0.966	0.907	0.892	0.926	0.872	0.823	0.858

Notes: The experiments were done at the California Institute of Technology *Sanctions:* "No" is a no sanction experiment; "Yes" means that a monitoring and sanctioning device was added to the no sanction experiment; "Yes*" indicates a different set of sanctioning parameters.

Experience: "No" means that no subject has ever participated in any one of these experiments before; "Yes" means that all the subjects have already participated in this type of experiment (on Dec. 9, 1997, at the earliest); "Yes+" means that all the subjects have participated the day before in this type of experiment with the same group of people. *No. of rounds:* Number of effective rounds of interaction, which excludes two practice rounds; (^) On #1 a paper copy of the "Return from investment" table was handed to the subjects between the 10th and the 11th round instead of before the 1st round. During the whole experiment the table was projected on the wall of the room. *Period endowment:* The endowment ω indicates the number of tokens given each period to each subject.

Some words need to be spent on the choice of the three experimental designs. The no sanction design adopts the model of a renewable resource well-known in the literature. The parameters values of $f(\cdot)$, α, $\hat{x}$, ω are similar to the levels found in OWG in order to make the comparison of results possible with this previous study. Some changes have been introduced to simplify the understanding by the subjects and to raise the monetary incentives to find the optimal strategy (see Appendix C). In particular, the marginal monetary incentives were increased three or fourfold compared to WGO and the minimum safe earning was reduced. In order to make it easier to understand the rules, the instructions were rewritten, special software developed, and the action space was rescaled.

The sanction designs represent in the simplest fashion the essential features of the Carte di Regola monitoring and sanctioning mechanism. The design relies on three parameters, k, h, and λ. The cost to inspect k has been chosen to be of the same order of magnitude than the amount at stake in the appropriation stage of the interaction. Inspecting one agent costs 17% and inspecting everybody else costs 121% of the maximum individual earnings from using of the common property resource ($\overline{\Pi}/N$). The value of k has been kept constant for weak and strong sanction design. Since in the classical model agents are identical, $p=p_i$ $\forall i$, only the two corner outcomes $p=0$ and $p=1$ are possible solutions in the two-stage game.

The weak sanction design ($p=0$) provides additional incentives for the subjects to converge to the classical Nash equilibrium, in particular to discourage low levels of cooperation. The inspecting stage of the game introduces a discontinuity in the payoff function at the individual classical Nash equilibrium, which should increase its salience.

Although the design has not explicitly taken into account the optimization procedure suggested by El-Gamal and Palfrey (1996), the value of λ was taken to be sufficiently far from the classical Nash equilibrium to make it distinguishable for the subjects.

The strong sanction design (p=1) intends to move the Nash equilibrium to the outcome with maximum efficiency, namely X=72. The lowest integer value of h able to accomplish it was chosen along with the corresponding value of λ.

There were eight subjects in each experimental session. All subjects were seated at terminals, separated by partitions, and assigned identification numbers. No communication was allowed. Instructions were read aloud to everyone. The experiments were run on networked personal computers using dedicated software for Netscape.

The problem was presented as an abstract decision-making situation where there was an opportunity to earn money by "investing" in a market. The use level was chosen without knowing the choices of the other subjects. Use levels were expressed in " tokens" and payoffs were in terms of "francs" (an artificial laboratory currency with a publicly known dollar-exchange rate) and in dollars.

An experiment lasted from 1 hour to 2 hours and 20 minutes including the preliminaries. Individual earnings ranged from \$5.80 to \$53.10. Each subject was paid privately in cash immediately following the experiment.

Within each period of the experiment, there was just one step in the no sanction treatment and two steps in the sanctioning treatments. During step one, the computer prompted a request for a number of tokens that the subject wished to put in the market. A subject could digit any real number between 0 and 50. After everybody completed the input, the total group use and gross group return were displayed. In the no sanction, treatment subjects could also see their individual period payoff (your share of gross, cost of tokens, period payoff), while in the sanctioning treatments this part was postponed until the end of step two. Step two gave a chance to inspect other subjects. By clicking on a box next to the subject identification number, a subject could ask to uncover the use level of any number of subjects from 0 to 7.

The period payoff was computed and explained in terms of its three components: result of use decisions, result of inspections asked, and notices of the eventual charge for an inspection targeting the subject. A full record of the past decisions could always be seen, including personal individual uses and cumulative payoffs, total group uses and gross group returns, and the individual use levels of inspected agents uncovered by anybody in the group.

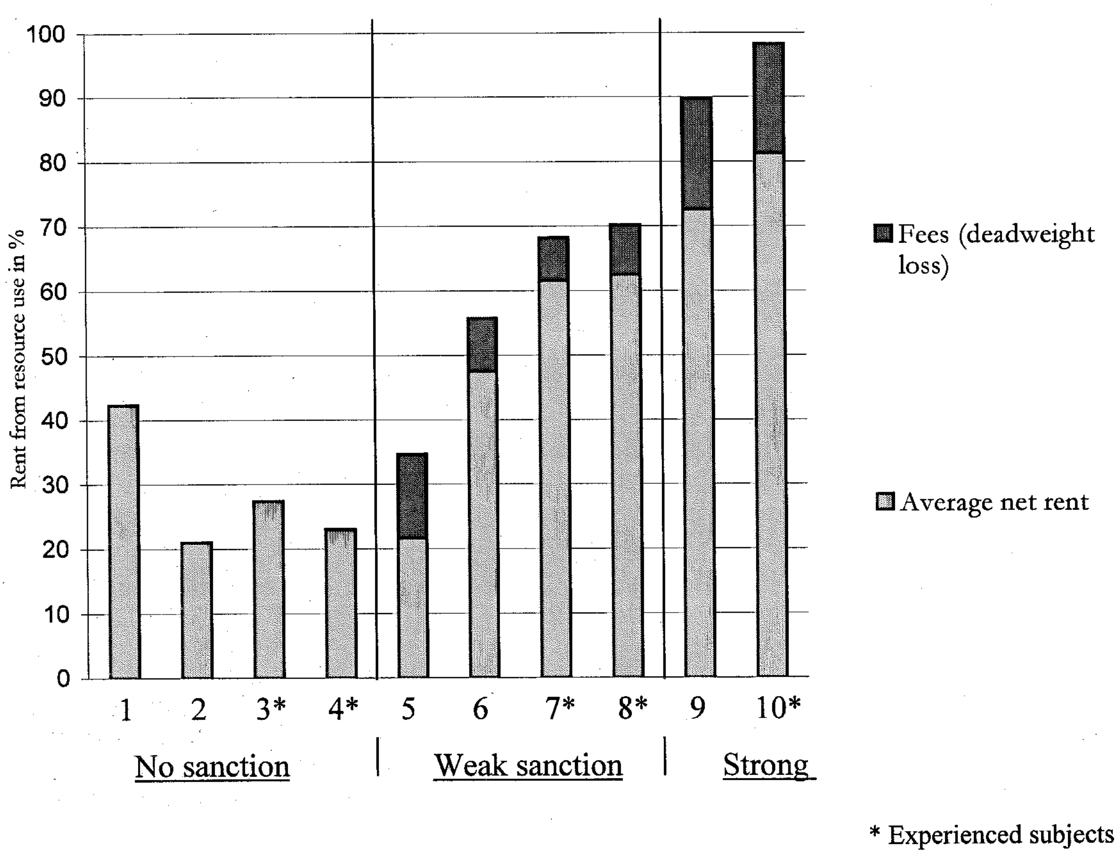
To ensure that the rules were well understood, we adopted the following procedure. First, the rules were publicly explained in detail and with examples. Second, a quiz was given. All the correct answers were read aloud after completion of the quiz and the ones where mistakes were noticed in the answers were further explained. Third, two practice periods were run, to help the subjects familiarize themselves with the rules of the experiment and with the software. After the two practice rounds, a number of periods from 27 to 33 were run. Subjects were not told the number of rounds that were to take place. At the end of the third-before-the-last period, an announcement was made that the experiment was going to end in two periods. After the experiment was over, a questionnaire was submitted to the subjects asking for the strategy they followed.

3.8 Results of No Sanction Experiments

The experimental results are compared with the predictions of the classical model (3.1A) and of the heterogeneous, other-regarding agent model (3.1B). The data demonstrate that the predictions of the classical model in the no sanction environment are subject to systematic errors. The other-regarding agent model does better.

Result 3.1A Without a sanctioning institution, the resource is overused relative to the Nash equilibrium with homogeneous, selfish agents ('classical' Nash equilibrium). People cooperate less than expected according to that model and are worse off than the model predicts.

Figure 3.3: Average Efficiency by Experiment



Support: In terms of efficiency the groups scored 28.4% of the maximum possible net return, a value that is lower than the classical Nash equilibrium level of 39.5%. The overall average of the group use for the four experiments was 131.3, which is statistically different from 128 at a 0.01[9] level (see Table 3.2 for details). The group use varied considerably across periods, ranging from a minimum of 85.5 to a maximum of 167 tokens.

Neither subject experience nor time effects alter the main conclusion that the group use is persistently above the one-shot classical Nash equilibrium level. In particular, experienced subjects do not perform better than inexperienced subjects do. Differences in efficiencies actually favor inexperienced subjects (25.2% versus 31.6%, Figure 3.3). Moreover, there is no indication of collusion among users. In fact, if a repeated interaction effect is present, the pattern in the total group use should be

(a) A convergence to the one-shot Nash equilibrium from below, i.e., in the range $X \in [72, 128)$;

(b) An eventual jump to the one-shot Nash equilibrium level after the end-of-experiment announcement has been made.

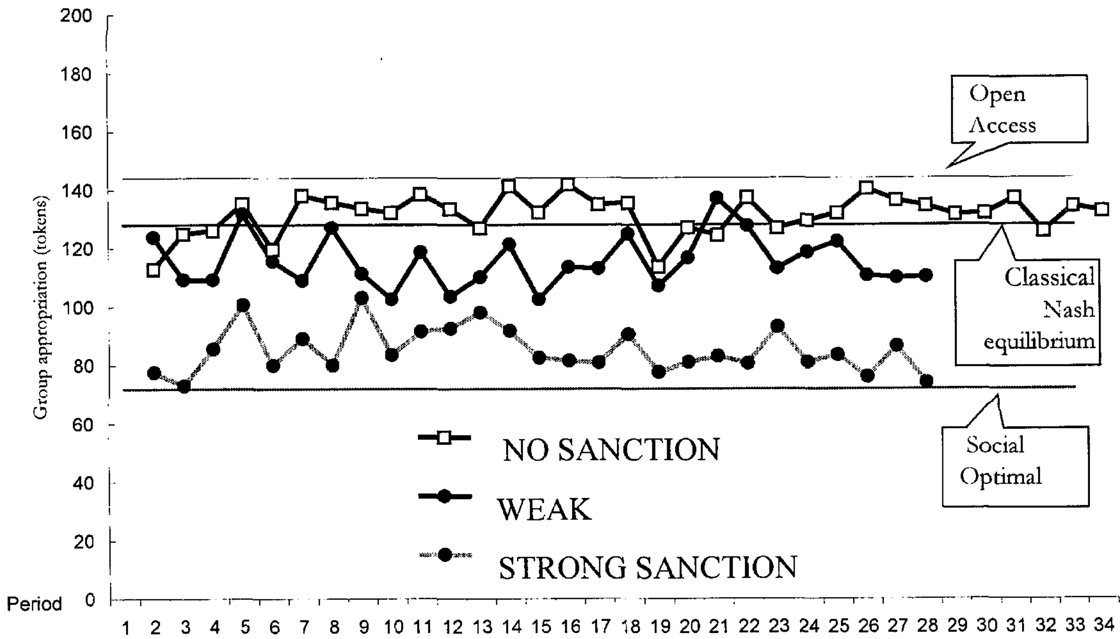
A comparison between the first half, second half, and after announcement period averages[10] show no statistical differences at 0.01 significance level. As an overall

[9] The symmetric Nash equilibrium value X=128 was never recorded in any of the 129 rounds in which the appropriation decisions were taken. The open access level is X=144.
[10] The subjects were not told the length of an experiment. In no sanction experiments, the first half includes periods 1-15, second half 16-30 (or 16-31), and after announcement 31-32 (or 32-33). In sanction treatment, the first half includes periods 1-12, second half 13-25, and after announcement 26-27.

average, the values are 131.37 in the first half, 131.39 in the second half, and 130.31 after the announcement (Figure 3.4).[11]

The volatility of the group use level decreases over time in three out of four experiments (see variance comparisons in Table 3.2) but it mostly reflects oscillations around the same average.

Figure 3.4: Average Group Use by Experimental Treatment



In conclusion, the observed level of group use can be explained by the heterogeneous, other-regarding agent model, given an appropriate pattern of group preferences that is biased toward spite.[12]

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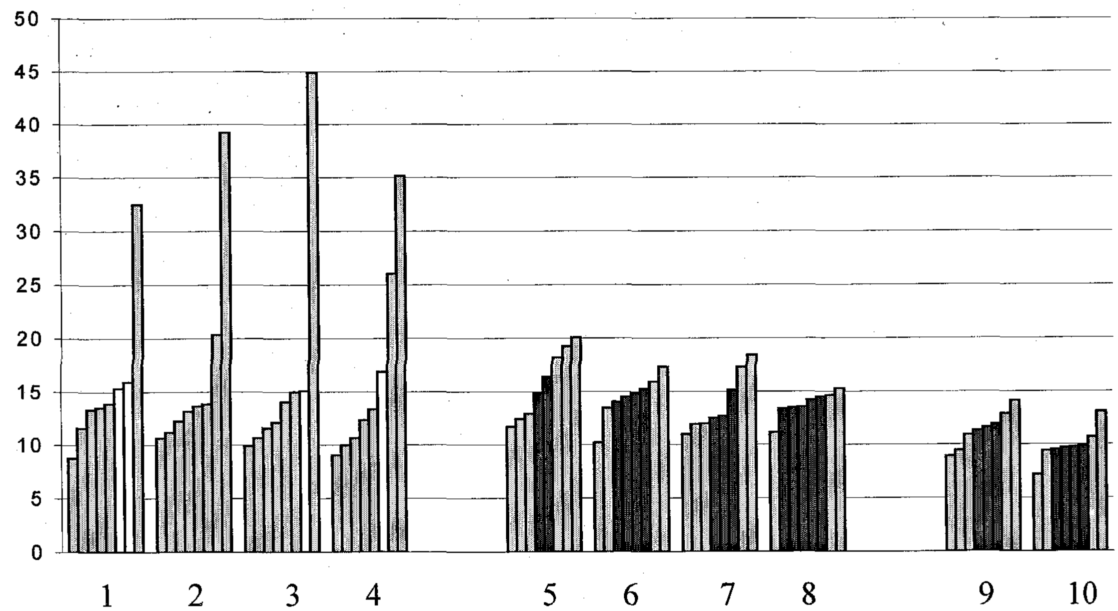
[11] The presence of a repeated interaction effect and of time effects was also evaluated using the Ashenfelter-El Gamal model, which is described in Noussair et al. (1995). The asymptote for the no sanction experiments is 134.0, which is statistically different from the equilibrium level of 128 but not significantly different from the overall average group use of 131.3 at a 0.05 level. This result confirms once more that the overuse of the resource persists and does not tend to die out. The convergence to the asymptote starts from below for all the experiments, which supports point (a) above.

Figure 3.5: Agent Average Use Levels



Notes: Compare to the individual classical Nash equilibria: x_i=16 for no sanction and weak sanction designs and $x_i \approx 8.9$ for strong sanction design. The white bars in the no-sanction experiments indicate the agents whose behavior is not statistically different from the classical Nash equilibrium at 0.05 level. The darker colored bars in the sanction experiments indicate the group of median agents that are not significantly different one from the other at 0.05 level.

Result 3.1B In a sanction-free environment, a model of heterogeneous, other-regarding agents is compatible with the patterns of individual resource use better than the classical model. Furthermore, some clues exist in the data suggesting that it is an appropriate modification to the classical model. Specifically, overuse and underused are properties of individuals. About 37% of the agents are other-regarding and most of them are spiteful.

Support: The patterns of individual use do not conform to the one-shot classical Nash equilibrium prediction of x_i=16 $\forall$i.

Consider for example a group with three types of agents: two are moderately altruistic γ_i =1/21, four self-interested agents, and two quite spiteful ones γ_i =- ¼. The group appropriation is X*=132 with individual appropriations x_i of 6, 12, and 36 respectively.

Individual actions are very dispersed in the action space (a) and this variability is due to individual heterogeneity (b). Individual heterogeneity is not a consequence of confusion (c) but is consistent over time (d) and is due to other-regarding preferences (e).

(a) Only 2.5% of all actions are x_i=16. The actions within a 25% bandwidth around the prediction (i.e., in the interval [14, 18]) account for 15.7% of all the actions and the rest are not symmetrically distributed around that value: about 61% are below and 23.3% are above. The mean is 16.4 and the standard deviation is 10.00.

(b) A brief look at the individual average use levels makes clear that heterogeneity is a trait of agents and that only a few agents were accountable for a systematic overuse (Figure 3.5). We can reject the hypothesis that the agent average use is at the individual symmetric Nash equilibrium (x_i=16) for 28 out of 32 agents at 0.05 level. Within each experiment, there are at least four different types of agents whose use behavior is statistically different at 0.05 level. The presence of different types of individuals is a common finding in the experimental literature (El-Gamal and Grether, 1995, Von Winden, Dijk, Sonnemans, 1998).

(c) There are reasons to believe that the differences in individual behavior are not due to confusion. The experimental design was not simple and a possible explanation of heterogeneity is that the "heavy users" might have been confused subjects who did not properly understand the incentive structure of the experiment.[13] The evidence from the quiz completed by each subject before the experiment does not show any support for this option. We have assigned a score to each quiz taken, which is 1 if all the answers are

[13] If the heavy investors are confused subjects, however, it is unclear why we do not find them in the experiment with the weak sanction treatment (see Figure 3.5). Such experimental design is more complex than the no sanction design, although the threshold level for sanctioning gives a vague clue about the equilibrium level and the monetary incentive against high appropriation levels are higher.

correct, 0.5 if some answers are not perfect but it is clear that the subject overall understood the rules, and 0 if there are substantial and repeated mistakes. The four highest users score an average of 0.92 against a general average of the 32 subjects of 0.89. In other words, the heavy users –are not less skilled than average.

(d) There is a remarkable consistency over time in the individual use patterns, which indicates that the differences across agents are purposive rather than random. Consider the ranking of agents by individual average use levels in the first and second half of the experiment. A rank correlation computed with an OLS regression without a constant term informs about the existence of any monotonic relation between the two rankings. A 1-value coefficient denotes a perfect positive correlation in agents' behavior over time. When all the no sanction experiments are pooled together, the estimated coefficient is 0.936 (number of observations is 32, R-squared 0.88. See Table 3.2 for single experiment regressions). This test supports the view that over time agents are consistently heterogeneous.

(e) The estimation of the individual best responses for the other-regarding agent model on the experimental data leads to consistent results. Since the difference between the classical and other-regarding model is just in the slope of the best response function (cfr. (2) and (2'')); see also Figure 3.2), the regressions assume a correct value for the intercept. The estimation is done under the assumption that the agents expect the others to act in period t as they did in period t-1: $x_{i,t} = 72 - \frac{(1+\gamma_i)}{2} x_{-i,t-1} + \varepsilon_i$. All the 32 agent-specific estimated values of the other-regarding parameter γ_i fall into the allowed interval [-1,+1]. The γ_i estimates range from a minimum of -0.40 to a maximum of 0.08. About 37% of the agents have a parameter γ_i significantly different from zero at a 0.05 level, and our model classifies them as either altruistic when γ_i is positive (2 agents) or spiteful when γ_i is negative (10 agents).

To sum up, in the experiments group efficiency of 28.4% is below the classical Nash equilibrium level of 39.5%. WGO reported an average negative efficiency (-3.2%) but at a closer analysis, the difference between the two studies turns out to occur in the earlier rounds and dies out over time.[14] Moreover, individual actions are widely heterogeneous. WGO reports that in the 48% of the rounds not a single agent used 16 tokens. In our experiments the figure is 90%.[15]

The predominance of spiteful agents over altruistic ones can account both for the overuse at the group level and for the observed pattern of individual actions. A model relying on homogeneous, selfish agents cannot explain either one of the two regularities.

3.9 Results of Weak Sanction Experiments

This section describes the outcome of four experiments run under the weak sanction treatment and in particular it focuses on the inspection decisions (Result 3.3) and their effects on use decisions (Result 3.2).

Result 3.2 With the introduction of weak sanctions, Group efficiency improves substantially. Resource use efficiency moves from below the classical Nash Equilibrium to above the classical Nash equilibrium. These results are not predicted by the classical

[14] The convergence values estimated with the Ashenfelter-El Gamal model are statistically indistinguishable (131.97 WGO and 133.78 ours), although our data reject the Nash equilibrium value of X=128 at a 0.05 level where WGO data are more noisy. Average group efficiency is computed using WGO's 3 experiments and the first 20 rounds of the 4 no sanction experiment in this paper. The 0.95 confidence interval of the Ashenfelter-El Gamal asymptotes are [124.38, 139.56] for WGO and [129.33, 138.22] for ours.

[15] Part of the increase observed in our experiments might be due to the re-scaling of the action space and to the opportunity to invest any real and not only integer number.

model (Proposition 3.2A), but they are consistent with the heterogeneous, other-regarding agent model (Proposition 3.2B).

Support: In other words, an institution – such as weak sanctioning – that according to the classical model should have no effect on behavior has instead a significant impact on the outcome. The classical model predicts an efficiency of 39.5% for both the no sanction and weak sanction treatment. The gross efficiency level with weak sanctions is 57.2%, which is roughly double the efficiency without sanctions (28.4%). When a correction is made for the differences in length among experiments, the situation does not change (28.9% versus 56.2% for the first 25 periods only).

The net efficiency – computed by subtracting the inspection fees (8.9%) – is 48.3%, which is about twenty points above the no sanction level (Tables 3.3 and 3.5). The inspection fee represents the cost of using the inspection mechanism and is a deadweight loss for the group. Instead, the fines are a plain transfer from an agent to another. Moreover, efficiency improves with experience: the net efficiency is on average 62% for experienced subjects versus 34.6% for inexperienced ones (Figure 3.3).

The total group use is substantially lower for sanction experiments than for no sanction ones. As an overall average, group use drops from 131.3 to 115.5 tokens (statistically different at 0.01 level). The aggregate use is statistically different from both the classical Nash equilibrium and the socially optimal level (0.01 level). The classical Nash equilibrium X=128 was recorded in 2 out of 108 periods. When considering the classical model, the overall group use average is not statistically different from the one-probability inspection prediction (X=113.7) (0.05 level). The group use across periods ranged from a minimum of 87 to a maximum of 186.8, which is wider than the same range for no sanction experiments.[16]

The increased cooperation at the group level comes from the ability of the *Carte di Regola* mechanism of turning the heterogeneity of preferences to socially advantageous ends. In particular, cooperation is the result not only of altruistic agents, now being able to benefit the group, but also of the fear of inspections by spiteful agents.

The comparison of the results in the no-sanction and sanction environments is carried on under the assumption that agents were drawn from a population with identical preference patterns. Even if the agents were not the same in the different experiments, we think that the conclusions drawn under the above assumption are reasonable.

Result 3.3 With the introduction of weak sanctions,

(i) About half of the actions are inspected.

(ii) The highest users are more aggressive inspectors than the lowest users.

These results are not predicted by the classical model (Proposition 3.3A) but they are consistent with the heterogeneous, other-regarding agent model (Proposition 3.3B).

Support: In the weak sanction treatment, 51.5% of the actions were inspected (Table 3.3). The classical model cannot explain either the magnitude of efficiency improvement nor why those inspections were requested in the first place. The introduction of different types of agents can account for the data. Under the classical model, if agents have a probability 0.5 of being inspected the Nash equilibrium is X=120.9 with a 53.9% efficiency. That seems to be a good fit of the data. When agents are experienced, however, the effect on efficiency is stronger than that (62% efficiency with 41.4% of

[16] Similar results come from the estimation of the Ashenfelter-El Gamal model explained above. The ordinary least squared asymptote of X=114.8 is not significantly different from the one-probability

actions inspected). The reason for the higher than expected increase in efficiency relative to the share of actions inspected comes from the fact that the agents that have been identified as the heavy user types face a much higher probability of being inspected than the others.

Table 3.3: Inspection Decisions

Number of actions		WEAK SANCTION Inspected? No	Yes	*Totals*	STRONG SANCTION Inspected? No	Yes	*Totals*
BALANCE IF ACTION IS INSPECTED	Negative, s_i-k<0	372	276	*648*	4	141	*145*
	Zero, s_i-k=0	20	37	*57*	0	0	*0*
	Positive, s_i-k>0	27	132	*159*	0	287	*287*
	Totals	*419*	*445*	*864*	*4*	*428*	*432*
		48.5%	*51.5%*	*100%*	*0.9%*	*99.1%*	*100%*

Why are so many inspections requested? Because inspectors are aware that agents are heterogeneous in their effort decisions and because some agents are willing to request unprofitable inspections. As the first point has been already documented, this section will focus on the second point.

According to the heterogeneous, other-regarding agent model, the "heavy user" types are spiteful agents. Those agents will purposely request some un-profitable inspections. In particular, the data support the prediction that spiteful agents are more aggressive inspectors than altruistic agents.

Agents were divided into three groups according to their average use level in the experiment. The inspecting behaviors of high versus low users was compared, keeping

inspection level (0.05 level) while it is different from the zero-probability level.

out of the analyses the group of median users among whom there were no significant differences in individual use at a 0.05 level. Relatively spiteful agents requested on average more inspections per period than relatively altruistic agents did, when controlling for the resource use by all the other agents in the group. This conclusion is based on the sign and significance of the coefficient of the dummy variable for highest users in Table 3.4 (positive for weak sanctions, negative for strong sanctions).[17]

Table 3.4: Spiteful Agents Inspect More than Altruistic Agents

	WEAK SANCTIONS		STRONG SANCTIONS	
OLS regression	Coefficient	p-value		Coefficient
p-value				
Dependent variable:	Total number of requests of inspections per period			
Sample size(without median users):	486		243	
Independent variables:				
Highest users (dummy variable)	0.34	0.015	-1.23	0.000
Period use of the other agents	0.06	0.000	0.03	0.159
Constant	-5.42	0.000	1.58	0.366

Notes: The classical model predicts insignificant coefficients for the highest users dummy variable. See Figure 3.5 to identify the median users whose actions were excluded from the regressions.

3.10 Results of Strong Sanction Experiments

Result 3.4 Strong sanctions have the effect of increasing resource use efficiency as predicted by both the classical and the heterogeneous, other-regarding agent models. Efficiency levels fall short of the Nash equilibrium of both models. Experienced subjects tend to be closer to the equilibrium.

[17] Regressions for each single experiment confirm this general conclusion with the exception experiment #5 where the highest investors dummy is not significant at 0.10 level.

Support: In the strong sanction experiments, the total group use was on average 85.1. This level was significantly (0.01 level) higher than the outcome predicted by both the standard model (71.1) and the heterogeneous, other-regarding agent model ([64, 72]).[18] The group use across periods ranged from a minimum of 69 to a maximum of 126. The efficiency level is very high, 94%, but still sub-optimal and lower than the target level. When the inspection fees (17.1%) are subtracted, the net rent is 76.9% (Tables 3.3 and 3.5). Sub-optimality might be due to the inexperience of subjects, since there is a significant improvement in the group efficiency when subjects are experienced (gross rent 98.2% versus 89.7%).[19]

Result 3.5 In the strong sanction environment,

(i) More than 99% of all actions are inspected

(ii) The lowest users are more aggressive inspectors than the highest users

Result (ii) is not predicted by the classical model (Proposition 3.5A) but is consistent with the heterogeneous, other-regarding agent model (Proposition 3.5B).

Support: (i) About 99.1% of the actions were inspected, a value definitely close to the 100% predicted. Although almost all the agents were inspected every period, not all the agents requested to inspect everybody every period, as predicted by the classical model. On average an agent requested less than 4 inspections per period instead of 7 (Table 3.3).[20]

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[18] This conclusion does not change when the Ashenfelter-El Gamal model is estimated. The ordinary least squared asymptote is 86.1 and none of the predicted values are in its 95% confidence interval.

[19] With weak sanctions, the inequality in the average use across agents is substantially lower than in the no sanction environment (Table 3.2). The average standard deviation of the agent period earnings from appropriation (when fines are subtracted) is of 1.6 francs and 5.6 francs, respectively.

[20] The large inspection balance is a surprise. In equilibrium with $(X^*,p^*) = (71.1, 1)$, the inspection balance is 1.4% of the maximum rent. The result is a balance of 18.8%, more than ten times higher than what was predicted. The reason of such "success" was not mainly in the exceptional ability in discovering high investors but in the high average value of total group appropriation.

(ii) Relatively spiteful agents (lower users) are more aggressive inspectors than relatively altruistic agents (higher users) as can be seen from Table 3.4. In the strong sanction treatment, the *highest user* variable is negatively correlated and significantly so with the number of inspections.

