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Bridging Contested Terrain: Linking Incentive-Based and Learning Perspectives on Organizational Evolution

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BRIDGING CONTESTED TERRAIN: LINKING INCENTIVE-BASED AND LEARNING PERSPECTIVES ON ORGANIZATIONAL EVOLUTION

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Abstract

In this paper we present a general model of organizational problem-solving in which we explore the relationship between problem complexity, decentralization of tasks and reward schemes. When facing complex problems which require the coordination of large numbers of interdependent elements, organizations face a decomposition problem which has both cognitive dimensions and reward and incentive dimensions. The former relate to the decomposition and allocation of the process of generation of new solutions: since the search space is too vast to be searched extensively, organizations employ heuristics for reducing it. The decomposition heuristic takes the form of division of cognitive labour and determines which solutions are generated and become candidates for selection. The reward and incentive dimensions fundamentally shapes the selection environment which chooses over alternative solutions.

The model we present begins to study the interrelationships between these two domains of analysis: in particular, we compare the problem solving performance of organizations characterized by various decompositions (of coarser or finer grain) and various reward schemes (at the level of the entire organization, team and individual). Moreover we investigate extensions of our model in order to account for (admittedly rudimentary) power and authority relationships (giving some parts of the organization the power to stop changes in other parts), and discuss the interaction of problem representations and incentive mechanisms.

1. Introduction

Social organizations - in their impressive variety over history, across societies and across domains of human activities - generally display also very diverse forms of division of operational and 'cognitive' labour, and, at the same time, equally diverse hierarchical arrangements, distributions of power, and mechanisms of elicitation of efforts by individual agents. While it is easy to see that this is generally the case, it is much more difficult to disentangle the different domains of analysis which tend to correspond to multiple, co-existing, levels of interactions amongst organizational members. These levels of interaction are also likely to map onto different forms of 'social embeddedness' of individual actions. In many respects, the understanding of these processes is one of the fundamental tasks of social sciences since their origins.

The task is obviously enormous. It may clearly begin from different angles. It happens that the dominant strand of contemporary analyses start with 'primitives' of the interpretation of the nature of organizations based on sophisticated, self-seeking, agents. Together, the behaviors of these self-interested actors are viewed as typically directed by market forces. Only in those settings in which, due to failures of information and contract incompleteness, markets are less effective in this task, then organizations are called for to surrogate such imperfections. It is a story too familiar to be repeated here.[1]

Conversely, a small - but not negligible and growing - minority of the economic profession has placed the (first approximation) "*primitives*" of the analysis of the nature of economic organizations in their *problem-solving features*, in turn nested in ubiquitous forms of human "bounded rationality", grossly imperfect processes of learning and diverse mechanisms of social distribution of "cognitive labour". Needless to say, it is a perspective which finds seminal roots in the works of Herbert Simon, James March and indeed Richard Nelson and Sidney Winter.

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[1] A few more detailed epistemological remarks are provided in Dosi (1995) and Coriat and Dosi (1998)

Let us offer the following caricature to illustrate the differences between the two interpretative philosophies. Suppose that two delegations of intelligent but totally uninformed beings from Mars are sent to the Earth with the mandate of reporting "what business firms are." The delegations are not allowed to visit the firms themselves. Rather, the first one is given to read, out of an enormous literature, say, Holmstrom and Tirole (1989), Grossman and Hart (1986), Laffont and Tirole (1993), while the second is given March and Simon (1958), Cyert and March (1963), Nelson and Winter (1982), and Dosi, Nelson, and Winter (2000). What would they report back to Mars? (We reasonably assume that these entities, given their empirical naiveté, are unable to catch all the caveats from footnotes, side remarks, etc…).

Well, the first delegation would probably convey the idea that earthly firms are places where one confines vicious and cunning people who are made to play extremely sophisticated games according to rules designed in order to prevent them from doing much harm to themselves and to others. Only casual mention would be made –if at all- to conventional labels by which the outcomes are denominated (being them "steel", "shoes", "computers" …), while lengthy accounts would be devoted to the details of the admissible rules and the mathematical equipment humans utilize in order to figure out how to behave.

The second delegation is likely to return with a strikingly different story. It would probably begin with a rather long description of the impressive variety of "things" that each day come out of earthly firms –that is, precisely, steel, computers, polypropylene, etc.- and the equally impressive diversity in the processes leading to them. Moreover, Mars visitors would almost certainly remark that no one has the entire plan of what to do in their heads. Most of the members of each organization repeatedly undertake recognizably few operations and still organizations coordinate their tasks in ways generally yielding coherent artefacts at the end of the day. Indeed, this second delegation is likely to suggest the analogy of a "firm" with a messy but most often reliable computer program, with little mention of possible conflict of interests among the individual carriers of various "sub-routines."

Notwithstanding its being a caricature, the foregoing story does convey the spirit of an actual major divide cutting across current theorizing about organizations, having at the two extremes *a pure incentive-governance view vs. a pure problem solving view*. Clearly, there are elements of truth in both perspectives (Coriat and Dosi, 1998): an ambitious research program ahead entails indeed connect the two.

The starting point for such a bridge building has important consequences for the sort of bridge that one creates. The starting point embodies a commitment to some assumptions on first order vs. second order effects. Forced to such a choice, we would pick the second *weltanschaung* as a provisional point of departure (which also happens to be the least explored one). We do need to assume a *weak incentive compatibility* to begin with (see Dosi and Marengo (1995)) in the loosest sense that there exists some selection pressure which, in turn, generates some connection between performance and rewards. However, having that, one precisely focuses (as a first theoretical approximation) on the diverse problem solving characteristics of different organizations, and only in the second instance one tackles the ways in which incentive structures interact with problem solving knowledge.

Putting it in another way, the archetype "incentive view" fully censors any competence issue associated with what organizations do and how well they do it –except for issues of misrepresentations of "intrinsic" individual abilities and adverse selection, or incentive misalignement in effort elicitation. As an extreme characterization, given the "right" incentives any firm can make microprocessors as well as Intel, or bioengineering as well as Genetech.

The second, "problem solving", archetype, on the contrary, censors precisely the incentive-alignment issue. In a sense, all agents are "angels" as their motives are concerned. Conversely, it focuses on the problem solving efficacy of what they do, especially in so far as what they do does not stem from any differential "ontological" ability but rather from the social division of tasks and their combinatorics.

So, in the first approximation of this latter view, the basic units of analysis are elementary physical acts, such as moving a piece of iron from one place to another, and elementary cognitive acts, such as applying inference rules. Problem solving can be straightforwardly understood as combinations of elementary acts, within a procedure, leading to a feasible outcome (e.g. an engine, a chemical compound, etc.).[2]

One can also describe it the other way round. Given all the problem solving procedures leading to a given "outcome" (e.g. an engine, etc. and, for that matter, a theorem, a statement about the purported structure of the observed world) - which might well be an infinite set - one may decompose them in sub-sequences of elementary acts of varying length that may be eventually performed according to various execution architectures (e.g. sequential, parallel, hierarchical…) At this level of analysis, an organization embodies problem solving in at least three senses.

First, it displays the operational competencies associated with its actual problem solving procedures (much in accordance with the routines discussed in Nelson and Winter (1982); see also Cohen et al. (1996)). *Second*, the organizational structure –both the formal and informal ones- determines the distribution of informational inputs of the processing tasks and of the "allowable acts" (i.e. "who can do what to whom") and, as such, it determines all the decompositions of problem solving procedures that are, so to speak, "legal". *Third*, it shapes the search heuristics for yet-unsolved problems –e.g. a new engine, a new chemical compound, etc.-, that is, broadly speaking, the heuristics of innovative search.

