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Effects of competition on collective learning in advice networks

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ABSTRACT

This paper looks at the effect of identifying alters as direct competitors on their selection as advisors. We differentiate between two kinds of competition: cut-throat vs friendly. We argue that, unlike cut-throat competition, friendly competition makes collective learning possible as a social process: when knowledge is built in interactions that are able to mitigate the negative effects of status competition and take place in homophilous social niches; and when the quality of this knowledge is guaranteed by members with epistemic status in these niches. Social niches and status facilitate advice seeking and collective learning because advice seeking between direct competitors is not obvious even when members have a common interest in sharing advice – a learning-related dilemma of collective action. We apply this reasoning to a network dataset combining identification of direct competitors and selection of advisors among the elite of cancer researchers in France. We use a procedure of multiplex stochastic block-modeling designed by Barbillon et al. (2015) to measure the effect of these identifications of direct competitors on the structure of the advice network. Results obtained with this dataset support our theory.

1. Is it rational to seek advice from direct competitors?

In her book on the legacy of high stalinism in China, Dream of a Red Factory (Kaple, 1993), Deborah Kaple tells a surprising anecdote of rotten advice shared between two powerful leaders at the highest level of geopolitics. This story begins 1949 with Comrade Mao waiting for weeks in his hotel room in Moscow before he is able to meet Comrade Stalin and seek advice about how to rebuild China after the 1949 Revolution and civil war. Stalin advises to implement in China a Soviet post-WWII Recovery Plan. He presents the Plan to Mao as a great success in rebuilding the Soviet Union in just five years. In fact the Plan worked in the Soviet Union in part because a "very large backlog of unexploited economic potential and more efficient repression were two sources of postwar Soviet economic resilience" (Harrison, 1985); the other part of the Plan was propaganda. Therefore the Chinese revolutionaries should not have trusted and taken at face value the idea that this overambitious and long-range Plan was recyclable at home. By taking the advice and using the Plan to organize the Chinese buildup, Mao fails and ends up wasting a decade of Chinese economic history (and probably dozens of millions of lives due to famine). Relationships between the two powers will more than suffer for two generations as a consequence. One could guess that, in this story, Mao does not think of Stalin as a direct competitor but as a Comrade, perhaps only as a "friendly" competitor. But Kaple (1993) shows that Stalin and his thousands of Soviet experts – who were sent to China to further advise – despise the Chinese and probably think in terms of direct competition between their leaderships and opposition between their countries. Such an asymmetry raises a more general question: What is the effect of competition on collective learning, i.e. on the way in which we think with others and build common knowledge with them? In some ways, competition should terminate the social exchange between advisor and advice seeker because it makes listening to advice provided by a "cut-throat" competitor quite risky. That piece of advice could be difficult to evaluate, if not rotten. But obviously it is not that simple. Sometimes actors do not have much choice in terms of selection of advisors. In other circumstances, many – like Mao – think that it is still rational or reasonable to seek advice from friendly competitors, if not from cut-throat competitors, but that assessment can be wrong. Thus the question becomes Under what circumstances do actors define a direct competitor as friendly, as opposed to cut-throat, and seek advice from him/her?

We can rephrase this question from a more theoretical perspective in sociology. At the individual level, status competition is both stimulating and potentially detrimental for individuals (where it can cause stress, frustration, and anti-social tendencies, to put it mildly). At the system level, it can hold members with status

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accountable, but also cause segregation and create severe obstacles to cooperation. For organizations and individuals to function, there need to be ways to mitigate these negative consequences, and eventually foster its potentially positive consequences. Relational embedding as such is one pathway for the latter: use of homophily and relationships by members (Lazega and Van Duijn, 1997) can provide this mitigation. But one puzzle remains: in many settings, individuals have to cooperate with competitors, or more specifically, they have to ask and give advice to/from other members whom they perceive to be direct competitors. This is the substantive research gap on which our study focuses, since to our knowledge the literature does not address this issue.

Our main argument is that unlike previous research, which pointed towards various forms of embeddedness, cooperation between competitors requires to think beyond embeddedness (Lazega, 2001), i.e. to think in terms of social processes that rely on existing relational infrastructures (social niches and social status in particular) helping members manage the dilemmas of collective action, i.e. cooperate with competitors. In particular a neo-structural approach defines a social niche analytically as a dense subset of structurally equivalent members of a collective among whom resources of all kinds can be exchanged and accessed at a lower cost than outside the niche. Indeed the individual and system level assumptions as they follow from a neo-structural approach are that members of a social niche share common reflexivity and appropriateness judgments (Lazega, 1992), i.e. identity criteria, cultural rules and status representation of the collective, which allows them to impose upon themselves a form of self-discipline that facilitates system-level social processes such as solidarity (and exclusion), control (and conflict resolution), socialization (and collective learning) and regulation (and institutionalization). These social processes represent social dynamics that are different from embeddedness or from routine solutions to the problem of status competition. They tend to be activated in contexts that are not bureaucratic.

From this perspective, it is useful to clarify the following: relationships between different forms of relational infrastructure (niches and status, for example) are not easy to assess. In particular, niches are a necessary condition to mitigate negative effects of status competition. This should become visible when specific social processes are examined and modeled using network analysis (Lazega, 2001). Here we focus on a relatively well known social process, i.e. collective learning, as measured by advice networks. One implication is that those who engage in advice relations with others not in the same social niche are likely to experience more negative consequences than if they do so within their niche. Without assuming deterministic relationship between niche-membership and advice-seeking, we argue that an indicator of the strength of this kind of management of dilemmas of collective action shows in the fact that individuals will tend to select advisors in their own niche, even if they perceive their advisor to be direct competitors. In this paper, our study measures and models advice relations among direct competitors and shows in what context such complex relationships are likely to emerge: contexts in which social niches include many members with high levels of social status. We do not measure and model the consequences of such advice relationships between direct competitors, but we use the consequences as a crucial assumption to formulate our hypotheses. We test this in our data using an adapted blockmodeling method and back up this claim with findings from previous research.