3.11 Capturing Additional Phenomena

One might argue that the model with heterogeneous, other-regarding agents fits the experimental data from the common-pool resource experiments better than the classical model because of the flexibility given by N additional parameters (one for each agent). Of course that is a concern, but additional credibility is given to the model – despite this argument - by its ability to provide insights about three additional perplexing aspects of behavior uncovered by these and other experiments.

The first phenomenon is the correlation between use decisions and inspections decisions at the individual level. As was illustrated by Result 3.3 (ii) and Result 3.5 (ii), the highest users are the most aggressive inspectors in the weak sanction experiments while the opposite is true for the strong sanction experiments. The phenomena cannot be explained by the classical model. However, this regularity has an elegant explanation within the heterogeneous, other-regarding model: spiteful agents are always more aggressive inspectors than altruistic agents and the use levels of spiteful agents are highly sensitive to the level of sanctions inflicted on themselves because part of the sanction they pay makes someone else better off. Such sensitivity goes to the point that in strong sanction experiments spiteful agents use the resource less than altruistic agents.

The second phenomenon is the spite/altruism paradox in the no sanction design. When agents are heterogeneous and other-regarding, this paradox can be explained looking at the boundary conditions of the individual "action space" and noticing that they are different in common-pool environments and public goods environments. Consider the following three designs that have the same classical Nash equilibrium $x^*_i=16$ and preserve the same features, except the action space: A (actual), where an agent can choose a use level in [0, 50]; B, where individual action space is [0, 20]; and C, where the action space is [0, 16]. From the point of view of the classical model, designs A and B simply supply agents with options that are irrelevant to their actions and there is no substantive difference with C. Common-pool environments are typically like A or B while public goods environments with an equilibrium of zero contributions by selfish agents are like C. In a common-pool environment the spiteful individuals have great latitude for harming others, while in the public good environment in which they cannot take away amounts of the public good provided by others, they have a relatively limited action space. Altruistic agents on the other hand are not placed in such asymmetric conditions between the two environments and thus the actions of altruists have a disproportionate influence on the outcome and efficiency levels in public goods experiments.

In the common-pool experiments, changes in behavior as a result of changes in the action space were first reported by WGO. An increase in efficiency is expected going from design A to B, although smaller than going from A to C, because the best response of some agents could be in (20, 50], either due to the high spite of some or the high altruism of others. This "surprising" efficiency improvement was observed and reported by WGO. Moreover, while individual data are not available from the WGO study, such data available suggest that some individual choices of use in design B were at the maximum possible.[21] On the public goods experiment side of the issue, data frequently reflect unexpectedly high levels of contribution (altruism), but typically the experimental design does not allow elements of spite to be expressed because the Nash equilibrium is at zero levels which leaves no room for spiteful behavior. When high levels of spite have relatively great possibility for expression in relation to altruistic attitudes in a public goods environment, then the aggregate outcome shows lower levels of cooperation.

The possible influence of spite in the context of the heterogeneous, other-regarding model can be seen in the data reported by Isaac and Walker (1998). A switch in behavior from efficiency above the Nash equilibrium to efficiency below the Nash equilibrium takes place as the action space is kept the same and the equilibrium is moved away from the boundary of zero contributions to the public good toward the Pareto Optimal levels.[22] As this takes place the range of spiteful actions that can be expressed are expanded relative to the range of possible altruistic actions and as a result, the system efficiency falls as spiteful actions emerge.

A third pattern of phenomena relates to a slightly different sanction institution studied by Ostrom, Walker and Gardner (OWG, 1992). Consider a system where an agent pays a cost in order to inflict a sanction on some other person but receives no monetary reward for doing so, similar to the system of vigilantes discussed in the next section. The model of a finitely repeated classical game predicts that no such sanctions should be requested.

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[21] In the experiments corresponding to our design B ("restricted action space"), the observed modal strategic response of individuals was to use the resource to the maximum of their ability (Ostrom, Gardner, and Walker, 1993, p.121).

[22] This change is similar than going from case C to B or from C to A.

Yet, in the experiments conducted by OWG such sanctions were frequently observed. Furthermore, when the amount of sanction per unit of cost was increased, the number of sanctions increased even though the result was a net decrease in system efficiency. Such behavior can be understood in terms of the heterogeneous, other-regarding model. Spiteful agents enjoy harming others and the more so, the more intense is the punishment for a given cost. Phenomena do exist in experiments that are difficult to explain without resort to either attitudes of fairness or repeated interactions. In the OWG experiments, the fines were not connected to guilt or innocence. Even an altruistic person would be forced to pay a fine if someone decided to inspect. In such a world, the spiteful people would not care who they inspect and altruists would have no incentive to inspect. Yet, people inspect others and, more importantly, they tend to target those who are heavy users of the common property resource. Without a modification, the spiteful model cannot explain such phenomenon. On the other hand, preferences reflecting fairness or envy would be leading to inspecting the richest people since that would lead to a more even distribution of the income.

Explanations other than the heterogeneous, other regarding model have been considered to account for the patterns of data reported in this paper. Specifically, the open access model can explain some of the results better than the classical model but does not perform as well as the other-regarding model. In the experiments without sanctions, the group use is in between the classical model prediction (X^{NE}=128) and the open access model prediction (X^{OA}=144) levels but statistically different from both. The introduction of weak sanctions raises the efficiency of 27.3 points, somewhat less than predicted by the open access model (39.5) and remarkably more than the no change predicted by the classical model. The actual level of cooperation achieved with weak sanctions is considerably higher than predicted by both models (57.2% vs. 39.5%). The open access model is closer than the classical model in explaining the results with strong sanctions (X^{OA}=80, X^{NE}=71.1, actual X=85.1). Neither model accounts for the observed individual heterogeneity in both use and inspection. Finally, the notes of the subjects after the experimental sessions show a widespread concern about the strategic interaction of one agent with the rest of the group.

3.12 Reflections of Institutions

The success of the *Carte di Regola* system appears to be related to its ability to use the heterogeneity of preferences to socially advantageous ends. The system also appears to have a type of robustness against institutional and parameter changes. Notice first that the *Carte di Regola* channels attitudes that might normally be considered as socially dysfunctional, such as spiteful preferences, into socially useful purposes. People with spiteful preferences choose to monitor and sanction at a monetary loss. However, when their preferences are considered as part of system efficiency, they are the ones who can perform the function most efficiently and are channeled into the activity for which they have a comparative advantage.

One might think that the *Carte di Regola* is similar to a system of vigilantes but there are important differences. In the model, spiteful people do not care who they hurt; they just enjoy hurting others, so it is important to direct and constrain them. The *Carte di Regola* directs them by reserving the judgment of guilt for the courts, as opposed to the vigilantes, who would be happy to judge anyone guilty. The court convicts a person only when the guilt is consistent with social purposes. The magnitude of punishment is also reserved for the courts in the *Carte di Regola* system, while in a vigilante system the inspector is allowed to judge and determine punishment. Therefore, the *Carte di Regola* constrains what the spiteful can do to the guilty. Thus, there are important differences (OWG, 1992).

The *Carte di Regola* also channels arbitrary or random behavior toward useful ends. Such behavior might ordinarily be regarded as dysfunctional from the point of view of economic efficiency. Mistaken inspections or impulsively random inspections are costly to the inspector and thus involve efficiency losses, but the fact that inspections take place has consequences for those who are excessive users of the common pool resource by increasing the likelihood that a sanction is imposed. Thus, random inspection behavior that would appear irrational helps preserve the commons.

One might think that the *Carta di Regola* would evolve in response to incentives to bribe inspectors and thus become ineffective as a management system. Instead, the *Carte di Regola* has a sort of "bribery proof" feature that could prevent a system of bribery from undermining its effectiveness. The antidote relies on the court's transfer of a portion of the fine to the inspector and, especially, on the existence of multiple potential inspectors. While an agent that detects a violator could be better off accepting a bribe from the violator than reporting the event to the court, the violator faces the possibility that other agents detect him after he has already bribed one agent. Indeed there may be nothing to prevent an inspector from extracting more than one bribe from the same violator by acting in collusion with other inspectors. When the level of the bribe relative to the sanction and when the number of potential inspectors is sufficiently high, the best choice of a discovered violator is to pay the fine instead of bribing. From this analysis, one would predict that anonymity (the identity of the inspector not being revealed) played no special role in the experiment.

One can easily imagine an enforcement system in which those who bear the cost of enforcement do so because of the benefits derived from repeated play. The willingness to bear the cost of inspection is balanced against the benefits of modified behavior in repeated play. Notice that the *Carte di Regola* system has a type of "replication independent" efficiency in that it does not depend on repeated play for the creation of efficient management of the commons. Those who do the inspections do so without looking at future behavior or rewards.

One can also imagine an enforcement system in which those who bear the cost of enforcement do so out of a sense of fairness and a willingness to punish those who are viewed as behaving unfairly. The *Carte di Regola* exhibits a type of "fairness independence" in the sense that such special preferences need not be in the population for it to work. In fact the *Carte di Regola* does not depend on the existence of spiteful agents for proper functioning but it does channel such people to useful purposes should they exist.

3.13 Conclusions

The primary purpose of the research reported here was to study the effectiveness of a special decentralized system of sanctioning rules applied to the problem of managing common property resources. The rules were fashioned after an ancient method of managing renewable resources in the Italian Alps called *Carte di Regola*, where people could inspect one another, inflict punishments and be rewarded for doing so according to well defined legal proceedings.

The paper reports three different types of results. Results of the first type are related to the performance as a system for managing the commons. Results of the second type are related to the relative accuracy of models of system behavior. Results of the third type reflect insights about the nature of these particular institutions that were uncovered by the research. The second and third types of results are related because the effectiveness and success of institutions are dependent upon behaviors.

The overriding result is that the *Carte di Regola* greatly improves the efficiency of resource use over a system that carries no sanctions. Importantly, the improvement is not only in terms of gross efficiency but also net efficiency, where the costs of administering the system (the inspection fees) are deducted. Under a weak sanction, treatment there was a spectacular improvement in gross efficiency from 28.4% to 57.2%. Once the inspecting costs are considered, (net) efficiency remains very high (48.3%). Group behavior in the strong sanction environment shows large improvements from 28.4% to 94% gross, or 76.9% net but is not at the optimal level.

The behavior of the system is largely understandable in terms of theory that explains previously observed inaccuracies and paradoxes. Two major changes in the classical game theoretic model account for the improvements. First, agents were assumed to have a capacity to be other-regarding and, second, the nature of the other-regarding capacity could differ from person to person. The other-regarding feature is captured by a parameter of the utility function that defines the weight placed on the monetary income of others in comparison with one's own monetary income. An individual is called altruistic if there is a gain in utility when the income of others increases while his own income remains constant. A spiteful agent loses utility when the income of others increases while his own income remains constant. About one-third of the agents are other-regarding to various degrees, either altruistic or spiteful, as measured by the model.

The heterogeneous, other-regarding model predicts observed behavior that the classical model does not predict. For example, while both the classical and heterogeneous, other-regarding agent models predict the observed increases in efficiency due to strong sanctions (Results 3.2 and 3.4), the increases in system efficiency resulting from weak sanctions are not predicted by the classical model but are predicted by the heterogeneous, other-regarding model. The patterns of resource use and agent's decisions to inspect the use levels of others also hold evidence of differential model accuracy. The prediction of the heterogeneous, other-regarding agent model is that spiteful agents are more aggressive inspectors than altruistic agents under all conditions (weak and strong sanctions). In fact, the spiteful agents are even willing to request unprofitable inspections. On the other hand, the level of use of the resource by the spiteful agents relative to altruistic agents reverses from relative heavy user to lowest level user as the treatment is changed from weak to strong sanctions. This seemingly perverse relationship, the flip in the relative behavior, is reflected in the data from the experiments (Results 3.3 and 3.5).

A spite/altruist paradox emerges from the experimental literature because reported individual behavior appears to be altruistic in public goods experiments while being spiteful in the theoretically similar common pool experiments. Given the results reported here, the paradox is potentially explained by the existence of both spiteful and altruistic agents in conjunction with a change in the action spaces available to agents in the public goods environment as compared with the common-pool environment. In the latter, the spiteful have greater latitude for action and the consequences of that latitude are manifest in system behavior.

The *Carte di Regola* seems to have been a successful system for managing common pool resources. The research provides insights into the features that might account for its success. First, the system holds a potential for increasing efficiency. Second, the system seems to have a type of resistance to infection of bribes. One might think that this legal arrangement could easily evolve to a system of widespread bribery. On the contrary, within the *Carte di Regola* rules the person caught in violation could readily prefer to pay the sanction as imposed by the court to the payment of a smaller bribe. Third, the *Carte di Regola* system channels possibly harmful human tendencies such as mistakes and spitefulness to useful social ends. Costly, random or mistaken decisions by some agents to inspect others serve as a deterrent to those who would otherwise exploit the commons and thus does not result in a total loss or waste of resources as do some types of economic mistakes. Spiteful attitudes that might ordinarily be considered as dysfunctional are channeled in a different way. Spiteful agents are those who find enjoyment in decreasing the earnings of others, and who willingly inspect others at a loss just for the thrill of inflicting damage. However, as it turns out such people provide a public good by bearing the monitoring cost of the system. The genius of the *Carte di Regola* is that it allows agents to specialize into activities that they like while controlling potentially dysfunctional behavior. The control and efficient direction of dysfunctional aspects is something that seems to be lacking in other decentralized management systems such as a system of vigilantes.

Chapter 4

Agents With Limited Cognitive Abilities in a Common Property Resource Environment

4.1 Introduction

The assumptions concerning the behavior of individuals play a crucial role in predicting the performance of institutions. For instance, given the same incentive structure, rational expectation agents might select a different equilibrium than adaptive expectation agents. "Most economic model presume that individual behavior is extraordinary rational, much more so than is warranted be either casual introspection or more careful empirical work." (Kreps, 1996). In particular, experimental economics has highlighted many instances of violation of the standard assumptions of rationality (Kagel and Roth, 1995).

This computational study considers the results of the common property resource experiments with and without a sanction mechanism presented in the previous chapter, which exhibit patterns that are poorly accounted for by the classical model. In order to explain the data, we need to depart from either the assumption that agents are purely selfish or from the assumption that they are maximizers and strategic in their behavior. We have already explored the former path in the previous chapter. Instead, this chapter postulates agents with limited cognitive abilities while maintaining their selfishness attitude.

One of the overwhelming results of the experiments is the high degree of individual heterogeneity of actions (El-Gamal and Grether, 1995). Allowing for diversity of goals is a way to accommodate such heterogeneity. A more powerful explanation is to rely on identical agents and still be able to obtain heterogeneity. The interaction of agents with limited cognitive abilities, where such limitations are identical for everybody, can in principle generate courses of actions that are individually diverse. There is always the option of assuming different degrees of limitation in cognitive abilities across individuals, but in this chapter we will look into the first, more challenging way.

We weaken the assumptions about the degree of rationality of the agents with respect to their abilities to store information, to perform computations, and to build expectations about the behavior of other agents. The decisional process is modeled through a genetic algorithm (GA) and explored using simulations. GAs were first developed by Holland as stochastic search algorithms by looking at the biological processes of evolution (Holland, 1975). They are increasingly being applied by economists to model economic agents in auctions (Andreoni and Miller, 1993, Dawid, 1999), in finance (LeBaron, 2000), foreign currency markets (Arifovic, 1996), and many other topics (Lucas, 1986, Axelrod, 1987, Dawid, 1996, Franke, 1997). GA agents are incapable of elaborating complex counterfactual scenarios and, instead, rely on adaptive search based on past experience for finding better solutions (Andreoni and Miller, 1993).

Genetic algorithms (GAs) are suitable tools to undertake the task outlined above because:

- They represent a class of behavioral models that can capture agents with a wide range of cognitive abilities (by changing behavioral parameters).
- The architecture of a GA can be easily adjusted to reflect the institutional details of the experimental design (environmental parameters).
- GA models provide insight into the dynamic and learning processes of agents' behavior.

Contrary to most of the works on GA, we employ a more sophisticated version of the algorithm that allows for individual learning. This feature originates from the adoption of an algorithm with memory sets, also known in the literature as multiple population GAs (Vriend, 1998, Arifovic and Ledyard, 2000).

Simulations are conducted under three different sanctioning institution designs (no sanction, weak sanction, strong sanction), and the outcomes are compared to the experimental data with human agents. Moreover, the effects of variations in both behavioral and environmental parameters are explored. The behavioral parameters relate to the cognitive abilities of the agents. Different processes to generate new hypothetical actions and different levels of computational sophistication affect the efficiency of the group outcome in using the common resource. In addition, the effect of adding or removing dominated strategies from the action space is studied.

An introduction to the behavioral model is given in Section 4.2, and a more detailed exposition of the genetic algorithm employed can be found in Sections 4.4 and 4.5. The incentive structure of the common property resource environment is summarized in Section 4.3. Section 4.6 explains how inspection decisions are modeled. Technical but important issues are discussed in Section 4.7 with reference to the binary coding of strategies and in Section 4.8 in relation to how new hypothetical actions are generated by the GA agents. The results of simulations are illustrated in Sections 4.9 and 4.10, and the conclusions follow (Section 4.11).

4.2. The Behavioral Model

While genetic algorithms have been introduced by computer scientists as search algorithms (Goldberg, 1989, Beck, 1996), their use in this work has an entirely different purpose (Riechman, 1999). The algorithm is considered successful not when it is faster than other decisional rules in reaching a maximum or an equilibrium, but when it reflects the behavior of human agents more accurately than other models. Before delving into the technical features of the specific version of GA, it is useful to unearth the implicit assumptions made about human behavior by using such algorithm. The purpose of this section is to clarify the characteristics of the genetic algorithm (GA) decision maker. Our GA agent has rather limited computational abilities. Consider in particular the following seven features of the decisional process:

A. While deciding the action to choose at each point in time, an agent takes into consideration only a limited set of hypothetical alternative moves, which is called the memory set. The size of the memory set is exogenously given and is related to the assumed level of sophistication of the decision maker. A larger memory size corresponds to a more sophisticated agent.

B. The decision maker is able to perform two operations: (1) to compute the payoff associated with a given action and (2) to perform pairwise payoff comparisons between actions in order to pick the best one. An agent does not maximize in the sense of choosing the best of all hypothetical moves in the memory set or of computing a best response function.

C. Agents learn by doing (adaptive learners) and do so at an individual level. The dynamic of the decision sequence comes from the continuous attempts to improve upon the old decisions. In particular, (a) successful ideas are reinforced (where an idea represents a hypothetical action/move); brilliant ideas gradually replace poor ideas over time through a stochastic process; (b) actions, namely the ideas that are implemented, are chosen out of the memory set. The memory set could be interpreted as the historical record of previous decisions and outcomes.

D. No imitation is taking place between agents. An agent cannot observe the hypothetical actions of other agents. Sometimes he cannot even observe the individual actions of other agents.

E. There is an active experimentation at the level of ideas (i.e., hypothetical actions). The generation of new hypothetical actions is modeled through a stochastic innovation process. A new hypothetical action does not automatically translate into an action but it might be selected in the subsequent periods, especially if good.

F. Agents have a very simple form of adaptive expectations, $x^e_{t+1} = x_t$, and do not think strategically. The behavior of all the other agents is treated as "the environment" and assumed constant from one round to the next. There is no strategic thinking regarding the number or type of agents or the possible reaction to the agent's changing of action. The only exception is the ability to compute what the agent would have earned in the previous period had he used one of the other hypothetical actions that are present in the memory set.

G. An agent cares only about his individual income.

4.3 The Common Pool Resource Experiments

For the convenience of the reader, we will report in this section a summary of the incentive structure of the experiments, which has already been discussed in detail in Chapter 3, as it will be the same faced by GA agents in the simulation. Agents face the same incentive structure for T interactions without carry-over from one period to the next.

A group of N agents interacts in the use of a common-pool resource. Each agent i decides an appropriation effort to use the resource, $x_i \in [0,\vartheta]$. The monetary payoff of agent i, $\pi_i = \frac{x_i}{X} \cdot f(X) + \alpha \cdot (\omega - x_i)$, has a revenue and a cost components. The revenues for agent i are a fraction $\frac{x_i}{X}$ of the total group revenues $f(X)$, which is given by the proportion of the agent's effort x_i relative to the group effort $X = \sum_{1}^{N} x_i$. The group revenues $f(X)$ are nonlinear in the group effort and first increase in X up to a maximal point and then decrease:

$$f(X) = \begin{cases} aX - bX^2, & if\, X \le 184 \\ 200 \cdot [e^{-0.0575(X-184)} - 1], & if\, X > 184 \end{cases}$$

The dynamic of renewable resources is generally modeled with a parabola as it is done in the first piece of $f(X)$. For high level of efforts, $f(X)$ has a lower bound at –200.

Using the resource involves a cost that linearly increases in the effort level according to the parameter $\alpha > 0$.

The parameters used throughout experiments are N= 8, ϑ=50, α = 5/2, a = 23/2, b=1/16. The choice of the endowment level ω has no effect on the incentive structure of the game, and in the simulations it is assumed that ω=0.

The basic features of the mechanism for monitoring and sanctioning are captured by a simple game where any agent i in the group has the option of selecting other individuals $j \neq i$ for inspection after he has privately decided his own exploitation level of the common-pool resource. At a unitary cost k, the inspector can view the decision of any individual. If the inspected individual has exploited the resource excessively, relative to a publicly known amount λ, a fine s_j is imposed and paid to the inspector:

$$s_i = \begin{cases} 0, & if \;\; x_j \le \lambda \\ h(x_j - \lambda), & if \;\; x_j > \lambda \end{cases}$$

The parameter h is the unitary fine for each extra token used and measures the stiffness of the punishment. Agent i makes a profit when the fee k paid to carry out the inspection is more than compensated by the transfer s_j from agent j to agent i, namely when $r_{ij} = (s_j - k) > 0$. As the transfer s_j is proportional to the use of agent j in excess of the "legal" threshold λ, a profit is made when agent j uses the resource more than $\tilde{x} \equiv \frac{k}{h} + \lambda$.

Considering both the use and the inspection decisions, the payoff of agent i is

$\pi_i = \frac{x_i}{X} \cdot f(X) + \alpha \cdot (\omega - x_i) - I_i s_i + \Sigma_{j \neq i} I_{ij} r_{ij}$, where $I_{ij} = 1$ indicates that agent i inspected agent j and $I_{ij} = 0$ indicates otherwise, while $I_i = 1$ if $\Sigma_{j \neq i} I_{ji} \ge 1$.

The interaction takes place sequentially into two steps. In step one agents decide the use in the common-pool resource. In step two agents take inspection decisions. An inspection involves at the same time information discovery as well as punishment. Before requesting an inspection, agents know only the total group use. After the inspection phase, the appropriation actions of the inspected individuals become public information. Another feature of the mechanism is that there is no accumulation of sanctions when more than one agent request to inspect the same action. When such cases arise, one inspector is randomly selected out of the requesting agents.

Experiments were performed under two levels of sanctions – a weak sanction and a strong sanction treatment. Under the strong sanction treatment, the unitary fine h is four times higher than in the weak sanction treatment, and the definition of excessive resource use λ is stricter (lower). The weak sanctions (k=7, λ=9, h=1) are designed to have no effect on the Nash equilibrium of the group outcome of the classical model (X=128). Strong sanctions (k=7, λ=7, h=4) are designed to move the equilibrium away from the inefficient outcome of the no sanction treatment to a fully efficient outcome (X=72).

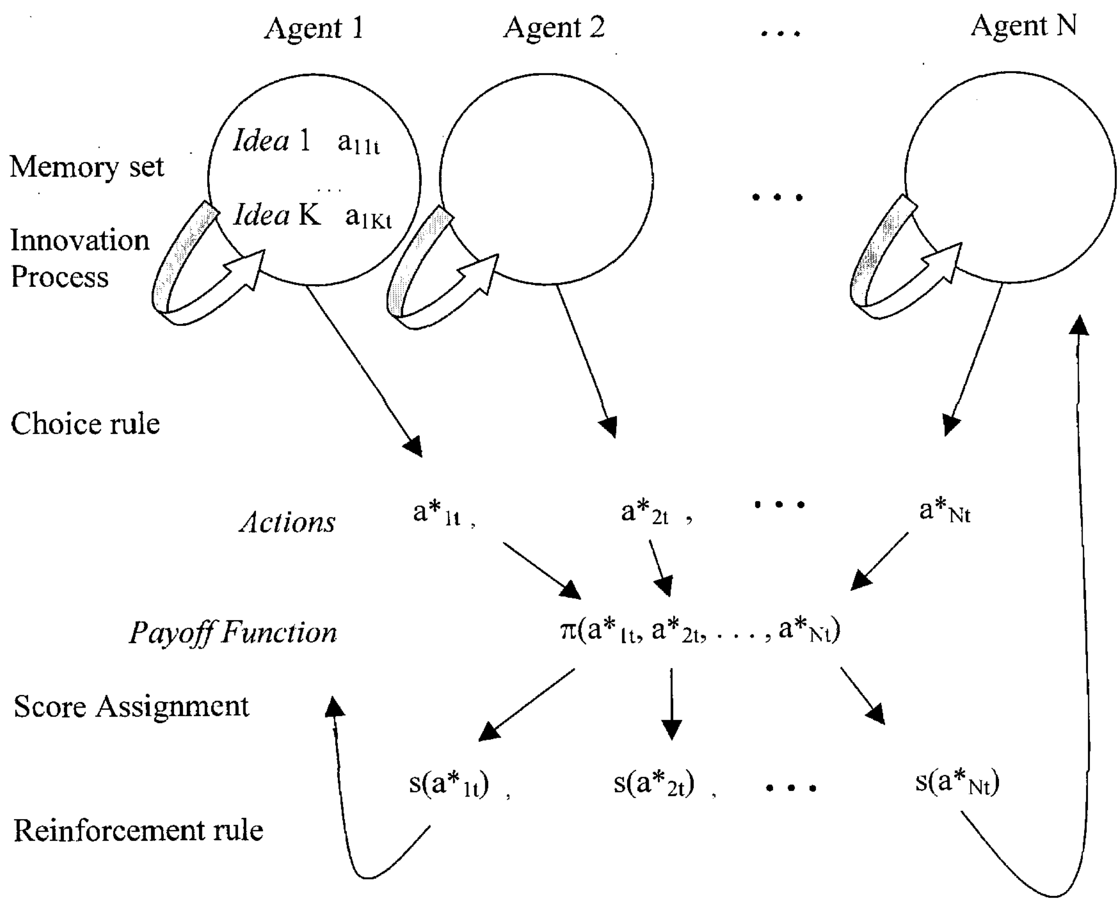
4.4. A Model of Adaptive Learning Agents

The artificial agents used in the simulations follow the decision making process described in this section. The structure of the process is modeled with a genetic algorithm (GA). A GA performs some operations, which will be described below, on a set of hypothetical actions over time. A hypothetical action $a_{ikt} \in [0,\vartheta]$ is a number that represents the use level of agent i at time t.

There are five major operators or components in a GA: a memory set, a reinforcement rule, an innovation process, a choice rule, and a score assignment (Figure 4.1).[1] Each component is now described in some detail. In the literature, GAs with a memory set are known as multiple population GAs.

[1] There is no recombination, i.e., crossover. Crossover in binary coding hardly relates to any aspect of the cognitive process. Moreover, it does not seem to alter significantly the results of simulations.

Figure 4.1: Architecture of the Genetic Algorithm



1. MEMORY SET. Agent i is endowed with a collection of hypothetical actions A_{it}= $\{a_{i1t}, \ldots , a_{iKt}\}$ that evolve over time t. Each hypothetical action has a score s_{ikt} associated with it, where a higher score denotes a "better" hypothetical action. These hypothetical actions will be sometimes called "ideas" because they do not have any impact on the outcome until they become "actions." The size of the memory set, K, is a measure of the level of sophistication of an agent since it determines how many ideas at each point in time an agent can evaluate and remember. The set size K does not change over time. The memory set can contain multiple copies of the same idea and, as a limiting case, K identical ideas.

2. REINFORCEMENT RULE. The memory set is initialized at random (uniform distribution over the action space) and then updated over time using a reinforcement rule similar to the replicator dynamics (proportional selection, see Appendix E). A reinforcement rule is a stochastic operator, R: $A_{it} \rightarrow A_{i,t+1}$, which "rewards" the "good" hypothetical actions in the memory set A_{it}. In other words, the higher the score s_{ikt} of a hypothetical action, the more probable it is to keep that hypothetical action at time t+1 and to increase the number of its copies. A key characteristic of a reinforcement rule is how quickly a successful hypothetical action displaces the others in the memory set. The measure suggested here is the expected takeover time (TOT), which indicates how many iterations it is expected to take for a new idea that has the highest score in the set, in the absence of any new idea, before all the ideas in the memory set are copies of that idea, and no other idea is there (Bäck, 1996). Faster is not necessarily better, though, because keeping the knowledge of old hypothetical actions can be useful when the "environment" changes.[2]

The reinforcement rule here adopted is a Pairwise tournament: (1) two hypothetical actions are randomly drawn with replacement from the memory set at time t; (2) within that pair, the one that scored the best is placed in the set for time t+1; (3) this operation is performed K times at each round of iteration. The take overtime of the Pairwise tournament rule is TOT=(ln K + ln(ln K))/ ln 2 (Bäck, 1996). An agent with a larger memory size K has a longer historical memory and abandons an idea only after a longer sequence of trials.