Note that, although a bit more abstract, this characterization of problem solving knowledge is well in tune with the evidence stemming both from the economics of innovation (for a survey, see Dosi (1988)) and capability-based views of organizations (Dosi, Nelson and Winter (2000), among others). Further, it has the advantage of being directly applicable to both the analysis of intra-organizational structures and of the boundaries between organizations and markets.[3] Indeed, such boundaries may be straightforwardly seen as a particular decomposition of an overall problem-

[2] See Marengo et al (2000) for further discussion of this point.

solving task, say the one leading from raw iron oxide to GM engines. Relatedly, one might inquire about the problem solving properties of particular decompositions, ranging from the totally centralised and autarkic one (no decomposition at all), to the analogue of a "pure market" - one person - one task -, with market transactions linking each elementary act. Note that, here one is facing a sort of "anti-Coasian" question asking whether, and under what circumstances, markets, i.e. highly decentralized decompositions of knowledge, bear some differential problem solving advantages, if any, when neglecting the more familiar arguments concerning the high powered incentives of markets. An analysis along these lines is presented in Marengo et al. (2000). Marengo et al. explore the effect of different decompositions of the same "true" environments on adaptive performance. We build on this analytical framework by incorporating *cognitive and political conflict* into the analysis, together with (admittedly rudimentary) issues of inventive-compatibility and effort elicitation. Or, putting it again in a sort of caricature, we begin to explore what happens in our stylized organizational models when adaptive, but not omniscient "angels" start a) clashing on diverse "visions of the world"; b) facing some hierarchical filtering and/or veto powers on their adaptive search; or, worse, c) they stop being "angels" but react to incentives and orders.

The following section presents the basics of our model. We then engage in some basic analysis of the effect of alternative problem decompositions and reward structures of the adaptive process. Global reward structures, while manifestly the desired payoff scheme for a population of omniscient and compliant actors, are not so clearly desirable in the face of not so omniscient, though still compliant, problem solvers. We find that there is an important interaction between issues of knowledge and issues of incentives. In particular, “wrong”, excessively local, reward structures, may help compensate for the problem of incorrect cognitive representations.

Narrow, group-wide incentives create conflict of interests among problem-solving teams. These conflicts, however, may help prevent organizations from locking into modest local peaks.

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[3] In the latter respect, it bears at least the same generality as the representation in terms of elementary transactions advocated by Oliver Williamson.

Together, these conflicts have the dysfunctional property that they may be unending and result in the continual perturbation of the problem space of one sub-unit, or actor, by another. We find that there is a further complement, a complement neither from the world of incentives or cognitively limited automatons but from the world of politics - that is, *power*. Power may be horizontal, in that one sub-unit is privileged above others, or, as more traditionally viewed, vertical. In either form, the presence of an asymmetrical power distribution within the organization helps to stem the potentially endless cycling of self-perturbing changes that result from incorrect decompositions of the actors' problem environment. More specifically, we explore how the ability of one sub-unit or a hierarchically superior to veto proposed policy changes may enhance the performance of the system.

Finally, we explore the more direct costs of problem decompositions and change efforts. Decompositions have costs not only as a result of the fact that they may incorrectly capture the "true" structure of the problem space, but more refined structures in and of themselves are difficult to sustain. Similarly, change efforts not only run the risk of yielding an inferior policy choice, they are also effortful. Maintaining an established routine surely requires less effort than initiating a new action pattern. We revisit the interaction among cognitive patterns (in the form of problem decompositions) and reward structures, while incorporating these features of the cost of more refined problem decompositions and the direct costs of organizational change. "Correct" decompositions may suffer not only because of the cost of sustaining refined problem decomposition but also because they may induce actors to engage in excessive search.

2. Model Structure

We explore complex, though structured, problem surfaces. That is, following on recent work on *rugged landscapes* (Kauffman, 1993; Levinthal, 1997), we highlight the role of interactions among policy choices. However, try to link to this line of modelling, with Simon's argument regarding the interpretative and importance of (quasi-)decomposable systems (Simon, 1969) and recent modeling work by Page (1996), Marengo (2000), Marengo et al (2000) and Ethiraj and Levinthal (2002). Interactions are certainly present among behaviours of organizational members and among organizational policy choices. However these interactions are not disbursed randomly among the set of possible combinations. Rather, they are tightly clustered within decompositions of the broader system. In keeping with the tradition of bounded rationality (Simon, 1955) and in contrast to many recent examinations of modular systems (cf., for example Baldwin and Clark, 2000), we do not presume that this interaction structure is known to the actors. The partitioning of the decision problem may or may not correspond to the "true" decomposition structure. A critical element of our analysis is indeed how the appropriate reward structure depends on the degree to which the task partitioning corresponds to the actual structure.

In tune with Kaufman (1993), let us define "landscapes" as some (highly "reduced form") mappings between some combinations of organizational traits/cognitive patterns/behavioural rules, one the one hand, and "performances" - no matter how defined, for the time being - organizations themselves, on the other. In this formal representation, whenever individual traits, behaviours, etc. bear totally distinct effects upon performances, it is easy to reproduce a familiar (*probably too familiar!)* conjecture according to which even "local", piecewise, ameliorations generally lead to global optima. Conversely, this might not be generally the case whenever the contributions of "traits" to "performances" are correlated, so that, say, the contribution of trait *a* depends on the presence and value of trait *b*, etc. - which in biology come under the heading of *epistastic correlations.*

In the model which follows landscapes are generated according to the following procedure. Let N be the number of bits or policy choices (N=20 in the simulations below). The decomposition defines the nature of epistatic interactions among these policy choices. For simplicity, we assume that policy choices within a partition are fully interactive, all elements of the partition interact with all other elements within the partition, while policy choices are assumed to have no interdependence with choices outside the partition. In this sense, we are assuming the problem corresponds to a fully decomposable system. We use the following decomposition scheme as a baseline characterization of the problem space:

$$D=\{\{1,2,3,4,5\},\{6,7,8,9,10\},\{11,12,13,14,15\},\{16,17,18,19,20\}\}$$

This structure implies that the 20 dimensions of the landscape can be decomposed (cf. Marengo 2000) and Marengo et al. (2000) into 4 separate blocks of 5 dimensions each, and each of these blocks can be optimised independently of the others. However, given that actors may adopt an incorrect partition, the false representation may induce lasting interaction effects across the perceived decompositions

Individual "fitness" (that is, plainly, actual performances) contributions for each bit, or policy choice, are generated by assigning a random number from a uniform distribution between 0 and 1. Each bit has 2^k individual fitness values, where k is the size of the block to which it belongs. For instance, suppose that N=6 and D={{1,2,3},{4,5,6}} is the true decomposition scheme. A random assignment of individual fitness values f_i (i=1,2...6) takes on the following form:

Table 1 – Example of individual fitness values

Bit	**Block**	f_1	f_2	f_3	f_4	f_5	f_6
0	**00**	0.29	0.73	0.64	0.99	0.83	0.35
0	**01**	0.67	0.68	0.28	0.24	0.75	0.03
0	**10**	0.74	0.33	0.18	0.34	0.55	0.69
0	**11**	0.63	0.63	0.57	0.33	0.54	0.46
1	**00**	0.41	0.19	0.47	0.76	0.58	0.48
1	**01**	0.25	0.58	0.67	0.74	0.89	0.58
1	**10**	0.55	0.64	0.44	0.56	0.34	0.73
1	**11**	0.85	0.67	0.39	0.08	0.55	0.47

The table indicates that when the first bit is set to 0, its fitness value is 0.29 if the second and third bit are both set to 0. In contrast, the fitness value of a 0 in the first bit is 0.67 if the second is set to

0 and the third to 1, while it take on a value of 0.63 if they are both set to 1. Analogously, if the 5^{th} bit is set to 1, its fitness value is 0.58 if the 4^{th} and 6^{th} bits are both equal to 0, while it takes on a value of 0.89 if the 4^{th} equals 0 and the 6^{th} equals 1, and so on.