1.1. Collective learning in advice networks

A useful starting point is a sociological theory of "how learning is social". A micro-sociology of knowledge focuses on how actors elaborate interactively what they can claim to know and what they perceive to be "appropriate" information (Lazega, 1992) to be taken into account in decision making and orientation of action. In order to be taken into account collectively, knowledge claims must be evaluated as appropriate. This elaboration of appropriateness judgments is not trivial, but it is often tacit. Also it is not exclusively carried out in one person's head, but interactive. In particular, when faced with uncertainties associated with non-routine tasks, actors can seek advice from others who will help build these appropriateness judgments more explicitly. Learning is thus collective[1] because members of a social setting access tacit knowledge through interactions with advisors who may themselves interact with each other. Advice networks are thus a collective learning mechanism because they help generate a form of shared knowledge. The structure of these networks matters for the ways in which this social mechanism takes place. For example since advice networks are usually centralized, specific members with higher indegrees are likely to set the premises of many decisions in that setting. Their role is thus crucial in the collective learning process.

Seeking advice is a complex interaction. Blau (1955, 1964) theorized advice seeking as a social exchange. The advice seeker obtains appropriate information in exchange for deference and recognition of social status of the advisor. Social exchange is needed – as opposed, for example, to market exchange – because it is not uncommon that the advice seeker comes to reformulate with the adviser the question itself which was being asked initially. The advice seeker is in a situation of uncertainty about the very nature of the demand, the latter often including a request for social approval or legitimization. Social status criteria are thus important when selecting an adviser. In such social exchanges the advice seeker nevertheless exposes him.herself to opportunistic behavior by the advisor who is sometimes in a position to take advantage of the advice seeker's weaknesses and resources.

Network analysts have studied advice networks (Agneessens and Wittek, 2012; Barley, 1990; Borgatti and Cross, 2003; Brass, 1984; Cerne et al., 2013; Cross et al., 2001; Hansen, 2002; Kilduff and Tsai, 2003; Krackhardt, 1987, 1990; Lazega and Van Duijn, 1997; McDonald and Westphal, 2003; Rulke and Galaskiewicz, 2000; Tsai, 2002), or sometimes simply discussion networks, as social exchange in Blau's sense. They confirm that recognition of social status gratifies the advisers and provides them with an incentive to share their knowledge and their experience. But social exchange can also have negative effects for the collective. For example, one consequence of such status competition in advice seeking is that, at least in formally organized contexts, members tend to avoid seeking advice from the colleagues "below" them in the formal hierarchy or in the pecking order regardless of whether or not the colleagues "below" are more competent.

We also know that members use homophily in relationships to mitigate such status constraints and help with access to advisors, upwards and downwards, who are usually inaccessible due to purely strategic considerations (Lazega and Van Duijn, 1997; McPherson et al., 2001). Indeed, empirical research finds that actors use many ways to attenuate the harshness of this status rule. They use several kinds of similarities among themselves to counteract the conflicting effects of status competition. This use of homophily in the choice of advisors allows members to find "shortcuts" in

[1] Terms such as collective learning are used in multiple ways in the social science literature, either at a very general level of abstraction (Brown and Duguid, 2000; Favereau, 1994; Lam, 2000; Wenger, 1998) or in more applied perspectives, for example in work on intra-organizational learning (Argyris and Schön, 1978 and the tradition that they created) and collective learning across organizations in many specialties such as education (for example De Laat and Simons, 2002), regional economics (for example Keeble et al. (1999)) or economic sociology (for example Pina-Stranger and Lazega, 2010). Given the purposes of this paper, we rely on a more neo-structural perspective based on network analysis (Lazega et al., 2004a, 2006).

the access to intelligence necessary to solve problems. Thus, to the extent that advice networks are structured by status competition and by its mitigation, they tend to become both hierarchical and cohesive, the hierarchical dimension being often stronger than the cohesive dimension. Of course there is, by definition, a structural limit to this, because higher degrees of hierarchy imply lower degrees of cohesion and vice versa. But one of the causes and consequences of this cohesive dimension is that advice networks are also strongly embedded in other types of social networks that help with mitigating the status rule.

This paper describes the way in which the intersection of networks can be a social and informal mechanism that helps collectives deal with potentially negative effects of status competition between members. We identify our main contribution as twofold. Firstly, we describe how a specific kind of relational infrastructure in members' networks provides this social and informal mechanism. Secondly, we use a specific data analysis method that is important to test the presence of this informal mechanism.

It is therefore worthwhile to ask whether advice seeking as a complex interaction and social exchange is disrupted when the advice seeker recognizes the advisor as a direct competitor, including status competitor. When carrying out complex and specialized tasks, for example, professionals often realize, when they need advice, that others who could help them out are in fact others specialized in the same area of expertise. These others could be, directly or indirectly, competitors. The nature of this relationship thus seems paradoxical. It is our purpose here to further explore this paradox by looking at the social conditions under which direct competitors are seen as friendly, as opposed to cut-throat.