[2] Suppose for instance that there is an exogenous 6-period-long cycle in the environment and that there are only two possible strategies: x, best for the first 3 periods, and y, best for the last 3 periods. If TOT=2 the agent will lose memory of one strategy and needs to learn it all over again by experimentation at every cycle. An agent with TOT=4 will perform better.

3. INNOVATION PROCESS. New hypothetical actions, or ideas, are introduced in the memory set through a random process. The two main features of that process are the probability that an existing hypothetical action is replaced by a different one (innovation level, p) and the statistical distribution of the new hypothetical actions in the action space (innovation distribution, $g(\cdot)$). A common choice in the GA literature is adopting a uniform binary mutation rate pm. The parameter $pm \in (0,1)$ indicates the probability that a digit '0' flips to '1' or vice versa. This rate is constant over time and is constant for all the digits irrespective of their position in the string, in particular of their high or low cardinality. The innovation level is $p=1-(1-pm)^L$ where L is the number of digits of the binary string. The nature of the innovation distribution of a uniform binary mutation process will be illustrated in Section 4.8 along with the nature of other alternative forms of innovation processes. Unless otherwise noted, a uniform binary mutation is used in the simulations. As the next point will make clear, a hypothetical action, old or new, does not automatically become an action (see also Propositions 4.2 and 4.3).
4. CHOICE RULE. Which idea a_{ikt} becomes the action of the agent a^*_{it} is determined by a choice rule, $C: A_{it} \rightarrow a^*_{it}$. *A choice rule is a stochastic operator that selects one action out of the memory set.* The agent is modeled with a Pairwise tournament choice rule. With such a rule, a better hypothetical action has higher chances to become an action than a mediocre hypothetical action. In general, the probability that a hypothetical action a_{ikt} is chosen as the action out of a set of K hypothetical actions depends on its ranking, $Pb_k = (2^* r_k -1)/K^2$, where $r_k \in \{1(\text{worst}), 2, .., K(\text{best})\}$ (Proposition 4.1 and Corollary 4.1). The actual ranking of a new hypothetical action

a_{ikt} depends on the diversity of the memory set, on how much learning has already taken place, and on the nature of the innovation process itself.

5. SCORE ASSIGNMENT. The score of each individual action (actual score) is a transformation of the payoff function from the use of a common pool resource in the experimental design, $s(a^*_{it})=\pi_i(a^*_{1t}, \ldots, a^*_{Nt})$+constant. The architecture of this GA is such that any strict positive monotonic transformation of π_i would not change the outcome (Proposition 4.4).

   More subtle issues are raised by the way in which scores are assigned to hypothetical actions, which did not become actions (hypothetical score, $s(a_{ikt})$ for $a_{ikt} \neq a^*_{it}$). An agent needs to know its individual profit function and to be able to use it to compute the hypothetical score of all the hypothetical actions in the memory set while holding constant the behavior of all the other agents. In other words, a higher level of information and computational abilities than the ones assumed so far are needed, in particular: (a) knowledge of the payoff function, π; (b) knowledge of the sum of the actions of all the other agents, $X_{-it} = \sum_{i \neq j} a^*_{it}$; (c) ability to evaluate the score assuming that a different hypothetical action was chosen as action, $s(a_{ikt})=\pi_i(a_{ikt}, X_{-it})$+constant.

The agent uses a mix of reinforcement learning and analytic model. When a score is assigned to an action, namely an idea that was effectively used (actual score), it is an instance of reinforcement learning. When a hypothetical score is computed for all the other hypothetical actions that were not actually used but could have been used in a given round, that computation is always done relying on a model, however subjective and imperfect, of the behavior of the other agents (Kreps, 1996). In this case the analytical model simply assumes that all the other agents will not change their actions in the following period (adaptive expectations).

Table 4.1: GA Agents and Resource Use

	Component/Operator	Parameters	Parameter Values
	Number of agents in the group		N=8
1	Memory set	$A_{it}= \{a_{i1t}, \dots, a_{iKt}\}$ K=set size	K=6
2	Reinforcement rule	R: $A_{it} \rightarrow A_{i,t+1}$	Pairwise tournament
3	Innovation process	• Innovation level • Innovation distribution	Uniform binary mutation pm=0.02, lchrom=8 (string length), p=0.15
4	Choice rule	C: $A_{it} \rightarrow a^*_{it}$	Pairwise tournament
5	Score assignment	• Actual score $s(a^*_{it})$ • Hypothetical score $s(a_{ikt})$	- score is updated at every interaction - payoff function is known π - score is a monotonic transformation of the payoff function - the sum of the actions of the other agents is known X_{-i}

There is no other strategic thinking by the agent. For instance, this GA agent does not have a model of the others' decision rules. As a consequence it is unable to make a prediction at the initial period about other people's actions because it is unable to compute "the equilibrium." It emphasizes past outcomes to devise a successful strategy to use. Moreover, a GA agent does not explicitly take into account how many other agents are in the group. The environment is treated as an aggregate.

What is a strategy in a game-theoretic sense for an artificial agent? The artificial agents could play any action that is in the memory set and nothing that is not in the set can be played. Each action is played with a positive probability, which is given by the Choice rule (i.e., draw with replacement two elements out of the memory set and play the one with the highest score). Thus, a strategy at time t is defined as the entire memory set at time t and can be seen as analogous to the concept of a mixed strategy. A strategy of an artificial agent changes over time in response to the actions/strategies of the other players.

A genetic algorithm can be represented as a Markov chain since the transition from one period to the next has a stochastic component and the current state of a population of strings P_t depends only on the population at the previous step, P_{t-1}. We will describe this mathematical representation of genetic algorithm and mention some of the theoretical results that have been proven. The focus of the paper is, however, on the computational aspect. The term population is here employed to indicate a single memory set and consists of K binary strings of length L. The set Ω denotes all the possible binary strings of length L, while S *indicates the set of possible states of the population.* A state of the population ϕ is given by a r-dimensional nonnegative vector describing the frequency distribution over Ω. The dimension $r=2^L$ comes from the mapping of the binary strings into the corresponding integer value q in decimal coding in such a way that $q\phi_t$ is the number of strings of value q in the population P_t. The set of all population states has cardinality $|S|=\binom{K+2^L-1}{2^L-1}$, which becomes very large as K increases. For example, when K=6 and L=8, there are more then 414 billions states. This formalization was first suggested by Nix and Vose (1992) and enables to discriminate between states which contain different strings, but, on the other hand, it does not discriminate between states where the same strings are contained in different order (Dawid, 1999).

Despite the large number of states, the transition probabilities from one state to another can be easily computed because we are dealing with time homogeneous Markov chain, whose probabilities are independent of time. The transition probabilities are influenced by both the reinforcement and innovation rules. Moreover, an operator $G:S_t \rightarrow S_{t+1}$ can be defined to describe the transition of a given population from one period to the next.

The version of the genetic algorithm employed in this study has three additional features in comparison with the simple genetic algorithm adopted in the literature:

1. Multiple populations. A state is described not by a single vector ϕ but by an array of vectors $(\phi_1, \phi_2, \ldots, \phi_N)$
2. State dependent payoff function. The payoff of an action is influenced by the value of the actions chosen by other players, $f:S^N \rightarrow R^{rN}$.
3. Reinforcement rule. Instead of using proportional selection, we employ a tournament reinforcement rule. Proportional selection is a discrete-time version of the replicator dynamics (Appendix E).

The analytical study of genetic algorithms focuses on the fixed points of the operator G and on the stability of those fixed points. A summary of some general theoretical results is provided in Dawid (1999) and Mitchell (1996). The line of reasoning is the following. First, when the innovation rate is positive, a Markov chain representing a single population genetic algorithm is irreducible. In fact any arbitrary string can be transformed into any other string just by the means of uniform binary mutation, and so the transition matrix of the process is strictly positive. Second, given this irreducibility, the process has a unique stationary distribution, which coincides with the limit distribution of the chain. Third, if the innovation rate is sufficiently small, this limit distribution is concentrated on the uniform states. A state is uniform if all the strings in the population are equal. Fourth, because of the strictly positive innovation rate, there is no convergence of the genetic algorithm to any uniform state. For small innovation rates, however, the population is, after a transient period, in a uniform state for almost all the time.

This last result is important for our analyses because it states that heterogeneous states are structurally unstable. The result about a convergence in probability to a uniform state has limited use because it holds only in the long run. Moreover, we don't know both how small the innovation rate needs to be and to which uniform state the algorithm is going to converge to. Once the GA is in a uniform state, it can be either stable or unstable. Some analyses have been done about the local asymptotical properties of a uniform state (Dawid, 1999).

4.5 Some Analytical Results

Some of the statements of the previous section about the choice rule, the innovation process, and the score function are presented more formally and then proven in this section. Although different from deterministic maximization, the GA agent's behavior is characterized by a probabilistic response that favors high score hypothetical actions, which is modeled as a tournament choice rule (Proposition 4.1).

An M-Tournament choice rule is in two ways a weaker form of maximization than the rule "pick the best hypothetical action in the set as your action." First, the number of hypothetical actions involved in the tournament is generally much lower that the size of the memory set, M<<K, and so only a subset of hypothetical actions is actually compared (with pairwise tournament it is M=2). Second, the value M is just an upper bound to the number of different hypothetical actions compared. In fact, even when M=K, the choice rule is different than deterministic maximization because the M hypothetical actions are drawn with replacement.

The GA agent actively explores the performance of the various hypothetical actions available and places a higher probability of use on promising ones and of reuse on the ones that scored highly. This feature holds irrespectively of the innovation process adopted since it is an effect of the choice rule. The larger the memory set, the more sophisticated is the agent in processing alternative hypothetical actions. In particular, this is because it evaluates more hypothetical actions at each point in time, because of the higher probability of choosing the best hypothetical action compared to the worst (Corollary 4.1), and because it tests a hypothetical action for a longer period before discarding it (Figure 4.2).

Proposition 4.1

The probability that a hypothetical action x is chosen by a pairwise tournament choice rule out of a set A of K ideas and becomes an action x* is $P\{x^* = x\} = \frac{2r_x - 1}{K^2}$, where r_x is the ranking of hypothetical action x within the set A (the worst hypothetical action ranks 1, r_x=1, and there are no ties).

Proof:

Consider the ranking of hypothetical action x in A, $\{1,2, \ldots, r_x, \ldots, K\}$ and a choice rule which operates by (1) drawing with replacement two hypothetical actions out of A, and (2) between the two it takes the one with the highest score.

Let's define $p_x = p_a \cdot p_b = P\{x \text{ is drawn out of A}\} \cdot P\{x \text{ is chosen after it has been drawn}\}$.

There are three possible cases in which the hypothetical action x can be drawn: $p_a = P\{(x,y)\} + P\{(y,x)\} + P\{(x,x)\} = \frac{1}{K} \cdot \frac{K-1}{K} + \frac{K-1}{K} \cdot \frac{1}{K} + \frac{1}{K} \cdot \frac{1}{K}$, where $y \neq x$.

When the competing hypothetical action is y, the probability that hypothetical action x is chosen against any of the other K-1 is $p_b = P\{ r_x > r_y\} = \frac{r_x - 1}{K-1}$.

Hence, $p_x = P\{(x,y) \text{ or } (y,x)\} \cdot P\{r_x > r_y\} + P\{(x,x)\} \cdot 1 = 2\frac{1}{K}\left(\frac{K-1}{K}\right) \cdot \left(\frac{r_x - 1}{K-1}\right) + \frac{1}{K^2} \cdot 1$.

The expression above defines a probability distribution since $\sum_{x \in MS} p_x = \sum_{r=1}^{K} \frac{2r-1}{K^2} = 1$.♦

Corollary 4.1

(i) The median ranking hypothetical action is chosen with probability 1/K.

(ii) The odds that the best versus the worst hypothetical action is chosen are increasing in the memory set size, (2K-1) (inverse of error odds).

(iii) Consider K even. The probability that the chosen action ranks above the median ranking hypothetical action is ¾, irrespective of the size of the memory set.

Proof:

(i) The median ranking is defined as $r_y = (K+1)/2$, hence $p_y = 1/K$.

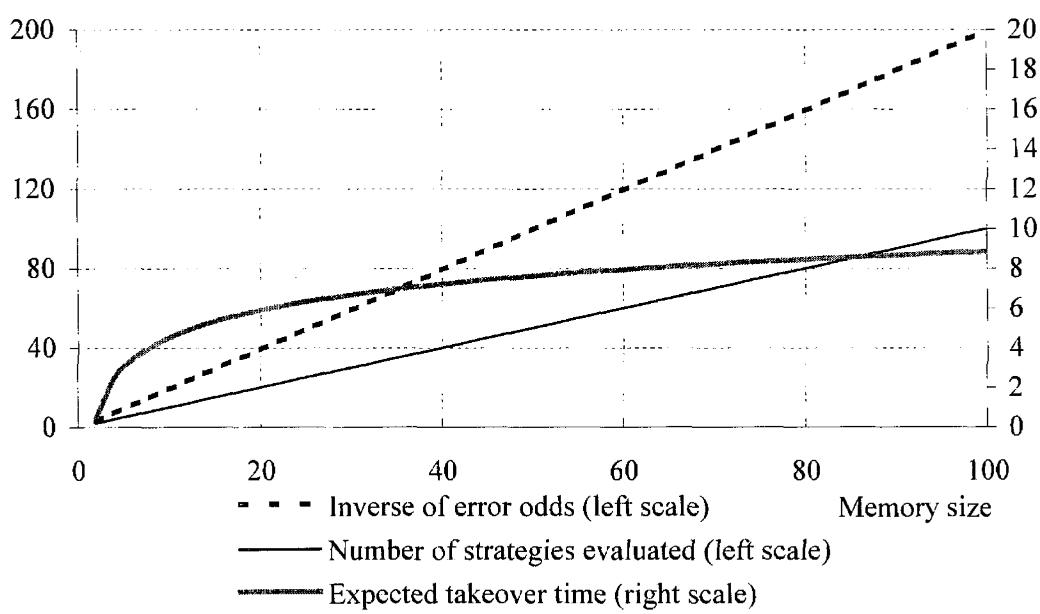
(ii) $P\{r_x = 1\} = 1/K^2$, $P\{r_z = K\} = (2K-1)/K^2$, $\text{odds} = p_z/p_x = (2K-1)$.

(iii) Suppose K is an even number, $\alpha = \dfrac{\sum_{r=K/2+1}^{K} \frac{2r-1}{K^2}}{\sum_{r=1}^{K/2} \frac{2r-1}{K^2}} = 3$, given that $\sum_{r=1}^{N} r = \dfrac{N(N+1)}{2}$ and

$$\sum_{r=w+1}^{K} r = w(K-w) + \sum_{r=1}^{K-w} r .\blacklozenge$$

Despite the interference of the choice rule between ideas and actions, the innovation level p is still a meaningful parameter to describe a GA process when there are memory sets. As Proposition 4.2 makes clear, p establishes a reference value also for the innovation at the level of actions.

Figure 4.2: Memory Size and Agents' Abilities



Proposition 4.2

Consider an innovation level of hypothetical actions p and a memory set $A=X_A \cup X_B$. If all hypothetical actions, old X_A and new X_B, have the same score, the probability that the hypothetical action that becomes the actual action x* is a new hypothetical action, $P\{x^* \in X_B\}$,

(a) is equivalent to the innovation level, $p= P\{x^* \in X_B\}$

(b) is independent from the size of the memory set

Proof:

Given an innovation level p (probability that an old hypothetical action is replaced by a new one), the expected number of new hypothetical actions in a memory set of size K is $E[|X_B|]=pK$. When all hypothetical actions have the same score, the probability that one of those new hypothetical actions becomes an action is $P\{x^* \in X_B\}=(1/K)\, E[|X_B|]=p$. ♦

While the innovation level among hypothetical actions is constant throughout a simulation, the actual level of innovation in terms of actions might change over time, and in particular it might decline when the agents approach an equilibrium point. This possible dynamic could emerge because new hypothetical actions, which are generated at random, do not perform as well as the current hypothetical actions, which were refined through many interactions.

Proposition 4.3

If the sum of rankings of new hypothetical actions within a memory set, $\sum_{x \in X_B} r_x$, declines, the probability that a new hypothetical action becomes the action, P{x* ∈ X_B}, declines as well.

Proof:

Consider the probability of a hypothetical action from the set X_B of becoming action, P{x* ∈ X_B}= $\sum_{x \in X_I} \frac{2r_x - 1}{K^2} = \frac{1}{K^2}(2R_B - pK)$, where $R_A = \sum_{x \in X_B} r_x$, and $|X_B|$=pK.

The proposition follows from $\partial\alpha/\partial R_B > 0$. ♦

The last proposition concerns the sensitivity of the results to the score assignment rule. In the biological interpretation of the score as measure of fitness, the very absolute value is important because, in conjunction with the reinforcement rule, it describes the number of offspring that are expected from that individual in the following period. On the contrary, this version of the GA does not require a cardinal interpretation of the score. The score function is ordinal and could be viewed as the utility function of the agents. This property, stated in Proposition 4.4, marks a difference with the replicator dynamics.

Proposition 4.4

The results of the decisional process are not effected by any strictly increasing transformation of the score function.

Proof:

When the score $s(a_{ik})$ is replaced by $v(s(a_{ik}))$, where v is a real function such that $\partial v/\partial\cdot>0$, the results of the decisional process are not changed by the operations performed through the reinforcement rule, the innovation process, and the choice rule.

The innovation process is modeled in three different ways. Uniform binary mutation and local innovation (Section 4.8.2) do not depend at all on the score. The cost driven innovation process does rely on some features of the payoff function, but those features are preserved by any transformation v because an ordinal version of the innovation process is adopted (Section 4.8.3).

Both reinforcement and choice rules are based on pairwise tournament, which operates on the ranking of the hypothetical actions. As v does not change rankings, the results are unchanged. ♦

4.6 Inspection Decisions With Adaptive Learning Agents

In some experiments the agents were simply required to choose a use level of the resource while in other treatments a monitoring and sanctioning mechanism allowed to select other agents for inspection. A decisional process similar to the one described for resource use applies to inspections, with a complication due to imperfect information.

Inspection decisions are taken under conditions of asymmetric information where an agent knows his own and the aggregate resource use levels but not the individual choices of the others. Hence an agent needs to have some sort of beliefs about the behavior of each one of the other agents in order to select the individuals to inspect. Moreover, the agent can take advantage of the knowledge of the aggregate use of the resource, which provides a useful indicator of the size of the potential profits that can be earned by appropriately inspecting the other agents.

The decisional process about inspections has a simple structure. The genetic algorithm (GA) agents develop beliefs about the use levels of the resource by others and inspect a selected subset of agents when the aggregate resource use, which is publicly available information, is higher than a threshold.

4.6.1 Beliefs

Each agent i has subjective beliefs about the use levels of the other N-1 agents. The beliefs of agent i about agent j, B_{ij}, are a collection of elements bel_{ijk} with k=1, … , KB. The single element bel_{ijk} is a number representing an agent type. For example, consider a situation where KB=6 and one element is bel_{ij1}=2 while all the other five elements are bel_{ijk}=3. This means that agent i attributes a much higher probability that agent j is of type 3 instead of type 2 and zero probability that the agent is of any other type.

A larger size KB of the belief set denotes an agent with a more refined partition of beliefs and one that keeps a longer memory of the past behavior of the agents. The expected takeover time measures the length of reputational effects (Figure 4.2).

An agent is classified into one of three types according to the profitability of inspecting him. Since the sanction is weakly increasing in the use level of the resource, the classification can be uniquely mapped into use levels as well. An agent is considered of a "standard" type (SG) if the balance of the inspection is about zero (+/-1 unit of resource use). "Good guys" (GG) are the agents that have a low use of the resource and yield a loss when inspected. The "bad guys" (BG) are the preferite targets of inspections since it is profitable to inspect them. In the algorithm the beliefs are coded with the following integer numbers: 0 (=GG), 1 and 2 (=SG), and 3 (=BG). The architecture of the decisional process for the beliefs is very similar to the one described for the use decisions when beliefs are interpreted as the hypothetical action (Table 4.3).

Few additional words need to be spent on the innovation process and on the assignment of the score. As will be explained later on, the innovation process is deeply affected by the binary coding of moves. Because of the peculiar assignment of the numbers {0,1,2,3} to the types {GG,SG,BG}, innovation on beliefs has instead regular features, like symmetry, as is apparent from Table 4.2, which exhibits the probabilities of one-step transition from one type to another.

Table 4.2: Innovation Process for Agent Beliefs: Transition Probabilities

		→ Agent type at period t+1			
		GG	**SG**	**BG**	Totals
Agent type	**GG**	$(1\text{-pm})^2$	2pm(1-pm)	pm^2	1
at period t	**SG**	pm(1-pm)	$\text{pm}^2+(1\text{-pm})^2$	pm(1-pm)	1
→	**BG**	pm^2	2pm(1-pm)	$(1\text{-pm})^2$	1

Note: type=(real number)=(binary number):GG=0=00, SG ε{1,2}={01,10}, BG=3=11; pm=mutation probability.

The second clarification regards the way in which the score is assigned to the various beliefs. In this context, the payoff function is the inspection balance, and the score is a weakly positive monotone transformation of it that assumes as possible values either 0,1, or 2 according to the instructions below:

If inspecting the agent	is profitable	then GG=0, SG=1, BG=2.
If inspecting the agent	has about a zero balance	then GG=1, SG=2, BG=1.
If inspecting the agent	turns into a loss	then GG=2, SG=1, BG=0.

Table 4.3: GA Agents and Inspection Decisions

	Component/Operator	Beliefs	Threshold levels	
			Set 1	Set 2
	Activation	Three types of agents: GG = good, SG = standard, BG = bad	Inspect BG when $t1^*_{ikt}<X_t-x_{it}$	Inspect SG when $t2^*_{ikt}<X_t-x_{it}$
1	Memory set	KB=6 for each of the other N-1 agents	KT1=12	KT2=12
2	Reinforcement rule	Pairwise tournament within each set	Pairwise tournament	Pairwise tournament
3	Innovation process	Uniform binary mutation pm=0.02 bchrom=2 p=0.04	Uniform binary mutation pm=0.02 tchrom=10 p=0.18	Uniform binary mutation pm=0.02 tchrom=10 p=0.18
4	Choice rule	Pairwise tournament within each set	Pairwise tournament	Pairwise tournament
5	Score assignment	- 0,1, or 2 according to inspection balance for the agent - score updated when the information in the group is available - sanctioning rule is known	- 0,1, or 2 according to inspection balance of BG agents and $t1_{ikt} \gtreqless X_{-i,t}$ - score updated when in the group all the information is available - sanctioning rule is known	- 0,1, or 2 according to inspection balance of SG agents and $t2_{ikt} \gtreqless X_{-i,t}$ - score updated when in the group all the information is available - sanctioning rule is known

Scores of beliefs about agents are updated every time j is inspected by somebody in the group. The use level of an inspected agent becomes public information, and everyone uses the information to update scores. When that information is not available, the old scores are kept. The agent is assumed to know how the sanction is computed.

4.6.2 Threshold Levels

Inspections are triggered when the use level of all the other agents combined (X_{-i}) is above a threshold value. Each agent has two threshold levels, $t1^*_{it}$ and $t2^*_{it}$. When the resource use is above the first threshold, all the agents believed to be high users (BG) are inspected. When the resource use is above the second threshold, all the agents believed to be medium users (SG) are inspected.

Threshold levels change over time according to a similar process that characterizes the evolution of individual use actions (Table 4.3).

The only peculiarity is relative to the score assignment. The payoff function is the sum of the inspection balances of BG agents in the case of the first threshold and of SG agents in the case of the second threshold. The score of a threshold level is assigned in the following way. Consider the threshold memory set of agent i $\{t1_{i1}, t1_{i2}, \ldots, t1_{iKT1}\}$ ordered by its numerical value from highest to lowest, $t1_{i(k)} \geq t1_{i(k+1)}$. Assume that the threshold level chosen to be played is $t1^*_i = t1_{i3}$. An inspection occurs when $t1^*_i < X_{-i}$, and no inspection is triggered otherwise. If an inspection occurs and the inspection balance is a profit, the scores are $\{ t1_{i1}=0, t1_{=i2}=0, t1_{i3}=1, t1_{i4}=2, .., t1_{iKT1}=2\}$. If the inspection balance is a loss or zero[3], the scores are $\{ t1_{i1}=2, t1_{i2}=2, t1_{i3}=1, t1_{i4}=0, .., t1_{iKT1}=0\}$.[4]

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[3] A zero inspection balance can occur in two instances: when nobody is inspected or when inspections are actually requested and there is no loss or profit.

[4] How is the inspection balance of an agent for a round computed? An inspection can be requested by more than one agent. In that case one inspector is randomly selected and all the others will not carry out the inspection. In other words, there is a distinction between a hypothetical inspection balance (if all the

The threshold action scores of agents are updated every time agent i requests to inspect. If no inspection was requested by agent *i*, some information is still freely available to him because of inspections requested by others. When a sufficient level of information is available, a new score is assigned to the hypothetical threshold levels of agent i. There is sufficient information for updating the score when the use level of all agents that would have been inspected had the threshold level been surpassed are publicly available.[5]

When the available information is not sufficient, the old score is kept. In other words, each hypothetical threshold in the memory set goes through the reinforcement operator while retaining either its old score or the old score of the action that originated it.

4.6.3 Impact of Inspections on Use Decisions

When agents face the possibility of being inspected, their incentive structure changes. In particular, their expected payoffs crucially depend on the perceived probability of being inspected.

The GA agent has a very simple form of adaptive expectations: if the agent was inspected in the previous period, then the score is computed assuming a probability one of inspection in the next period; otherwise the probability is assumed to be zero. This rule is not as crude as it seems because it is mediated by the past evolution of hypothetical actions in the memory set. For example, if an agent has always been

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requests are executed) and an actual inspection balance (when only some requests are executed). Which one of the two balances should be used for establishing the success of a threshold strategy (its score value)? I always use the hypothetical balance. The assumption is that agents are smart enough to recognize that they made a good/bad decision looking at the uncovered use levels but they are aware to have been unlucky enough of not being selected by the random device used to allocate an inspection among all those who requested it. Moreover there is an assumption that agents are risk neutral.

inspected except at time t, his memory set contains all hypothetical actions that perform well when the agent is inspected, and it will take few iterations without inspections to develop a good response for the new situation. This process mimics the transition from a situation where the perceived probability is one to another where such probability slowly declines to zero.

4.7 Implications of the Binary Coding

The GA algorithm translates all the moves into equivalent binary strings of 0s and 1s. The operators are applied on binary numbers and not on real numbers. Although not essential to the nature of GA, binary coding is commonly used also in social science applications (Arifovic, 1994, Dawid, 1999, Franke, 1997, Andreoni and Miller, 1995). The choice of the coding, real or binary, is not irrelevant in terms of implicit assumptions about human behavior. In particular there are consequences in two realms, action space and innovation process.

When using binary coding, the action space is divided into a grid and only the points on the grid are available actions for the agents. The number of points on the grid is decided upon as part of the GA architecture through the choice of a string length. For example, the action space [0,50] is coded with a string of 8 characters, which allows for 2^8-1=255 grid points. Although infinitely many moves become unavailable, partitioning the action space is not in contradiction with what people do. While in the experiment with human agents any real number could be chosen, only 13% of the actions were not integer numbers.

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[5] If no agent would have been inspected had the group use gone beyond the threshold level, there is always updating. This is the case when no agent is believed to be BG or SG.

A more annoying feature of the binary coding is that the grid points do not necessarily include the integers or the equilibrium values. Increasing the string length can bring the available actions closer to the equilibrium points by any degree of approximation wanted, and differences in outcome are usually going to be small.[6] Some theoretical results point out that the way in which a problem is coded affects the stability property of the genetic algorithm (Dawid, 1999).

The second consequence of adopting binary coding is on the nature of the innovation process. The level of innovation is controlled by two parameters, the mutation rate, pm, and the string length, L. The probability that a hypothetical action is replaced by a different one when pm=0.02 and L=8 is equal to 0.15. Notice that the mutation rate alone is not a sufficient measure of the innovation level. The next section will describe the distribution of innovations in the action space induced by the binary coding.

4.8 The Innovation Process

The generation of new hypothetical actions takes place in two steps. First, for each hypothetical action x_{ik} in the memory set a biased coin is flipped to decide whether replacing it or not with a new one. The probability of replacement is called *innovation* level. Second, once the decision to replace the old hypothetical action has been taken, a new hypothetical action z_{ik} is drawn from a random variable with density function g(z) (innovation distribution). In general, there is a class of densities g(z|x), which are parametrized by the values of the old hypothetical action x.