In addition to considering the fitness contribution of an individual policy choice, possibly contingent on other choices, let us consider the value of broader aggregations of policy strings. In line with Kauffman (1993) we assign "fitness values" to broader systems by merely averaging the fitness contributions of the individual elements; however, in contrast to this earlier tradition, we are sensitive to the possibility of different levels of aggregation. Performance, and in turn rewards, may be based on the fitness value of the entire policy string, or some partition of this broader string. In particular, a special case of more refined partitions is the set of partitions consisting of singletons, or individual policy choices.

Using the illustrative fitness table provided in Table 1 above, let us evaluate performance at different levels of aggregation. Consider the string 101110. We can define three notions of "fitness":

1) **individual** fitness, which are respectively:
$f_1=0.25$, $f_2=0.63$, $f_3=0.44$, $f_4=0.56$, $f_5=0.34$, $f_6=0.46$

2) **block** fitness, defined for each of the two blocks of the decomposition scheme:
$F_{\{1,2,3\}}= (f_1+f_2+f_3)/3=(0.25+0.63+0.44)/3=0.44$
$F_{\{4,5,6\}}= (f_4+f_5+f_6)/3=(0.56+0.34+0.46)/3=0.453$

3) **global** fitness (of the entire string):
$F= (F_{\{1,2,3\}}+F_{\{4,5,6\}})/2= (f_1+f_2+f_3+f_4+f_5+f_6)/6 = 0.4465$

These same three levels - individual, block, and global - not only can be the basis for evaluating actual performance at different levels of aggregation, but they can also define the search space by which alternatives are generated and evaluated. The nature of alternative generation mechanisms, in fact, is determined by ways the choice problem is decomposed. The organisation explores the landscape according to its own decomposition scheme Δ, which may or may not coincide with the "real" decomposition scheme D (i.e. the one which generates the landscape). Different actors, or subunits within the organisation, may explore each of decomposition sets.

Consider, for instance, the illustrative 6 bit landscape provided above. Suppose that this landscape is explored by an organisation characterised by the following *incorrect* decomposition scheme: $\Delta=\{\{1,2\},\{3,4,5,6\}\}$. Search within a block of the decomposition Δ (in our example either {1,2} or {3,4,5,6}) involves mutating at least one and at most all the bits of the selected block.[4] We explore settings in which we restrict the mutation to be a change in a single bit within the decomposition (corresponding to ideas of local search (Levinthal, 1997)), as well as settings (following Marengo (2000)), in which one of the full set of possibilities is drawn at random.

Independent of the problem decomposition, the reward structure faced by the actors may be more or less aggregate. For instance, the imposed decomposition of the problem space may be quite narrow; however, each subunit could still be evaluated on the basis of the global fitness of the overall system. As a result, in such a setting, action would be ‘local’, while thinking would be ‘global’. The benefit of having a reward structure that maps more or less closely to the task partition depends, in turn, on the degree to which the task partition itself reflects the actual problem decomposition.

Thus, under a global reward structure, a new policy alternative is adopted if it enhances the fitness of the overall system. Depending on the problem decomposition, this policy initiative could consist of a single, one-bit mutation or, under more aggregate problem decompositions, it could consists also of more radical changes in the set of actions or policies. Under a block, or team reward structure, proposed alternatives are viewed favourably if they enhance the fitness level of the set of policies corresponding to the overall partition of the problem decomposition. Note that this reward scheme is equivalent to the global one if the “conjectural” decomposition Δ and the

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[4] In our example, if block {1,2} is selected, mutation could produce one of the following three strings: 100000,010000,110000).

“real” one D are identical. With individual level rewards, a proposal is viewed favourably if the fitness contributed of the particular policy choice being changed increases.

Let us clarify how the three schemes actually work by referring again to the above example. Suppose that fitness values are those of Table 1, that the real decomposition is D={{1,2,3},{4,5,6}}, the conjectural one is Δ={{1,2},{3,4,5,6}}, and the current string is 000000. Suppose now that the block {1,2} is selected and the current string gets randomly mutated into 110000. Let us examine the rewards computed by the three different schemes in this case:

1) global reward:

000000 has global fitness 0.638, 110000 has global fitness 0.667. Thus 110000 is retained.

2) team reward:

For block {1,2} the configuration 00 has fitness 0.51 (i.e. (0.29+0.73)/2), while 11 has reward 0.595 (i.e. (0.55+0.64)/2). Thus 11 is retained.

3) individual reward:

For the first bit choice 0 within string 000000 has fitness 0.29, while choice 1 within string 110000 has fitness 0.55. Thus choice 1 is retained;

for the second bit, choice 0 within string 000000 has fitness 0.73, while choice 1 within string 110000 has fitness 0.64. Thus choice 0 is retained.

All in all, both global and team reward schemes select string 110000, while the individual scheme selects string 100000.

In the following, at each period of the simulation, the "behavioural"/"policy" configuration of any single block of the perceived decomposition of the problem structure is chosen at random. In some of our analyses, we restrict this random draw to consist of a one-bit mutation from the existing policy choice; in other settings, the random draw is not restricted and, as a result, potentially all elements of the partition could be changed in the proposal. The former setting corresponds to ideas of incremental search. In contrast, the latter structure assumes that search is only limited by the problem decomposition. The new alternative is evaluated on the basis of the reward structure (global, team, or individual) and adopted if it enhances performance from the perspective of the relevant reward structure.

When we explore the role of power on the process of adaptation, an additional criterion is added to the evaluation of a proposal. Proposals must look attractive from the perspective of the initiating subunit, but must also be attractive (i.e., "fitness improving") from the perspective of the ‘powerful’ subunit. Thus, proposals may be subject to vetoes.

3. Analysis

The following simulations consider a problem of size N=20, generated by the following “true” decomposition: D={{1,2,3,4,5},{6,7,8,9,10},{11,12,13,14,15},{16,17,18,19,20}}
The following figures present results, respectively, for one typical simulation run and for averages and standard deviations over 200 different simulations. Each of the 200 replications uses the same structure in terms of the partitioning of the problem, but the seeding of the landscape is independently drawn in terms of fitness values.

Alternative Problem Decompositions and Local Search

The “conjectural” decomposition on which organisational search is based has a double role, which is typical of any division of labour. On the one hand, it defines a “cognitive” structure under which the problem is considered. This cognitive structure translates into a decomposition of the problem into sub-problems, which are treated as if they were independent and, in turn, constrain the portion of the search space that can undergo examination. The perceived decomposition also influences the potential reward structure. In particular, the team, (or block) reward is a function of what the organisation conceives of as a block. We are interested in exploring this double role, but in the initial simulations we isolate the reward structure definition role by supposing that search always proceeds by one bit mutation only.

Figure 2 illustrates the average performance over 200 replications for a process of local search (one bit mutations) for a conjectured problem decomposition consisting of the minimum partitions of single choice variables, i.e., $\Delta=\{\{1\},\{2\},\{3\},.....,\{N\}\}$, while Figure 1 illustrates a particular run among this set of 200. Given this task partitioning, the individual and team based evaluation scheme result in the same evaluation.