1.2. *Relational infrastructure turning cut-throat competition into friendly competition*

This statement is equivalent to asking what are the organizational and social conditions under which competition becomes manageable and productive instead of destructive. We use a neo-structural theory to guide research that answers this question. It would be far too long, and it is not our purpose, to present all the assumptions at the actor level and at the system level that we include in this theory, not to mention how they are linked. Nor is it our purpose to test this theory, which is based on social exchange, against another theory, such as specific versions of social capital theory (Agneessens and Wittek, 2012) as an alternative set of explanations of the choice of advisors emphasizing different motives (i.e. seeking advice creates obligations that the advice giver may 'cash in' at a later stage). Instead, we first list some of our main assumptions, derive new hypotheses from them, and propose a rare set of data and a methodological innovation, multiplex stochastic blockmodeling, to test them.

From our perspective, preferences and constraints at the actor level are the following. Individuals value status, and want to avoid status loss. Carrying out professional tasks produces status. Carrying out professional tasks requires specialized knowledge. Seeking advice reduces status. Seeking advice from a similar other does not lead to status loss (or at least leads to less status loss than seeking advice from a dissimilar other) (Lazega and Van Duijn, 1997). Seeking advice from competitors reduces status and carries the risk of additional damages (e.g. wrong information). Seeking advice from non-competitors reduces status, but does not carry additional risks. Seeking advice from competitors in the same social niche does not reduce status, and does not carry additional risks.

In addition, we build on several system level assumptions. Not all individuals in the system have all the necessary specialized knowledge that is necessary to carry out their tasks on their own. Specialized knowledge is distributed in the system so that there is a high likelihood that the only source for the necessary knowledge is a competitor, rather than a non-competitor. Seeking advice from actors in the system under investigation (here the case of French cancer researchers) is the main instrument to increase specialized knowledge (i.e. alternatives are not relevant or too costly). The system is composed of structural positions that either qualify as social niches or do not qualify as such. Analytically, a position qualifies as a social niche if its members are highly interconnected through cooperation relations (including advice ties), are highly similar in terms of a variety of attributes, and share a similar pattern of relationships to members outside the social niche (Lazega, 2001).

There is not much room in this paper for a systematic theoretical discussion of these underlying assumptions. Some are more debatable than others. For example, we assume that asking advice from similar others would temper status competition. This is so because similarities can become the basis for homophilous choices. One could of course argue that status competition increases with similarity, because the more similar we are, the more likely we compete for the same scarce goods. But based on neo-structural approach, actors involved in social exchange use decision criteria that are not cost-benefit reasonings, but appropriateness judgments. Based on such judgments, rivalry is kept in check by affiliation in the same reference group, sharing the same norms and alignment towards the same significant others (Lazega, 1992). Accordingly, we consider that social niches are the first condition to enable cooperation among competitors, and that individuals know their position as a member of such a niche. This is what explains that their advice seeking behavior is facilitated by their niche membership. We believe that it is very likely that individual actors are aware of which structural position in the system s.he occupies. Of course they do not compute such positions as network analysts do, but they perceive and endogenize the structure (defined in terms of vertical and horizontal differentiations) and think in terms of "people in my position/group/role behave in such or such a way".

If social niches are intuitively perceived by actors who belong to them, the system that such niches create together (with inter-niches dependencies) may not be known or perceived by all individuals in the same way. At the system level, it is more realistic to assume that the system of social niches is the (partly unintended) outcome of individual actors trying to use advice seeking as an instrument to reach their desired outcomes (status), given specific constraints (a pre-existing organizational structure, knowledge, risk of damages), and that the relative social price of seeking advice differs across potential advice givers depending on their qualities (knowledge, competitor, similar or not).

The neo-structural theory of cooperation among competitors (Lazega, 2009, but see also, from a different perspective, Porac et al., 1989) predicts that cut-throat competition can be managed and transformed into friendly competition (for example monopolistic competition into an oligopolistic cartel) when competitors succeed in building stabilized relational infrastructure carrying with them a form of social discipline[2] that facilitates the management of their dilemmas of collective action. These elements of relational infrastructure are mainly social niches and social status. Social niches are defined analytically as dense and multiplex blocks in which members use homophily in their social exchanges to get easier access to resources and precisely to mitigate the potentially negative effects of status competition. Social status helps with providing members with a mandate to speak on behalf of the collective, as well as with resources, among which knowledge with the right incentives to share this knowledge in Blau-type social exchange, in legitimizing or authorizing this sharing by watching over their own status as

[2] Emphasizing relational infrastructure does not mean that culturally acquired social skills are not necessary to reach this goal and enforce this discipline; we focus here on factors that can be identified through social networks.

advisors and over the status of other niche members (Burt, 2004). Watching means both "paying attention to" and, up to a point, "protecting" each other's status, i.e., for example, defending a reputation, provided the favor can be returned, when it is attacked (Burt, 2005).[3] These are not equivalent conditions: vertical and horizontal differentiations are always present in collective actors but they come in a great variety of realizations. Our theoretical argument is indeed that social niches are a necessary condition to mitigate negative effects of status competition, but we also want to show how the distribution of status in the system provides social niches with enough members with status yielding enough authority to maintain and guarantee members' commitment to the quality of advice that is exchanged in the niche. These elements of relational infrastructure should thus help turn cut-throat competition into more friendly competition from which advice can be, in principle, sought out more safely.