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[6] In this case the closest value to X^{NE}=128 is 128.04 when three agents use the resource 15.88 (grid point 81) and five agents use the resource 16.08 (grid point 82).

The properties of the uniform binary mutation will be described as well as the features of three other innovation processes: local, cost driven, and "mountain top." An innovation distribution is characterized by its support, symmetry, mode, and single peakness (Table 4.4).

Table 4.4: Four Types of Innovation Processes

	Uniform Binary Mutation	Local	Cost Driven	Mountain Top
Support	Entire action space	Entire action space	Entire action space	Subset of action space
Symmetry	NO	NO	NO	YES
Mode	x_{ik}	x_{ik}	Best response To X_{-i}	x_{ik}
Single Peakness	NO	YES	YES	YES

4.8.1 Uniform Binary Innovation Process

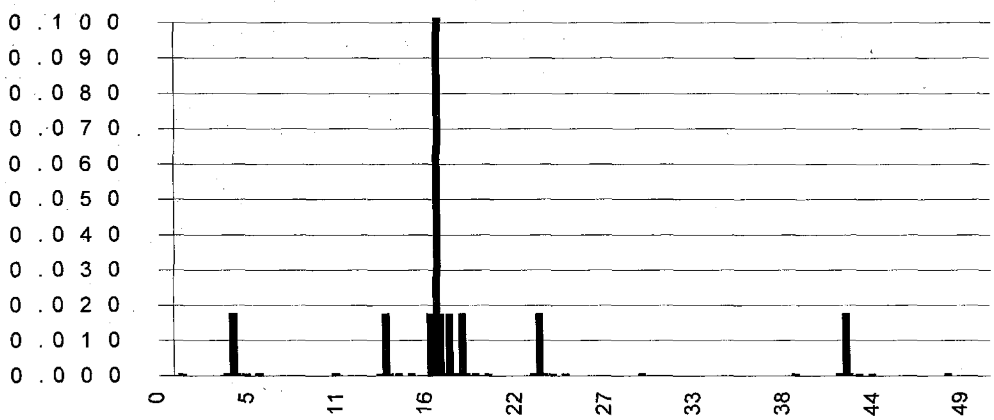
Given a hypothetical action coded in binary symbols {0, 1}, a uniform binary mutation assigns a constant probability of mutation pm to each digit in the string.

The support of the innovation distribution is the entire action space. Whatever the old hypothetical action is, any hypothetical action in the action space can be reached with a positive probability. In particular, given a length L of the binary string it takes $M \leq L$ independent mutations to reach any point. The probability of the transition is $pm^M(1-pm)^{L-M}$.

For pm<0.5, the modal value of the distribution is the old hypothetical action x. For instance, given pm = 0.02 and L=8, the status quo is chosen with probability 0.8508. In other words, the innovation level of the process is 0.1492.[7]

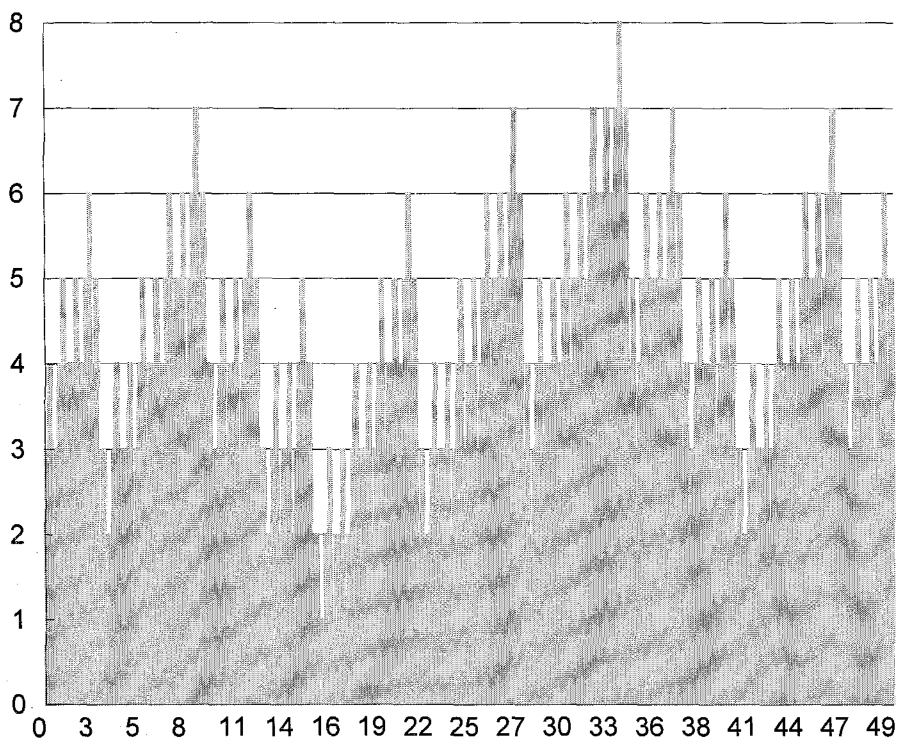
[7] Scholars have put forward several formulas to set an optimal mutation rate for the search of a global optimum in a "difficult" environment, based either on empirical of theoretical arguments. The relations among the three variables above found by Schaffer, Carun, Eshelman, and Das (1989) and Hesser and Männer (1991) imply that $[p_m \cdot K \cdot \sqrt{l}]$ should be kept constant. None of these arguments applies here because the aim is not to build an efficient search algorithm, but to have an accurate model of human behavior.

Figure 4.3: Innovation Distribution Induced by Uniform Binary Mutation



Note: pm=0.02, L=8, action space [0,50], initial hypothetical action x=16.08; mode probability 0.8508

Figure 4.4: Uniform Binary Mutation: Number of Mutations Needed to Reach the Nash Equilibrium from Other Points



Notes: L=8, action space [0,50], initial hypothetical action 16.08.

The induced density function is not single picked and is not symmetric. As can be seen from Figure 4.3, the induced innovation distribution is rather unintuitive as a process for human behavior in generating new ideas. Figure 4.4 represents the number of mutations necessary to transition from reference point, 16.08 = 01010010, to other points in the action space [0, 50] using a binary representation with a string of L = 8.

4.8.2 Local Innovation Process

An appealing property of an innovation distribution is to attribute a higher probability of transitioning to hypothetical actions that are closer to the initial hypothetical action than to the ones further away.

Definition 4.1:

An *innovation density function* g :$[0,\vartheta]\rightarrow[0,1]$ is LOCAL if, given an Euclidian notion of distance d:$[0,\vartheta]\times[0,\vartheta]\rightarrow\Re$ and a reference hypothetical action x, for every *y, z* that satisfy one of the following conditions: (i) $d(0, y) - d(0, x) > 0$, $d(0, z) - d(0, x) > 0$, and $d(y, x) < d(z, x)$ or (ii) $d(0, y) - d(0, x) < 0$, $d(0, z) - d(0, x) < 0$, and $d(y, x) < d(z, x)$;

it implies g (y) > g (z).

An instance of local density function is a unimodal beta distribution with a mode corresponding to the old hypothetical action *x*: α, β > 1 such that $\frac{x}{\vartheta}=\frac{\alpha-1}{\alpha+\beta-2}$ (Figure 4.5).

Let us define "local innovation" processes to be a rule where an old hypothetical action x is replaced with probability $(1\text{-pm})^L$ by another hypothetical action z drawn out of a beta distribution with mode x. The variance of the beta distribution,

$\text{var}\left(\frac{x}{\vartheta}\right)=\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$, is set such that it equals the variance of the uniform binary mutation distribution when the initial hypothetical action is the Nash equilibrium level (x=16.08, var=16.4614, pm=0.02). The beta distribution has two properties in common with the uniform binary mutation: it is not symmetric and its support is the entire action space.

In a sense, also the uniform binary mutation induces a local innovation distribution when the function of distance is appropriately redefined. Instead of an Euclidian consider the Hemingway notion of distance, d(x,y)= $\sum_{i=1}^{L} Abs(bx_i - by_i)$, where b$x$ is the binary string representing the decimal number x, bx_i is the i^{th} digit of the string, and L is the length of the longest binary string.[8]

The question is whether the human mind reasons in terms of Euclidian or Hemingway distance or something else. For instance, human agents seem to prefer integer numbers to the other numbers. Can a notion of distance stressing this idea be a better representation of the decision process of human beings? This path is left for future work.

The local innovation process presents three advantages over uniform binary innovation. First, it is more transparent. Both the innovation rate and the density function are clearly stated. In the case of a uniform binary innovation, while the innovation rate can be derived with a simple formula, the density function depends in non-obvious ways on technical choices about the length of the binary string (grid). Second, a random process that stresses exploration or trembling of hypothetical actions in a neighborhood of past actions is a more intuitive concept than the one implicit in a uniform binary innovation

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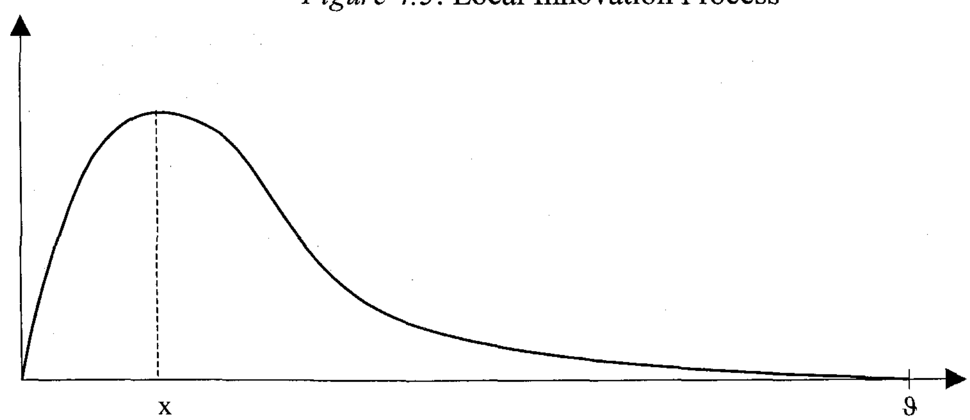
[8] Thank you to Mohamed Coker for suggesting this point.

process. Third, it does not require the use of binary coding, but works also with coding in real numbers.

Figure 4.5: Local Innovation Process



Note: Beta density function with mode in x.

4.8.3 Cost Driven Innovation Process

A local innovation process assigns higher chances of being generated to ideas with higher proximity to the original idea. Another option is a cost driven process where more promising ideas are generated with higher probabilities than bad ideas, irrespective of their distance from the old hypothetical action. The measure of the expected quality of an idea is given by how it would have performed in the previous period if it was selected as action. An agent who follows a cost driven innovation process engages in more strategical thinking and has higher computational abilities than the previous two types. In particular, he has a model of how the other agents behave and is aware of the possible consequences of using a new hypothetical action. The support of the innovation distribution is still going to be the entire action space, as even bad hypothetical actions have a chance of being chosen.

The mode of the distribution is now the best response to the actions of everybody else, $x^*_i = \arg\max_z \{\pi_i(z, X_{-i,t-1})\}$. The shape of the distribution around the mode is affected by the cost of deviating from the best response, $C(x^*_i, z) = \pi_i(x^*_i) - \pi_i(z)$. There are two basic classes of density functions coming either from cardinal or ordinal transformations of the loss function C. A cardinal transformation is $g(z) = -\delta C(x^*_i, z)$, where $\delta > 0$ is such that $g(z) \geq 0 \ \forall z$ and $\int_0^{\vartheta} g(z)dz = 1$. An ordinal transformation is $g(z) = v(C(x^*_i, z))$, where v is a strictly increasing function such that g(z) has the two properties mentioned above, i.e., it is a density function.

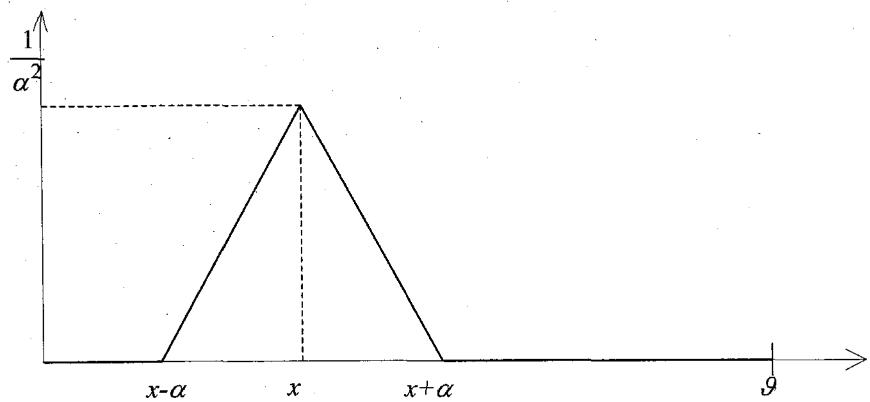
The cost driven innovation process here explored is an ordinal transformation, which is modeled as a beta density with mode in the best response value. The ordinal option presents two advantages. First, it is less demanding on the computational abilities of the agents since it relies on the knowledge of the derivative sign of the loss function and not on its exact value. Second, the variance of the distribution is a free parameter and can be chosen to match the variance of the uniform binary mutation process.[9]

4.8.4 Mountain Top Innovation Process

The last type of innovation process here described is local but is less affected by weakly dominated strategies available to the agent than the previous three types. The name given to this process, "Mountain Top," recalls its shape (Figure 4.6). The size of the action space does not alter the support of the innovation distribution, provided that the initial hypothetical action is far enough from the edges, namely $x > \alpha$ and $x < \vartheta - \alpha$.

[9] Notice that the ordinal version of the cost driven innovation process can be computed using either the score or the payoff function.

Figure 4.6: Mountain Top Innovation Process



This process is characterized by the density function below.

$$g(z \mid \alpha) = \begin{cases} \dfrac{z - x + \alpha}{\alpha^2}, & x - \alpha \le z < x \\ \dfrac{-z + x + \alpha}{\alpha^2}, & x \le z \le x + \alpha \\ 0 \quad , & otherwise \end{cases}$$

4.9 Simulations of Resource Use Without Sanctions

The results of the simulations with artificial agents (i.e., genetic algorithm agents) under several parameter conditions are presented in this and in the following section. The simulations were run on a PC and the GA agents were programmed in Turbo Pascal. A sample code can be found in Appendix F. Unless otherwise noted, the parameter setting is the one outlined in Table 4.1.

The results of the simulations are illustrated and the sensitivity of the results to variations from the baseline architecture of both behavioral and environmental parameters is explored. Although many statistics will be presented, the focus of the analysis is on aggregate resource use, individual resource use, share of actions inspected, and individual inspection behavior.

The behavioral parameters are related to the level of sophistication of the agents. The roles of the memory size and of the innovation process are studied. Once the values have been calibrated using the experimental data with humans from Design 1 of Table 4.5 (resource use without sanctions), they will be kept constant throughout the simulations of the four designs. In a few cases, an additional test of robustness is then performed by simulating three different innovation process.

Table 4.5: Experimental Designs with Human Agents

	Designs	Individual action space [0,ϑ]	Inspections	Symmetric Nash equilibrium (X*,p*)	
				X*	p*
1	No sanctions	Normal [0,50]	No	128	--
2	No sanctions	Reduced [0,20]	No	128	--
3	Weak sanctions	Normal [0,50]	Weak	128	0
4	Strong sanctions	Normal [0,50]	Strong	71.1	1

The environmental parameters represent the external constraints and incentives that the agents face. We look at the predictive power of the model of artificial effects by changing the action space and by adopting different sanctioning treatments (Table 4.5).

The GA agents are adaptive learning agents whose behavior evolves as the agents gain experience by interacting with one another. Two types of analysis of the simulation data are possible, a dynamic and a steady state. The following sections look at both perspectives. (Tables 4.7, 4.10, 4.12, 4.15-19 are about learning, and Tables 4.8, 4.9, 4.11, 4.13, 4.14 are about the steady state at T=400.)

Simulations are different in the total duration T of a run and in the number of periods considered to compute the statistics, which are the last τ periods. For example, the results of a simulation with T=400 and τ=100 generate statistics that are averages over the last 100 periods of each run and where the outcome of the first 300 periods is not considered. When the results of the artificial agents are compared with human agents, τ=32 or τ=27 have been chosen to match the actual length of the experiments of no sanction and sanction treatments, respectively.

This section focuses on the simulations of resource use without sanctions while the next section will comment on the effects of the sanctioning mechanism.

4.9.1 Baseline Simulations (Design 1)

As explained in Chapter 3, experiments with groups of human agents using a common pool resource without a sanctioning mechanism in place exhibit three main patterns:

1. Agents cooperate less than the Nash equilibrium (use the resource more than Nash equilibrium).
2. Group use fluctuates over time (pulsing patterns).
3. Individual behavior is heterogeneous and does not converge to a common value over time.

Similar results were highlighted in a previous experimental study (WGO, 1990).

Result 4.1 (Baseline simulation)

In the no sanction environment, the artificial agents

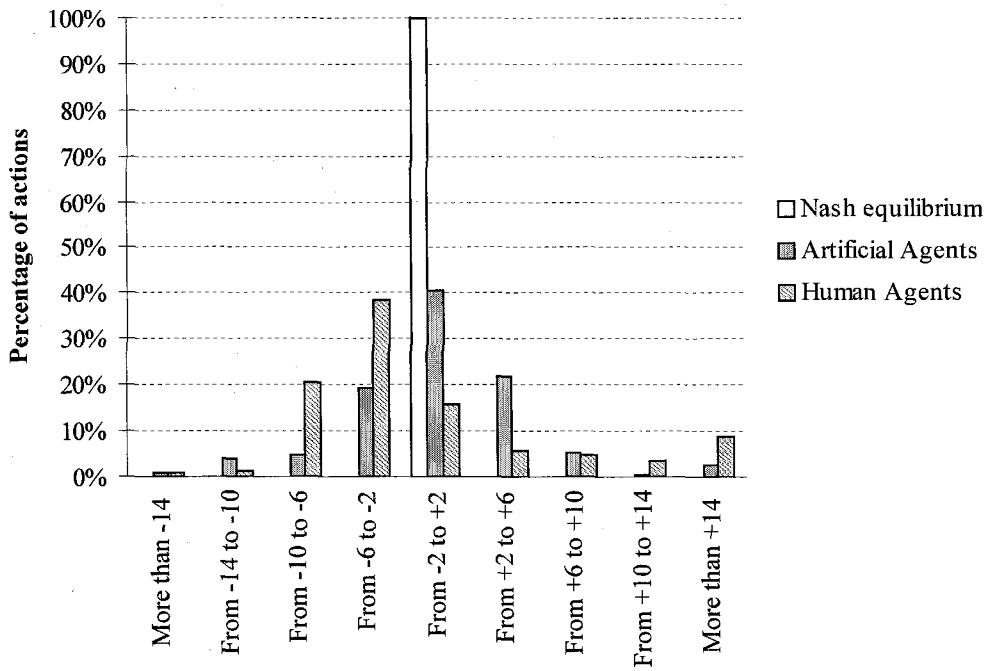
a) replicate the aggregate behavior of humans in terms of level and variability over time of the resource use.

b) exhibit a significant degree of individual heterogeneity in resource use. Inexperienced artificial agents exhibit a heterogeneity level comparable to human agents. While persisting over time, the magnitude of individual heterogeneity declines with experience.

The aggregate resource use of artificial agents cannot statistically be distinguished by the human data at a 0.05 level (Table 4.15). The variability of group use is also close to the human data: standard deviations are 14.04-17.50 vs. 12.9, and the percentages of periods with negative payoffs decline over time to levels close to 15.5%.

The discussion now turns from the aggregate to the individual actions. The variability of individual actions can be decomposed into variance within each agent's pattern of actions and variance across agents (individual heterogeneity). Most of the focus in this work is on individual heterogeneity, but before taking that direction, some considerations will be made about the broader concept of variability of individual actions. To this end, an analysis of a representative run of the simulation data is presented. The distribution of the individual actions for a single run is depicted in Figure 4.7. The empirical distribution is generated by the interplay of the innovation process, namely uniform binary mutation, and the reinforcement rule. The median resource use level of GA agents is above the individual Nash equilibrium level while it is below for human agents. The distribution is fairly regular and has a median of 16.3 vs. 13.0 for human agents.[10]

Figure 4.7: Individual Actions



Note: See notes to Table 4.6. *Deviations from symmetric Nash equilibrium*

Let's now discuss the heterogeneity across agents. As already stated, individual heterogeneity is present and does persist over time with artificial agents. We measure such notion with two statistics, the difference Δ between the average use of the agent who used the resource the most and the average use of the agent who used the resource the least within each run, and the variance of individual use. In a simulation of 10,000 periods, only a slight decrease in individual heterogeneity can be noticed. For T=100,

[10] One might speculate that the mode of the distribution is around the equilibrium $x_i=16$ because of the presence of a reinforcement rule, and it is skewed toward higher values because several points in that

Δ=18.05, which reduces to Δ=13.13 for T=1000 and to Δ=11.93 for T=10,000 (Table 4.7). Although significant, these values are considerably lower than the ones recorded in experiments with humans, Δ=28.35. Depending on the length T of the simulation, between 1/3 and 4/5 of the individual heterogeneity is reproduced by GA agents (Table 4.15). The remaining part might be due to either more severe limitations in computational abilities or to differences in the goals of the agents. There is a decline in *individual heterogeneity over time when measured by individual variance.* In particular, artificial agents cannot be distinguished from human agents when T=32 but show a lower heterogeneity for T=400 (Table 4.15).

Table 4.6: Deviation of Individual Use Decisions from Symmetric Nash Equilibrium

Deviation of individual use from x_i=16 (symmetric Nash equilibrium)	HUMAN AGENTS	ARTIFICIAL AGENTS
More than –14 units	0.78%	0.76%
From -14 to -10 units	1.45%	3.87%
From -10 to -6 units	20.35%	4.86%
From -6 to –2 units	38.47%	19.39%
From -2 to +2 units	*15.69%*	*40.68%*
From +2 to +6 units	5.82%	21.73%
From +6 to +10 units	4.84%	5.19%
From +10 to +14 units	3.69%	0.60%
More than +14 units	8.91%	2.76%
Totals	*100.00%*	*100.00%*
Number of observations	1032	8000
Mean	0.42	0.51
Median	-3.0	0.27
Standard Deviation	10.0	6.10

Notes: Upper limit of interval included. Artificial agents: v.5.0, simulation of one run with seed 0.005, T=1000, pm=0.02, lchrom=8, K=6, N=8.

interval of the action space are easier to reach through uniform binary mutation (compare Figure 4.4 with Figure 4.7).

Some possible explanations for individual heterogeneity are put forward and discussed in the remainder of this section. According to the theoretical results reported in Dawid (1999) for single population genetic algorithm, heterogeneous states are structurally unstable. Why, instead, do the results of our simulations show individual heterogeneity? This section addresses this issue by looking at five possible reasons.

- *Reinforcement rule.* The reinforcement rule plays an important role in ensuring the convergence of the memory set toward a homogeneous state. In this version of genetic algorithm we employ a different, stronger reinforcement rule (Pairwise Tournament) than the one used to prove the theoretical results (proportional). According to Bäck(1996), the expected takeover time with proportional reinforcement when the score function is exponential, $f(x)=\exp(cx)$, is approximately $(1/c)\ K \ln K$, while for Pairwise Tournament reinforcement is $(1/\ln 2)\ (\ln K + \ln(\ln K))$. Given that the former is of order $o(K \ln K)$ and the latter $o(\ln K)$, for large memory sizes tournament rules are always reinforcing good strategies faster than proportional selection rules. The same inequality holds for small numbers under mild conditions. For instance, for every $K>2$ when $c<2$. Since the theorems of convergence to uniform state were proven under the milder proportional reinforcement rule, they should hold even more strongly when we use tournament rules. In other words, the difference in reinforcement rule cannot explain why we obtain heterogeneous behavior at the individual level. We have to look somewhere else.
- *Length of simulation.* Simulations were generally run for 400 iterations. One might think that it is not enough. When some simulations were run for 30,000 rounds,

individual heterogeneity decreased overtime but appears to be still quite significant. If the long-run requires so many iterations, the short-run might be of interest in itself when it comes to study field application of a mechanism like the *Carte di Regola* institutions.

- *Multiple population algorithm.* The result of convergence was proven under the assumption that all hypothetical actions co-evolve together (single population genetic algorithms). It is unclear whether this result extends to the case of individual learning, where the hypothetical actions evolve more independently agent by agent (multiple populations). When each agent is endowed with a separate set of hypothetical actions, there might well be homogeneity within each set along with heterogeneity across sets of different agents. Dawid (1999) claims that his results about convergence to a homogeneous state holds also for multiple populations. It is not clear whether the version of genetic algorithm Dawid (1999) uses is the same here used, in particular with reference to the hypothetical score assignment and to the choice rule. The area to be explored is whether Nash equilibrium can be unstable when agents are modeled with genetic algorithm.
- *Number of agents in the group.* One conjecture is that individual heterogeneity might be higher because the number of agents in the group is more than two. This remark is relevant in the context of multiple-population genetic algorithm, while it is irrelevant for single population algorithms. Not many studies have been conducted with multiple population genetic algorithm. Two studies with five and six agents, respectively, show convergence at the aggregate and individual level (Arifovic and Ledyard, 2000 and Arifovic, 1994).

- *Innovation level.* The theoretical result of convergence toward a homogeneous state is proved under the limit condition that the innovation level goes to zero. If innovation levels are high enough the system will spend most of its time outside a homogeneous state. Is the chosen level of experimentation rate too high? First, the actual innovation levels adopted – namely 15% - is significantly above zero but in the range of values that can be found in the literature.[11] Second, the innovation level should be chosen to match the level of experimentation propensity of human subjects and not the need of convergence. Such level might be high enough in our case to destabilize convergence.

In order to understand the role of the innovation level and of the coordination problem induced by having eight agents in the group, we have run additional simulations whose results are reported in Table 4.20. In comparison with the baseline simulations reported in this Section, two variations have been studied, a reduction in the innovation level from p=14.92% to p=1.59% and an initialization of the hypothetical actions of each agents at values close to the individual Nash equilibrium (instead of drawing random values). The results from the five additional simulations can be summarized in three points.

First, some of the individual heterogeneity is indeed generated by the high innovation level, but cannot be entirely explained by it. Lowering the innovation level from the baseline simulation does not reduce individual diversity of behavior (columns (1) vs. (2) in Table 4.20). When agents are initialized close to Nash equilibrium, their behavior

[11] The innovation levels in this paper are 4% for beliefs, 15% for use actions, 18% for inspections, respectively. The values in four other studies: Arifovic (1996) uses L=30 and pm=0.0033 or pm=0.033, which translates into p=0.0944 or p=0.6346; Andreoni and Miller (1995) L=10, pm=0.08 with exponential decay and half-life of 250 generations: p=0.5656 for t=1 and 0.0489 for t=1000; Bullard and Duffy (1998), L=21, pm=0.048: p=0.6441; Nowak and Sigmund (1998), p=0.001.

keeps homogeneous when the innovation level is low, while is disrupted by a high innovation level and ends up being heterogeneous ((6) vs. (3), (4), (5) in Table 4.20).

Second, individual heterogeneity might be the result of a problem of coordination among agents that is hard to solve. When the agents start very close to the Nash equilibrium values, individual diversity of actions after 400 iterations is at most half of the levels obtained with a random initialization ((3), (4), (5), (6) vs. (1), (2)). As already pointed out, the situation does not improve significantly when the randomly initialized agents interact for 30,000 periods instead of 400.

Third, the tendency to converge to the Nash equilibrium at the aggregate level seems stronger than at the individual level. For a given aggregate outcome, there are wide differences in the underlying individual behavior ((1) vs. (3), (4), (5)) and a result closer to the equilibrium in the aggregate might exhibit higher heterogeneity in individual behavior ((2) vs. (1)).

While more work needs to be done to assess the source of individual heterogeneity, this study finds that the innovation level and the need to coordinate among many agents plays an important role in generating diverse behavior across agents.

4.9.2 Impact of Memory Size

Result 4.2 (Memory size)

a) As the artificial agent becomes more sophisticated, the aggregate resource use moves closer to the Nash equilibrium, and its variability decreases.

b) Simple, artificial agents exhibit large degrees of individual heterogeneity. As they become more sophisticated, individual differences have a tendency to decrease.

When the size of the memory set is K=2, the group uses the resource at X=136.3, well above the Nash equilibrium, while it decreases to 130.0 for K=90 (Table 4.9). Similarly, the standard deviation decreases from 18.13 to 12.71. Overall, efficiency increases 18.4 points. There is evidence to support for the conjecture that when agents are all selfish and have the same incentives, individual heterogeneity is not possible unless agents have limited cognitive abilities and are unable to maximize. As the memory set size increases the individual heterogeneity substantially decreases, from Δ=18.4 at K=2 to Δ=4.7 at K=90.

Simulations of just the first 32 periods confirm the same pattern (Table 4.16). Artificial agents exhibit a significantly different behavior at 0.05 level for K=2, 6, 90 in both aggregate resource use and individual use variance.