Insert Figure 1 to 3

Consider now that the same kind of landscape is explored by an organisation whose conjectural decomposition are almost correct. In particular, suppose that the conjectural decomposition catches most of the epistatic interactions but misses some of them, as in the following conjectural decomposition:

$\Delta=\{\{1,2,3,4\},\{5,6,7,8\},\{9,10,11,12\},\{13,14,15,16\},\{17,18,19,20\}\}$

Insert Figures 4 to 6 here

Under the global reward structure, the organisations rapidly reach a local optimum in the fitness landscape.[5] This fact is not surprising. A global reward structure by design only accepts proposed changes that enhance overall system performance.

[5] A local optimum consists of a point such that any one-bit mutation of the vector of policy choices decreases fitness. However, the fact that a point constitutes a local optimum does not imply that the simultaneous shift in multiple policies

More interesting is the behaviour of less aggregate reward structures. Such a reward structure provides, in some sense, a *false* signal of the value of a proposed alternative. A subunit may accept an initiative (i.e., a change in one of the policy choices) that enhances its own performance, but may degrade the fitness of the overall organisation. As a result, such an organisation may walk “downhill” on a fitness landscape. Indeed, evidence of such occasional downhill movement is provided in the Figure 1 depiction of an individual run. Despite such "inefficient" behaviours, this type of organisations, on average, tend to increase their performance. Indeed, in the long-run, they reach similar levels of performance as organisations with a global reward structure.

The conflict generated by local reward structure has functional, as well as dysfunctional implications. The selfish, parochial perspective induced by a local reward structure may cause the organization to adopt new policy strings that are inferior to its prior actions. While in an immediate sense such action is dysfunctional, this behaviour also acts to reduce the likelihood that the organization will remain absorbed on an inferior local peak. Indeed, close examination of Figure 2 reveals that even after a 1000 periods, there is still a slight positive gradient to the performance curve for the team=individual reward structure while performance under the global reward structure reaches its maximum value by period 100 and remain fixed at that level in all remaining periods.

Goal conflict acts as an effective substitute for an accurate partitioning of the problem space. With a perfectly accurate decomposition of the problems space, then there is no conflict between the team, (or block), evaluation of a proposed initiative and a global perspective. As a result, with an accurate partitioning of the problem, one sees no distinction between the long-run performance under the team and global reward: both these more aggregate structures perform better than an individual reward structure that fails to capture the actual interactions among policy choices. However, this property is not robust to "imperfect" decomposition structures.

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could not lead to improved fitness. In general, fitness landscapes with interaction effects among policy choices have

Veto Power

We model veto power in the following way: one of the blocks of the decomposition Δ that characterises the organization can stop any mutation of the other blocks that decreases its own fitness. Consider, again, the decomposition:
Δ={{1,2,3,4,5},{6,7,8,9,10},{11,12,13,14,15},{16,17,18,19,20}} and assume that block {1,2,3,4,5} is endowed with veto power. Any mutation taking place in, for instance, block {11,12,13,14,15} will be retained if and only if it increases the team-fitness of block {11,12,13,14,15} *and* it does not decrease the team-fitness of block {1,2,3,4,5}. When the second condition is not satisfied the mutation is vetoed. Note that veto power is meaningless when the reward scheme is global.

As seen in Figure 7, indicating fitness level over time for a single run of the model, and Figure 9, providing the standard deviation over a set of 200 iterations of the model, the introduction of veto power has in general a stabilising effect with respect to variability of the corresponding reward scheme. This analysis was done assuming, as before, that the "real" decomposition is D={{1,2,3,4,5},{6,7,8,9,10},{11,12,13,14,15},{16,17,18,19,20}}, while the organization searches the landscape according to:
Δ={{1,2},{3,4},{5,6},{7,8},{9,10},{11,12},{13,14},{15,16},{17,18},{19,20}}. Thus, the perceived partitioning of the problem space is more fine-grained than the actual partition.

Insert Figures 7 to 9 here

Team and individual reward schemes with veto power are effective in stabilising good solutions when attained. These results appear to be linked to the following factors: 1) the subjective decomposition on which organizational search is based must be finer than the "real" decomposition

multiple local peaks (Kauffman, 1993).

which originates the landscape and 2) the latter must not be too complex. In fact, the result is stronger if we consider a "real world" generated by the following simpler decomposition structure:

D=={{1,2},{3,4},{5,6},{7,8},{9,10},{11,12},{13,14},{15,16},{17,18},{19,20}}

and the organizational decomposition is the finest possible: Δ={{1},{2},{3},.....,{18},{19},{20}}. In this case, we see that team rewards, in conjunction with veto power, can actually lead to a superior performance than a global reward structure.

In the face of an incorrect decomposition, the conflict that stems from team rewards induces more search than that which results from a global reward structure. This greater search effort may identify a superior solution than that identified under global search; however, a team based reward structure is ineffective in “holding on” to the strong policies that are identified. Under a team reward structure, as opposed to a global reward structure, the organization tends to cycle among possible solutions. One unit initiates changes that appear attractive from its vantage point which, in turn, disrupts the performance of another unit and provides an incentive for that unit to initiate change which in turn feed-backs to the original sub-unit that initiated change, and so on. The presence of a veto breaks such cycling. Only a subset of proposed changes are allowed to become policy; the subset that will not disrupt the performance of the powerful sub-unit.

Insert Figures 10 to 11 here

Decompositions, span of control and elicitation costs

Next, let us extend our model in order to introduce costs which the organization has to bear in order to induce its members to act in a given fashion. What we are trying to model here is not a principal-agent relationship in a strict sense, because we do not assume any given relationship between effort and outcome. Rather, we focus instead on *control*. The principal, the residual claimant of the organizational total payoff, wants to induce the agents to keep performing some given action or to switch to a different one. But when actions are linked by interdependencies, the control function itself cannot be entirely decomposed into independent control problems. Thus, the cognitive dimension (given by the decomposition) and the control dimension interact in some non-trivial way.

In order to explore these issues, let us refine the above model, introduce a costly control function and analyze the relationship between conflict arising from "cognitive" factors, - that is from incorrect decomposition of the problem -, on the one hand, and conflict arising from control and incentives, on the other.

In particular, we assume that the costs of action elicitation grow with the span of control, i.e. the size of elements of the decomposition, and that they are higher when the principal wants to elicit a change in the agent's action than when he wants to elicit the same behaviour. This assumption is based on two independent premises. First, we assume that agents are naturally adverse to change. Second, we assume that the observation and elicitation of “business as usual” can be routinised and take advantage of standard procedures and devices.

More specifically, in the following analysis we assume that elicitation costs have two components:

1) the "business as usual component": $C_1 = c \times span^2$

2) the "new action component": $C_2 = c \times n\_mutation^2$

where **span** is the size of the blocks of the decomposition and **n_mutation** is number of bits which have been mutated. Finally, **c** is a constant coefficient. Total elicitation costs, C, simply equals $C_1 + C_2$.

The principal obtains the profit which is given by the total fitness of the organization after payment of the total effort elicitation costs: $\Pi = F - C$. We assume that the principal is profit- (rather than fitness-) seeking. That is, the principal incorporate the effect of the cost of effort in determining whether a policy is enhancing or diminishing performance.

