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Organizational performance in hierarchies and communities of practice

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Performances organisationnelles dans les hiérarchies et communautés de pratiques

Résumé

Nous avons étudié dans un article précédent les conditions d'émergence des communautés de pratique. Pour ce faire, nous avons développé un modèle d'agents faisant face à un flux continu de problèmes à résoudre. Nous centrons maintenant l'analyse sur la performance de cette forme organisationnelle en comparaison avec une forme plus hiérarchique qui contient un *manager* et un ensemble d'agents. Le manager reçoit les problèmes et en délègue le traitement aux agents qu'il choisit. Nos principaux résultats montrent que les structures de communautés sont effectives dans la construction des compétences et qu'il existe une complémentarité entre la hiérarchie et la communauté comme l'avait argumenté Bowles et Gintis [2000].

Mots-clé : *Communautés de pratique, apprentissage, émergence de réseaux, efficacité organisationnelle, hiérarchie.*

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Keywords: *Communities of practice, learning, emergence of networks, organisational efficiency, hierarchy.*

JEL : D2, D83, L2

Organizational performance in hierarchies and communities of practice

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1 Introduction

The idea that informal social structures play an important role in the behavior and capabilities of organizations is a long-standing idea in disciplines such as the sociology of organizations [Crozier and Friedberg, 1977] or management studies [Brown and Duguid, 1991; 1998]. The studies of such informal structures have gained a growing interest with the recent stress put on the knowledge-based economy and the collective learning processes that become the key factor for success of firms in such a framework. Indeed, an important part of the learning processes within organizations are increasingly seen as taking place within the informal networks nested in them.

In particular, the concept of community of practice is deemed particularly useful by a number of scholars to account for the learning processes taking place within an organisation [Brown and Duguid, 1991; 1998; Wenger, 1998]. The concept of community of practice was introduced by Lave and Wenger [1990] who, by focusing on individuals' practices, identified groups of persons engaged in the same practice, communicating regularly with one another about their activities. Members of a community of practice essentially seek to develop their competences in the considered practice. Communities of practice can then be seen as a means to enhance individual competences, they are oriented toward their members [Lave and Wenger, 1990; Brown and Duguid, 1991]. This goal is reached through the construction, the exchange and the sharing of a common repertoire of resources [Wenger, 1998]. According to this definition, communities of practice appear as important loci for competence building within firms. As Wenger [1998] puts it, communities of practice are elementary regimes of competence. "These communities might be found in traditional work divisions and departments, but they also cut across functional divisions, spill over into after-work or project-based teams, and straddle networks of cross-corporate and professional ties. For example, within firms, classical communities include functional groups of employees who share a particular specialisation corresponding to the classical division of labor (e.g. marketing or accounting). They also include teams of employees with heterogeneous skills and qualifications, often coordinated by team leaders and put together to achieve a particular goal in a given period of time" [Amin, Cohendet, 2003].

However, although some works, either empirical or theoretical, investigate the impact of communities of practice [Orr, 1990; Hubermann and Hogg ,1995] upon the performance of the organisation as a whole, such studies remain rare. More precisely, some measures of performance of communities themselves would be desirable. Moreover, the interplay between communities and hierarchy and the output of this interplay deserves deeper analysis. These issues are difficult to tackle in traditional ways since the impact of communities upon hierarchical structures and their potential benefits in terms of performance remain largely invisible in case studies. Their existence can be evidenced but the true input of their activities for the firm are hard to assess. Besides, most of the theoretical work on communities of practice leaves some questions (such as the boundary of communities, for instance) unanswered. The concept is thus difficult to formalize using for example a mathematical apparatus. In a previous work [Dupouët et al., 2003], we explored the emergence of communities of practice from a collection of individuals engaged in problem-solving activities. We evidenced sufficient conditions for the emergence of such social structures and show the usefulness of some indicators to characterize networks of communities of practice. This paper takes one step further and seeks to shed some light on the role of communities in the performance of organizations, using computational methods.

By resorting to computer simulations based on the multi-agent system paradigm, this contribution explores the performances of various organizational settings and, in particular, the role of communities in the performance of a firm. Mainly, two types of structures are contrasted: a pure network of communities of practice and a hierarchical structure. Further, within the later, one can either authorize the potential emergence of communities by allowing the communication between agents, or remain in a strictly top-down decision process. It is then possible to compare the outcomes of each of these organizational settings.

This work is organized as follow. First the different components of the model - the role and capabilities of individual agents and the overall structures - are presented. Next, the results in terms of comparative performances of organizational structures and the specific impact of learning and communities are considered. The last part of the article uses regression trees to analyse the role of the parameters of the model using the Monte Carlo method.

2 The model

The model we present here is divided in two parts. The first one -that we call communities of practice (**CP** thereafter) is a collection of agents having to solve a flow of problems and endowed with the abilities to learn by themselves or by interacting with one another. Each problem is randomly chosen from the problem space and is sent to an agent chosen randomly. If the problem belongs to the ”core competences” that the agent has built over time through learning processes, it gives an answer. Otherwise, it consults its community that it has constructed over the past interactions. If the agent does not receive any response from the contacted agents, it passes the problem to the next agent in a random list. If the last agent in the list cannot provide any answer, the problem remain unsolved (the system does not have the competences to deal with this specific problem). Such a situation corresponds to a loss for the firm and hence a decrease in performance. The overall dynamics thus result both from individual learning by doing and learning by interacting between agents.

The second part of the model consists of an hierarchical structure where a *manager* is added on top of the community of the agents. The role of the manager is to receive the problems from the environment and to select the agent it deems the most able to solve this problem. Its role is thus to carry out a division of labor. We called this part of the model hierarchy with delegation (**HD**, thereafter), since the manager has to ask its subordinates for advice in order to answer the problems submitted by the environment. In addition, we consider two possibilities: either agents are able to communicate horizontally between them or not.

The article questions the various dimensions of these different organizational settings, with a particular interest in the role of communities in the global performance of a firm. In the remaining of this section, we present the problem space that organizations are facing, the learning processes of agents, the implemented communication processes and the role of the manager.

2.1 The Environment: Evaluating Financial Projects

The simulation is based on a specific empirical context: a population of agents whose task consists in allocating financial warranties for bank loans to small enterprises. For each enterprise, a given agent has to determine a certain amount of warranty by considering a set of criteria. In their endeavor to determine the optimum level of warranty, agents can communicate between them. They can thus exchange the “best practices” concerning a particular subspace of the problem space. This way, communities of practice are susceptible to emerge.