4.9.3 Impact of Innovation Processes

Result 4.3 (Innovation processes)

a) *Individual differences do not disappear by adopting other innovation processes. Their magnitude is twice as large with uniform binary mutation than with either local innovation or cost driven innovation.*

b) *The aggregate resource use with cost driven innovation is closer to the Nash equilibrium level than is with uniform binary mutation. Its variance is higher than for uniform binary mutation.*

Table 4.8 provides a numerical comparison of the results.

4.9.4 Role of Action space (Design 2)

Consider a modification of the experimental design where the action space [0,9] is restricted or expanded, but nothing else changes, and in particular the Nash equilibrium remains the same (Design 2). Despite the fact that the classical model does not predict any difference in the outcome, experiments with human agents yielded significantly different results. For instance, WGO (1990) reports a 40 point increase in efficiency by simply restricting the individual action space from [0,50] to [0,20] (Ostrom, Gardner, Walker, 1994, p.116).

Result 4.4 (Action space)

The outcome of the interaction of artificial agents is affected by the availability of weakly dominated alternatives. In particular, a restricted action space for using a common pool resource increases group efficiency.

When the action space is restricted, GA agents use the resource with an increased efficiency of +11.7 points from a baseline value of 30.6%. When it is expanded from [0,50] to [0,80], efficiency drops –14.4 points (Table 4.11). When GA agents are inexperienced the effect is even more dramatic (+14.9, -29.9, Table 4.17). The reason can be found in the property of the innovation process that gives a positive probability of transitioning to any point in the action space. Agents can reach by mistake, or by active experimentation, any point off equilibrium. The higher the number of those weakly dominated alternatives the more the payoff earned there will effect the average outcome.

In this specific environment, lifting upward the upper bound of the action space yields increasingly lower group payoffs. Since in Table 4.11 the upper bounds of the action space are respectively 1.25, 3.12, and 5.00 times the Nash equilibrium level, the efficiency shown by GA agents declines. Similar results are obtained with inexperienced artificial agents (Table 4.17, T=32). Support for this explanation comes also by the increasing values of standard deviations in resource use as the action space is enlarged. If the explanation given is correct, GA agents with an innovation process of a "mountain top" type are expected to yield outcomes that are independent from the size of the action space. This prediction can be tested in a future work.

Figure 4.8: Aggregate Resource Use Over Time

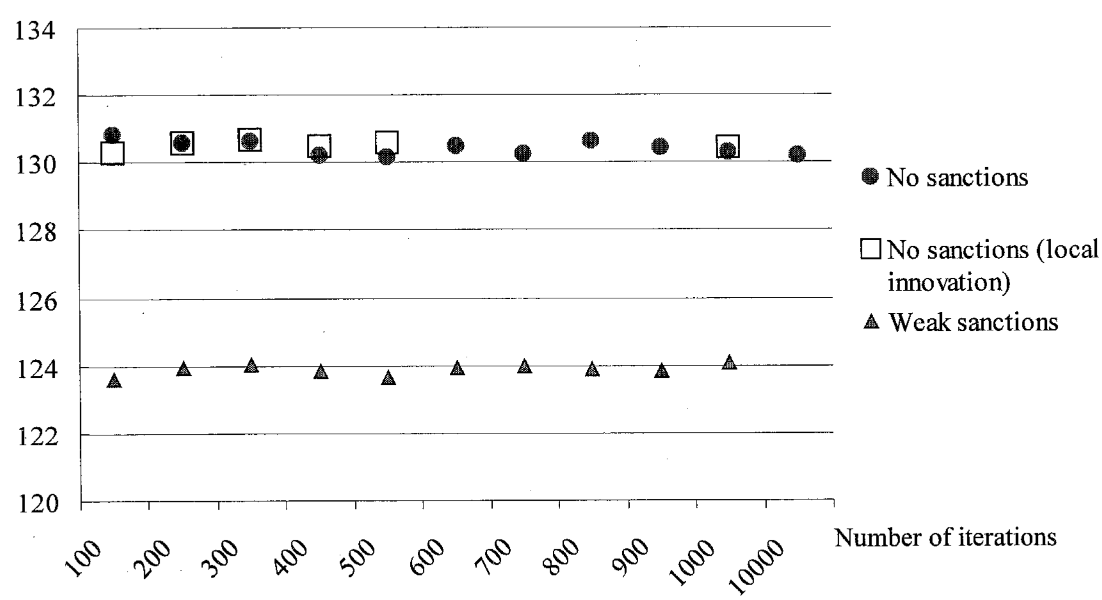
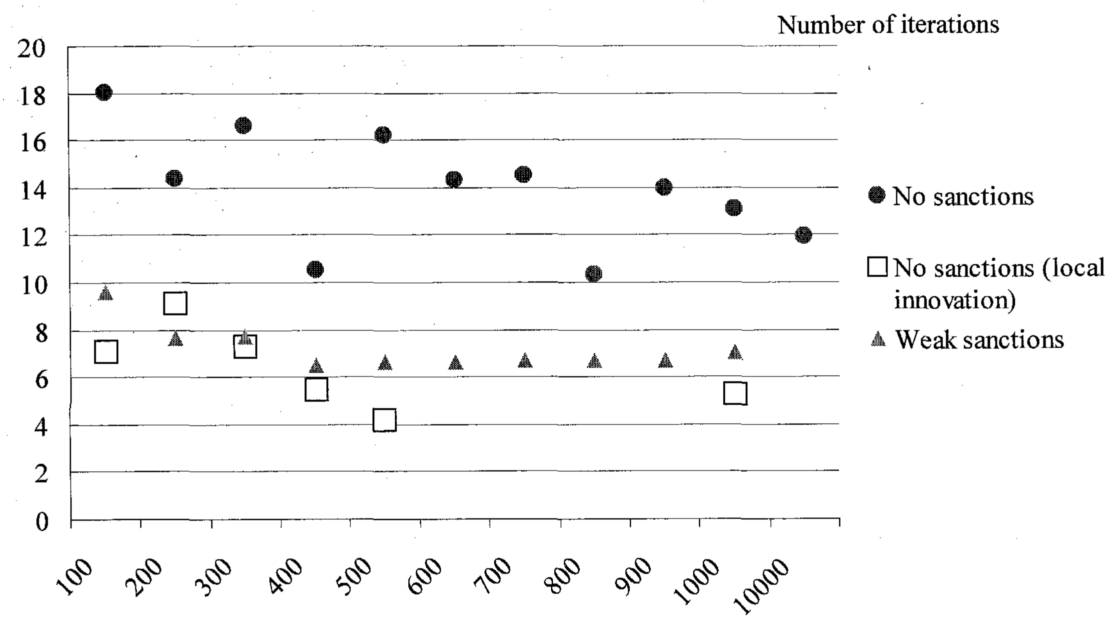


Figure 4.9: Individual Differences in Resource Use



4.10 Simulations of Resource Use With Sanctions

When there are sanctions, the artificial agents have a richer structure in order to model the decision to inspect others. In addition to the algorithm for resource use described in Table 4.1, there is a second stage in the decisional process that is modeled in Table 4.2. This section will illustrate the results of simulations carried on under such framework.

4.10.1 Simulations With Weak Sanctions (Design 3)

Result 4.5 (Weak sanctions – aggregate)

a) Similarly to human agents, the weak sanction mechanism is widely used by artificial agents.

b) The artificial agents use the resource more efficiently with the introduction of the weak sanction mechanism. The sanction mechanism is more effective in raising efficiency of resource use for human than for artificial agents.

Artificial agents inspect 53.8% of actions compared to 51.5% of human agents, while the classical model predicts no inspections (Table 4.13). In comparison with the unstructured use of the resource, the gross efficiency with artificial agents increases by 12.97 percentage point, while net efficiency merely by 3.68 points. The effect of a similar frequency of inspections has, however, lower effects on artificial than human agents. Gross efficiency of GA agents (43.6%) is above the Nash level (39.5%) but lower than for human agents (57.2%). Net efficiency of artificial agents is below both Nash and human agent levels (34.3%, 39.5%, 48.3%).

In particular, agents learn over time how to use the sanction mechanism. The learning process is apparent from the substantial decline in the share of actions inspected from T=27, to T=54, to T=400 (Table 4.18). Human agents learn faster than artificial agents: they inspect significantly less in comparison to T=27, but cannot be distinguished from either T=54 or T=400.

Two conjectures can be put forward to explain why inspection rates are similar, but resource use levels are different. The first is that human agents are smarter than artificial agents in taking inspection decisions. Differences in inspection balances, though, do not seem to support this position (0.0% vs. +0.9%). This consideration needs to be evaluated taking into account that human agents inspect in a more difficult environment because of the lower group resource use.

The second conjecture is that human agents deal in a different way than GA agents with the perceived probability of being inspected. As a reference value consider that when every agent perceives a probability of being inspected to be p=0.5, the Nash equilibrium in terms of aggregate is X*=120.9. Human agents act as if the probability p was much higher (X=115.5, when X*=113.7 for p=1). On the contrary, artificial agents seem to under-react to the threat of sanctions (X=123.8).[12]

Result 4.6 (Weak sanctions – individual actions)

a) Individual heterogeneity in resource use is similar in magnitude between artificial and human agents.

b) Artificial agents exhibit individual heterogeneity in sanctioning. With experience the level approaches the one of human agents.

Individual heterogeneity of human agents in resource use is statistically indistinguishable from artificial agents (Table 4.18). In the experiments with human agents, the highest inspector requested 11.1 times more inspections than the lowest inspector. The same statistics for artificial agents is 4.1. The reason seems to be that artificial agents learn how to use the sanctioning mechanism more slowly than humans. Over time the ratio increases from 4.1 (T=27), to 6.6 (T=54), to 10.8 (T=400) (Table 4.8). Given that agent use levels are different, some degree of diversity in inspecting behavior can be explained by the different level of information that each agent has on the others considering that $X_{-i} \neq X_{-j}$ when $x_i \neq x_j$. A higher level of heterogeneity in resource use implies a higher level of heterogeneity in inspections. There are, however, other factors

[12] The explanation might rely in the different levels of individual heterogeneity between the two cases.

at work because the evidence does not support this explanation. Over time diversity in resource use decreases while diversity in inspection behavior increases.

4.10.2 Simulations With Strong Sanctions (Design 4)

Result 4.7 (Strong sanctions – aggregate)

a) A high share of actions is inspected by both human and artificial agents (>85%).

b) With strong sanctions, efficiency in resource use is below the Nash equilibrium level for both human and artificial agents. The strong sanction mechanism seems more effective in raising efficiency of resource use for human than for artificial agents.

Both gross and net efficiency of artificial agents are lower than the corresponding values for human agents (Table 4.14). The significance of the average values is, however, difficult to evaluate because of the very limited number of experiments carried out with humans under the strong sanction treatment (just 2). No difference is statistically significant at 0.05 level. In order to still make a comparison, consider the following thought experiment. Would the differences be statistically significant had the averages of human experiments come from a sample of size 4 instead of size 2? If that were the case, human agents would be different from artificial agents in both aggregate use and inspection rate but not in individual heterogeneity (Table 4.19, T=32). The two conjectures already put forward for the weak sanction environment are now reexamined. Although operating in an easier context, artificial agents have a better inspection balance than human agents (28.3% vs. 18.8%). As far as the conjecture about the perceived probability goes, there is again a stronger underestimation by artificial agents of the probability of an inspection. Consider that with p=0.9, the Nash equilibrium is X*=76.8. Human agents are above that level (X=85.1), and artificial agents are even more so (X=92.9).[13]

Result 4.8 (Strong sanctions – individual actions)

a) Individual heterogeneity in resource use is similar in magnitude between artificial and human agents.

b) Artificial agents exhibit individual heterogeneity in sanctioning, but to a lower degree than human agents.

In the experiments with human agents, the ratio between the requests of the highest vs. the lowest inspector is 7.4 while it is 2.5 with artificial agents (Table 4.18). As variability in individual use is not significantly different between human and artificial agents, we conclude that, besides the differences in information levels, there ought to be another source of diversity that is driving up inspection heterogeneity in human agents.

4.10.3 Impact of Innovation Processes

Result 4.9 (Innovation processes – sanction treatments)

The previous results 4.5-4.8 do not change when using an innovation process different from uniform binary mutation except in the following two cases:

[13] The suggestion that individual heterogeneity might play a role in this respect is contradicted by the strong sanction data since artificial agents show a higher diversity in resource use than human agents.

a) In both weak and strong sanction environments, resource use is lower with local innovation than with uniform binary mutation (in reference to Results 4.5a and 4.7b).

b) In a strong sanction environment, artificial agents with local innovation are more effective in raising efficiency of resource use than with uniform binary mutation (in reference to Result 4.7b).

4.11 Discussion on Other-Regarding Versus Genetic Algorithm Agent Models

In this dissertation two rather different explanations of the experimental data presented in Chapter 3 have been put forward, the other-regarding theory in Chapter 3 and a genetic algorithm agent model in this Chapter. This section suggests possible ways to disentangle these two alternative models.

The other-regarding agent model presented in Chapter 3 posits the existence of several types of agents endowed with constant but heterogeneous preferences. Under such model, agents strive to reach individually defined goals in a fully rational fashion. On the contrary, the genetic algorithm agent model belongs to a class of models where agents are all identical and selfish, but where they have bounded rationality.

We outline below three areas where the two models predict different outcomes and that could therefore be exploited to discard one model in favor of the other. The first issue relates to the stability of individual behavior. Under the assumption that agents are endowed with other-regarding attitudes that differ across agents, the over- or under-use of the resource is an inherent feature of an individual. As a consequence, a constant behavior should be observed over time, in particular, in the long run. Moreover, there should be coherence between the use of the resource and the inspection decisions. Neither one of these outcomes should be expected if the correct model is the adaptive agent model. According to the GA model, if an agent is the heaviest user of the resource at a given point in time, he can be the lightest user in a later period. This behavior is the result of the co-evolution of a group of agents and not an intrinsic imprint of an individual. In addition, there is no predicted correlation between actions taken in resource use and inspection, once differences in information endowment are factored in.

The second way to discriminate between models is to study the comparative statics. In particular the effects on efficiency of modifications of the action space. As already pointed out in section 3.11 for the other-regarding agent model, given a preference profile, the group efficiency of the resource use changes when the individual action space is modified. There exist an upper bound, though, such that an expansion of the action space above that bound will be irrelevant for the efficiency of the outcome. On the contrary, the adaptive agent model predicts that *any* modification of the action space affects the efficiency of the group outcome.[14]

Finally, learning might take place under both models but the object of learning is different. Under other-regarding preferences the best response depends on the preference profile of the other agents in the group. As preferences are private information, there is a discovery process about the agent types that can take place in the early interactions. Boundly rational agent, instead, learn first of all about how to improve their strategy given the incentive structure of the environment. The environment is composed of the rules of the game and of the strategies of the other agents. Both are challenging aspects in

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[14] This prediction hold when the innovation process is uniform binary, local, or cost-driven but not when it is mountain top.

the search for a better strategy. Consider two group of subjects in experiments, group A is inexperienced in the particular game and group B is experienced but nobody has interacted together before. If learning is about preference, there should be no significant difference between group A and group B, while if it is about the rules of the interaction there should be more learning in group A than in group B, however learning is measured.

4.12 Conclusions

A model of agents with limited computational abilities is put forward, and the results from their interaction are compared to the experimental data that were reported in Chapter 3.

The decision making process of the agents is modeled as an adaptive learning process through a version of a genetic algorithm (GA) where each decision-maker is endowed with a memory set (multiple population GA). The results presented are the outcomes of simulations done under different sets of parameter values. The focus is on the use of a common property resource by a group of agents either with or without a monitoring and sanctioning institution.

The model replicates most of the patterns that can be found in the data from human agents. The analysis has especially focused on four statistics: aggregate resource use – which is closely related to efficiency – individual heterogeneity in resource use, share of actions inspected, and individual heterogeneity in inspection decisions. Artificial agents behave like human agents in the baseline design (Result 4.1). They perform similarly well in the weak sanction treatment, with two qualifications. First, GA agents need time to learn how to use the sanctioning mechanism, and second, the increase in resource use efficiency is lower than for human agents (Results 4.5 and 4.6). Behavior in the strong sanction environment is easily matched as the results are not significantly different between human and artificial agents due to the small number of human experiments. After further analyses we conclude that GA agents in the strong sanction environment seem less responsive to the threat of sanctions than human agents (Results 4.7 and 4.8). Overall, the simulations mimic fairly well the experimental data.

In addition to replicating existing data, the model makes four testable predictions.

(a) A modification of the action space through the addition or removal of weakly dominated alternatives has a systematic effect on the efficiency of the outcome. In particular, increasing the upper bound of the action space will decrease efficiency (Result 4.4). This prediction depends on the specific procedure adopted to generate new hypothetical actions.

(b) The level of sophistication of the decision maker influences both the group resource use and the individual heterogeneity in use (Result 4.2). A possible way to test this prediction might be to sort out people by type and level of education.

(c) A rescaling of the payoff function should have no effect on the outcome (Proposition 4.4). An example would be doubling the monetary rewards in the experiments. This prediction relies on the ordinal characteristics of the Choice and Reinforcement rule of this version of GA.

(d) Experience, as measured by the number of interactions among a group of agents, has two effects. First, it improves the performance of the sanctioning mechanism. Second, it decreases individual heterogeneity in resource use (but does not make it disappear).

This study leads to two methodological observations on the modeling of adaptive agents with genetic algorithms; one is related to the innovation process, and the other the level of sophistication of the GA agent. The innovation process is the operator that, within the genetic algorithm, controls the generation of new hypothetical actions. While maintaining a binary coding of the action space, a comparison between uniform binary mutation and two other alternatives, local innovation and cost driven innovation, is carried out. The adoption of one scheme instead of another relates to different assumptions about human cognition, and is not neutral in terms of simulation outcomes. The uniform binary mutation process introduces new hypothetical actions by randomly switching in binary strings a "0" digit into a "1" with a probability rate that is constant for all digits and throughout time. This widely used scheme generates higher levels of individual heterogeneity in resource use and a different behavior in sanctioning than the other processes. The local innovation is a promising alternative process. Ideas - i.e. hypothetical actions - that are closer to the old idea are more likely candidates to replace it in comparison to ideas that are further away. Although more work needs to be done in this area, an innovation process based on the expected cost of experimenting with new hypothetical actions does not seem to improve the predictive power of the model.

There is support for the conjecture of a correlation between individual heterogeneity in behavior and the level of sophistication of the decision-maker. The finding of heterogeneity across agents in the experiments presented in Chapter 3 is by no means a unique finding in the literature. What is more novel is the attempt considered here to explain such individual diversities assuming identical decision-makers. Agents have the same goal of increasing personal income and have all equally limited computational abilities. The conjecture that we put forward is that the less "smart" the decision-makers are, the higher is the degree of individual heterogeneity in resource use in the group. Three arguments are presented to support this claim:

1) Genetic algorithm (GA) agents exhibit a significant individual heterogeneity in resource use, which does not disappear even after a very prolonged interaction. The prediction of the classical model when agents can maximize is instead of homogeneous behavior (Result 4.1).
2) Within the class of GA agents, more sophisticated decision-makers (larger memory set) exhibit a lower degree of individual heterogeneity (Result 4.2).
3) Smarter agents, who evaluate the potential cost of experimenting with new hypothetical actions, show less individual heterogeneity than the standard GA agents (Result 4.3).

A different way to look at the results of this study is to assess whether the *Carte di Regola* institutions can deliver a good performance when agents are not smart. Simulations with genetic algorithm agents could be interpreted as a robustness check on the institution. What is the effect on resource use efficiency with the introduction of weak and strong sanctions? Under the weak sanction treatment, efficiency improves (same direction of change as human agents) but with a lower magnitude than for human agents. Artificial agent outcomes are positioned in-between human data and the classical Nash equilibrium prediction (+5.82, +19.90, 0.00 change in net efficiency). Under the strong sanction treatment, the efficiency improvement is correct in direction and close in magnitude to human agents. This time the classical Nash equilibrium prediction is in-between human data and artificial agents data (+43.19, +48.46, +38.97 change in net efficiency). When the GA agents are endowed with local innovation instead of uniform binary mutation, the results of artificial agents are always in-between those of humans and the Nash prediction.

There are possible extensions and limitations to this study. The discussion has pointed out some possible sources of individual heterogeneity generated by artificial agents, but a definitive answer has not been given yet. An interesting extension of the artificial agent model is to introduce a more sophisticated way to deal with the probability of being inspected. The current setting performed not as well as other features of the model. One adjustment is to adopt a belief set, in a similar fashion as the beliefs on other agents' type are structured. Another issue is the exploration of other decisional structures for inspection decisions. There is no strong justification for the specific choice made. Finally, the processes to generate new hypothetical actions have an impact on the simulation outcomes, but their mechanisms of operation need further understanding.

Table 4.7: Simulations of Resource Use Without Sanctions – Uniform Binary Mutation (Design 1)

τ=100, T	100	200	300	400	500	600	700	800	900	1,000	10,000
GROUP RESULTS											
Use	130.80	130.60	130.61	130.21	130.16	130.50	130.26	130.65	130.42	130.31	130.20
Standard deviation of use	15.81	14.69	14.60	14.43	14.43	14.64	14.55	14.44	14.89	14.40	14.73
Efficiency	28.53%	29.59%	29.57%	30.59%	30.73%	29.80%	30.41%	29.62%	29.88%	30.38%	30.97%
Periods with negative earnings	17.56%	16.29%	15.89%	15.55%	15.55%	16.14%	15.84%	15.84%	16.28%	15.50%	16.26%
INDIVIDUAL RESULTS											
Agent with maximum use											
Average (1)	27.08	25.85	25.64	22.30	24.88	25.48	25.43	23.86	25.09	24.85	24.36
Minimum (2)	17.38	17.88	17.65	17.59	17.51	17.18	17.77	17.39	18.02	16.59	17.25
Agent with minimum use											
Average (3)	9.04	11.45	9.05	11.75	8.67	11.15	10.92	13.51	11.12	11.72	12.43
Maximum	14.90	14.85	14.98	14.81	15.41	15.33	14.51	14.99	14.73	15.61	14.91
Individual difference (1)-(3)	18.04	14.4	16.59	10.55	16.21	14.33	14.51	10.35	13.97	13.13	11.93

Notes to Table 4.7:

K=6, N=8, lchrom=8, pm=0.02; GA v.5.0.

The basic action is the use level of the resource, x_{itk}, by agent i=1,..,8 at period t=1,..,T for run k=1,..,100 (random seeds 0.005 through 0.995).

The aggregate resource use $X_{tk}=\sum_{i=1}^{8} x_{itk}$ and its average for each run is $\overline{X}_k = \frac{1}{\tau}\sum_{t=T-\tau+1}^{T} X_{tk}$.

Simulations are run for a total number of T periods; the statistics in the tables are computed using the last τ periods (T-τ+1,..,T). The use statistics reported in the tables are $\overline{X} = \frac{1}{100}\sum_{k=1}^{100}\overline{X}_k$. The average standard deviation of aggregate use over time is $\frac{1}{100}\sum_{k=1}^{100}\sqrt{\frac{1}{\tau-1}\sum_{t=T-\tau+1}^{T}\left(\overline{X}_k - X_{tk}\right)^2}$. Efficiency and number of periods with negative earnings are computed as averages across runs. The maximum individual use of the resource is characterized by two statistics. The average is $\frac{1}{100}\sum_{k=1}^{100}\left[\max_i\left\{\frac{1}{\tau}\sum_{t=T-\tau+1}^{T} x_{itk}\right\}\right]$ and the minimum is $\min_k\left[\max_i\left\{\frac{1}{\tau}\sum_{t=T-\tau+1}^{T} x_{itk}\right\}\right]$. The minimum use by agent is computed in a similar fashion.

Individual variance in resource use takes each $\overline{x}_{ik} = \frac{1}{\tau}\sum_{t=T-\tau+1}^{T} x_{itk}$ as a single observation.

The significance tests are carried out, using $\overline{X}_k$ as a single observation, under the null hypothesis H_0 that the random variables Z_i are iid and normally distributed.

Table 4.8: Simulations of Resource Use Without Sanctions
Impact of Innovation Processes

	Human agents	Nash equilibrium	Artificial agents, T=400, τ=100		
			Uniform binary mutation	Local innovation	Cost driven innovation
GROUP RESULTS					
Use	131.32	128.00	130.21	130.47	129.20
Standard deviation of use	12.95	0.00	14.43	15.82	19.41
Efficiency	28.4%	39.5%	30.59%	29.24%	29.74%
Periods with negative earnings	15.5%	0.00%	15.55%	18.15%	19.33%
INDIVIDUAL RESULTS					
Agent with maximum use					
Average (1)	37.92	16.00	22.30	19.67	18.47
Minimum (2)	32.5	16.00	17.59	17.39	17.03
Agent with minimum use					
Average (3)	9.57	16.00	11.75	14.17	13.62
Maximum	10.6	16.00	14.81	15.21	15.02
Individual difference (1)-(3)	28.35	0.00	10.55	5.50	4.85

Notes: K=6, N=8, lchrom–8, pm=0.02; GA v.5.0 (uniform binary innovation process), GA v.5.2 (local innovation), GA v.5.3 (cost driven innovation). See notes to Table 4.7.

Table 4.9: Simulations of Resource Use Without Sanctions – Impact of Memory Size

	Nash equilibrium	Artificial agents, T=400, τ=100					
Memory size, K		2	4	6	12	30	90
Expected takeover time, TOT		0.47	2.47	3.43	4.90	6.67	8.66
Inverse of error odds		3	7	11	23	59	179
GROUP RESULTS							
Use	128.00	136.29	131.26	130.21	130.23	129.93	129.99
Standard deviation of use	0.00	18.13	15.51	14.43	13.97	12.82	12.71
Efficiency	39.5%	13.62%	27.56%	30.59%	30.82%	32.10%	31.98%
Periods with negative earnings	0.00%	29.31%	18.18%	15.55%	15.37%	13.63%	13.52%
INDIVIDUAL RESULTS							
Agent with maximum use							
Average (1)	16.00	27.83	25.59	22.30	25.79	17.21	17.94
Minimum (2)	16.00	20.73	17.86	17.59	16.95	16.50	16.45
Agent with minimum use							
Average (3)	16.00	9.44	9.76	11.75	11.37	14.33	13.26
Maximum	16.00	13.45	14.40	14.81	15.86	15.81	15.98
Individual difference (1)-(3)	0.00	18.39	15.83	10.55	14.42	2.88	4.68

Notes: TOT = expected takeover time with Pairwise tournament reinforcement rule, TOT=(lnK+ln(lnK))/ln2
Inverse of error odds = chances of choosing the best hypothetical action in the set relative to the worst with Pairwise tournament choice rule, (2K-1), N=8, lchrom=8, pm=0.02; GA v.5.0 (uniform binary innovation process). See notes to Table 4.7.

Table 4.10: Simulations of Resource Use Without Sanctions – Local Innovation (Design 1)

τ=100, T	100	200	300	400	500	600	700	800	900	1,000
GROUP RESULTS										
Use	130.30	130.58	130.67	130.47	130.59	130.57	130.56	130.68	130.39	130.43
Standard deviation of use	16.53	15.81	15.83	15.82	15.86	15.80	15.79	15.98	15.72	15.74
Efficiency	29.21%	28.99%	28.78%	29.24%	28.92%	29.03%	29.04%	28.67%	29.47%	29.34%
Periods with negative earnings	18.76%	18.48%	18.28%	18.15%	18.73%	17.99%	18.35%	19.02%	18.08%	18.27%
INDIVIDUAL RESULTS										
Agent with maximum use										
Average (1)	19.41	22.21	20.36	19.67	18.77	17.99	20.11	20.93	19.52	19.49
Minimum (2)	18.06	17.92	16.69	17.39	17.23	17.21	17.53	18.09	17.68	17.46
Agent with minimum use										
Average (3)	12.29	13.10	13.09	14.17	14.61	15.03	12.55	13.19	11.27	14.21
Maximum	14.86	15.33	15.45	15.21	14.87	15.43	15.36	15.08	15.06	15.31
Individual difference (1)-(3)	7.12	9.11	7.27	5.50	4.16	2.96	7.56	7.74	8.25	5.28

Notes: K=6, N=8, lchrom=8, pm=0.02; GA v.5.2. See notes to Table 4.7.

Table 4.11: Simulations of Resource Use Without Sanctions – Impact of Action space

	Nash equilibrium	Artificial agents, individual action space $[0,\vartheta]$, T=400, τ=100: Restricted [0,20]	Full [0,50]	Expanded [0,80]
GROUP RESULTS				
Use	128.00	126.42	130.21	134.31
Standard deviation of use	0.00	5.64	14.43	22.73
Efficiency	39.5%	42.26%	30.59%	16.18%
Periods with negative earnings	0.00%	0.03%	15.55%	25.86%
INDIVIDUAL RESULTS				
Agent with maximum use				
Average (1)	16.00	17.09	22.30	20.44
Minimum (2)	16.00	16.33	17.59	18.01
Agent with minimum use				
Average (3)	16.00	15.30	11.75	11.65
Maximum	16.00	15.26	14.81	15.09
Individual difference (1)-(3)	0.00	1.79	10.55	8.79

Notes: K=6, N=8, lchrom=8, pm=0.02; GA v.5.0 (uniform binary innovation process). See notes to Table 4.7.