Simulation results:

Again, we consider a landscape with N=20 and generated by the following decomposition: D={{1,2,3,4,5},{6,7,8,9,10},{11,12,13,14,15},{16,17,18,19,20}}. We explore four classes of perceived decompositions:

1) **Right**, have the correct decomposition

2) **Almost right**, use the size four decomposition:

Δ={{1,2,3,4},{5,6,7,8},{9,10,11,12},{13,14,15,16},{17,18,19,20}}

3) **Wrong**: have a decomposition of correct size but biased:

Δ={{1,2,3,19,20},{4,5,6,7,8},{9,10,11,12,1314,15},{14,15,16,17,18}}

4) **Minimal**: have the finest decomposition:

Δ={{1},{2},{3},.....,{18},{19},{20}}

The following figures report respectively fitness and profit for a typical simulation with a cost coefficient c=0.01.

Insert Figure 12 to 13 here

Agents with the right decomposition perform worse both in terms of profit (indeed this might be expected because of costs proportional to the span of control) but also in terms of fitness. The former result is due to the fact that fitness improving changes may be too costly (because of the C_2 component) and reduce profits. Smaller than right decompositions have higher performance both in profit and in fitness and will tend to prevail in the population. An additional disadvantage of using a large decomposition is that if they are "wrong" the performance easily becomes extremely poor.

The virtues of a "false" decomposition in conjunction with the challenge of motivating and monitoring action are compounded in the context of more complex problem environments. Consider the environment generated by the following decomposition of size 10:

D={{1,2,3,4,5,6,7,8,9,10},{11,12,13,14,15,16,17,18,19,20}}. In this setting, we model four types of agents characterised by decompositions of different sizes, called respectively:

1**) K=1**, with decomposition:

Δ={{1},{2},{3},.....,{18},{19},{20}}

2**) K=2**, with decomposition:

Δ={{1,2},{3,4},.....,{17,18},{19,20}}

3) **K=4**, with decomposition:

Δ={{1,2,3,4},{5,6,7,8},{9,10,11,12},{13,14,15,16},{17,18,19,20}}

4) **K=5**, with decomposition:

Δ={{1,2,3,4,5},{6,7,8,9,10},{11,12,13,14,15},{16,17,18,19,20}}

Indeed, if there is something of this stylized analysis which robustly carries over to the interpretation of enormously more complex real world phenomena, that has also to do with ubiquitous dilemmas between "explorations" and "exploitation", in March (1991) language, and *together*, the dilemmas linking the efficacy of routines, the varying costs of hierarchical controls of behaviours, the promising but costly liberties to chose and search.

To highlight the effect of the interaction between problem decompositions and problems of control, we contrast the behaviour of a system with agents that require control with that of a system with “angels” --- a set of actors that do not require such control measures. When these cooperating individuals (i.e., angels) are also perfectly knowledgeable, then we get the expected result that cooperative actors perform better than those agents that require control measures. However, if actors have the wrong cognitive representation of the problem space - that is they enact an incorrect partition - then non-cooperative agents may actually generate a higher level of performance. Figure 14 compares the fitness achieved by an organization in which cooperating individuals have a high dimensional representation of the environment that corresponds in partition width to the true problem representation but the elements are not correctly assigned, with agents that require control who have a “simplistic” view of the problem space as consisting of two element partitions.

Insert Figure 14

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5. Conclusions

We started with a stark imagery of how discordant major current perspectives on firm behaviours are. It is not simply that the perspectives pose contradictions; it is as if, figuratively speaking, they are from different planets. Theorists start with fundamentally different principles as to what constitutes the critical underlying elements of a theory of the firm. We have strived to a) be able to engage issues of capabilities and incentives on a common analytical platform and to b) demonstrate that there is real value to such an exercise. There are important interactions among the theoretical perspectives and treating them in a separable manners might be deeply misleading. The problem of specifying task decomposition intimately relates to the problem of incentives and to issues of power.

Notwithstanding our utterly simple assumptions, we already find a useful complementarity between the imposition of local incentives to induce "selfish" behaviour in a problem context in which the task decomposition is ill-specified and there are linkages across partitions of task decompositions. While in such a setting, local incentives provide an impetus to search by provoking subunits to perturb each other's search process, such mutual perturbation can be excessive. Power, a factor generally absent in discussion of capabilities, turns out also to be a useful complement. Power can inhibit the endless cycling that such behaviour might engender.

Thus, factors such as incentives and power that recent capability-based writings have tended to shy away from turn out to be important sets of considerations in addressing the problem of firm behaviour form either a normative or descriptive point of view. At the same time, clearly power and incentives are not the only relevant considerations. For us, with a behavioural starting point rooted in notions of bounded rationality, the problem of capabilities is foremost a problem of search and discovery.

We are not the first to in some fashion make such linkages. Indeed, in the seminal source documents of March and Simon (1958), Cyert and March (1963), and Nelson and Winter (1982), such linkages among the problem of search, incentives, and power are present. However, as we have refined our notions of capabilities and the problems of knowledge and as neoclassical economists refined the apparatus of contract theory, such linkages have largely been lost. There have been some recent calls for rebuilding these linkages (c.f., Coriat and Dosi (1998)). In the present work, we have not only issued such a call, but have provided a potential analytical structure with which to pursue this objective. Using recent advances in computational modelling (Marengo, 2000 and Marengo et al, 2000), we can provide a platform in which behaviouralists can enter the world of mechanism design (Levinthal and Warglien, 1999). The current work provides some promising initial findings that attest to the merit of such an endeavour. Perhaps more importantly, we hope that others will exploit this analytical platform and further build "bridges" between these two "worlds".

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Figure 1: One Bit Mutation on Minimal Decomposition
(Single run)

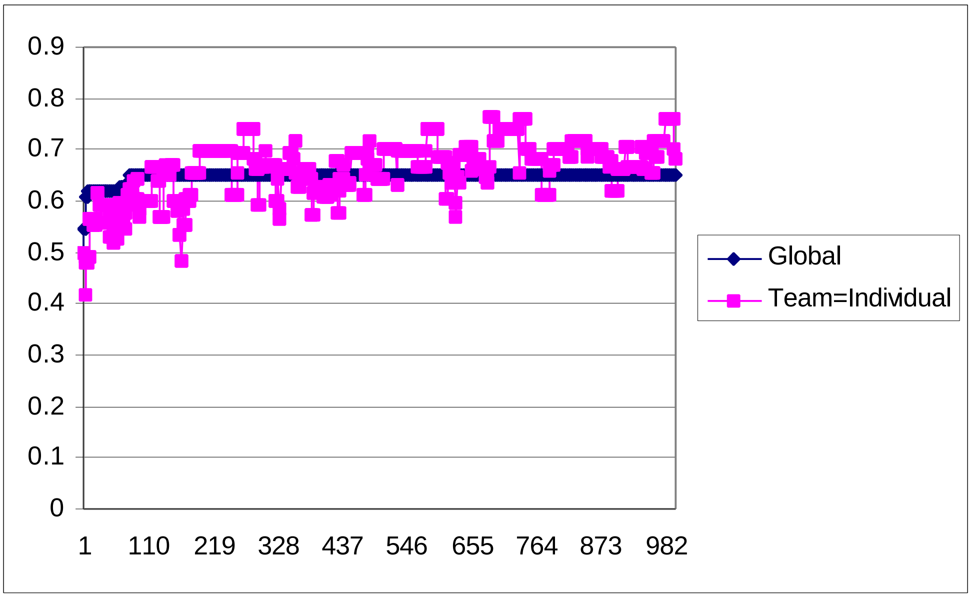

Figure 2: One Bit Mutation on Minimal Decomposition
(Average over 200 repetitions)