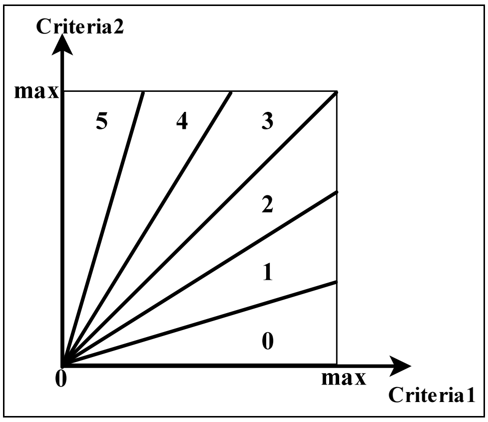

Figure 1: The problem space

Formally, we suppose that a project is characterized by two criteria stocked as a eight bits long binary string. The first four bits code the value of the first criterion and the four last bits the value of the second one. The problem space is thus a grid and each binary string represents a particular situation and occupies a position on that grid. An action is associated to each situation (for the agent, the various possibilities take the form $condition : action$, where the condition is the binary string and the action is an integer). According to each particular situation, the agent must propose an amount of warranty (the action): 0%, 10%, 20%, 30%, 40% or

50% (respectively coded as actions 0, 1, 2, 3, 4, 5 – *see* Figure 1).The task of the agents is then to determine the amount of warranty associated to each situation. The gap between the correct amount of warranty and the answer proposed by the agent determines the reward of the agent. The reward is computed as follow: $f(a) = C \cdot \exp(|a^* - a|)$ where C is a constant, a^* is the correct answer expected by the environment and a the answer proposed by the agent. If the agent proposes an amount of warranty lower than the optimum, it does not obtain the full amount of commissions that it could have expected from the situation. If, on the contrary, it proposes a value greater than the optimal one, then in case of bankruptcy of the warranted firm, the loss would be greater than for the correct answer. The reward hence takes into account these two types of costs. The agent uses the reward it receives from the environment to actualize and refine its behavior.

2.2 Modeling of individual learning

Each agent has to classify the various situations (projects represented as binary strings) in one of the six areas defined by these six possible actions (*see* Figure 1). Its experience (the results it obtained from past trials) must help it in refining the judgement of the agent. This process corresponds to the individual learning process. This is a typical classification problem and, given the multi-agent system we adopt, a rather natural way to represent this kind of process is the Learning Classifier System (LCS). Indeed, a LCS is a relevant tool for simulating relatively realistic learning processes [Lanzi and Riolo, 2000].

More specifically, the structure we adopt for each individual agent is an XCS [Wilson, 1995], an algorithm from the family of LCS. An XCS carries out a two-step procedure (*see* Figure 2). It first establishes a cartography of the whole problem space and associated rewards. Once this mapping is complete, it can choose in its memory the answer leading to the highest reward in each situation. An XCS receives a signal (problem) from the environment through a detector. This signal is then compared to the set of rules the agent has in its memory. These rules are made of a condition part and an action part. Moreover, several parameters are associated with each rule: p, the prediction of performance, ε, the error associated to the prediction of performance, F, the fitness which is a measure of the accuracy of the rules (a function of the inverse of the error) and that is used in the genetic algorithm used by the XCS to explore the problem space. Rules of which the condition part fits the signal from the environment are stored in an array called the match set. A prediction array is then constituted in order to evaluate the reward associated with each advocated action. Based on this array, an action is chosen and triggered in the environment. In our implementation, the agent can select the action predicting the highest reward from the environment or use a roulette wheel process to select the action to be fired. A parameter *selectAg* controls the choice of the selection mode : When set to 1, the best action is chosen, when set to 0, the roulette wheel is used. In the latter case, each rule has a positive probability of being chosen and this probability increases with the performance of the rule. The environment then rewards the XCS which uses this reward to adjust the parameters of its rules.

Based on the literature on communities of practice, we endow the agents with the following characteristics: An agent seeks to develop its competences on a given practice. This practice does not constitute its entire activity but is nonetheless deemed critical by the agent. Moreover, the learning process of each agent is oriented: new rules produced by the genetic algorithm are inserted in its memory only if they are in its core competences (specialisation). The surface of the specialisation is controlled by the parameter *compRange* that can rank from 0 to 1. When *compRange* is equal to 1, the agent is not specialised and can accept all the problems submitted by the environment. When it is close to 0, the agent becomes highly specialised. Using the fact that the problem space is a grid, *compRange* is the euclidean distance between the condition part of the received problem (the signal) and the best rules of the agent. This is intended to account for the focused learning taking place in communities of practice. An agent has a limited memory that does not permit it to deal by itself with the whole problem space.

2.3 Learning by Interacting

In our implementation, a parameter, *communication*, determines whether or not the agents have the ability to communicate. This parameter can take the values 0 or 1; When it is set to 1, the communication is allowed.

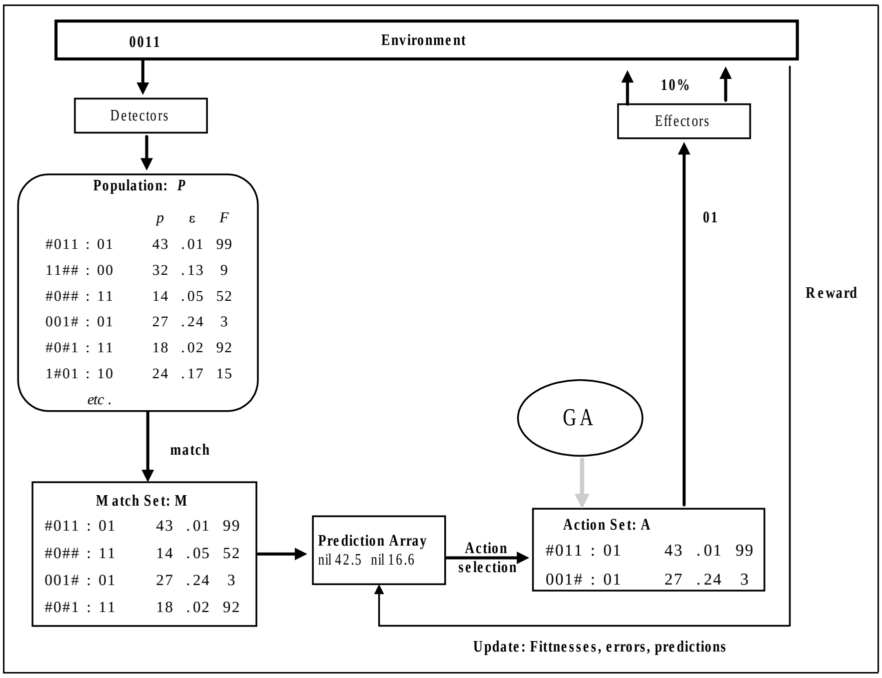

Figure 2: Schematic XCS (adapted from Wilson [1995])

We now present the communication process.