Thus we argue that an individual member of the niche will be more inclined to seek advice from another niche member whom s.he perceives to be a direct competitor if they are both members in a social niche with many high status players, compared to a situation in which both are in a social niche with few high status players. If someone is a member of only one social niche, and this niche happens to fall into the first category, then we argue that this individual would find a safer environment to engage in this advice relationship. This individual would face more risks if s.he would choose a direct competitor from another niche, regardless of whether this other niche has less or more high status players. But this individual would also face more risks if s.he would choose as an advisor another niche co-member who is perceived to be a direct competitor if their common niche has less high status members. This is equivalent to saying that niches with few high status members provide somewhat less protection (to their own members) against the negative consequences of status competition than niches with many high status players. Many high status members in the same niche lower niche members inclination to engage in cut-throat competition with other niche members when they happen to be direct competitors. We argue that when many high status players coexist in a social niche they are able collectively to enforce the rules of this protection against opportunistic behavior.

Based on our assumptions and description of the resulting mechanisms, we derive the following hypotheses.

2. Hypotheses

In theory, it is mainly in social niches that advice seeking among competitors should take place and that members can afford to take the risk to seek advice from direct competitors. Interdependencies increase the cost of opportunistic behavior. This leads to a first testable hypothesis:

> Actors tend to seek advice from direct competitors when both focal actors and competitors belong to the same social niche.

Belonging to the same social niche leads actors to define competitors as friendly more easily, and allows them to seek advice from these competitors more easily than if the latter did not belong to the same niche. This does not mean that a friendly competitor is only someone whom actors would seek out for advice. Actors can define an alter in a niche as a friendly competitor also if they do not seek advice from them or if they have other kinds of relationships with them (e.g. the competitor could be just a friend, not an advisor). Our purpose is not to restrict the conceptualization of a friendly competitor to someone who can be sought out for advice. It is to identify a niche effect on competitive behavior using advice seeking as an indicator of this effect.

In addition members with high social status will help guarantee and legitimize this use of homophily and the quality of the knowledge shared in homophilous interactions. They do so, for example, by watching over their own status as advisors and over the status of other niche members, whether in the face of external threats to status or internal threats to status by members who want to break away from cooperation and switch to cut-throat competition, i.e. for example providing deliberately wrong advice, like Staline with Mao, and/or behaving in a predatory way with the advice seeker's resources or projects. This would have as a consequence, in the advice network, that direct competitors would be avoided. With this avoidance valuable knowledge and perspective would be lost instead of being shared, with collective benefits (collective learning) also lost for the whole group. A second testable hypothesis can therefore be formulated as follows:

> The more high status members in a social niche, the more focal actors are likely to seek advice from direct competitors in that social niche.

In our view Hypothesis 2 is a further specification of Hypothesis 1. Both are true at the same time but Hypothesis 2 adds a new dimension to the general argument in which Hypothesis 1 is already a basic proposition. Hypothesis 1 is about likelihood of seeking advice from a direct competitor in the niche, compared to seeking advice from a direct competitor not in the niche: the reference category are dyads in which advice seeker and advice giver are members of different niches - one expects within-niche advice dyads to be more likely than other advice dyads – which is what the analysis in the paper will try to show. For Hypothesis 2, the reference category is other social niches: we expect a higher incidence of advice dyads in which the advisor is perceived (by the advice seeker) to be a direct competitor to occur in niches with a specific characteristic, i.e. high number of high status players, compared to niches with a low number of high status players.

3. Coopetition among cancer researchers: a case study in the sociology of science

Our empirical setting is the community of elite cancer researchers in France in 1999–2000. Coopetitive situations, i.e. situations in which actors cooperate with direct competitors, are particularly interesting settings to test these ideas about determinants of collective learning in social exchange. Previous empirical research in coopetitive milieux has identified the existence of these elements of relational infrastructure but it has always just "assumed", based on ethnographic research, that friendly competition existed where it was detecting them and combined with successful outcomes in terms of performance. In this paper we are able to further confirm this theory and ground it empirically using a previously unexploited variable that measures who identifies whom as a direct competitor in a coopetitive milieu for which we also have social network data about advice relationships between members. The coopetitive milieu on which we focus is scientific research, in which members have conflicting interests: one the one hand they need to master collectively new tasks and instruments in order to solve a whole series of problems as quickly as possible; but on the other hand they also want to defend their own individual interest in this competitive endeavor characterized by a 'winner-take-all' rule.

[3] A niche member's high status, expressed for example in good reputation, can benefit the other members of the niche. Burt (2004), for example, calls this reflected prominence. This is an incentive to care about and watch over the status of others. This provides a net individual and collective payoff which helps managing underlying social dilemma.

The focus is on researchers very active in their field at that time, all part of the French research establishment. Being all tenured, competition can be strong, turn friendly or cut-throat (even if the cut-throat dimension is probably less frequent than in more private settings) because they have the possibility to hurt each other's interests.[4] An "elite" among them was selected based on the number of highly rated publications that they signed during 1996, 1997 and the first semester of 1998. This produced a list of 168 "multipublishers" who were particularly productive and "visible". Out of 168, 128 persons (76%) accepted to be interviewed. Each time a researcher was selected, the directors of his/her laboratory was also selected so that we could keep track of the multilevel connection. The directors of the largest 82 laboratories were also interviewed.

Researchers were considered to be "entrepreneurs" who need resources to produce – resources that can be social as much as monetary (Blau, 1964). Their work was analytically decomposed into a sequence of tasks. We focused on the non routine tasks generating a high degree of uncertainty[5] and triggering advice seeking. We assume that, in these situations of uncertainty and in a competitive environment, access to advisors constitutes an important social resource for the actor. Performing these tasks is made easier if the researcher can, for each task, seek advice from competent colleagues. This analytic decomposition of the production process distinguished five steps: (1) Discuss the global orientation of one's work in progress or of one's projects; (2) consult with colleagues to find the right contacts to develop the project; (3) consult with colleagues concerning financial issues before submitting the project to funding institutions or companies; (4) consult with colleagues for the recruitment of collaborators; (5) seeking advice on one's manuscripts before submission to journals.