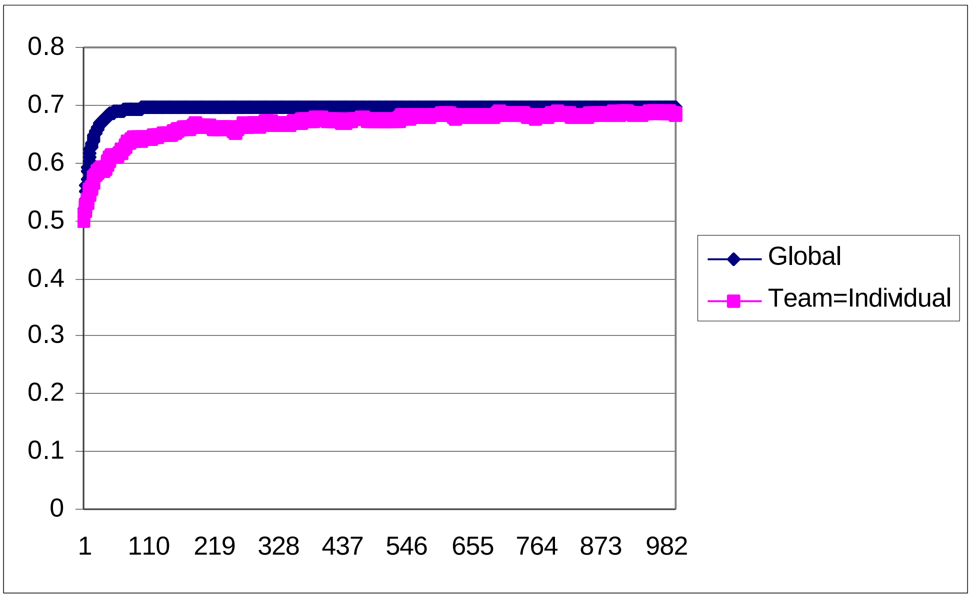

Figure 3: One Bit Mutation on Minimal Decomposition

(Standard deviation over 200 repetitions)

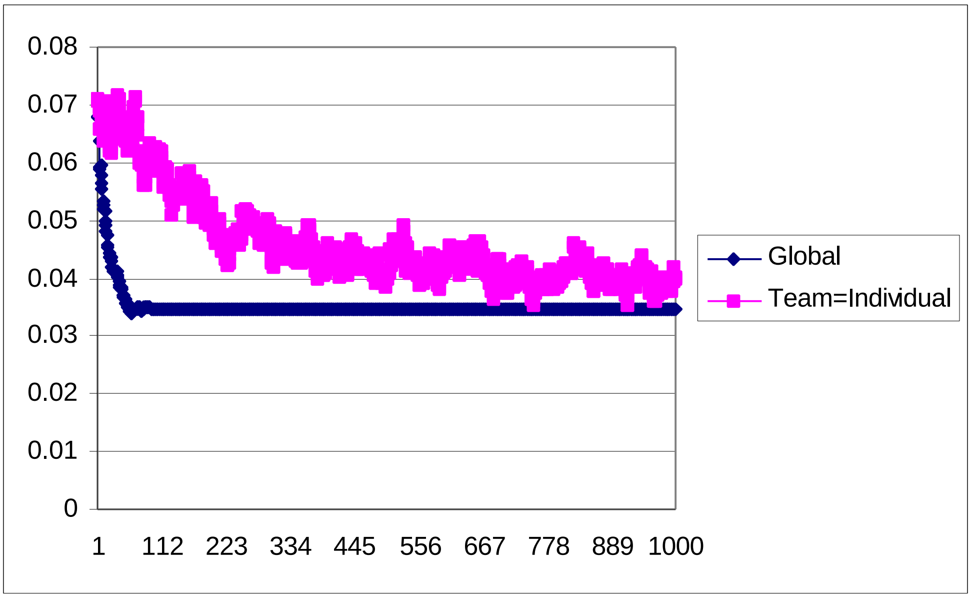

Figure 4: One Bit Mutation on "Almost right" Decomposition

(Single run)

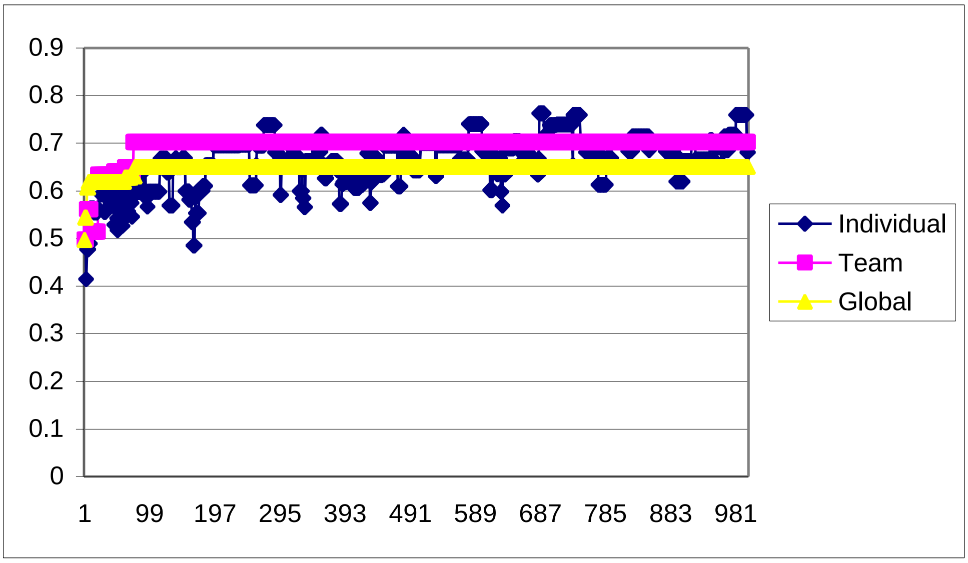

Figure 5: One Bit Mutation on "Almost right" Decomposition
(Average fitness over 200 repetitions)

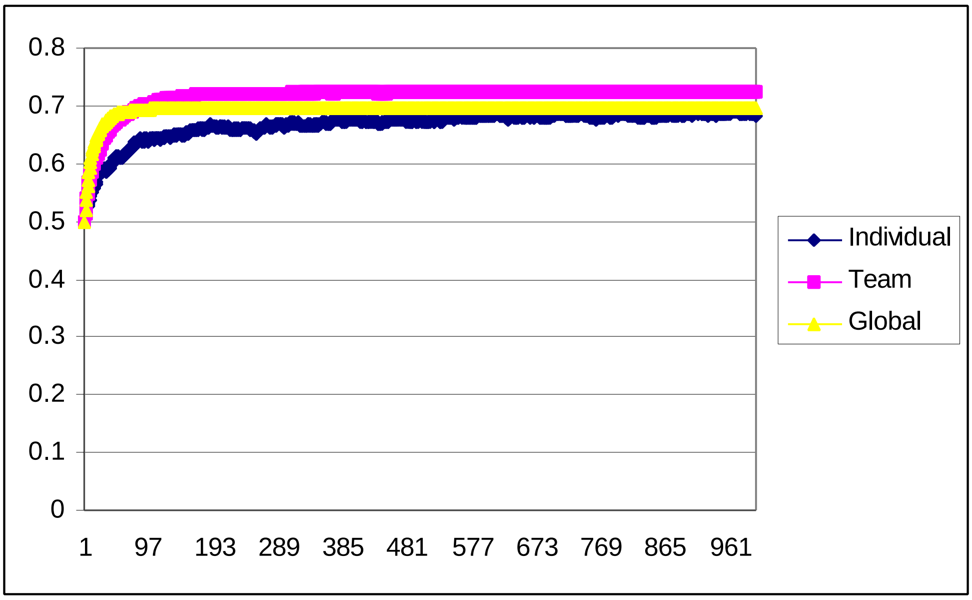

Figure 6: One Bit Mutation on "Almost right" Decomposition
(Standard deviation across 200 repetitions)