The agent can have no rule satisfying the signal from the environment or only have a *poor* rule (with a prediction of performance below an acceptable threshold – common to all agents). If an agent does not possess a satisfying rule to answer a problem but the problem lies nonetheless in the realm of its core competences, it engages a communication process by requesting help from other agents. It receives answers and evaluates them:

- If a received rule offers a better prediction of performance, then it adopts it.
- If predictions are equivalent (either several rules it received have identical prediction, or the rules it received and the ones it already possesses have identical prediction), it compares the prediction error and opts for the rule having the lowest one.
- In case of equivalence between prediction errors, it compares fitnesses and chooses the rule with the highest fitness. When all these parameters are not discriminating, the agent choses a rule at random.

By choosing a rule, the agent copies it in its memory and uses it to answer the signal from the environment.

Each agent uses an address book to keep in memory successive communications with different partners. This address book is originally empty. When an agent first launches a communication process, it asks a percentage $(consultRatio)$ of the whole population at random. It then stores in its address book the references of agents answering him (not only the ones giving him the best answers). In the following periods, the agent will question the agents present in its address book. If none of these agents answers its enquiry, it will then ask once again *consultRatio* of the total population of agents, which can be seen as an exploration of its social environment and a search for new partners. In order to avoid the presence of non relevant agents in the address book, a counter $(exval)$ is associated with each agent present in a given address book. If an agent does not answer to *exval* consecutive enquiries, it is removed from the address book. *exval* is thus a parameter indicative of the stability of links established by agents.

Hence,

- in order to enhance its practice, an agent engages with other agents in the building and the sharing of a common repertoire of knowledge resources. In particular, this implies that the agent is always willing to cooperate with other potential members of a community and that there is no direct costs associated with the establishment of a new relation;

- the agent then nurtures this community of practice with its experience and in turn relies on this community to enhance its practice.

Behaviors of agents are then twofold: they are engaged in a practice involving individual learning and they are committed to social interactions. However, these two parts are inter-related in that communication informs practice and practice fosters exchanges.

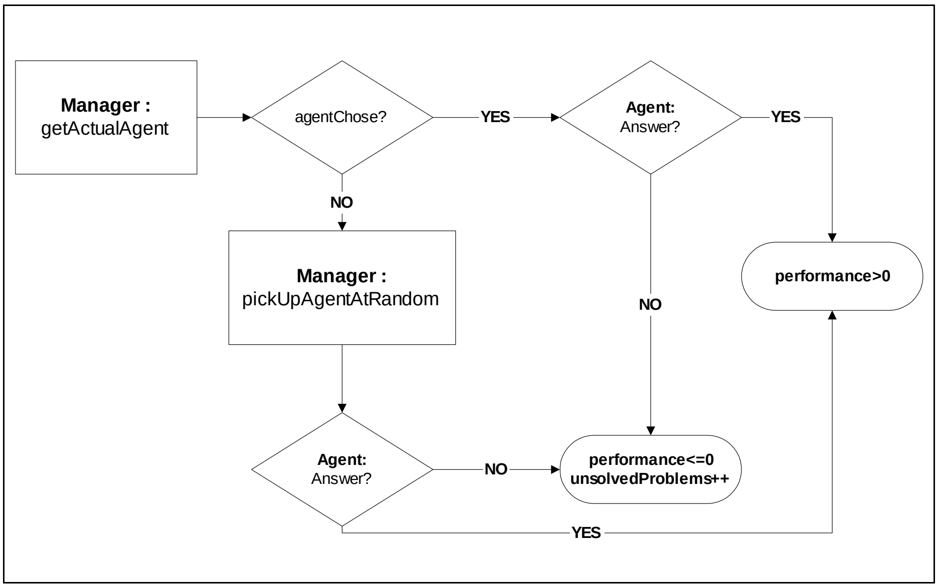

Figure 3: Problem solving procedure of the manager

2.4 The Role of the Manager

The second organizational structure implemented consists in the simple addition of a manager on top of the structure presented so far. The environment remains the same. However, in this new organisation, the signals from the environment are directly received by the manager. The duty of the manager is to allocate the task of answering a given signal to the most suited agent for this specific problem. The role of the manager can then be seen as twofold. On the one hand, it has to allocate efficiently the tasks as they are submitted by the environment. On the other hand, since the allocation of tasks made by the manager will influence the learning processes of the agents, it can also be viewed as a guide for the learning of agents.

From the modelling standpoint, the manager is an XCS similar to the ones used for modeling agents. The condition part of the manager's rules corresponds to the signals arising from the environment. The action parts consist of the references to the agents (i.e. each agent is referenced to by an integer).

To chose an agent for answering a given problem, the manager proceeds as follow (*see* Figure 3). First, the manager tries to find an agent by selecting in its memory a rule that matches the signal from the environment. If it does not have any rule, then the manager chooses an agent that is not often called and that has a core competence close to the signal submitted by the environment. In the latter case, the manager adds in its memory a new rule of which the condition part is the signal from the environment and whose action part is the reference to the selected agent. As in the case of agents, the manager can select the rule with the best prediction of performance or use a roulette wheel process to chose the action. This is controlled by the parameter *selectMan* (when *selectMan* is 1, the rule with the best prediction is chosen, when it is 0, the roulette wheel is used). Once an agent has been selected by the manager, the problem is passed to this agent and it tries to answer it.

To answer the problem, the agent can either solve it alone or ask for help from other agents (if *communication* is set to 1). However, the problem is not passed to another agent when the selected agent cannot answer. In that case, the problem remains unsolved and this incurs a loss (opportunity cost) for the organisation.

The selected agent returns its answer directly to the environment that evaluates it and gives a reward. The reward is then used by the agent and the manager to carry on their learning processes and refine the parameters associated with their rules.

3 Simulation protocol and main results

3.1 The simulation protocol and methodology

Given the complexity of the interactions we model and the strong non-linearity of the decision processes of the agents, we adopt a methodology that allows quite a systematic exploration of the parameter space of the model. This methodology is close to Monte-Carlo method. For each of our two models, we run 500 series of 15 000 problems each where the results from each problem has a probability of 1% of being saved. So, for each run we obtain an average number of 150 randomly chosen observations for all the measured variables. All series are initialised with a randomly drawn vector of values for the main parameters of the model. As a result, we obtain, for each model, a set of 75 000 observations covering quite a diversified subset of the parameter space and the problem space. The values from which different parameters are drawn can be read in the appendix. We analyse these random samples using box plots (giving the four quartiles of the distributions of the variables), Student tests between subsets, histograms and regression trees. The statistical analysis is conducted using R (see Ithaka and Gentleman [1996]).