The picture of the researcher's work that this analytic decomposition provides is necessarily simplified. However qualitative interviews show that these were among the main social resources that researchers seek out in their non-routine work at least in the French institutional context. This decomposition helped to examine the flows of specific social resources in the elite of French cancerology of that time. Based on the methodology of social network analysis (Wasserman and Faust, 1994), data also includes characteristics of researchers, of their various networks (in the elite of researchers), and a series of dependent variables. At the level of laboratories the data includes characteristics of the top 86 laboratories and exchanges of resources among them. Interorganizational networks were reconstituted for several resources tracking the sharing of equipment, recruitment of post-docs and researchers, etc. The goal at the time was to look at the extent to which success in publishing so much could be explained by the researcher's personal network among the elites of other researchers, or by the characteristics of the laboratory (including their boss's network) and its position in the system of laboratories. Performance was measured by a score based on the impact factor of the journal in which the publications of each researcher come out.

French cancer research in 1999 brings together a great number of sub-specialties; each sub-specialty focuses on a different organ of the human body and represents a specific scientific subculture. A collegial oligarchy consisting of roughly thirty persons, most of whom belong to the category that was labeled the "big fish in the big pond" (Lazega et al., 2008), controlled the circulation of resources in inter-individual and inter-organizational networks. The "oligarchs" are often directors of a unit, and between 40 and 56 years of age. As in other areas of scientific research, middle-aged actors are key actors of the system (Zuckerman, 1977). They worked more frequently in institutions situated in Ile-de-France (i.e. in and around Paris) than the other researchers interviewed. They were usually professors of medicine, and, with the exception of three among them (who identify themselves with pure fundamental research), they were involved in both clinical and fundamental research. As expected from the literature (Crane, 1972; Hagstrom, 1965), different kinds of homophilous social preferences, as well as formal or informal markers of compartmentalization, characterize the interactions between the members of this population. Clinicians and professors of medicine, for example, have a tendency to cite amongst themselves (as sources of advice) more often than they cite fundamental researchers. Research laboratories are connected by the proximity of their research topics and by mutual surveillance resulting from competition among them. But they are also connected by scientific exchanges, and by the sharing of materials in complex configurations that combine disciplines, localization, and institutional membership. The units that exchanged the most housed the researchers who obtained the highest impact factor scores. Fundamental researchers had less administrative responsibilities and probably signed their own research. Located primarily in Ile-de-France, they worked in specialties generating high impact factor scores (hematology-immunology in particular), especially when combined with fundamental research.

Members of the collegial oligarchy at the top of this milieu are more often cited as former professors and former colleagues by the researchers interviewed. They are also more present than the others in boards of research and hospital institutions, scientific committees and scientific journals. In addition to this status hierarchy each specialty has its own history and dense niches. 'Health campuses' such as research hospitals (e.g. Marie Curie hospital, or the Institut Gustave Roussy) work on facilitating exchanges between specialties by looking for complementarities between them (Lazega et al., 2004b). This history of patronage relations (seniors who were thesis advisors of juniors, etc.) points to a common history of cooperation – other than in the form of advice relations – between the actors in this system. Especially within specialties, these researchers publish together, so many dyads may have a history of collaboration.

French oncology was a young discipline (Mulkay et al., 1976; Stofer, 2001) dominated, during this period, by studies in hematology-immunology. Blood cells were easily available for analysis. In addition, as explained by one of the researchers of our population at the time (2000) "(. . .) the problems that leukemia poses are relatively simple: the tumors are monoclonal, you find pure molecular events there (. . .) Hematologists-immunologists consequently recruited sharp molecular biologists very quickly. Solid tumors are infinitely more complex; they are just starting right now to become accessible to fundamental research". The "small world" at the top of French cancer research was stratified, but this sub-specialty (hematology-immunology) was also well organized, prestigious, and recognized by the general public. For several generations, it had benefited from considerable institutional investments. In particular, it was the first in French cancer research specialty to learn and use collectively the methods of molecular biology. During the 1970s a famous and politically well-connected hematologist, Jean Bernard, was able to incite the members of the specialty to learn very quickly how to use this approach (or else to lose funding). A spectacular collective learning process took place that helped the specialty to become world leader in publications on leukemia for twenty years.

Hematologists became an aristocracy among cancer researchers, but also among MDs in general. It became a very tightly structured specialty characterized by a form of social discipline

[4] We heard many paranoid, Goffman-like stories (always happening in "other labs") about how competition can bring your laboratory on its knees, for example by having someone switch off your freezers for a couple of hours.

[5] About non routine tasks and personalization of work relationships as indicators of collegiality, see Lazega (2001)).

that led them to collaborate and publish together under the above-mentioned history of patronage relations. As shown by Gueneau de Mussy (2011), over time (between 1989 and 2010, i.e. from ten years before fieldwork to ten years after fieldwork), copublication networks are denser among hematologists than in the other specialties of this population. These researchers' performance was in turn an outcome of this coordination and collective learning capacity. This capacity is all the more impressive that the members of this specialty were all involved in status competition with each other as well as in competition for resources and publication. Belonging to a social niche allowed them to mitigate this status competition, benefit from rapid coorientation and convert these advantages into higher than average performance, even among elites. This discipline also characterized the relationship between laboratory directors, especially the largest ones, who participated in the *collégiale* of their specialty – a committee that managed careers and budgets that could be compared to the economic equivalent of a guild or even a cartel. The social capital of the laboratories mattered even more than the relational capital and strategies of the researchers in explaining this performance and productivity (Lazega et al., 2008).