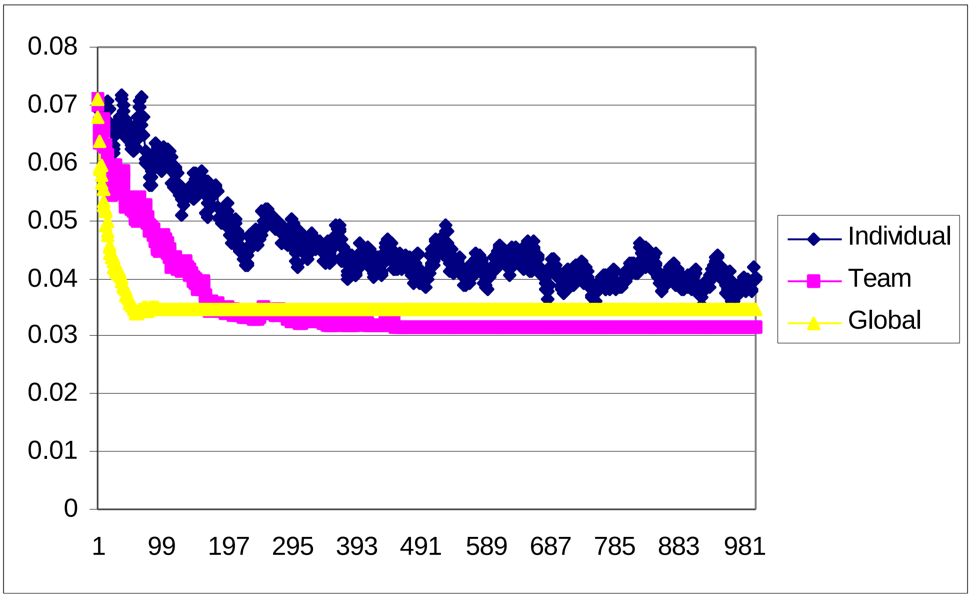

Figure 7: Veto Power with Partitions of Two
(Single run)

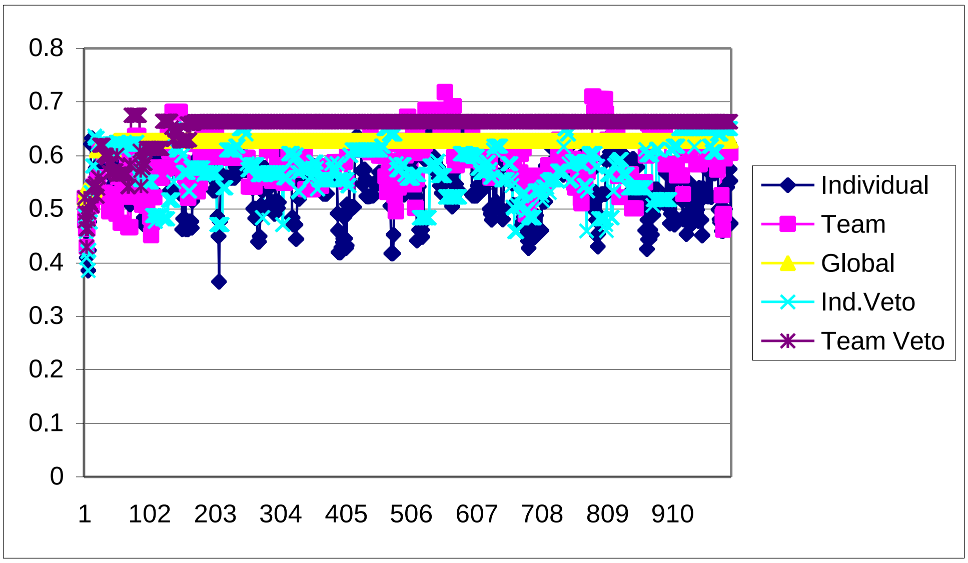

Figure 8: Veto Power with Partitions of Two
(Average fitness across 200 repetitions)

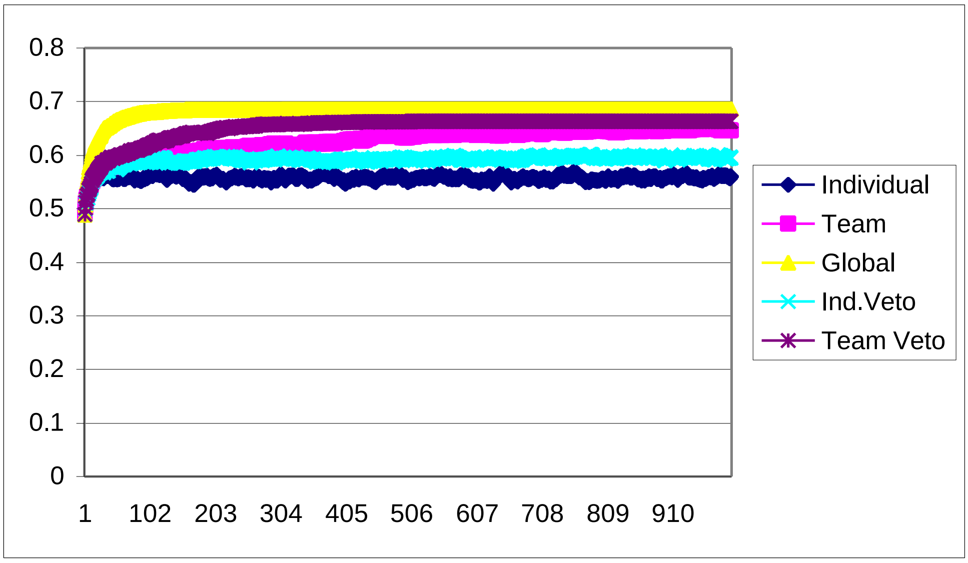

Figure 9: Veto Power with Partitions of Two
(Standard deviation across 200 repetitions)

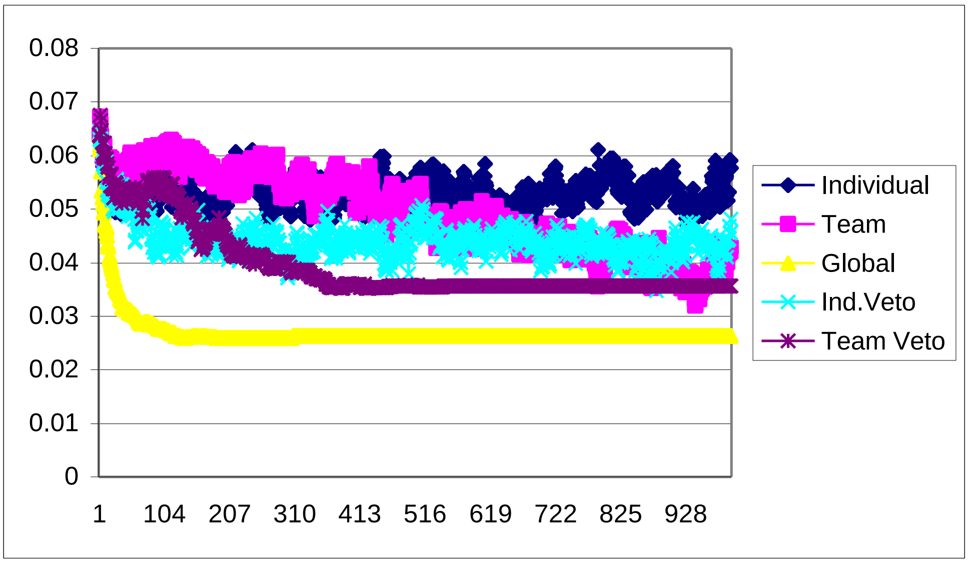

Figure 10: Veto Power with Perceived Partitions of One and Real Partitions of Two
(Average fitness across 200 repetitions)