We use some specific indicators in order to qualify the organizational performance. The first and the most direct indicator is the gross performance that belongs to $[-1000, 1000]$. When the organisation faces a problem, it can find a solution and obtain the actual performance returned by the environment, or it can be unable to provide a solution, in which case the problem remains unsolved, and the performance is equal to an opportunity cost: the negative of the past average performance (the opportunity that the organisation has missed by being unable to solve the problem). This indicator is quite crude but it nevertheless measures the pay-off that the organisation gets through problem solving.

However, the gross performance neglects another important dimension of the efficiency of the organizations: the cost of communication. If a solution is found after a tremendous amount of communication between agents, it would correspond to a relatively high organizational cost. In order to take into account the cost as well as the benefit of each decision, we develop another indicator:

$$efficiencyRatio = \frac{performance}{nbCommunications} \tag{1}$$

3.2 Main results of the simulations

We focus the analysis of the results on issues concerning the performance of organizations in problem solving. We first proceed by comparing these organizational forms from the point of view of gross performance. These first results are refined afterwards through the analysis of the role of communications and communities of practice. The last step of the analysis clarifies the role of different parameters in these results using regression trees.

3.2.1 Comparative analysis of the organizational performance

As it will clearly appear in the rest of this analysis, the possibility of communication plays a crucial role in the performance of the organisations. The Figure 4 compares the distribution of the performances of hierarchy (HD) and communities of practice (CP) between two cases: with communications (1) and without communications (0). The graphic (a) shows that the hierarchy needs communications for attaining better payoffs, while the communities of practice need communications for better avoiding the negative payoffs

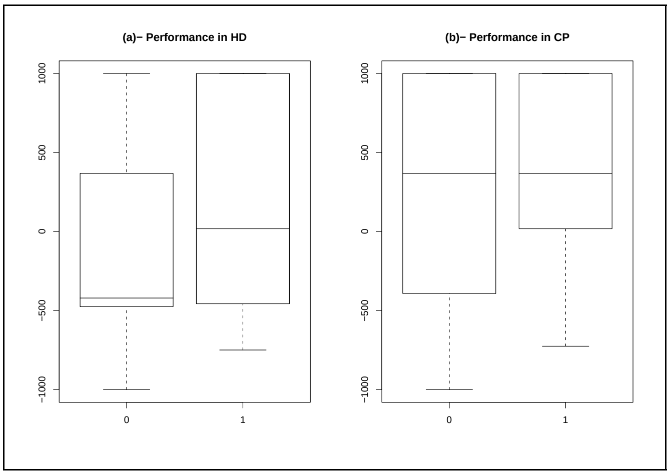

Figure 4: Comparison of gross performance between organizations: with (1) and without (0) communication

(due to unsolved problems). As a consequence, communications do not play the same role in these two organizational structures. The role of communication will be analysed more in detail in the next section.

The comparison of results between HD and CP shows that CP is able to attain, on average, better payoffs than HD. The organizational structure plays the main role in the determination of the performance, but communities with communication $(CP\,(communication = 1))$ attain the highest performances and the complete ordering between these four cases is given by

$$CP\,(1) \geq CP\,(0) \geq HD\,(1) \geq HD\,(0) \tag{2}$$

Student tests between these cases give the following results:

$H_1 : CP < HD$	$\rightarrow$	$t = 64.2951,\ df = 149390.3,\ p-value = 1$
$H_1 : CP\,(1) < HD\,(1)$	$\rightarrow$	$t = 51.3433,\ df = 122334.1,\ p-value = 1$
$H_1 : CP\,(1) < CP\,(0)$	$\rightarrow$	$t = 8.9367,\ df = 31741.86,\ p-value = 1$
$H_1 : CP\,(0) < HD\,(1)$	$\rightarrow$	$t = 27.6562,\ df = 32190.58,\ p-value = 1$
$H_1 : HD\,(1) < HD\,(0)$	$\rightarrow$	$t = 41.9592,\ df = 12777.20,\ p-value = 1$
$H_1 : CP\,(0) < HD\,(0)$	$\rightarrow$	$t = 55.6133,\ df = 18648.14,\ p-value = 1$

Communications play an important role, especially for the emergence of the communities of practice.

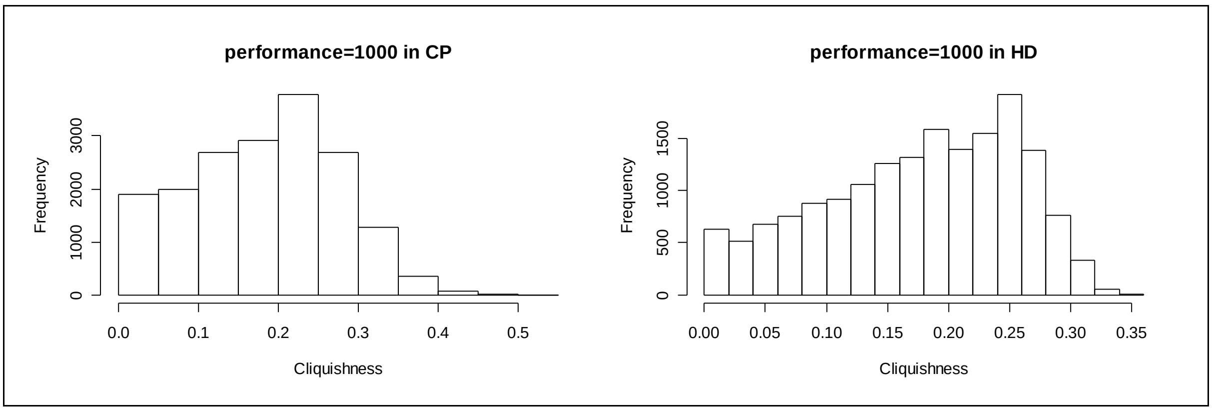

Figure 5: Distribution of cliquishness for the cases with the maximal performance

3.2.2 Emergence and performance of the communities of practice

The comparative analysis of performance indicates that communications among agents outside the hierarchical line play a role in the behavior of the system as a whole. In our setting, to allow communication is to allow agents to build relational structures outside the mere hierarchy. In other words, when communications occur, one can hope to observe the emergence of communities of practice. To account for the emergence of communities of practice, we here use an indicator well-known in social network analysis, the *cliquishness* [Wasserman and Faust, 1994]. Cliquishness captures the idea that two agents connected to another agent are likely to be connected to one another. It is thus an indicator of the existence or not of groups of tightly connected agents within the graph. Cliquishness can rank from 0 to 1. When it is equal to 0, no triangles exist within the graph. When cliquishness equals 1, the graph is made of fully connected subgraphs. In a random graph, the *cliquishness* is typically equals to 0.02. Values of *cliquishness* that are greater than that by several orders of magnitude are indicative of structures having social origins within the graph [Newman et al., 2001].