This was made possible by the fact that, more than fundamental, bench-centered researchers, hematologists are usually clinical researchers interacting with real patients, which in general encourages advice seeking between colleagues around the patient.[6] It was also made easier by the fact that all these researchers are tenured. They still compete for resources from the same sources, for access to equipment, for the best collaborators, etc. The organization of research did set them against each other. But in such a situation cut-throat competition is more likely to be counter-productive than in other contexts.

We insist on both long term investments in this specialty and in the social discipline that hematologists-immunologists were able to bring into their scientific discipline because the latter represents an important factor to bear in mind to understand results of analyses presented below. Indeed that fact that an interpersonal social niche existed in this system for hematologists working on leukemia, bringing together competing laboratories in the field is an indicator of the social discipline that characterized this segment of the system. Its members were direct competitors, had relatively cooperative relational strategies and were at the time the most successful actors in cancer research. These analyses were based on the observation of advice networks between researchers associated to the five steps identified above and by measurements of impact factor scores associated with their publications. In the present paper we combine this dataset with a previously unexploited variable measuring who identifies whom as a direct competitor in this coopetitive milieu.

4. Data on direct competitors and method of analysis

Indeed we were able to test these hypotheses by using the network dataset described above but also the fact that the persons interviewed were willing to identify their own direct competitors after having identified their sources of advice. The question about competitors was formulated as follows: "Is there in this list one or several persons whom you consider to be direct competitors in your specialty?". One possible reason for which these scientists were willing to provide these names is that our survey was conducted with the help (funds and introduction) of a charity that represented for many of them a respectable proportion of their research budget. They know that the evaluation of the projects that they used to submit to this organization was carried out by colleagues who were often direct competitors. They were all at the same time principal investigators with submitted projects and evaluators of other colleagues' project. By naming their direct competitors, some of our respondents were explicitly thinking that this information would be used by this charity so that direct competitors would not be selected as reviewers for their projects.[7]

In order to test these hypotheses, it is important to recall that a social niche is not just a clique, a dense subgroup in a predefined social milieu. As defined in Lazega (2001), it is a cohesive subgroup where members are (approximately) structurally equivalent, i.e. a dense block in a system of blocks. A social niche makes sense only in a system of social niches. In the spirit of White et al. (1976), it is a position in a system of positions that represents a role set, i.e. a form of division of work, exactly what blockmodeling helps tease out of network data. Therefore blockmodeling is an ideal method to test these hypotheses. In the following section we present two approaches used for these tests: firstly multiplex stochastic blockmodeling designed by Barbillon et al. (2015); secondly, an analysis of the status of the members of these niches that will help check that status – that is needed for this process to succeed – is indeed observable in the niches.

4.1. Stochastic Block Models for multiplex data

At the end of their Generalized Blockmodeling (2005) (Doreian et al., 2005), Doreian, Batagelj and Ferligoj invite researchers to explore new block types and new blockmodels and to examine the use of these methods in various disciplines. Stochastic Block Models (SBM) are now a widespread approach for grouping individuals (actors) with respect to their social behavior and characteristics (see Nowicki and Snijders, 2001; Snijders and Nowicki, 1997 and references inside) because it allows to conclude – as will be shown below – both at the dyadic and group level simultaneously. In a stochastic blockmodel (SBM) pairwise relations between nodes are the fundamental unit. Each node is assigned to a block and ties are realizations of independent random variables between nodes pairs with probabilities depending only on the group memberships of the nodes. The distribution of ties is assumed to be homogeneous conditionally on the clusters of the nodes. Consistency and asymptotic normality of maximum likelihood estimation of probability of connection between nodes allow the comparison as well the test of hypothesis about cluster properties. The basic assumption underlying dyadic models is that dyads are conditionally independent given the model's parameters.

SBM is not a purely exploratory and inductive technique. It assumes that relationships in data can be explained by latent clusters and its modeling has been expanded to handle stochastic processes. This model-based method uses statistical tools to estimate the relational structure in the observed system as in the classical approach by Snijders and Nowicki (Snijders and Nowicki, 1997; Nowicki and Snijders, 2001). The generative process of SBM starts with a cluster membership of the actors: two actors are stochastically equivalent if they are similar with respect to a probability distribution. All nodes in a given block share the same probabilities of connection with other nodes in the network. This stochastic equivalence is used to group nodes together according to their similarity of connection patterns. SBMs consider the observed network as a random realization from a sample space of all possible networks. The relational structure is seen as a system of blocks. This model-based method relates the observable network data to unobservable parameters of interest with a statistical model.

[6] Actually, in 2009, nine years after fieldwork, it became mandatory in France to discuss the cases formally for the constitution of a patient-centered dossier called DCC (i.e. dossier communicant de cancérologie).

[7] As indicated explicitly to the interviewees, however, our confidentiality rules did not allow us to share this data with the charity that funded our study.

One of the main interests of SBM is the ability to finalize and test hypotheses about the structure of the network both at the dyadic and block levels. Originally developed for uniplex networks, they were extended to multiplex networks by Barbillon et al. (2015). In this work, we observe two networks, respectively the "competition" and "advice" networks, defined on the same set of actors. For any pair of actors $(i, j) \in \{1, n\}^2$ $(i \neq j)$, we set $C_{i,j} = 1$ if j is designed by i as a direct competitors, $C_{i,j} = 0$ otherwise. Similarly, we set $A_{i,j} = 1$ if i declared that s.he seeks advice from j, $A_{i,j} = 0$ otherwise. Multiplex SBMs set a joint probability distribution on the couple $(C_{i,j}, A_{i,j}) \in \{(0, 0), (0, 1), (1, 0), (1, 1)\}$.