Table 4.12: Simulations of Resource Use With Weak Sanctions – Uniform Binary Mutation (Design 3)

τ=100, T	100	200	300	400	500	600	700	800	900	1,000
					RESOURCE USE RESULTS					
GROUP RESULTS										
Use	123.59	123.94	124.02	123.85	123.66	123.95	124.01	123.90	123.85	124.07
Standard deviation of use	16.59	15.25	15.31	15.33	15.36	15.38	15.42	15.37	15.18	15.27
Efficiency	43.41%	43.43%	43.22%	43.56%	43.94%	43.32%	43.19%	43.47%	43.66%	43.17%
Net Efficiency	32.87%	34.02%	33.81%	34.27%	34.42%	33.99%	33.79%	34.07%	34.24%	33.92%
Periods w/ neg. earnings	10.83%	10.84%	10.88%	10.70%	10.61%	11.26%	11.22%	10.69%	10.96%	11.05%
INDIVIDUAL RESULTS										
Agent with maximum use										
Average (1)	21.28	20.10	19.90	18.85	19.18	19.20	19.18	19.21	19.08	19.57
Minimum (2)	16.49	16.16	16.27	16.08	16.35	16.07	16.38	16.30	16.15	16.41
Agent with minimum use										
Average (3)	11.71	12.45	12.21	12.33	12.58	12.60	12.50	12.55	12.38	12.57
Maximum	14.16	14.72	14.69	14.62	14.54	15.15	14.72	14.95	14.57	15.08
Ind. difference (1)-(3)	9.57	7.65	7.69	6.52	6.60	6.60	6.68	6.66	6.70	7.00
					INSPECTION RESULTS					
Share of actions inspected	60.94%	54.47%	54.43%	53.76%	55.08%	53.98%	54.39%	54.39%	54.46%	53.50%
Inspection fees	10.53%	9.42%	9.41%	9.29%	9.52%	9.33%	9.40%	9.40%	9.41%	9.25%
Sanctions	12.27%	10.70%	10.69%	10.23%	10.56%	10.31%	10.41%	10.39%	10.41%	10.38%
Inspections with neg. bal.	49.19%	47.67%	46.62%	45.13%	45.83%	45.47%	45.56%	45.60%	45.95%	45.78%
No. of requests/ inspection	2.57	2.25	2.16	2.02	2.09	2.07	2.04	2.06	2.07	2.09
Number of requests to inspect by agent										
Minimum	0.77	0.50	0.48	0.43	0.48	0.45	0.43	0.42	0.44	0.42
Maximum	2.31	1.93	1.94	1.81	1.86	1.84	1.82	1.85	1.86	1.84

Notes: Parameters of resource use, K=6, N=8, lchrom=8, pm=0.02; parameters of inspections, KT=12, tchrom=10, pm=0.02, KB=2, bchrom=2; GA v.6.1. See notes to Table 4.7.

Table 4.13: Simulations of Resource Use With Weak Sanctions – Impact of Innovation Processes

	Human agents	Nash equilibrium	Artificial agents, $\tau=100$		
			Uniform binary mutation, T=400	Local innovation, T=200	Cost driven innovation, T=200
		RESOURCE USE RESULTS			
GROUP RESULTS					
Use	115.5	128.00	123.85	122.03	121.61
Standard deviation of use	16.51	0.00	15.33	15.65	18.80
Efficiency	57.19%	39.5%	43.56%	46.97%	45.77%
Net Efficiency	48.3%	39.5%	34.27%	34.80%	34.03%
Periods with negative earnings	7.00%	0.00%	10.70%	8.81%	11.13%
INDIVIDUAL RESULTS					
Agent with maximum use (1)	17.7	16.00	18.85	17.43	17.15
Agent with minimum use (2)	11.0	16.00	12.33	13.20	13.18
Individual difference (1)-(2)	6.7	0.00	6.52	4.23	3.97
		INSPECTION DECISIONS			
Share of actions inspected	51.5%	0.00%	53.76%	70.42%	67.90%
Inspection fees	8.9%	0.00%	9.29%	12.17%	11.74%
Sanctions	8.9%	0.00%	10.23%	12.08%	11.61%
Inspections with neg. bal.	62.02%	--	45.13%	42.17%	39.56%
No. of requests/ inspection	2.43	--	2.02	2.16	1.96
Number of requests to inspect by agent					
Minimum	0.23	0.00	0.43	0.85	0.69
Maximum	2.56	0.00	1.81	2.29	2.05

Notes to Table 4.13: Parameters of resource use, K=6, N=8, lchrom=8, pm=0.02; parameters of inspections, KT=12, tchrom=10, pm=0.02, KB=2, bchrom=2; GA v.6.1 (uniform binary innovation process), GA v.6.2 (local innovation), GA v.6.3 (cost driven innovation). See notes to Table 4.7.

Table 4.14: Simulations of Resource Use With Strong Sanctions – Impact of Innovation Processes

	Human agents	Nash equilibrium	Artificial agents, τ=100		
			Uniform binary mutation, T=400	Local innovation, T=200	Cost driven innovation, T=200
	RESOURCE USE RESULTS				
GROUP RESULTS					
Use	85.1	71.11	92.91	79.66	79.30
Standard deviation of use	9.86	0.00	16.81	11.86	12.84
Efficiency	93.98%	99.97%	85.68%	96.09%	95.71%
Net Efficiency	76.86%	82.69%	70.30%	79.38%	78.88%
Periods with negative earnings	0.00%	0.00%	0.80%	0.03%	0.06%
INDIVIDUAL RESULTS					
Agent with maximum use (1)	13.5	8.89	14.98	11.51	11.33
Agent with minimum use (2)	8.5	8.89	8.90	8.82	8.83
Individual difference (1)-(2)	5.5	0.00	6.07	2.69	2.50
	INSPECTION DECISIONS				
Share of actions inspected	99.1%	100.00%	88.99%	96.70%	97.38%
Inspection fees	17.12%	17.28%	15.38%	16.71%	16.83%
Sanctions	35.91%	18.67%	43.65%	29.44%	28.81%
Inspections with neg. bal.	32.9%	0.00%	61.64%	47.30%	47.28%
No. of requests/ inspection	3.97	7.00	4.10	4.52	4.44
Number of requests to inspect by agent					
Minimum	0.89	7.00	2.64	2.90	2.74
Maximum	6.55	7.00	4.62	5.59	5.60

Notes to Table 4.14: Parameters of resource use, K=6, N=8, lchrom=8, pm=0.02; parameters of inspections, KT=12, tchrom=10, pm=0.02, KB=2, bchrom=2; GA v.6.1 (uniform binary innovation process), GA v.6.2 (local innovation), GA v.6.3 (cost driven innovation). See notes to Table 4.7.

Table 4.15: Simulations of Resource Use Without Sanctions – Dynamic Over Time

	Human agents, X	Nash equilibrium	Artificial agents, Y (last 32 rounds, τ=32)		
			T=32	T=64	T=400 (384)
GROUP RESULTS					
Use (1)	131.32	128.00	131.02	130.40	130.02
0.95 confidence interval	[127.25, 135.39]	-	[130.96, 131.08]	[130.35, 130.45]	[129.98, 130.06]
Standard deviation across runs	4.43	0.00	2.78	2.26	2.08
Standard deviation of use over time	12.95	0.00	17.50	15.03	14.04
Efficiency	28.4%	39.5%	26.85%	29.75%	31.16%
Periods with negative earnings	15.5%	0.00%	19.59%	16.00%	14.97%
INDIVIDUAL RESULTS					
Agent with maximum use (2)	37.92	16.00	28.71	27.72	27.01
Agent with minimum use (3)	9.57	16.00	5.93	8.75	11.35
Individual difference (2)-(3)	28.35	0.00	22.78	18.97	15.66
Individual use standard deviation (4)	9.05	0.00	5.76	4.79	4.09
0.95 confidence interval of (4)	[5.13, 33.42]	-	[5.04, 6.65]	[4.19, 5.53]	[3.58, 4.72]
Test of H_0 $\{\mu_X=\mu_Y\}$ on (1)			Cannot reject H_0	Cannot reject H_0	Cannot reject H_0
Test of H_0 $\{\sigma^2_X=\sigma^2_Y\}$ on (4)			Cannot reject H_0	Cannot reject or accept H_0, p-value=0.05	H_0 rejected

Notes: K=6, N=8, lchrom=8, pm=0.02; GA v.5.0 (uniform binary innovation process), GA v.5.2 (local innovation), GA v.5.3 (cost driven innovation). See notes to Table 4.7.

Table 4.16: Simulations of Resource Use Without Sanctions – Impact of Memory Size With Inexperienced Agents

	Nash equilibrium	Artificial agents, $T=\tau=32$					
Memory size, K		2	4	6	12	30	90
Expected takeover time, TOT		0.47	2.47	3.43	4.90	6.67	8.66
Inverse of error odds		3	7	11	23	59	179
GROUP RESULTS		Y		X			Y
Use (1)	128.00	139.42	131.82	131.02	130.16	129.63	129.66
0.95 confidence interval	-	[139.19, 139.65]		[130.96, 131.08]			[129.62, 129.70]
Standard deviation across runs	-	11.58		2.78			1.90
Standard deviation of use over time	0.00	20.40	17.77	17.50	18.75	18.13	18.08
Efficiency	39.5%	3.56%	24.86%	26.85%	28.20%	29.64%	29.70%
Periods with negative earnings	0.00%	34.69%	24.86%	19.59%	18.97%	17.69%	17.16%
INDIVIDUAL RESULTS							
Agent with maximum use (2)	16.00	34.90	28.28	28.71	18.42	24.59	20.85
Agent with minimum use (3)	16.00	2.74	5.39	5.93	14.29	12.36	13.83
Individual difference (2)-(3)	0.00	32.16	22.89	22.78	4.13	12.23	7.02
Individual use standard deviation (4)	-	8.87		5.76			2.45
0.95 confidence interval of (4)	-	[7.75, 10.24]		[5.04, 6.65]			[2.14, 2.82]
Test of H_0 $\{\mu_X=\mu_Y\}$ on (1)		reject H_0		-			reject H_0
Test of H_0 $\{\sigma^2_X=\sigma^2_Y\}$ on (4)		reject H_0		-			reject H_0

Notes: See notes to Table 4.12.

Table 4.17: Simulations of Resource Use Without Sanctions – Impact of Action space With Inexperienced Agents

	Nash equilibrium	Artificial agents, individual action space, $T=\tau=32$:		
		Restricted [0,20]	Full [0,50]	Expanded [0,80]
GROUP RESULTS				
Use	128.00	124.90	130.40	139.30
0.95 confidence interval				
Standard deviation of use	0.00	8.25	15.03	30.64
Efficiency	39.5%	44.62%	29.75%	2.88%
Periods with negative earnings	0.00%	0.09%	16.00%	31.81%
INDIVIDUAL RESULTS				
Agent with maximum use (1)	16.00	17.60	27.72	42.93
Agent with minimum use (2)	16.00	9.40	8.75	8.09
Individual difference (1)-(2)	0.00	8.20	18.97	34.84
Individual variance				
0.95 confidence interval of variance				

Notes: K=6, N=8, lchrom=8, pm=0.02; GA v.5.0 (uniform binary innovation process). See notes to Table 4.7.

Table 4.18: Simulations of Resource Use With Weak Sanctions – Impact of Innovation Processes With Inexperienced Agents

	Human agents, X	Nash equilibrium	Artificial agents, Y, τ=27		
			T=27	T=54	T=400 (384)
RESOURCE USE RESULTS					
GROUP RESULTS					
Use (1)	115.5	128.00	122.10	123.49	123.87
0.95 confidence interval	[108.90, 122.02]	-	[122.03, 122.17]		
Standard deviation across runs	7.16		3.34	3.44	3.13
Standard dev. of use over time	16.51	0.00	18.36	15.31	15.30
Efficiency	57.19%	39.5%	42.25%	44.09%	43.38%
Net efficiency	48.3%	39.5%	32.67%	34.32%	34.30%
Periods with negative earnings	7.00%	0.00%	11.00%	10.85%	10.89%
INDIVIDUAL RESULTS					
Agent with maximum use (2)	17.7	16.00	24.06	22.17	21.16
Agent with minimum use (3)	11.0	16.00	8.89	10.53	10.90
Individual difference (2)-(3)	6.7	0.00	15.17	11.64	10.26
Individual use standard dev. σ (4)	2.45	-	4.96	3.86	3.46
0.95 confidence interval of (4)	[1.39, 9.04]	-	[4.33, 5.73]		
INSPECTION DECISIONS					
Share of actions inspected η (5)	51.5%	0.00%	72.78%	56.56%	52.58%
Inspection fees	8.9%	0.00%	12.58%	9.78%	9.09%
Sanctions	8.9%	0.00%	14.22%	11.29%	9.96%
Inspections with neg. bal.	62.02%	-	47.52%	48.74%	44.15%
No. of requests/ inspection	2.43	-	2.65	2.48	2.03
Number of requests to inspect by agent					
Minimum	0.23	0.00	0.79	0.38	0.20
Maximum	2.56	0.00	3.25	2.52	2.16
Test of H_0 $\{\mu_X=\mu_Y\}$ on (1)	-		H_0 rejected	H_0 rejected	H_0 rejected
Test of H_0 $\{\sigma^2_X=\sigma^2_Y\}$ on (4)	-		Cannot reject H_0	Cannot reject H_0	Cannot reject H_0
Test of H_0 $\{\eta_X=\eta_Y\}$ on (5)	-		H_0 rejected	Cannot reject H_0	Cannot reject H_0

Table 4.19: Simulations of Resource Use With Strong Sanctions – Impact of Innovation Processes With Inexperienced Agents

	Human agents, X	Nash equilibrium	Artificial agents, Y, τ=27		
			T=27	T=54	T=400 (384)
	RESOURCE USE RESULTS				
GROUP RESULTS					
Use (1)	85.1	71.11	91.95	91.86	95.33
0.95 confidence interval	[9.45, 161.33]	-	[91.82, 92.08]		
Standard deviation across runs	8.49	-	6.27		
Standard dev. of use over time	9.86	0.00	20.70	16.28	16.74
Efficiency	93.98%	99.97%	83.47%	85.90%	84.72%
Net efficiency	76.86%	82.69%	67.37%	70.56%	69.47%
Periods with negative earnings	0.00%	0.00%	2.63%	0.89%	1.07%
INDIVIDUAL RESULTS					
Agent with maximum use (2)	13.5	8.89	18.32	18.30	17.54
Agent with minimum use (3)	8.5	8.89	7.53	7.73	7.91
Individual difference (2)-(3)	5.5	0.00	10.79	10.57	9.63
Individual use standard dev. σ (4)	1.78	-	3.81		
0.95 confidence interval of (4)	[0.80,+∞)	-	[3.33, 4.41]		
	INSPECTION DECISIONS				
Share of actions inspected η (5)	99.1%	100.00%	93.13%	88.75%	88.22%
Inspection fees	17.12%	17.28%	16.10%	15.34%	15.25%
Sanctions	35.91%	18.67%	47.24%	42.18%	43.98%
Inspections with neg. bal.	32.9%	0.00%	54.96%	56.69%	61.38%
No. of requests/ inspection	3.97	7.00	3.73	3.83	4.13
Number of requests to inspect by agent					
Minimum	0.89	7.00	2.00	1.90	2.36
Maximum	6.55	7.00	5.03	4.97	5.04
Test of H_0 $\{\mu_X=\mu_Y\}$ on (1)	-		Cannot reject H_0		
Test of H_0 $\{\sigma^2_X=\sigma^2_Y\}$ on (4)	-		Cannot reject H_0		

Table 4.20: Simulations of Resource Use Without Sanctions
Initialization close to Nash equilibrium

	Random initialization		Initialization close to Nash equilibrium, T=400, τ=100			
	Regular innovation (1)	Low innovation level (2)	Closest to NE (3)	Slightly below NE (4)	Slightly above NE (5)	Closest to NE, low innovation level (6)
GROUP RESULTS						
Use	130.21	129.58	130.07	130.07	130.21	128.36
Standard deviation of use	14.43	4.15	14.76	14.51	14.59	3.84
Efficiency	30.59%	35.62%	30.76%	30.85%	30.50%	38.43%
Periods with negative earnings	15.55%	1.88%	15.60%	15.76%	15.88%	1.73%
INDIVIDUAL RESULTS						
Agent with maximum use						
Average (1)	22.30	24.51	18.26	18.73	21.94	16.49
Minimum (2)	17.59	18.58	17.13	17.28	17.34	16.09
Agent with minimum use						
Average (3)	11.75	12.45	13.10	15.05	13.36	16.04
Maximum	14.81	12.48	15.17	15.13	15.01	16.04
Individual difference (1)-(3)	10.55	12.06	5.16	3.58	8.85	0.45

Notes: K=6, N=8, lchrom=8; Random initialization GA v.5.0, Initialization close to Nash equilibrium (NE) GA v.5.5. Regular innovation level pm=0.02, Low innovation level pm=0.002 (p=0.0159). In this case the closest value to $X^{NE}=128$ is 128.04 when three agents use the resource 15.88 (grid point 81) and five agents use the resource 16.08 (grid point 82). Initialization slightly below NE is when all agents are at 15.88, slightly above when all agents are at 16.08. See notes to Table 4.7.

Appendixes

Appendix A

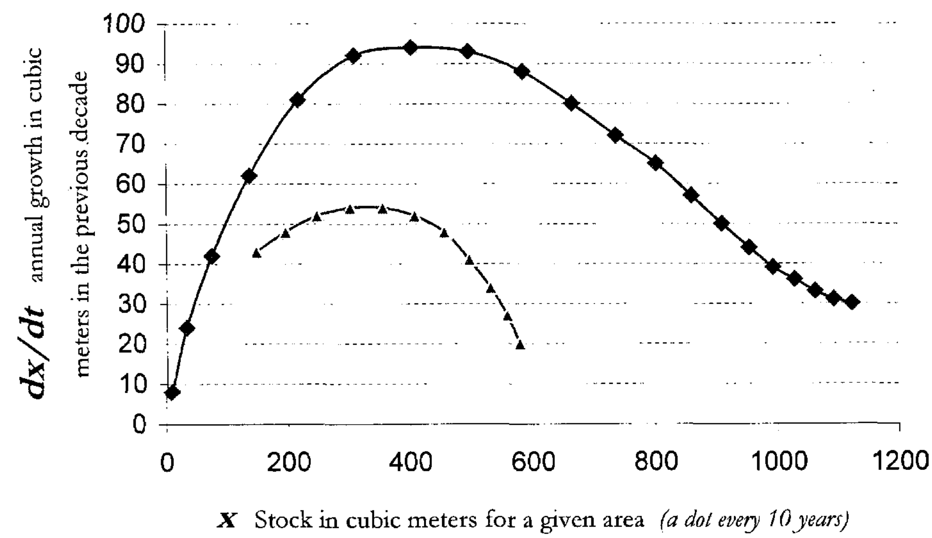
Technology of a Renewable Resource

The purpose of this section is to describe the model of a renewable resource that is presented in Section 2.2 of the paper.

The production function is a relation between the quantity of input (level of effort in exploiting the resource) and the quantity of output (amount of resource obtained in harvesting). The derivation of the production function involves three steps. The first step is to model the growth of a renewable resource, the second step is to introduce a harvesting technology, and the third is to consider prices.

The biologic dynamic of a renewable resource over time can be described with the logistic equation $\frac{dx}{dt} = rx\left(1 - \frac{x}{K}\right)$ that is widely employed in the literature (Gordon, 1954; Clark, 1990; Baland and Platteau, 1996). The evolution of the population x over time t is a quadratic function of x itself. The parameter K is the maximum size of the population level (or resource stock) that is usually called the carrying capacity. Loosely speaking, the parameter r measures the growth rate, that is, the time needed to reach K. Figure 2.3 shows a real world example of a growth function for two types of forest resources.

Figure A.1: Example of a Biological Dynamic of a Renewable Resource: Forest Growth



Note: the empirical data for red fir (upper line) comes from Trentino and for beech (lower line) from another region of Italy. The maximum sustainable yield (MSY) for the fir is at 70 years. ISAFA (82)

So far the model describes the dynamic of a biological resource not subjected to harvesting activity. The next step is to model the harvest function. Assume that the marginal return of one unit of effort Q is proportional to the population level x : $S = n\,x$, where S stands for the physical amount of the harvest. In other words, the higher the stock of the resource, the more productive the harvesting activity will be. The production function is obtained by solving the zero-growth condition $\frac{dx}{dt} = S$ in the equilibrium population level x*: $S = Qx^* = QK - Q^2\frac{K}{r}$. In general, there is also the solution $x^{**}=0.$, when the resource is totally depleted and the harvest is zero. The zero-growth condition implies that, in a given period of time, the natural growth of the resource must be equal to the quantity of resource harvested. The stock level x^* is the steady state equilibrium and $S = Qx^*$ is the perpetual constant flow of harvest that the resource yields in equilibrium.

From the graph, we can see that "at any population below a certain level K, a surplus production exists that can be harvested in perpetuity without altering the stock level. If the surplus is not harvested, on the other hand, corresponding increase occurs in the stock level, which ultimately approaches the environmental carrying capacity K, where the surplus is reduced to zero." (Clarke, 1990, p.1) The maximum surplus that can be obtained in perpetuity is called MSY (Maximum Sustainable Yield) and is reached at $x = \frac{K}{2}$.

The last step is the introduction of prices. Let c be the cost of one unit of effort and p the selling price v of one unit of harvest. The sustainable level of revenues from the application of Q units of effort to the resource is $Y = vS$ or $Y = aQ - bQ^2$, where a = Kv and $b = \frac{Kv}{r}$ (see Figure 2.2). There is an assumption that every unit of effort has the same return, namely $\frac{Y}{Q}$.

To sum up, the assumptions about technology are as follows:

(1) Resource dynamic is logistic

(2) Harvesting efficiency is linear in the population level

(3) Marginal cost of one unit of effort is constant

(4) Earnings are divided in proportion of harvesting efforts

Appendix B

B.1 Analogy With Oligopoly

The problem faced by appropriators of a renewable resource is formally equivalent to the problem that firms face when they decide the amount of goods they want to sell in a market. The unregulated common ownership solution (tragedy of the commons or NE in Figure 2.2) is the Cournot equilibrium of an oligopoly when the competition in on quantity and entrance of new firms is blocked. The reinterpretation of the parameters is straightforward: q_i is the quantity sold by firm i in a market with a linear demand function $Y = a - bQ$ and a constant returns to scale technology. The socially optimal case corresponds to a monopoly and the open access case is like a market with perfect competition. While the formal analysis of the two problems is exactly the same, the welfare evaluation of the different regimes is opposite. In the case of a monopoly, the solution is not socially optimal because the firm does not consider the consumer surplus, while in the case of a renewable resource the rent - the new label for firm profits - is the only welfare consequence to consider and so its maximization leads to the socially optimal solution. In the new setting, a zero-profit outcome means complete rent dissipation.

B.2 Protection from Trespassing

This section presents a model of property rights enforcement toward outsiders. The goal is to show that under some reasonable conditions some trespassing occurs in equilibrium.

Detecting and convicting trespassers were costly activities. We could assume that the trial involved a constant cost while the cost of monitoring the land was increasing with the degree of its completeness. Under the assumptions that as the enforcement of property rights becomes complete its cost goes to infinity, a partial enforcement was socially optimal and that might explain why outsiders still attempted to trespass.

Consider the following three assumptions: (i) outsiders' actions were detectable at a cost, (ii) monitoring cost was increasing in the probability to detect the trespassing action and moreover (iii) as the probability *po* to observe the action approaches one, monitoring costs *mo* go to infinity. We can model this concept with the function $mo(po) = \dfrac{po}{1-po}$, where $po \in [0,1)$.

The interaction between the potential trespassers and the community is modeled as a game where the community has the powers to levy fines on trespassers when they are caught. A trespassing action involved harvesting a given amount of resources *d* that is subtracted to the community profits. As explained, monitoring was costly, but no extra deadweight loss is in this model for the activity of collecting the fine. A decision based on a cost-benefit analysis would have considered the loss of resource caused by trespassing, the revenues from the fines, as well as the monitoring costs:

$$\max_{\{po\}} \{-d \cdot M(po) + f \cdot po \cdot M(po) - mo(po)\}$$

Where M is the expected number of trespasser attempts, $M = \pi^*/(d + f \cdot po)$ and π^* is the actual rent enjoyed by the insiders from the common resource. The number of trespassing attempts in equilibrium M^* is a proxy for the degree of enforcement of the property rights toward outsiders. Under some quite reasonable conditions ($f > d/2 \cdot \pi^*$ and $f+d>0$) there exist only one acceptable solution $0 < po^*_1 < 1$ while the other solution is too big, $po^*_2>1$. The solutions are both equal to 1 in the degenerate case when f+d=0, which is not possible since by assumption d >0 and f≥0.

The enforcement could be improved by increasing the expected sanction of trespassing $f{\cdot}po$.which could be done either by boosting monitoring activity or increasing the nominal sanction *f*. I call the enforcement complete when there is no expected attempt to trespass, M*<1. Given a level of punishment f, the optimal monitoring policy in general involves some positive effort but not detecting every single trespassing, $0<po^*<1$. The punishment ceiling f" is binding when the amount f* defined by M(f*,po*(f*))=1 is such that f*>f".

As Barzel puts it: "If it is assumed that for any asset each of these costs is rising and that both the full protection and the full transfer of rights are prohibitively costly, then it follows that rights are never complete, because people will never find it worthwhile to gain the entire potential of 'their' assets" (Barzel,1997, p.2).

B.3 Monitoring Insiders

The costs to monitor insiders *mi* could be thought as similar to the one for outsiders, *mo*. Consider the following three assumptions about the cost of the joint activity of monitoring outsiders and insiders, *m*:

(i) It exhibits economies of scale because the guards that are on the common land to patrol for trespassers can detect violations by insiders at a low additional cost, $m(po,pi) < mo(po) + mi(pi)$, for any $po,pi>0$;

(ii) The function m should reduce to the elementary functions mo and mi when one of the target groups, either insiders or outsiders, is not monitored, $m(po,0) = mo(po)$ and $m(0,pi) = mi(pi)$;

(iii) The joint activity should be still more expensive than one single component carried out independently, $m(po,pi) > mo(po)$ and $m(po,pi) > mi(pi)$, for any $po,pi>0$.

An example is the cost function $m(po,pi) = mi(pi) + (1- s\cdot pi)\ mo(po)$, where $0<s<1/2$ satisfies properties (i) through (iii), or more specifically the function is $m(po,pi) = \frac{pi}{1-pi} + (1 - s \cdot pi)\frac{po}{1-po}$. Property (i) is obvious since (1-s·pi)<1. The two properties (ii) can be easily verified by substituting pi=0 or po=0. The first of properties (iii) is verified when $m(po,pi) - mo(po)>0$, which reduces to $x>1-(1-s)/s\cdot po$, which is true when $s<1/2$. The second of properties (iii) is verified when $m(po,pi) - mi(pi)>0$, which reduces to $x<1/s$, which is true when $s<1$.

B.4 Social sanctions

An informal sanctioning alternative to the collective overuse of the resource could be used to support cooperation, namely social sanctions. A social sanction occurs when an agent voluntarily performs a costly act in order to punish somebody who has violated a norm of the society. The strategies employed in a Folk theorem usually consider punishments taking place in the same realm of the resource use in the form of a temporary or permanent non-cooperative mode. People living in the same village, however, were involved in several other interactions besides the use of the common resource. Free-riding behavior on the common resource could have been punished with a denial of credit, with the refusal to rent a privately owned field, or the rejection of a marriage proposal. An advantage of social sanction is that the punishment was targeted to the individual free rider. On the other hand, inflicting individual punishments requires knowledge of individual actions and hence monitoring was still necessary to avoid a high rate of 'undeserved' punishments. Unless we use legal regulations, there was no need to build costly institutions.

Despite the advantages, the community adopted legal sanctions where community officials were in charge of punishing the individual defector through a monetary fine. A social sanction, in fact, entails a loss for both the agent who inflicts it as well as for the targeted agent. At the societal level social sanctions bring destruction of resources. As have already been mentioned, a legal sanction instead is often voluntarily paid (under the threat of violence by higher authorities) and is mostly a transfer of resources within the community. Its aim is to be costly for the targeted agent, but at the community level there is no destruction of resources besides collecting costs. In addition to this economic reason there are probably sociological and anthropological aspects that deals with the risk of social disruption due to unlimited revenge (Girard, 1972). The risk is higher when there is not a well-defined norm for how much punishment should be considered enough.