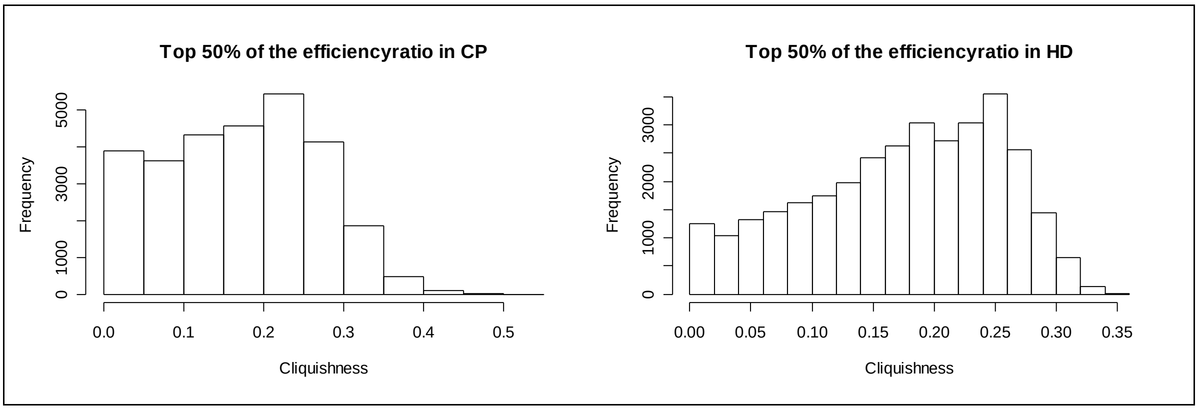

Figure 6: Distribution of cliquishness for the cases with the highest 50% efficiencyratios

To study the role of communities in the overall performance, we thus map the distribution of cliquishness in each quartile of $efficiencyRatio$ and $performance$ both for the case of pure communities of practice and hierarchy. Recall that $efficiencyRatio$ is the aggregated parameter that indicates the quality of the answer given by the system to the environment in terms of performance and delay of response.

We give the quartiles of the distributions of these variables in Table 1.

	CP		**HD**	
Quartiles	$performance$	$efficiencyRatio$	$performance$	$efficiencyRatio$
Q_1	$[-725.26;18[$	$[-612.27;0.05[$	$[-749.10;-456.48[$	$[-739.20;-36.52[$
Q_2	$[18;368[$	$[0.05;4.23[$	$[-456.48;18[$	$[-36.52;6[$
Q_3	$[368;1000[$	$[4.23;22.73[$	$[18;1000[$	$[6;66.66[$
Q_4	$\{1000\}$	$[22.73;1000]$	$\{1000\}$	$[66.66;1000]$

Table 1: Quartiles of performance indicators

First let's consider the role of the communities of practice in the gross performance of the organisation. Figure 5 shows that in CP as well as in HD, the most frequent values of the cliquishness, when the performance is maximal, are the ones that also corresponds to the emergence of the communities of practice (the distributions possess a cumulation around $0.2-0.3$. As a consequence, we can conclude that the communities of practice are the most common network structures that imply the highest gross performance.

But does this conclusion remain valid if we include the cost of communications in the evaluation of the performance ? The Figure 6 gives the distribution of the cliquishness in the last two quartiles of the $efficiencyratio$. Even if the result is slightly weaker for CP, the values of the cliquishness close to the communities of practice are the most common ones in the observations with the 50% highest $efficiencyratios$ when communication is allowed.

These results show that for both types of organisations, the highest performances are attained mainly in the cases where the communities of practice emerge. Even if it is practically quite arbitrary to determine a limit value of the *cliquishness* corresponding to the emergence of the communities of practice, the correspondence between the highest performances and the presence of the structures similar to the communities of practice is quite strong.

3.2.3 Role of the communications

The constitution of communities relies on the fact that communications exist. In order to refine the results from the previous section, we thus display the boxplots of each structure, considering in each case the situations with or without communications (Figures 7 and 8).

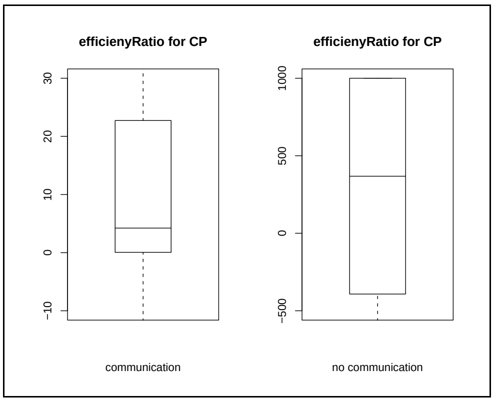

Figure 7: Boxplot of efficiency ratio with and without communications in CP

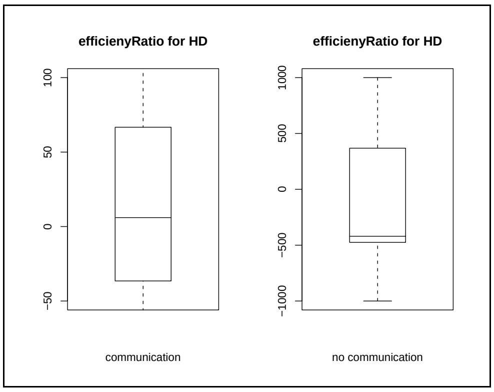

Figure 8: Boxplot of efficiency ratio with and without communications in HD

That the $efficiencyRatio$ reaches greater values when no communication takes place is not a surprise. This simply shows that when agents are able to communicate, they do so. This increase their response time, thereby decreasing their $efficiencyRatio$. This phenomenon is more important in the case of communities of practice since the manager does impose a limit in terms of the number of communications allowed (and hence in terms of the time allocated to give an answer to the environment).

The $efficiencyRatio$ of communities of practice remains higher than the one of hierarchy when communication is allowed in both structures. This is due to the fact that the performance of communities is higher than the ones of the hierarchy. In particular, given that the problem can be passed to the whole population of agents in the case of communities, this system has a high probability to provide an answer and hence it seldom receives negative rewards. Nonetheless, the boxplots show that the $efficiencyRatio$ of the hierarchy often reaches higher values than the communities alone when communications are allowed in both cases. In that case, the two structures, the hierarchical one and the informal one, are complementary in reaching the best efficiency level [Bowles and Gintis, 2000].