In the clustering context, we assume that any actor i belongs to a group q $(q \in \{1, \ldots, Q\})$ and these memberships drive the probabilities of connexion. In other works, let Z_i be a non-observed random variable such that Z_i is equal to q if the individual i belongs to group q. For any $i = 1, \ldots, n$:

$$P(Z_i = q) = \alpha_q, \quad \forall q = 1, \ldots, Q \tag{1}$$

and $\sum_{q=1}^{Q} \alpha_q = 1$. Given these memberships to Q groups, we define a probability distribution for $(C_{i,j}, A_{i,j})$ as: for any $w \in \{(0, 0), (0, 1), (1, 0), (1, 1)\}$:

$$P((C_{i,j}, A_{i,j}) = w \quad |Z_i = q, Z_j = l) = \pi_{ql}^{(w)}, \quad \forall (i, j) \in \{1, n\}^2$$

with, $\forall (q, l) \in \{1, \ldots, Q\}$, $\sum_w \pi_{ql}^{(w)} = 1$.

Remark 1. Note that, conditionally to the group memberships Z_i, the pairs of variables $(C_{i,j}, A_{i,j})_{(i,j) \in \{1,\ldots,n\}^2}$ are independent. However, the integration over the random variables $(Z_i)_{i \in \{1,\ldots,n\}}$ introduces a dependence and so models patterns of connection between the individuals that are not purely regular.

The parameters of interest are not only $\theta = (\pi_{ql}^{(w)}, \alpha_q)_{(q,l) \in \{1,\ldots,Q\}}$ but also the membership variables $(Z_i)_{i \in \{1,\ldots,n\}}$. An estimation of these parameters is obtained by likelihood maximization. However, due to the presence of the latent variables (Z_i), maximizing the likelihood function is a challenging computational task. Daudin et al. (2008) proposed a variational version of the Expectation-Maximization (EM). The algorithm was adapted to the multiplex context by Barbillon et al. (2015). The authors also propose criteria to select the adequate number of groups Q. Based on this algorithm, SBM is used in the next session to analyze the network and attribute data collected among French cancer researchers who seek advice from selected peers.

5. Results on the interaction between identification of direct competitors and selection of advisors

Together, the dataset and the method provide a good test of our hypotheses and of the robustness of this neo-structural theory of advice-seeking among cut-throat vs. friendly competitors and collective learning in advice networks.

5.1. Preliminary description of the data

Overall few individuals in this population identify a colleague as a direct competitor and even fewer are identified as such. We plot in Fig. 1 the distributions of the indegrees and outdegrees for the competition and advice networks.

We note that the competition indegree distribution is heavy tailed, meaning that a small set of individuals are often identified as direct competitors, whereas the majority of researchers are never identified as such. Moreover, by calculating the correlation

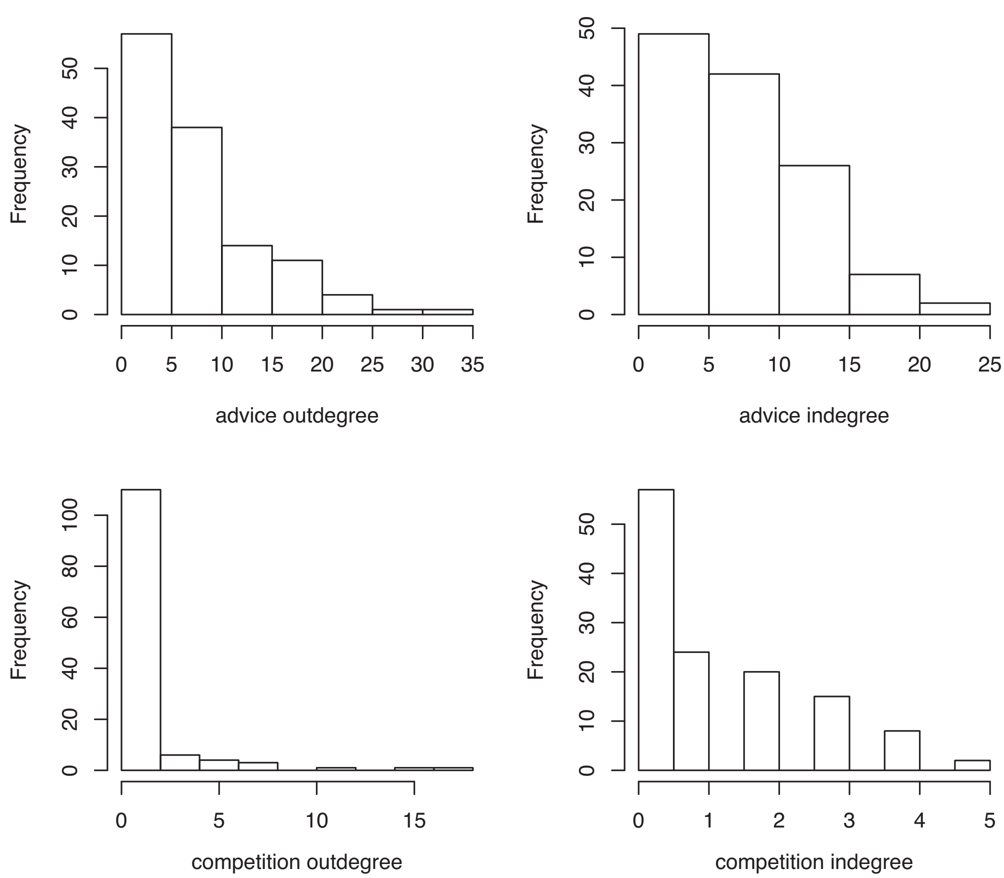


Fig. 1. Distributions of indegrees and outdegrees for the competition identification and advice networks.