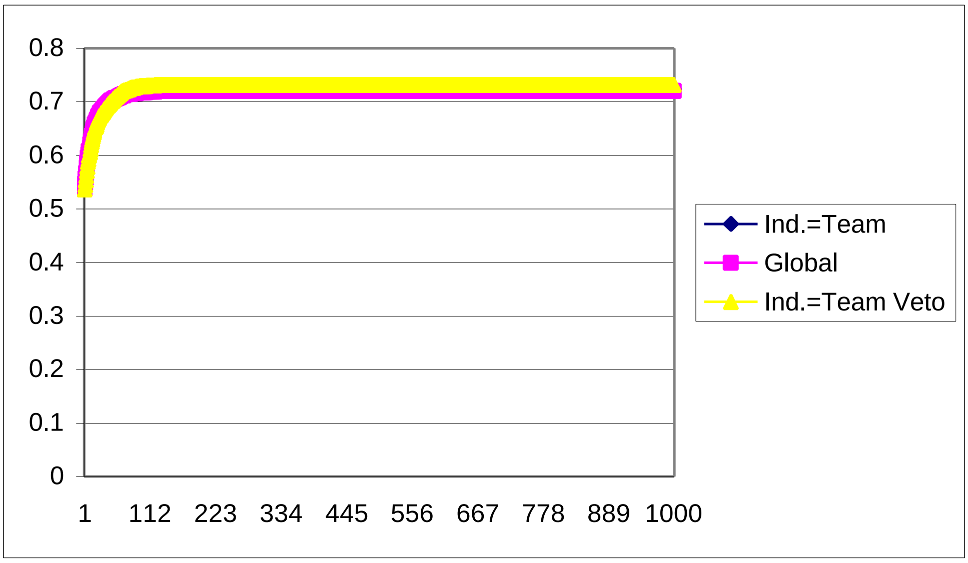

Figure 11: Veto Power with Perceived Partitions of One and Actual Partitions of Two

(Standard deviation across 200 repetitions)

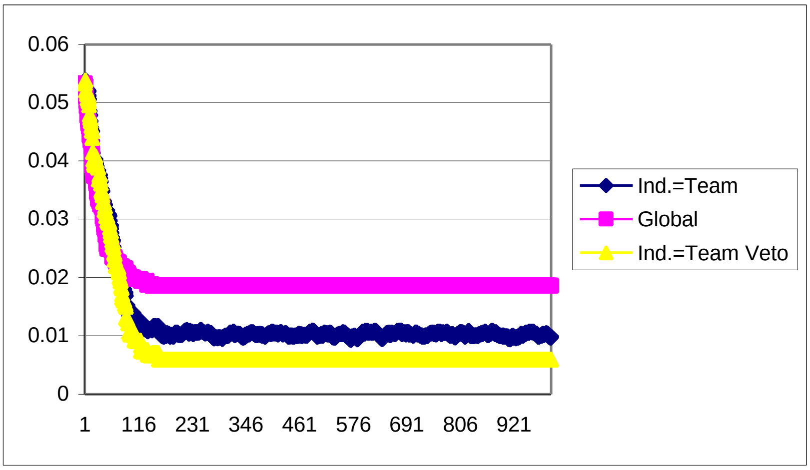

Figure 12 : Agency Costs

(Average fitness level over 200 repetitions)

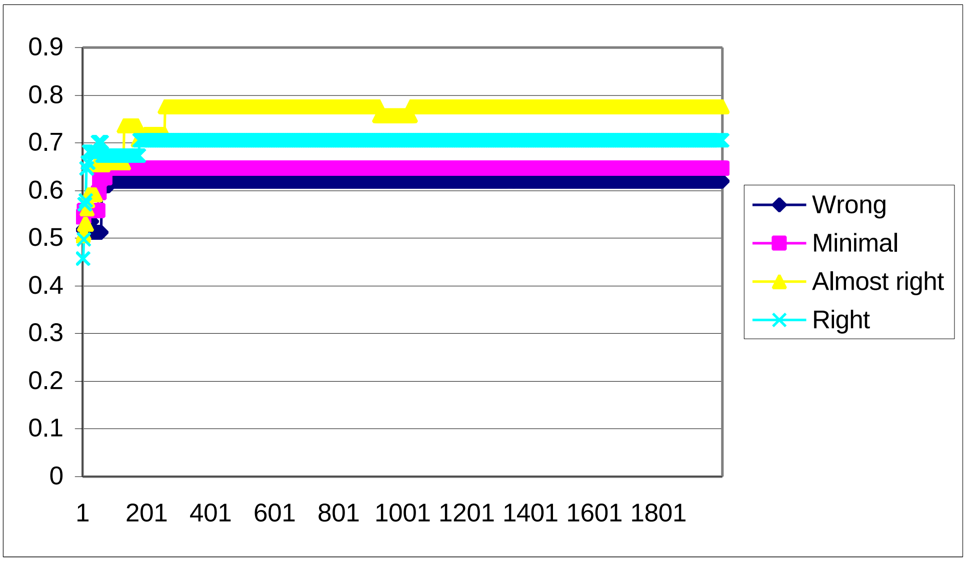

Figure 13 : Agency Costs

(Average profit value over 200 repetitions)

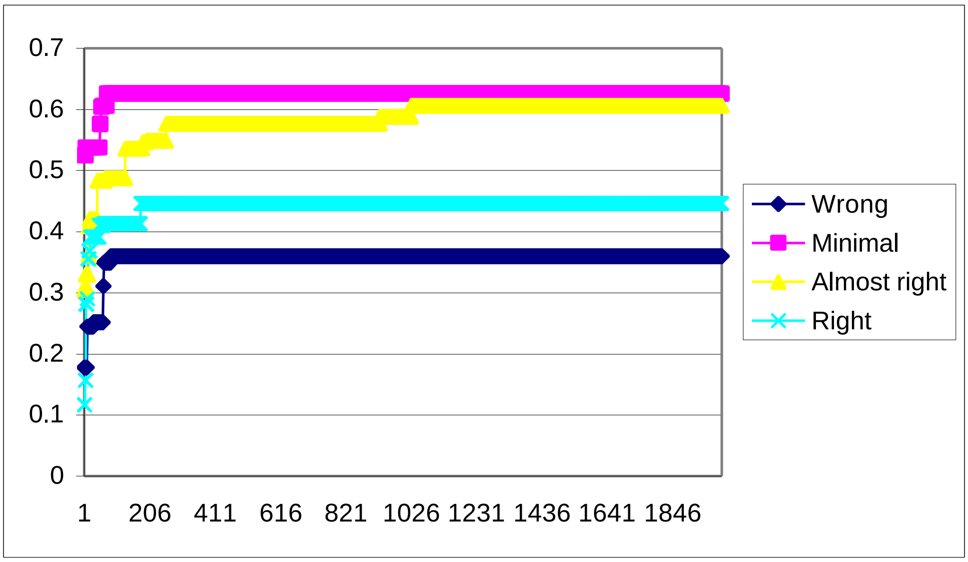

Figure 14 : Interacton of Cognition and Control

(Average profit over 200 repetitions)