3.2.4 Behind the curtains: the role of the main parameters

We analyse the role of different parameters of the model using regression trees (Venables and Ripley [1999], chapter 10). A regression tree establishes a hierarchy between independent variables using their contributions to the overall fit (R^2) of the regression. More exactly, it splits the set of observations in sub-classes characterized by their value in terms of their contribution to the overall fit and of their predictions for the dependent variables (all parameters that are modified by the Monte Carlo procedure are included as explanatory variables in each of the following regressions). This value is validated against a fraction (10%) of the sample that is not used during the estimation. Regression trees are very flexible and powerful in the clarification of the structure of the observations. We now consider the determinants of the main performance variables of our model.

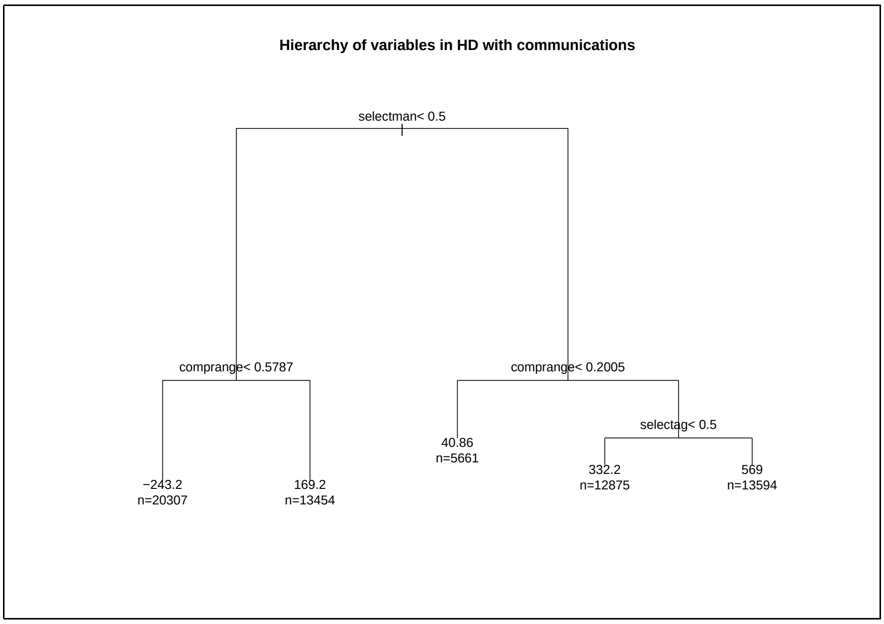

Figure 9: Regression tree for the gross performance in HD

Determinants of the gross performance The Figures 9 and 10 exhibit the variables that contribute more than 1% to the overall fit in both cases (HD and CP) with communications.

HD with communications In the case of the hierarchy, the main determinants of the gross performance are $selectMan$, $compRange$ and $selectAgent$. The other variables play only a marginal role. Higher performance is obtained when $selectMan = 1$, and hence, when the manager chooses the best agent in its agents set, for each problem (instead of choosing each agent with a positive probability, even if it is increasing with the performance, $selectMan = 0$). When the manager uses this best action rule, the agents should not be too specialized ($compRange \geq 0.20$) in order to have a significant global performance. This performance is even higher if the agents also use the best action rule ($selectAgent = 1$) for choosing their actions. When the manager uses a more explorative strategy ($selectMan = 0$), the organisation is only able to treat problems if the agents are not too specialized.

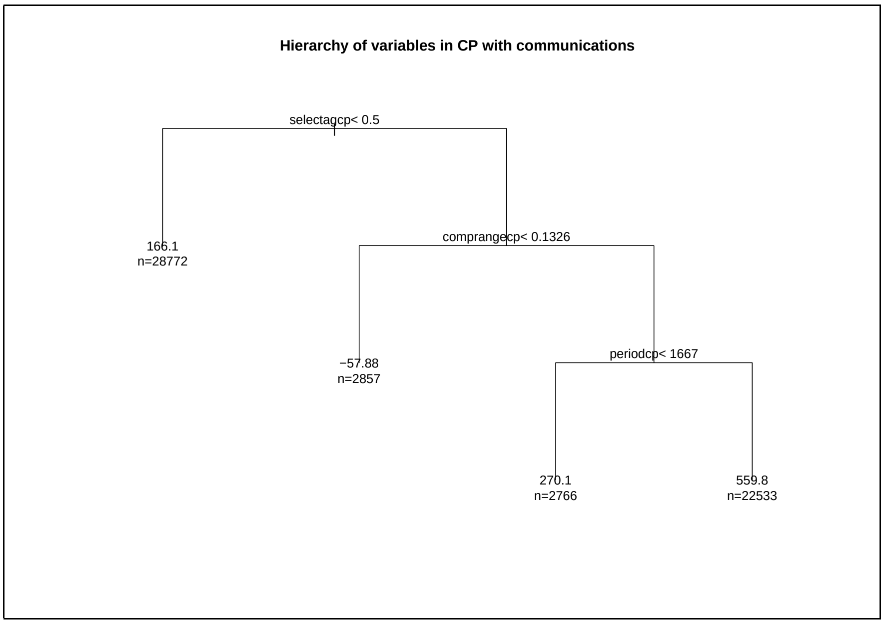

Figure 10: Regression tree for the gross performance in CP

CP with communications In the communities, the hierarchy between the determinants is slightly different. Even if *selectAgent* plays the main role in the segregation of different cases, the specialisation of the agents clearly appears as the main determinant of the performances. The community can only attain significant performances if the agents are not too specialised (*compRange* ≥ 0.13). When conditions upon *compRange* and *selectAgent* are fulfilled, then time matters (i.e. *period*). There is a learning trajectory of the system over time. Since this does not happen in HD, it seems that the initial conditions in CP are less determining than in HD. It is interesting to observe that other dimensions of the communication (like the *consultRatio*) play only a marginal role in the determination of the gross performance. Their role only appears when we consider more qualitative aspects of the performance.

Determinants of the EfficiencyRatio The efficiency ratio gives the relative efficiency of the communications in the organisation (performance/total communications). At an intuitive level, it compares the benefits with the costs due to communications, especially when they are *excessive* in a sense that they only happen because the agents are not able to treat the problem – a case that concerns the efficiency of the communities. The Figures 11 and 12 exhibit the determinants of this relative efficiency for both organizational forms.

HD with communications In the case of the hierarchy, the main determinants of the efficiency ratio are the specialisation of the agents (*compRange*), the percentage of the agent consulted (*consultRatio*) and the selectivity of the manager's decision rules (*selectMan*). For *compRange* < 0.17, the hierarchy is not very efficient and has difficulties to find solutions for the problems. So, if the agents are very specialized, the efficiency ratio is very low. With less specialised agents, the hierarchy can find solutions for the problems but the communications are most efficient when the manager is selective and the agents more strongly consult other agents.