Appendix C

Comparison With a Previous Experimental Design

There are differences between our no sanction design and Walker, Gardner, and Ostrom (1990) (i.e., WGO) both in the incentive structure (1-4) and in the way the information is conveyed (A-D):

1. The range of the choice variable x_i has been rescaled from [0,25] to [0,50] to increase the perceived distance between Nash equilibrium and open access level. Moreover, the socially optimal use level corresponds to an integer individual use (9 versus 4.5 tokens in WGO). In the experimental design of WGO, a change in the endowment ω is tied to the upper limit in the individual use of the common-pool resource because $\omega - x_i \geq 0$. In our experimental design the endowment level ω is chosen for the sole purpose of ensuring some minimum earnings to the agents and the range of choice is $0 \leq x_i \leq \hat{x}$. Our design has a continuous decision space (i.e., any real number) that avoids the problems of asymmetric equilibria that WGO had (see Saijo, 1994).
2. The conversion rate franc/dollar has been increased four times from \$ 0.01 to \$ 0.04 (or \$ 0.03) per 1 franc in order to maintain a higher effort level by the participants in the experiment. As a result, the *difference* in terms of *individual* earnings between the social optimum and open access points has increased from \$ 0.405 to \$ 1.62 (these figures and all the earnings are expressed in dollars per person per period).
3. The minimum safe earning level has been decreased. If nothing is used in the "risky" market 2, the original earnings are \$1.25. In our setting a zero use (x_i=0) yields a

period return of \$0.4 (when w=4). The change implies a downward shift in the payoff but does not affect the incentive structure. The reason of the change is to limit the maximum earnings that would have otherwise been too high given the new conversion rate (point 2).

4. The gross group return has been modified in the interval [184, 400]. The function $f(X)$ now has a lower bound at –200 francs that is much higher than it originally was. A group use of X=184 has an efficiency of –142% in both settings. At X=400 the difference in dollar earnings is small (\$ –5.6 instead of \$ –6.75). The reason for the change is to limit the maximum loss given the new conversion rate in case people "go crazy" (see point 2). In the experiments conducted, we observed a use level above 184 just in one round out of 291.

A. Graph instead of formula. WGO provided the subjects with the analytical expression of the gross group return from market 2. The expression may have been used to compute the equilibrium. We replaced it with a plot of the function f(X) because we think that the graph would improve the understanding of the basic underlying phenomenon. The graph in the instructions is similar to the upper part of Figure 3.1 once the cost line is removed.

B. Detailed table. In order to compute the equilibrium, subjects could use a very detailed table of gross group return. The table gives the gross group return and the return per token used for 100 values of the total group use, compared to the 10 values given by WGO. All theoretical equilibrium points are listed in the table given to the subjects. Our table does not supply the marginal returns, which instead WGO provided.

C. Different software. The software was run on Netscape and was written specifically for this application. It includes a calculator to compute the cost of tokens, the gross group return, and the individual share of gross for every possible real level of use in the admissible range.

D. In WGO, market 1 represents the *opportunity cost* of the use and yields a constant return. The way in which it was presented to the subjects in this study is as a *direct cost* of the use. You can order the tokens to use and pay a constant unit price for them. This change may make the decision of the agents easier by suggesting a comparison of the price of tokens with the return from the market.

Appendix D

Experimental Instructions

Important note: The instructions reported below are for weak sanction experiments with E=4 (0225, 0824, 0408). The instructions for sanction-free experiments with E=4 (0216, 0908, 0407) did not include the parts in square brackets.

This is an experiment in decision making. If you follow the instructions carefully and make good decisions you may earn a considerable amount of money. You will be paid in cash in private at the end of the experiment.

You will make most of your money by [either (1)] placing an order for tokens and INVESTING them in a market that will give you a cash return for your tokens [(See example #1 below), or (2) MONITORING other people's decisions and eventually getting some revenues from the inspections (See example #2 below)].

The experiment in which you are participating is comprised of a sequence of periods. In each period you will be asked to make an investment [and a monitoring] decision.

INVESTING

Each period you can place an order for a ***number of tokens between 0 and 50,*** which will be automatically invested in the market. There are also ***seven*** other persons in this experiment who are making investment decisions on the same market. Everybody can place orders up to 50 tokens and so the total group investment is at most 400 (= 50 times 8 people).

For every token you order, you will be ***charged 2.5 francs*** and you will be credited a cash return from the market.

The return from the market is a bit complicated to explain. The return depends on the number of tokens you invest as well as the amount all others in the group invest. The total group investment determines the gross group return (See table on the board) and you will receive a fraction of it according to your personal investment level. The example below explains the computation in detail.

You make your decision before knowing other people's investment decisions on that period. You are not to reveal your investment decision to anyone.

EXAMPLE [#1]

Suppose you place an order of 6 tokens to be invested in the market and everybody else does exactly the same.

The cost of your tokens is 15 francs, that is 6 tokens times 2.5 francs.

To compute your earnings in the market,

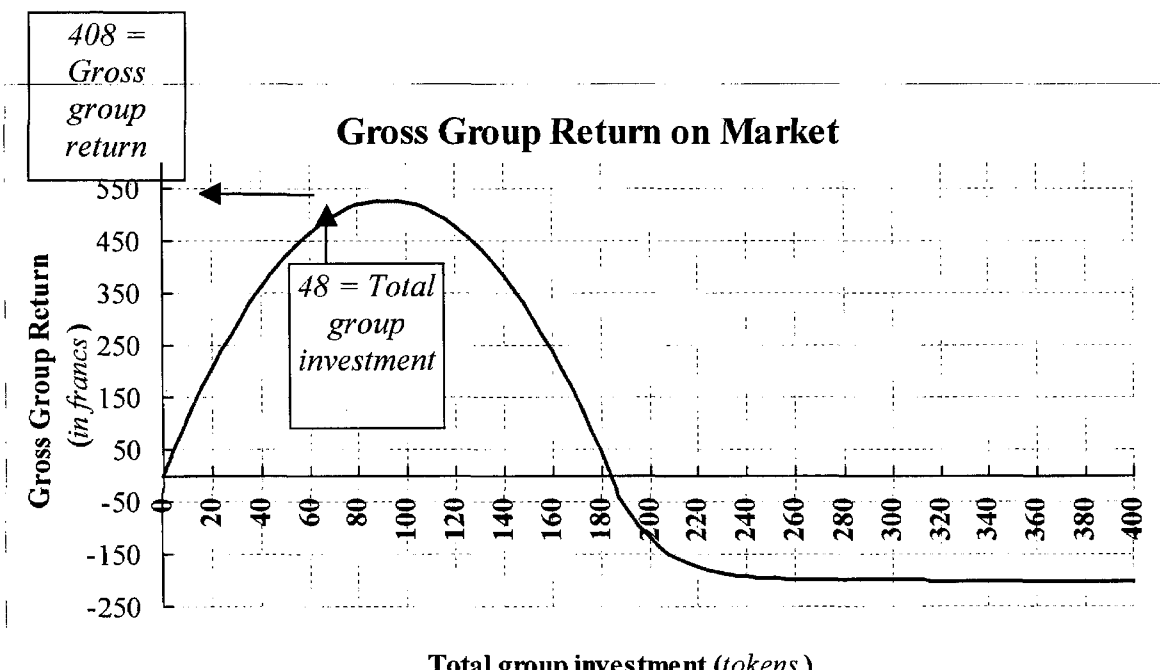
(1) first, compute the total group investment. In this example, the total group investment is 48 tokens (6 tokens times 8 people). The corresponding ***gross group return*** is 408 francs, as shown in the table on the board. The first column of the table lists the total group investment and the third column gives you the corresponding gross group return.

(2) The second step is to compute ***your share of gross***. You will receive a ***fraction of the gross group return that is equal to your fraction of total group investment.*** You have invested $\frac{6}{48} = 0.125$ of total group investment and you will receive 0.125 of the gross group return: 51 francs is your share of gross (408*0.125).

Your net return is 36 francs (your share of gross, 51, minus the cost of the tokens, 15).

As a ***computational shortcut*** for your share of gross, you can multiply your personal investment level by the "Return per token invested" column of the table on the board,
that is 6 * 8.5 = 51. ■

The gross group return is graphed below.



Notice that the gross group return on the market can be negative if the total group investment is sufficiently large. For instance, if each person invests 42 tokens, the total group investment is 336 tokens and the gross group return is –200 francs. When considering the cost of the tokens, each person has to ***pay*** 130 francs.

To sum up, your ***period earnings*** [***from investment***] in francs are given by:

+ Your share of gross	51 +	←	See example [#1]
– Cost of tokens	15 –		
= *Your net return*	*36*		
+ Period endowment	10+	←	Fix amount
= *Period earnings*	*46*		

The period endowment is a constant amount and does not depend on the investment decisions.
In the example the period earnings in dollars are ______ (1 franc = ____ cents).

If you have any questions concerning the instructions feel free to raise your hand and an instructor will assist you.

[***MONITORING***

After the total group investment is revealed, you will have the chance to ***impose a payment to the people that invested more than 9 tokens in the market***. This payment will be given to you. Notice that if the total group investment is more than 72 tokens (that is 9 tokens times 8 people), at least one person invested more then 9 tokens.

You don't know the individual investments of the other people, but you can ask to uncover them by ***paying 7 francs for every person you ask to inspect*** (inspection fee). If the person inspected invested more than 9 tokens, she pays ***1 franc for every extra token***. You get this money (inspection revenue) and ***everybody will know the investment level of the person inspected.***

You make the monitoring decision when you know the total group investment, but before knowing other people's monitoring decisions.

An identification number will be assigned to every person to maintain anonymity and it must be considered *strictly confidential.*

EXAMPLE #2

Suppose the total group investment is 172 tokens and your investment is 24 tokens (you are ID #1). Before the monitoring, you know that 100 extra tokens were invested (=172 - 72) but you don't know who invested them. Well, you did part of the job with 15 tokens (=24 - 9), but there are other seven people around that invested 85 extra tokens. Suppose you ask to inspect person #2 and she has invested 34 tokens. You pay an inspection fee of 7 francs and get an inspection revenue of 25 francs (= (34 - 9) * 1). After your inspection, everybody will know that person #2 has invested 34 tokens, but ***your identity will not be revealed.***

Besides the period earnings from investment already explained above, your earnings will be affected by your and other people's monitoring decisions as follows:

	ID#1	ID#2
Inspection Fee		- 7
Inspection Revenue	+ 25	
Payment	___	- 25
= *Balance*	+18	- 25

◄— See example #2

■

If two or more people ask to inspect the same person, only one inspection will be executed. A person will be ***randomly selected*** and she will pay the inspection fee and get the eventual inspection revenue. The other inspectors will be treated as if they did not ask to inspect that person.
If you have any questions concerning the instructions feel free to raise your hand and somebody will assist you.]

Please go through the review session in the next page and fill in the blank lines with the values you think are correct.

PRACTICE ID _____

REVIEW

Consider the following investment decisions:

ID#	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*Total group investment*
tokens	11	11	11	11	11	11	11	27	104

Suppose you are person #1. To compute your net return on the market let use the computational shortcut mentioned in the example [#1]. Take your investment of 11 tokens and multiply it by 5.00 (Return per token invested, second column of the table on the board) = 55 francs is your share of gross. Your net return is 27.5 francs (your share of gross = 55 minus the cost of tokens = 27.5).
Now, you go on.

Gross group return ____________
Person #2: Share of gross _______________ Net return _________________
Person #8: Share of gross _______________ Net return _________________
[Suppose you inspect person #2 and #8. Your inspection revenues will be:
Inspection Revenue from person #2 __________ Balance (Insp. Revenue - Insp.Fee) ______

Inspection Revenue from person #8 __________ Balance (Insp. Revenue - Insp.Fee) ______]

Now, suppose you decide to increase your personal investment to 43 tokens, while everybody else stays the same, hence the total group investment raises to 136 tokens.

Gross group return ____________

Person #1: Share of gross _______________ Net return _________________

Person #2: Share of gross _______________ Net return _________________

Person #8: Share of gross _______________ Net return _________________

[Suppose this time somebody asks to inspect you (you will pay for every token above 9):

Person #1: Payment ______________]

■

Please raise your hand if you have any questions and an instructor will assist you.

[Otherwise, please go on to the next page.]

PRELIMINARIES

1. At the beginning we will run a two-period experiment to get familiar with the rules. It will NOT affect your earnings.

2. During the real session, ***an announcement will be made two periods before the end of the experiment.*** The total number of periods is unknown to you.

3. Please sign and date the following financial agreement.

Should my total earnings from the experiment be negative, I agree to work in the Experimental Economics and Political Science Laboratory at a rate of 7 dollars per hour until the loss is repaid.

Name and Signature ____

Date ____________

(Please detach this sheet and give it to the experimenter)

GROSS GROUP RETURN on the market

Total Group Investment	*Return per token invested*	*Gross Group Return*
0	0.00	0.0
4	11.25	45.0
8	11.00	88.0
12	10.75	129.0
16	10.50	168.0
20	10.25	205.0
24	10.00	240.0
28	9.75	273.0
32	9.50	304.0
36	9.25	333.0
40	9.00	360.0
44	8.75	385.0
48	8.50	408.0
52	8.25	429.0
56	8.00	448.0
60	7.75	465.0
64	7.50	480.0
68	7.25	493.0
72	7.00	504.0
76	6.75	513.0
80	6.50	520.0
84	6.25	525.0
88	6.00	528.0
92	5.75	529.0
96	5.50	528.0
100	5.25	525.0
104	5.00	520.0
108	4.75	513.0
112	4.50	504.0
116	4.25	493.0
120	4.00	480.0
124	3.75	465.0
128	3.50	448.0
....	....	....
380	-0.53	-200.0
384	-0.52	-200.0
388	-0.52	-200.0
392	-0.51	-200.0
396	-0.51	-200.0
400	-0.50	-200.0

1. Find out the actual *group* investment

2. Look at the average return of each token

3. Multiply the average return by the number of tokens *you* have invested

Appendix E

Comparison Between Reinforcement Rules: Pairwise Tournament vs. Replicator Dynamics

There are four main differences between the replicator dynamics and the reinforcement rule adopted in the genetic algorithm (Pairwise Tournament).

The first difference refers to the use of the score of a strategy to compute the probability of being replicated. In the replicator dynamics the score needs to be positive, and the absolute magnitude of it is important to compute the probability of being replicated. Instead of this cardinal property, the Pairwise Tournament rule is ordinal, in the sense that the probabilities are based only on "greater than" comparisons among strategies. This feature makes it more attractive because it can deal with negative score values and does not rely on a "biological" interpretation of the score as perfect measure of the relative advantage of one strategy over another.

The second difference is in the expected takeover time of a superior strategy. It is shorter for a Pairwise Tournament rule than for replicator dynamics. In other words, bad strategies are discarded faster by Pairwise Tournaments than by replicator dynamics. According to Bäck(1996), the expected takeover time with proportional reinforcement when the score function is exponential, $f(x)=\exp(cx)$, is approximately $(1/c)\ K \ln K$, while for Pairwise Tournament reinforcement is $(1/\ln 2)\ (\ln K + \ln(\ln K))$. Given that the former is of order $o(K \ln K)$ and the latter $o(\ln K)$, for large memory sizes tournament rules are always reinforcing good strategies faster than proportional selection rules. The same inequality holds for small numbers under mild conditions. For instance, for every $K>2$ when $c<2$.

The third difference is more substantial and concerns the place of the reinforcement rule within the general architecture of the genetic algorithm (GA). As already mentioned there are two types of GA, single population and multiple populations. With single population GA, all hypothetical actions co-evolve together in one set and the reinforcement rule is applied to that set. The use of the replicator dynamics in evolutionary game theory is done with reference to the equivalent of a single population design. With multiple populations each agent is endowed with a separate set of hypothetical actions that evolves independently one from another. In fact, there is no imitation of hypothetical action from one agent to another (i.e., across different sets). In this latter case, the reinforcement rule operates separately on each memory set.

The fourth difference regards the use of either continuous or discrete time in the reinforcement process. Replicator dynamics generally works in continuous time while a genetic algorithm works in discrete time. It is shown in Weibull (1995) that in discrete time strictly dominated strategies need not to get wiped out as they instead are in continuous time.

Appendix F

Code for Genetic Algorithm

The simulations have been carried out through algorithms coded in Turbo Pascal version 7.0. The following code is version 5.0 of MPGA (Multiple Population Genetic Algorithm) and it was used in the simulations of common property resource use without sanctions.

```
program CPRmp;

{ A MULTIPLE POPULATION GENETIC ALGORITHM - MPGA - v. 5.0 (my notation) }
{ Based on David Edward Goldberg (1986) and on v. 4.0 single population SGA   }
{ Apr 2001 - Marco Casari -  marco@hss.caltech.edu}


const   maxpop          = 30;      {max no. of strategies for each agent}
        maxstring       = 30;   {max length of one strategy}
     mindomain     = 0;   {CPR problem}
     maxdomain      = 400;          {CPR problem}
        eps             = 0.0001;          {for real no. comparisons}
        maxiteration   = 100;
        nagent          = 8;       {Number of agents in the simulation}
        interval  = 100;  {periodicity of PLUS report}


type    allele          = boolean;                  { Allele = bit position}
        chromosome      = array[1..maxstring] of allele;  { string of bits }
        individual      = record
                          chrom:chromosome;       {genotype=bit of string}
                          x       :real;            {phenotype = unsigned integer}
                xfit :real;       {rescaled value in fitness domain}
                          fitness:real;      {objective function value}
                          parent1, parent2, xsite:integer; {parents and cross point}
                          new: boolean;
                          good: boolean;
                         end;
        population        = array[1..maxpop] of individual;  {for a single agent}
        agentpopulation = array[1..nagent] of population;  {set of agents' populations}
        ag                = record
                            choice          : integer; {individual that is chosen for playing}
                            xfit    : real;  {actual strategy played}
                            fitness         : real;  {actual fitness earned}
```

```
                    xmin  : real;  {across strategies of the same agent}
                    xmax  : real;
                    xavg  : real;
                    xsd   : real;
                    minfit: real;
                    maxfit        : real;
                    avgfit : real;
                    ninnova       : integer;
                    naccepted     : integer; { not active }
                    ndiverse   : integer;
                   end;
agentsint       = array[1..nagent] of ag; {summary statistics for each agent}
groupsint       = record
                    groupx        : real; {actual resource use for the generation}
                    groupfit      : real; {actual group profit for the generation}
                    xmin  : real;   {across agents}
                    xmax  : real;
                    xavg  : real;
                    xsd   : real; {standard deviation}
                    minfit: real;
                    maxfit        : real;
                    avgfit : real;
                    ninnova       : integer;
                    naccepted     : integer;  {not active}
                   end;

grouptime       = record
                          xavg,xmin,xmax, xsd :real; {over time}
                          avgfit : real;
            perneg : real;
                          agsdt : real; {at period t}
                    end;

oneagenttime    = record
                    xavg, xmin, xmax, xsd : real;
                    avgfit : real;
            diverset: real;  {diverse = ndiverse at t}
                   end;

agenttime       = array[1..nagent] of oneagenttime;
memagent        = array[1..nagent] of real;  {for PLUS report}

Gensummary      = record
                          xavg,xmin,xmax: real;      {across runs}
                          xsd, xsdmin, xsdmax :real;
                          avgfit, minfit, maxfit : real;
            perneg, minneg, maxneg : real;
                          agmin, agmaxmin : real; {across runs and players}
                          agmax, agminmax : real;
                          agdif, agmindif, agmaxdif : real;
                          avgdiv, mind, maxd : real;
                    end;

var     oldpop, newpop                  :population;      {two non-overlapping populations}
        oldagentpop, newagentpop: agentpopulation; {group variables}
        agentstat                : agentsint;
```

```
      groupstat                          : groupsint;
      group50t                           : grouptime; {for PLUS report}
      agent50t                  : agenttime;
      AllinAll                  : Gensummary;
      popsize, lchrom, gen, maxgen,w     :integer; {integer global variable}
      pcross, pmutation, avexfit :real;            {real global variables}
      pmuse                              : real;
      nmutation, ncross         :integer;
      coef                               :real;
   exc, lst, con, tem, all        :Text;
   rseed                   :real; {random seed used for the 10 iterations}
      nplayers, agent,z         : integer;
      sumxagent, sumx2agent, sumfitagent : memagent; {for PLUS report}
      Allxgroup, Allx2group, Allfitgroup : real;  {for PLUS report}
      Allxagent, Allx2agent, Allfitagent : memagent; {for PLUS report}
      sumxgroup, sumx2group, sumfitgroup : real;  {for PLUS report}
      sumfitness, xgroup                 : real;
   det                     : char;


{ INCLUDE PROCEDURES, UTILITIES, AND FUNCTIONS }

{$I utility.mp}              {various routines}
{$I random.mp}               {pseudo-random number generator and random utilities}
{$I compuCPR.mp}             {decode and objfunc with random sampling}
{$I stat.mp}                 {statistics}
{$I plusrep.mp}          {summary report over time}
{$I initial.mp}        {initialize, inidata, initpop, initreport}
{$I report.mp}               {report and writechrom}
{$I 4operat.mp}              {tournament selection, crossover, mutation, (w.election disabled)}
{$I generate.mp}         {generation routine}

begin                    {M A I N   P R O G R A M}

    inidata;

    assign (exc,'G:\sumMP.TXT');
       rewrite (exc);      {one period is one line}
       assign (tem,'G:\temMP.TXT');
       rewrite (tem);      {summaries of of time intervals}
       assign (all,'G:\allMP.TXT');
       rewrite (all);      {average of last interval over runs}

       If ((det='Y') or (det='y')) then
        begin
           assign (lst,'G:\runMP.TXT');
              rewrite (lst);       {detailed report}
        end;

    initreport;
    rseed:=-0.005;
       write('I AM WORKING  ');

   for w:=1 to maxiteration do
    begin
       write('.');
```

```
        gen := 0;
            rseed:= rseed+0.01;
        initialize;
        repeat
          report (gen);
              gen :=gen+1;
              for agent:=1 to nagent do
                   begin
                    generation(oldagentpop[agent], newagentpop[agent]);
                   end;
              for agent:=1 to nagent do
                   begin
                    agentstat[agent].choice:=select(popsize, newagentpop[agent]);
             oldpop := newagentpop[agent];
                    agentstat[agent].xfit:=oldpop[agentstat[agent].choice].xfit;
                end;
          Resourceuse(agentstat, groupstat);
              for agent:=1 to nagent do
                   begin
             statistics1 (agent, agentstat[agent], newagentpop[agent]);
                   end;
              statistics2 (agentstat, groupstat);
              statistics3 (agentstat, groupstat);
              IF gen = maxgen- (maxgen mod interval)
                then statistics4 (agent50t, group50t);
              oldagentpop := newagentpop;  {advance the generation}
             until (gen > maxgen);
    end;

      If ((det='Y') or (det='y')) then close(lst);
      close(exc);
           close(tem);
           close(all);
           greetings;
end.
`````````````````````````````````````````````````````````````````````````````````````````

{ GENERATE.SGA }

procedure IsChildNew (VAR parent, child :individual);

VAR different   : boolean;
   j   : integer;

begin
  {Is children different from parent?}
  different:=false;
  for j:=1 to lchrom do
   begin
    If (parent.chrom[j] <> child.chrom[j])
           then different:=true;
   end;
   child.new := different;
end;
```
```

```
procedure generation (VAR oldpop, newpop: population);
 { CREATE A NEW GENERATION of individuals for AGENT K
THROUGH SELECT, CROSSOVER, MUTATION, and  NO ELECTION}
 { note: generation assumes an even-numbered popsize}

var      j, mate1, mate2, jcross:integer;

begin
         j:=1;
         repeat
                  mate1 :=select(popsize, oldpop); {pick pair of mates}
                  mate2 :=select(popsize, oldpop);

                  crossover(oldpop[mate1].chrom, oldpop[mate2].chrom,
                           newpop[j   ].chrom, newpop[j+1  ].chrom,
                           lchrom, ncross, nmutation, jcross, pcross, pmutation);

          If jcross>0  {if there was any crossover operation}
          then    SwitchWhenEqual (jcross,lchrom, oldpop[mate1], oldpop[mate2],
                                                      newpop[j    ], newpop[j+1  ]);
                           {Switch childs when equal to parents
                  is an essential part of the Weak election operator}

                  with newpop[j] do begin
                           x:=decode(chrom, lchrom);
              xfit:=(x/coef)*(maxdomain-mindomain)+mindomain;
                           parent1 := mate1;
                           parent2 := mate2;
                           xsite := jcross;
                  end;
                  with newpop[j+1] do begin
                           x:=decode(chrom, lchrom);
              xfit:=(x/coef)*(maxdomain-mindomain)+mindomain;
                           parent1 := mate2;
                           parent2 := mate1;
                           xsite := jcross;
                  end;

          If jcross=0 then
           begin
            newpop[j].parent1:=0;  {if no crossover}
            newpop[j].parent2:=0;
            newpop[j+1].parent1:=0;
            newpop[j+1].parent2:=0;
           end;

                  {Is child different from parents?
                           needs to be after crossover and mutation}
          IsChildNew(oldpop[mate1],newpop[j  ]);
          IsChildNew(oldpop[mate2],newpop[j+1]);

      {     WeakElection (oldpop, mate1, mate2, newpop[j], newpop[j+1]); }

                  j:=j+2;
         until j>popsize;
 end;
```

``````````````````````````````````````````````````````````````````````````````````````````````````````````

```
{ 4OPERAT.SGA }

{ 4 operators:
1. Reproduction through TOURNAMENT SELECTION (select, adjusted from Jasmina Arifovic)
2. Crossover (crossover, modified to correctly assign childs to parents),
3. Mutation (mutation),
4. Weak Election (from Franke's description)        }


function select(popsize:integer; var pop:population):integer;

        { SELECT A SINGLE INDIVIDUAL VIA TOURNAMENT SELECTION}

var firsto,secondo:integer;

begin
  firsto:=rnd(1,popsize);
  secondo:=rnd(1,popsize);
  if pop[firsto].fitness > pop[secondo].fitness
    then select:=firsto
    else select:=secondo;
end;



function mutation(alleleval:allele; pmutation:real;
            var nmutation:integer):allele;
{ Mutate an allele w/pmutation, count number of mutations }
var mutate:boolean;
begin
 mutate := flip(pmutation);   { Flip the biased coin }
 if mutate then begin
  nmutation := nmutation + 1;
  mutation := not alleleval;  { Change bit value }
 end
 else mutation := alleleval;      { No change }
end;


procedure crossover(var parent1, parent2, child1, child2:chromosome;
             var lchrom, ncross, nmutation, jcross:integer;
             var pcross, pmutation:real);

{ Cross 2 parent strings, place in 2 child strings }
var j:integer;
begin
 if flip(pcross) then begin   { Do crossover with p(cross) }
  jcross :=rnd(1,lchrom-1); { Cross between 1 and l-1 }
  ncross := ncross + 1;     { Increment crossover counter }
  end
  else           { Otherwise set cross site to force mutation}
  jcross := 0;


 { 1st exchange, 1 to 2 and 2 to 1 }
```
```

```
for j := 1 to jcross do begin           {the lower bits have lower values:see decode fct}
 child1[j] := mutation(parent2[j], pmutation, nmutation);
 child2[j] := mutation(parent1[j], pmutation, nmutation);
end;

{ 2nd exchange, 1 to 1, 2 to 2 }
 for j := jcross+1 to lchrom do begin
  child1[j] := mutation(parent1[j], pmutation, nmutation);
  child2[j] := mutation(parent2[j], pmutation, nmutation);
 end;
end;


procedure SwitchWhenEqual (jcross,lchrom:integer; VAR parent1,parent2,child1,child2:individual);

{it needs to be considered integral part of the weakelection operator}
{switches childs when they are equal to the parents}
{I don't know if Franke uses this part}

VAR different                     : boolean;
   j                              : integer;
   generic                        : individual;

begin
 {Are children really different from parents?}
 different:=false;
 for j:=jcross+1 to lchrom do       {if the most important bits are the same}
  begin                             {what matters for paternity are the other bits}
   If (parent1.chrom[j] <> parent2.chrom[j])
        then different:=true;
  end;
 If NOT different
   then begin
        generic:=child1;
        child1 := child2;
        child2 := generic;
   end;

end;


`````````````````````````````````````````````````````````````````````````````````````````````