CP with communications Quite interestingly, the *mechanics* of the communication efficiency are quite different in the case of the communities. Three variables play a significative role: the *consultRatio*, which gives the lowest efficiency when it is really too low, *compRange*, which conditions the efficiency for higher values of *consultRatio*. Lastly, as was the case for the gross performance, time intervenes when the best conditions upon the two other parameters are met. It is interesting to observe that in all these

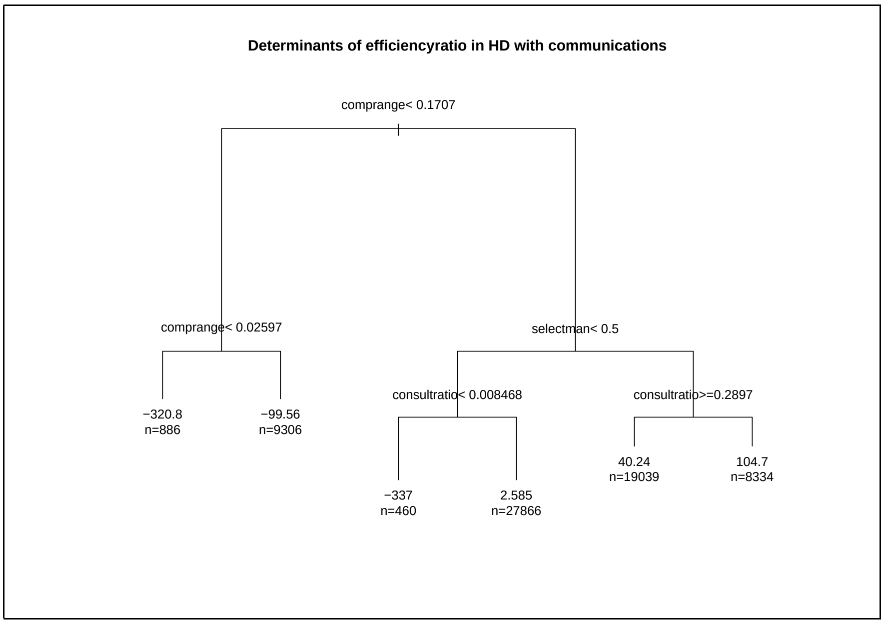

Figure 11: Regression tree for the efficiency ratio in HD

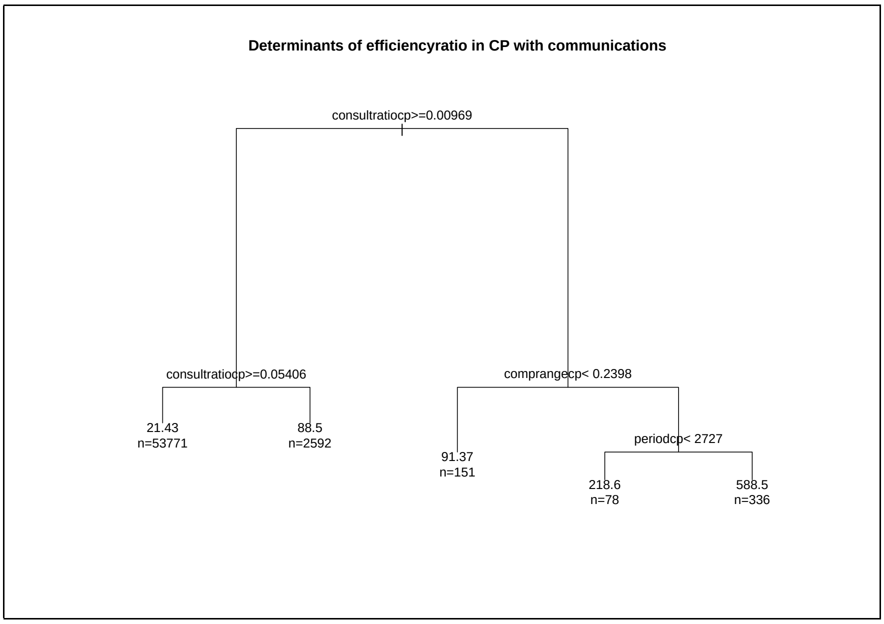

Figure 12: Regression tree for the efficiency ratio in CP

cases, the communities have good rates of treatment of problems (the expected efficiency ratio is positive in each case).

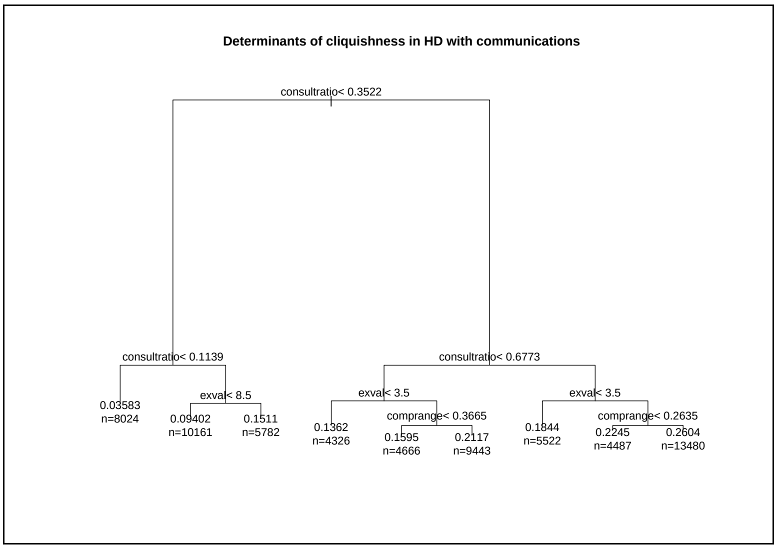

Figure 13: Regression tree for the cliquishness in HD

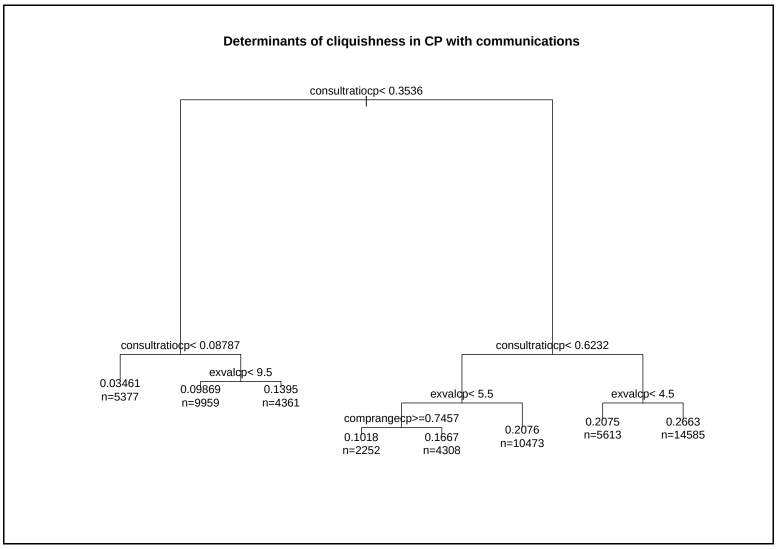

Figure 14: Regression tree for the cliquishness in CP

Determinants of the cliquishness The role of cliquishness in the characterization of the emergence of the communities practice has been studied by us in a previous article (see [Dupouët and al., 2003]) and above. In particular, we have established in this article that the communities of practice should correspond to a *cliquishness* around 0.3. Figures 13 and 14 show that the determinants of the social structure are quite different in these two organizational structures.

HD with communications Three variables intervene in the emergence of communities in the case HD: *consultRatio*, *exval* and *compRange*. When *consultRatio* is low (*consultRatio* ≤ 0.11), then no communities can emerge and the value of *cliquishness* is almost one of a random graph. When $0.11 \leq$ *consultRatio* $<$

0.35, then *exval* has to be quite high, that is there must be some kind of fidelity in relationships between agents, in order to observe communities. Even when *consultRatio* is higher, *exval* still has to be above 3.5 to obtain high values of *cliquishness*. In any case, *compRange* has to be above a certain threshold to have values of *cliquishness* corresponding to full-fledged communities of practice.

CP with communications The same three parameters are the determinants in the emergence of communities in the case CP. However, *compRange* (that is the level of specialisation of agents) plays here a less important role than in the case HD. As in the previous case, when *consultRatio* is low, high values of *exval* help reaching reasonably high values of *cliquishness* (i.e. $exval = 0.14$). The highest values of *cliquishness* are attained for high values of *consultRatio* and *exval*. Hence, in order to build communities of practice, agents needs both a great ability to screen their social environment and a certain stability in their relationships.

4 Conclusion

This article analyses the potential impact that can have informal social structures, communities of practice, upon the performance of firms or subunits of firms.

The first result of this work is to show that community structures are efficient for competence building, and particularly, if one considers learning in the long term (i.e. without strong time constraints). However, real firms are required to answer demands from the market in a timely fashion. In these cases, this work tends to show that hierarchy altogether with communities of practice is the most efficient structure among those we explore. This paper thus backs the claim made by Bowles and Gintis [2000] that hierarchy and communities are complementary rather than substitute modes of governance.

Moreover, the examination of the interrelations between variables reveals that two of them are especially crucial for the emergence of communities and their performances: the degree of specialisation of agents and the conditions of communication between them. If the former clearly depends on the individual agent, the second can be seen as part of the environment in which communities exist (e.g. the efforts made by the management to ease communication, the existence of an intranet, etc.). In the case of HD, one must add the behavior of management to the two previous parameters. The way managers apprehend their task has an influence both on the conditions of emergence of communities within the firm and on the global performance of the organisation. It is the interplay between agents idiosyncratic capacities and manager's behavior that ends up in an organisation's specific outcome.

However, we are well aware that this can only constitute an exploratory work on these issues. Regarding communities, the detailed dynamics of their behavior has not been explored. In particular, the legitimate peripheral participation process that Lave and Wenger [1990] put at the heart of the evolution of communities' structure has not been explored. Besides, concerning the incentives and motivations for agents to enter in a community, we have assumed that the agents are always willing to enhance their individual competences by resorting to communities. This assumption is common in the literature about communities of practice but would certainly deserve a deeper exploration.

Our model with hierarchy also focuses on some key aspects and leaves many other features unaddressed. For instance, the fostering of communities of practice is not considered as a strategic issue by the manager, whereas this is certainly a main concern in management studies today. Moreover, we here only dealt with a specific form of hierarchy where the manager is engaged in a learning process. It could also be interesting to investigate a more rigid hierarchy where the manager strongly prescribes the tasks to agents without seeking to take into account their learning curves or specialisation.

All these limitations highlight the work that remains to be done in modeling the behavior and the role of communities within firms. It is hoped that this work contributes to open the way to these future researches.

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Appendix: Values of the exogenous parameters and initialisation of the model

Meaning	**Name**	**Value**
Number of experiments	*nbRuns*	500
Number of problems submitted to the system during one experiment	*maxProblems*	15000
Probability to save the data for statistical treatment	*saveProb*	0.01
Number of agents in the organization	$totalNumberOfAgents$	50
Number of bits used to code one variable of the problem	*Bits*	4
Number of variables in the problem	*NbVar*	2
Level of specialization of agents (1=maximally generalists, 0=maximally specialized)	*compRange*	$\in [0,1]$
Percentage of the population that can be asked at random during agents' communications	*consultRatio*	$\in [0,1]$
Number of periods during which an agent is kept in an addressbook even if it does not provide any answer anymore	$n\ (exval)$	$\in [1,14]$
Select the mode of selection of agents by the manager (0 = roulette wheel, 1 = best action)	*selectMan*	$\in \{0,1\}$
Select the mode of selection of answers to the environment by agents (0 = roulette wheel, 1 = best action)	*selectAg*	$\in \{0,1\}$
Number of dontCare symbols allowed in classifiers	*P_dontCare*	$\in [0,0.025]$
Threshold for the application of GA in the action set of agents and manager	*theta_GA*	$\in [15,35]$
Parameters of the XCS:		
Number of classifier in agents' memory	*maxPopSize*	50 for agents;
		3000 for manager
Decrease rate for fitness evaluation	$alpha$	0.1
Learning rate for fitness, error, prediction and action set size updating	*beta*	0.2
Fraction of the mean fitness below which a classifier enters in its probability of deletion	*delta*	0.1
Exponent in the function of fitness evaluation	*nu*	5
Error threshold below which prediction error of a classifier is set to 1	*epsilon_0*	10
Experience threshold above which a classifier can be deleted	*theta_del*	20
Probability of crossover (in GA)	*pX*	0.8
Probability of mutation (in GA)	*pM*	0.03
Decrease in error when a new classifier is generated by GA	$predictionErrorReduction$	0.25
Decrease in fitness when a new classifier is generated by GA	$fitnessReduction$	0.1
Initial prediction of a classifier	*predicitonIni*	10.0
Initial error of a classifier	$predictionErrorIni$	0.0
Initial fitness of a classifier	$fitnessIni$	0.01