{ INITIAL.MP  contains initdata, initpop, initreport, initialize }

procedure inidata;
                    { INTERACTIVE DATA INQUIRY AND REPORT }
var     ch: char;
        j: integer;

begin

        Clean;
     assign(con,'CON:');
        repchars(' ',20); writeln('~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
        repchars(' ',20); writeln('MULTIPLE POPULATION GENETIC ALGORITHM - MPGA');
        repchars(' ',20); writeln(' based on David Edward Goldberg (1986) and');
```
```

```
repchars(' ',20); writeln(' on SGA v.5.0 of Marco Casari          ');
repchars(' ',20); writeln('~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
repchars(' ',20); writeln('                         April 2001');

writeln ('******* MPGA Data Entry and Initialization *************');
writeln ('There are ',nagent,' agents in this simulation');
write ('Enter no. strategies per agent ---> '); readln(popsize);
write ('Enter chromosome length   -------> '); readln(lchrom);
write ('Enter max generations     -------> '); readln(maxgen);
write ('Enter crossover probability-------> '); readln(pcross);
write ('Enter mutation probability -------> '); readln(pmutation);
write ('Need a detailed report ? '); readln(det);
nplayers:=nagent;
     {comupute max aggregate value - use oldpop just for convenience}
for j:=1 to lchrom do
oldpop[1].chrom[j]:= true;

coef:=decode(oldpop[1].chrom, lchrom);
coef:=coef*nplayers;        { this line is crucial for CPR }
                              { coef is used in the computation of xfit}


pause(2); Clean;

end;



procedure initreport;
                { INITIAL REPORT }
var j:integer;

begin
 If ((det='Y') or (det='y')) then
  begin
     writeln(lst,'                      file name: runMP.TXT');
     writeln(lst);
     writeln(lst,'~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
     writeln(lst,' MPGA = G E N E T I C   A L G O R I T H M  v.5.0');
     writeln(lst,'~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
     skip(5);
     writeln(lst,'                GA Parameters (MULTIPLE POPULATION)');
     writeln(lst,'     ^^^^^^^^^^^^^^^');
     writeln(lst);
     writeln(lst,'     Population size (popsize)  =   ',popsize);
     writeln(lst,'     Number of agents (nagent)=   ',nagent);
     writeln(lst,'     Chromosome length (lchrom)        =   ',lchrom);
     writeln(lst,'     Maximum no. of generation (maxgen)=  ',maxgen);
     writeln(lst,'     Crossover probability (pcross)        =   ',pcross:6:6);
     writeln(lst,'     Mutation probability (pmutation)=    ',pmutation:6:6);
     writeln(lst);
     writeln(lst,'                Initial Generation Statistics');
     writeln(lst,'     ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^');
     writeln(lst);
  end;
     writeln(exc,'                     file name: sumMP.TXT');
```

```
   writeln(exc);
writeln(exc,' MPGA = G E N E T I C   A L G O R I T H M v.5.0');
   writeln(exc,'~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
   writeln(exc,'                GA Parameters (MULTIPLE POPULATION)');
   writeln(exc,'       ^^^^^^^^^^^^^^^^^^^');
   writeln(exc,'       Population size (popsize)  =   ',popsize);
   writeln(exc,'       Number of agents (nagent)=   ',nagent);
   writeln(exc,'       Chromosome length (lchrom)        =   ',lchrom);
   writeln(exc,'       Maximum no. of generation (maxgen)=  ',maxgen);
   writeln(exc,'       Crossover probability (pcross)        =   ',pcross:6:6);
   writeln(exc,'       Mutation probability (pmutation)=    ',pmutation:6:6);
   writeln(exc);
writeln (exc,'  S U M M A R Y   O F   R E S U L T S   ');
writeln(exc,'Generation ~~~~~~ Agent Actions ~~~~~~ Fitness ~~~');
write(exc,'    ');
   for j:=1 to nagent do
   begin
     write(exc,'  ',j,'  ');
end;
writeln(exc,'| Group use| Group fit| stand.dev. : new strategies');
writeln(exc);

   writeln(tem,'                        file name: temMP.TXT');
   writeln(tem);
writeln(tem,' MPGA = G E N E T I C   A L G O R I T H M v.5.0');
   writeln(tem,'~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
   writeln(tem,'                GA Parameters (MULTIPLE POPULATION)');
   writeln(tem,'       ^^^^^^^^^^^^^^^^^^^');
   writeln(tem,'       Population size (popsize)  =   ',popsize);
   writeln(tem,'       Number of agents (nagent)=   ',nagent);
   writeln(tem,'       Chromosome length (lchrom)        =   ',lchrom);
   writeln(tem,'       Maximum no. of generation (maxgen)=  ',maxgen);
   writeln(tem,'       Crossover probability (pcross)        =   ',pcross:6:6);
   writeln(tem,'       Mutation probability (pmutation)=    ',pmutation:6:6);
   writeln(tem);
writeln (tem,'  S U M M A R Y   O F   R E S U L T S   ');
writeln(tem);


   writeln(all,'                        file name: allMP.TXT');
   writeln(all);
writeln(all,' MPGA = G E N E T I C   A L G O R I T H M v.5.0');
   writeln(all,'~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~');
   writeln(all,'                GA Parameters (MULTIPLE POPULATION)');
   writeln(all,'       ^^^^^^^^^^^^^^^^^^^');
   writeln(all,'       Population size (popsize)  =   ',popsize);
   writeln(all,'       Number of agents (nagent)=   ',nagent);
   writeln(all,'       Chromosome length (lchrom)        =   ',lchrom);
   writeln(all,'       Maximum no. of generation (maxgen)=  ',maxgen);
   writeln(all,'       Crossover probability (pcross)        =   ',pcross:6:6);
   writeln(all,'       Mutation probability (pmutation)=    ',pmutation:6:6);
   writeln(all);
writeln (all,'A V E R A G E   R E S U L T S   ');
writeln (all);
writeln (all,'OF THE LAST INTERVALS OF ',interval,' PERIODS OVER ',maxiteration,' RUNS');
writeln(all);
```

```
      With AllinAll do            {initialization of variable - one time only}
   begin
      xavg :=0;
      xmin:=maxdomain;
      xmax :=mindomain;
      xsd :=0;
      xsdmin:= maxdomain*maxdomain;
      xsdmax :=0;
      avgfit :=0;
      minfit := 100;
      maxfit := 0;
      perneg :=0;
      minneg := 100;
      maxneg := 0;
      agmin :=0;
      agmax :=0;
      agmaxmin :=mindomain/nagent;
      agminmax :=maxdomain/nagent;
      agdif := 0;
      agmaxdif := 0;
      agmindif := maxdomain/nagent;
      avgdiv := 0;
      maxd := 0;
      mind := popsize;
  end;

end;


procedure initpop (VAR pop: population);
                 {INITIALIZE A POPULATION OF AGENT K AT RANDOM }
var     j, j1: integer;

begin

   nmutation:=0;
      ncross:=0;

   { attribute random variable to popolation }
      for j:=1 to popsize do with pop[j] do
      begin
       for j1:=1 to lchrom do chrom[j1]:= flip(0.5); {a fair coin toss}
       x:=decode(chrom, lchrom);
    xfit:=(x/coef)*(maxdomain-mindomain)+mindomain;
       parent1:=0;
       parent2:=0;
       xsite:=0;
       new:=true;
       good:=false;
      end;
      avexfit:=0;
end;


procedure initialrun;
```

```
            { INITIALIZATION OF A SINGLE RE-RUN }

begin
 randomize;  {initialize random number generator}
 writeln (exc,'RANDOM SEED:  ', rseed:2:2,'>>>>>>>>>>>>>>>');
 If ((det='Y') or (det='y')) then
   begin
    writeln (lst,'<<<<<<<<<<<<<<<<<<<<<<<<>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>');
    writeln(lst);
    writeln(lst,'RANDOM SEED:  ',rseed:2:2);
    writeln(lst);
   end;
 writeln(tem);
 writeln(tem,'RANDOM SEED:  ',rseed:2:2);
 writeln(tem);

end;


procedure initialize;
                       { INITIALIZATION COORDINATOR }
begin
 initialrun;

 for agent:=1 to nagent do
 begin
   initpop(oldagentpop[agent]);
 end;

 for agent:=1 to nagent do
 begin
   agentstat[agent].choice:=trunc(1+(random*(popsize-1)));
   agentstat[agent].ninnova:=0;
   agentstat[agent].naccepted:=0;
   newpop := oldagentpop[agent];
   agentstat[agent].xfit:=newpop[agentstat[agent].choice].xfit;

 end;

 Resourceuse(agentstat,groupstat);

 for agent:=1 to nagent do
 begin
   statistics1 (agent, agentstat[agent], oldagentpop[agent]);
 end;

 statistics2 (agentstat, groupstat);  {for the group}
{  statistics3 (agentstat, groupstat) NOT RUN, DOES NOT INCLUDE PERIOD O}

end;
``````````````````````````````````````````````````````````````````````````````````

{ PLUSREP.MP}

procedure BeginInterval (allagents:agentsint; thegroup: groupsint);

var j : integer;
```
```

```
begin

 sumxgroup := 0;    {for the group}
 sumx2group :=0;
 sumfitgroup := 0;
 group50t.perneg:=0;
 group50t.xmin := maxdomain;
 group50t.xmax := mindomain;

 for j:=1 to nagent do
  begin with agent50t[j] do
   begin
         sumxagent[j] := 0;    {for agents}
      sumx2agent[j] := 0;
         sumfitagent[j] := 0;
         xmin := maxdomain/nagent;
         xmax := mindomain/nagent;
         diverset :=0;
   end;
  end;

end;


procedure EndInterval (allagents:agentsint; thegroup: groupsint);

var i: integer;

begin

  {FOR THE GROUP }
  group50t.xavg := sumxgroup/interval;
  group50t.avgfit :=(sumfitgroup/interval)/3.24;
  group50t.xsd := sqrt((sumx2group-((sumxgroup*sumxgroup)/interval))/(interval-1));
  group50t.perneg := 100*group50t.perneg/interval;

  group50t.agsdt:=0;
  for i:=1 to nagent do
  begin
   group50t.agsdt := group50t.agsdt + (allagents[i].xfit - thegroup.xavg)*
                          (allagents[i].xfit - thegroup.xavg);
  end;
  group50t.agsdt:=sqrt(group50t.agsdt/(nagent-1));


  { FOR AGENTS }
  for i:=1 to nagent do
   begin with agent50t[i] do
    begin
         xavg := sumxagent[i]/interval;
         avgfit :=100*(sumfitagent[i]/interval)/40.5; {average fitness as % of max}
   (*    xsd := sqrt((sumx2agent[i]-(sumxagent[i]*sumxagent[i]/interval))/(interval-1));*)
         diverset := allagents[i].ndiverse;
    end;
   end;
```

```
 {WRITING TO FILE TEMMP.TXT}
 writeln(tem);
 writeln(tem,'~~~~~~~~~~ Period: ',gen-interval+1,' - ',gen);
 writeln (tem,'GROUP USE:avg  min  max  sd  GROUP FITNESS  %Neg.fit. agent sd at t=',gen);
 with group50t do begin
  write (tem,'     ',xavg:4:2,' ',xmin:4:2,' ',xmax:4:2,' ',xsd:4:2,'   ');
  writeln(tem,avgfit:3:2,'%  ',perneg:2:2,'%  ',agsdt:4:2);
 end;
 writeln(tem);
 writeln(tem,'AGENT  USE:avg  min  max  sd  | FITNESS diverse at t=',gen);
 for i:=1 to nagent do with agent50t[i] do
  begin
   write (tem,i,'     ',xavg:4:2,' ',xmin:4:2,' ',xmax:4:2,' ',xsd:4:2,' | ',avgfit:2:2);
   writeln (tem,'%  ',diverset:2:0);
  end;
end;



procedure statistics3 (allagents:agentsint; thegroup: groupsint);

var     j          :integer;

begin

IF abs(int((gen-1)/interval)-((gen-1)/interval))<eps {49,99,149, ...}
 then BeginInterval (allagents, thegroup);
 { PERIOD ZERO IS NOT INCLUDED IN STATISTICS}

 sumxgroup := sumxgroup + thegroup.groupx;    {for the group}
 sumx2group := sumx2group + thegroup.groupx*thegroup.groupx;{for the group}
 sumfitgroup := sumfitgroup + thegroup.groupfit;
 if thegroup.groupx>144 then group50t.perneg := group50t.perneg + 1 ;
 if group50t.xmax < thegroup.groupx then group50t.xmax:=thegroup.groupx;     {new max}
 if group50t.xmin > thegroup.groupx then group50t.xmin:=thegroup.groupx;     {new min}

for j:=1 to nagent do                    {for the agents}
 begin with agent50t[j] do
  begin
        sumxagent[j] := sumxagent[j] + allagents[j].xfit;
        sumx2agent[j] := sumx2agent[j] + allagents[j].xfit*allagents[j].xfit;
        sumfitagent[j] := sumfitagent[j] + allagents[j].fitness;
        if xmax < allagents[j].xfit then xmax:=allagents[j].xfit;          {new max}
        if xmin > allagents[j].xfit then xmin:=allagents[j].xfit;          {new min}
  end;
 end;

IF abs(int((gen)/interval)-((gen)/interval))<eps  {50, 100, ...}
 then EndInterval (allagents, thegroup);

end;
```

```
procedure EndStat;

var i: integer;

begin



 {WRITING TO FILE ALLMP.TXT}
 writeln(all);
 writeln (all, '( one run is one observation, ',interval*maxiteration,' obs. )');
 writeln (all);
 With AllinAll do
  begin
   writeln (all);
   writeln (all, 'GROUP USE AVERAGE');
   write (all, 'average:  ',xavg:4:2);
   write (all, '        minimum:  ',xmin:4:2);
   writeln (all, '       maximum:  ',xmax:4:2);
   writeln (all);
   writeln (all, 'GROUP USE STANDARD DEVIATION');
   write (all, 'average:  ',xsd:4:2);
   write (all, '        minimum:  ',xsdmin:4:2);
   writeln (all, '       maximum:  ',xsdmax:4:2);
   writeln (all);
   writeln (all, 'GROUP EFFICIENCY');
   write (all, 'average:  ',avgfit:4:2,'%');
   write (all, '        minimum:  ',minfit:4:2,'%');
   writeln (all, '       maximum:  ',maxfit:4:2,'%');
   writeln (all);
   writeln (all, 'PERIODS WITH GROUP NEGATIVE EARNINGS');
   write (all, 'average:  ',perneg:4:2,'%');
   write (all, '        minimum:  ',minneg:4:2,'%');
   writeln (all, '       maximum:  ',maxneg:4:2,'%');
   writeln (all);
   writeln (all);
   writeln (all,'( one run and one agent is one observation, ',interval*maxiteration*nagent,' obs.)');
   writeln (all);
   writeln (all, 'MAXIMUM OF AVERAGE INDIVIDUAL USE');
   write (all, 'average:  ', agmax:4:2);
   writeln (all, '         minimum:  ',agminmax:4:2);
   writeln (all);
   writeln (all, 'MINIMUM OF AVERAGE INDIVIDUAL USE');
   write (all, 'average:  ', agmin:4:2);
   write (all, '                    ');
   writeln (all, '       maximum:  ',agmaxmin:4:2);
   writeln (all);
   writeln (all, 'DIFFERENCES IN INDIVIDUAL USE AVERAGES');
   write (all, 'average:  ',agdif:4:2);
   write (all, '        minimum:  ',agmindif:4:2);
   writeln (all, '       maximum:  ',agmaxdif:4:2);
   writeln (all);
   writeln (all, 'DIVERSITY WITHIN INDIVIDUAL STRATEGY SETS at t=',gen);
   write (all, 'average:  ',avgdiv:4:2);
   write (all, '        minimum:  ',mind:4:2);
```

```
   writeln (all, '       maximum:  ',maxd:4:2);
 end;

end;


procedure statistics4 (Aveagents:agenttime; Avegroup: grouptime);

var      j          :integer;
         tmax, tmin, tdif : real;

begin
writeln ('iteraction= ',w,' gen= ',gen);
 with AllinAll do begin
  xavg := xavg + Avegroup.xavg/maxiteration;    {for the group}
  xsd := xsd + Avegroup.xsd/maxiteration;
  avgfit := avgfit + Avegroup.avgfit/maxiteration;
  perneg := perneg + Avegroup.perneg/maxiteration;
  if xmax < Avegroup.xavg then xmax:=Avegroup.xavg;          {new max}
  if xmin > Avegroup.xavg then xmin:=Avegroup.xavg;          {new min}
  if xsdmax < Avegroup.xsd then xsdmax:=Avegroup.xsd;        {new max}
  if xsdmin > Avegroup.xsd then xsdmin:=Avegroup.xsd;        {new min}
  if maxfit < Avegroup.avgfit then maxfit:=Avegroup.avgfit;  {new max}
  if minfit > Avegroup.avgfit then minfit:=Avegroup.avgfit;  {new min}
  if maxneg < Avegroup.perneg then maxneg:=Avegroup.perneg;        {new max}
  if minneg > Avegroup.perneg then minneg:=Avegroup.perneg;        {new min}
 end;


 tmax:=mindomain/nagent;
 tmin:=maxdomain/nagent;
 for j:=1 to nagent do                    {for the agents}
  begin
   if tmax < Aveagents[j].xavg then tmax:=Aveagents[j].xavg;
   if tmin > Aveagents[j].xavg then tmin:=Aveagents[j].xavg;
  end;
  tdif:=tmax-tmin;
  AllinAll.agdif := AllinAll.agdif + tdif/maxiteration;
  If tdif < AllinAll.agmindif then AllinAll.agmindif :=tdif;
  If tdif > AllinAll.agmaxdif then AllinAll.agmaxdif :=tdif;
  AllinAll.agmin := tmin + AllinAll.agmin/maxiteration;
  AllinAll.agmax := tmax + AllinAll.agmax/maxiteration;
  If tmax < AllinAll.agminmax then AllinAll.agminmax := tmax;
  If tmin > AllinAll.agmaxmin then AllinAll.agmaxmin := tmin;

 tmax:=0;
 tmin:=popsize;
 for j:=1 to nagent do                    {for the agents}
  begin
   if trunc(tmax) < Aveagents[j].diverset then tmax:=Aveagents[j].diverset;
   if trunc(tmin) > Aveagents[j].diverset then tmin:=Aveagents[j].diverset;
   AllinAll.avgdiv := AllinAll.avgdiv + (Aveagents[j].diverset/(nagent*maxiteration));
  end;
  if tmin < AllinAll.mind then AllinAll.mind:=tmin;
  if tmax > AllinAll.maxd then AllinAll.maxd:=tmax;
```

```
IF w=maxiteration
 then EndStat;

end;
```

`````````````````````````````````````````````````````````````````````````````````````````````````````````````````

```
{ STAT.MP }


Function IsDifferent (Qui, Quo :individual):boolean;
{ TRUE is two strategies are different }

VAR j   : integer;

begin
 {Is Qui different from Qua?}
 IsDifferent:=false;
 for j:=1 to lchrom do
  begin
   If (Qui.chrom[j] <> Quo.chrom[j])
          then IsDifferent:=true;
  end;
end;



procedure HowManyStr(VAR howmany: integer; VAR pop: population);
{ count how many of the strategies withing pop are actually different one from another }
var j, h: integer;

begin

howmany:=1;
for j:=2 to popsize do
begin
 h:=j-1;
 repeat
  If IsDifferent(pop[j],pop[h])
   then h:=h-1 else h:=-1;
 until (h<=0);
 howmany:=howmany+(h+1);
end;

end;


procedure statistics1        (k: integer; var oneagent: ag; var pop:population);
{Starting from pop Calculate population statistics for agent k and put them in oneagent}

var      j          :integer;
         sumfitness, xgroup :real;

begin
 for j:=1 to popsize do
 begin
  Resultif (k, pop[j]);
```
```

```
 end;

 with oneagent do begin
  sumfitness :=pop[1].fitness;
  maxfit :=pop[1].fitness;
  minfit :=pop[1].fitness;
  avgfit :=pop[1].fitness;
  xmin  :=pop[1].xfit;
  xmax  :=pop[1].xfit;
  if pop[1].new then ninnova:=1 else ninnova:=0;
  if pop[1].good then naccepted:=1 else naccepted:=0;
 end;
 xgroup:=pop[1].xfit;

 for j:=2 to popsize do
 begin with pop[j] do
  begin
        sumfitness := sumfitness + fitness;              {accumulate fitness sum}
     xgroup:=xgroup+xfit;
        if xfit>oneagent.xmax then oneagent.xmax :=xfit;     {new max}
        if xfit<oneagent.xmin then oneagent.xmin :=xfit;     {new min}
     if fitness>oneagent.maxfit then oneagent.maxfit :=fitness;
     if fitness<oneagent.minfit then oneagent.minfit :=fitness;
        if new then oneagent.ninnova:=1+ oneagent.ninnova;
        if good then oneagent.naccepted:=1+ oneagent.naccepted;
  end;
  oneagent.xavg := xgroup/popsize;
  oneagent.avgfit :=sumfitness/popsize; {average fitness of individual strategies}
 end;

 HowManyStr (oneagent.ndiverse, pop);

 oneagent.xsd:=0;
 for j:=1 to popsize do with oneagent do
 begin
  xsd:=xsd+(xavg-pop[j].xfit)*(xavg-pop[j].xfit);
 end;
 oneagent.xsd:=sqrt(oneagent.xsd/(popsize-1));
end;


procedure statistics2 (allagents:agentsint; VAR thegroup: groupsint);
 {routine to compute statistics at the group level and put them into thegroup}

var     j          :integer;
        sumfitness, xgroup :real;

begin

 sumfitness :=allagents[1].fitness;
 thegroup.maxfit :=allagents[1].fitness;
 thegroup.avgfit :=allagents[1].fitness;
 thegroup.xmin   :=allagents[1].xfit;
 thegroup.xmax   :=allagents[1].xfit;
 thegroup.xmin   :=allagents[1].xfit;
 thegroup.ninnova :=allagents[1].ninnova;
```

```
thegroup.naccepted :=allagents[1].naccepted;
xgroup:=allagents[1].xfit;

for j:=2 to nagent do with allagents[j] do  begin
        sumfitness := sumfitness + fitness;              {accumulate fitness sum}
    xgroup:=xgroup+xfit;
    thegroup.ninnova :=ninnova+thegroup.ninnova;
    thegroup.naccepted :=naccepted+thegroup.naccepted;
        if xfit>thegroup.xmax then thegroup.xmax :=xfit;      {new max}
        if xfit<thegroup.xmin then thegroup.xmin :=xfit;      {new min}
    if fitness>thegroup.maxfit then thegroup.maxfit :=fitness;
    if fitness<thegroup.minfit then thegroup.minfit :=fitness;
end;
thegroup.xavg := xgroup/nagent;
thegroup.avgfit :=sumfitness/nagent; {average fitness of agents}

thegroup.xsd:=0;
for j:=1 to nagent do with thegroup do
begin
 xsd:=xsd+(xavg-allagents[j].xfit)*(xavg-allagents[j].xfit);
end;
thegroup.xsd:=sqrt(thegroup.xsd/(nagent-1));

end;
````````````````````````````````````````````````````````````````````````````````````````

{ COMPUCPR.MP : contains Resourceuse, decode, Resultif }

function decode(chrom:chromosome; lbits:integer):real;
                                   {decode string as unsigned binary integer - true=1, false=0}
var   j   : integer;
         accum, powerof2: real;

begin
         accum :=0.0;
         powerof2 := 1;
         for j:= 1 to lbits do begin
                  if chrom[j] then accum := accum + powerof2;
                  powerof2 := powerof2 * 2;
         end;
         decode := accum;
end;

procedure Resourceuse(VAR agentstat:agentsint; VAR groupstat:groupsint);
{compute the ACTUAL fitness of all strategies played;
compute the group use and overall rent}

VAR   y,sumxfit   : real;
     j   : integer;

begin
 sumxfit:=agentstat[1].xfit;
 FOR j:=2 to nagent do
   begin
    sumxfit:=sumxfit+agentstat[j].xfit;
   end;
```
```

```
 y := 11.5*sumxfit-(sumxfit*sumxfit/16)-2.5*sumxfit;
 if sumxfit>184
     then y:=200*(-1+exp(-0.0575*(sumxfit-184)))-2.5*sumxfit;
 groupstat.groupx:=sumxfit;
 groupstat.groupfit:=y;

 FOR j:=1 to nagent do
  begin
   agentstat[j].fitness:=(agentstat[j].xfit/sumxfit)*y;
  end;
end;



procedure Resultif (ouragent:integer; VAR pippo: individual);
{compute the HYPOTHETICAL fitness of the INDIVIDUAL pippo within the
set of individual strategies of agent [ouragent]}

VAR     y,sumxfit                    :  real;
     j                        :  integer;

begin
 sumxfit:=groupstat.groupx-agentstat[ouragent].xfit+pippo.xfit;
 y := 11.5*sumxfit-(sumxfit*sumxfit/16)-2.5*sumxfit;
 if sumxfit>184
     then y:=200*(-1+exp(-0.0575*(sumxfit-184)))-2.5*sumxfit;
 pippo.fitness:=(pippo.xfit/sumxfit)*y;
end;

``````````````````````````````````````````````````````````````````````````````

{ RANDOM.APB contains random number generator and related utilities
        including advance_random, warmup_random, random, randomize,
        flip, rnd }

{ global variables - Don't use these names in other code }

var   oldrand   :array[1..55] of real;
     jrand   :integer;

procedure advance_random;
{ CREATE NEXT BATCH OF 55 random numbers }

VAR   j1: integer;
     new_random:real;

BEGIN
   for j1:=1 to 24 do
    begin
     new_random:= oldrand[j1] - oldrand[j1+31];
     if (new_random < 0.0) then new_random := new_random+ 1.0;
     oldrand[j1] :=new_random;
    end;

   for j1:=25 to 55 do
    begin
     new_random:= oldrand[j1] - oldrand[j1-24];
```
```

```
    if (new_random < 0.0) then new_random := new_random+ 1.0;
    oldrand[j1] :=new_random;
   end;
END;



PROCEDURE warmup_random(random_seed:real);
{ GET RANDOM OFF THE RUNNIN }

VAR  j1, ii :integer;
    new_random,
    prev_random:real;

BEGIN
   oldrand[55] := random_seed;
   new_random := 1.0e-9;
   prev_random := random_seed;
   for j1:=1 to 54 do
     begin
      ii := 21*j1 mod 55;
      oldrand[ii] := new_random;
      new_random := prev_random - new_random;
      if (new_random < 0.0) then new_random:=new_random + 1.0;
      prev_random := oldrand[ii];
     end;
   advance_random; advance_random; advance_random;
   jrand :=0;
END;

FUNCTION random : real;
{ FETCH A SINGLE RANDOM NUMBER BETWEEN 0.0 AND 1.0 - Subtractive method}
{ see Knuth, D. (69) v.2 for details }

BEGIN
   jrand := jrand +1;
   if (jrand > 55) then
     begin
      jrand:=1;
      advance_random;
     end;
   random := oldrand[jrand];
END;

FUNCTION flip (probability:real):boolean;
{ FLIP A BIASED COIN - True if heads }

BEGIN
   if probability = 1.0 then flip := true
     else flip := (random<=probability);
END;


FUNCTION rnd(low, high:integer):integer;
{ PICK A RANDOM INTEGER BETWEEN LOW AND HIGH }
```

```
VAR    i :integer;

BEGIN
   if low>=high then i:=low
    else begin
      i :=trunc(random * (high-low+1) + low);
      if i > high then i:= high;
    end;
   rnd := i;
END;

PROCEDURE randomize;
{ GET SEED NUMBER FOR RANDOM AND START IT UP }
VAR randomseed: real;

BEGIN
   repeat
    { write ('Enter seed random number (0.0..1.0) > '); readln(randomseed);}
   randomseed:= rseed;  {CHANGE INTRODUCED IN THIS VERSION}
   until (randomseed>0) and (randomseed<1.0);
   warmup_random(randomseed);
END;
``````````````````````````````````````````````````````````````````````````````````````````

{ UTILITY.SGA contains pause, page, repchar, skip, power}

procedure pause(pauselength:integer);
                    { PAUSE A WHILE }
const   maxpause = 2500;

var   j, j1: integer;
           x :real;

begin
           for j:=1 to pauselength do
                      for j1:=1 to maxpause do x:=0.0 + 1.0;
end;

procedure Clean;
var j: integer;

begin
           for j:=1 to 50
           do writeln;
end;

procedure page(var out:text);
                    { ISSUE FORM FEED TO DEVICE OR FILE }
begin write(out, chr(12)) end;

procedure repchar(ch:char; repcount:integer);
                    { REPEATEDLY WRITE A CHARACTER TO the printer }
```
```

```
var       j: integer;

begin for j:=1 to repcount do write(lst,ch) end;

procedure repchars(ch:char; repcount:integer);
                    { REPEATEDLY WRITE A CHARACTER TO the screen }
var       j: integer;

begin for j:=1 to repcount do write(ch) end;


procedure skips (skipcount:integer);
                    { SKIP SKIPCOUNT LINES ON the screen }
var       j: integer;

begin
    for j:=1 to skipcount do writeln;
end;

procedure skip (skipcount:integer);
                    { SKIP SKIPCOUNT LINES ON the printer }
var       j: integer;

begin
    for j:=1 to skipcount do writeln(lst);
end;



function power(x,y:real):real;
                    { RAISE TO THE yTH POWER}
begin
   power :=exp(y*ln(x));
end;


procedure greetings;

begin
      writeln; writeln;writeln;
      write('OPEN FILES');
      if (det='y') or (det='Y')
       then writeln ('        runMP.TXT (with Excel)');
      writeln('         sumMP.TXT              TO SEE THE RESULTS !');
           writeln('         temMP.TXT');
      writeln('         allMP.TXT');
      writeln;
      writeln ('The simulation is done.');
      writeln (' Enter an integer and then press enter to return to Pascal');
      read(w);
end;
```

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