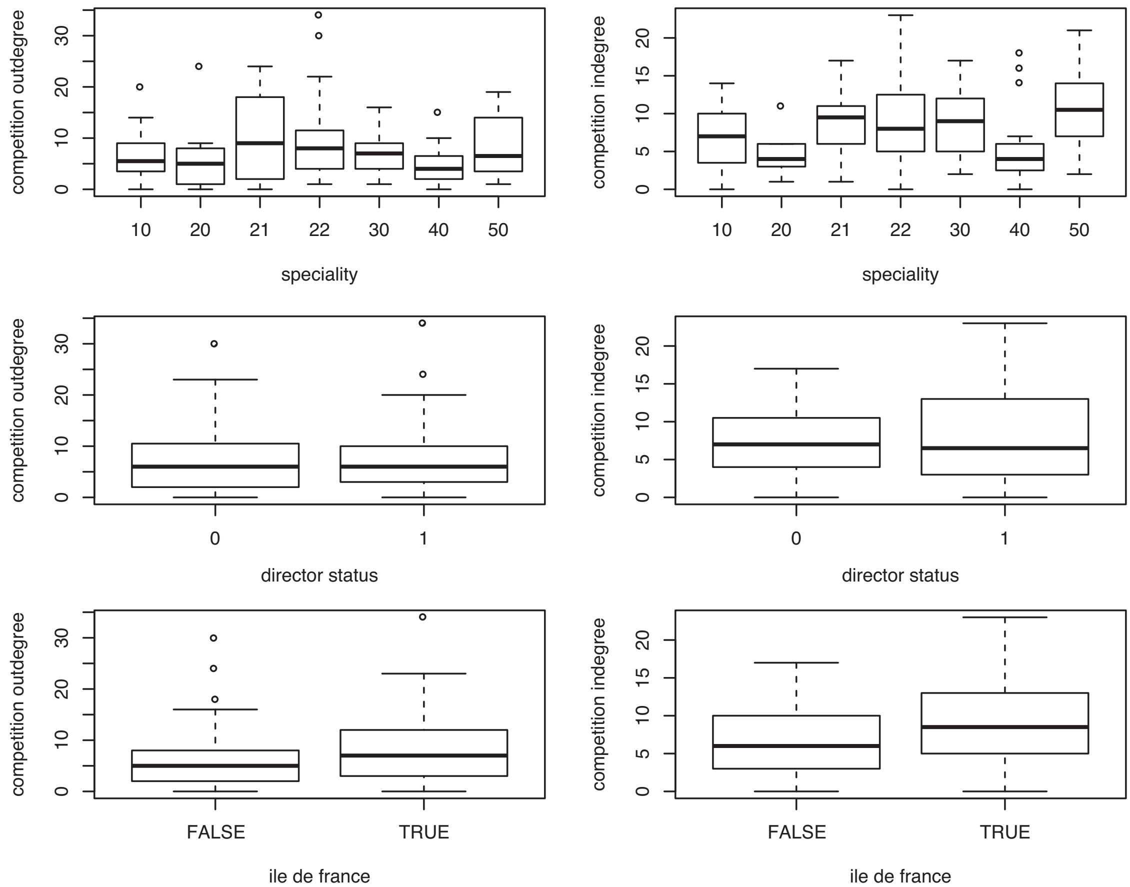


Fig. 2. Boxplots for the advice network. Specialty codes are given in Footnote 8.

between the advice outdegree and the competitors indegree (equal to 0.34), we also note that the more an actor seeks advice, the more s.he is identified as a direct competitor. Besides, those identified as competitors very often are also those identified as central advisors (high indegree) (correlation between the two indegrees here being 0.48).

To study the covariates, Figs. 2 and 3 provide the boxplot of the in and out degrees for the advice and competition networks, with respect to specialties, formal status (director or not) and localization (around Paris or not). It demonstrates that formal status does not influence the competitor and advisors position. However, it is interesting to notice that the proportion of persons who are identified as direct competitors varies with the specialties.[8]

5.2. Application of multiplex SBM

Applying this method provides an estimated relational structure for the system and a model for the connectivity between blocks. We use this as a way to test our first hypothesis. The estimation identifies the best possible decomposition of the two networks into such blocks as well as the associated connectivity rules.

Multiplex blockmodeling models these aggregated advice and competition networks together as a duplex network and shows several features of this system of epistemic interdependencies. Firstly, according to the ICL criteria, the blockmodel with three groups provides the best fit with the data.[9] The three blocks identified by Multiplex SBM have respectively 61, 17, and 48 researchers.

Figs. 4 and 5 present the probabilities of connexions once the multiplex clustering has been carried out. More precisely, Fig. 4 presents the estimated marginal and conditional probabilities of advice connections within and between groups whereas Fig. 5 presents the estimated marginal and conditional probabilities of identification of direct competition connections within and between groups. In each case, the complete matrix connexion on the right is summarized by a graph on the left. In the graph, vertex size is proportional to the block size and edge width is proportional to the probabilities of connection; if this probability is smaller than 0.1, edges are not displayed.

First, a quick examination of Figs. 4 and 5 proves that the two kinds of links are dependent. Indeed, for instance, the conditional probabilities $P(A_{ij}=1|C_{ij}=1, Z_i, Z_j)$ are greater than the marginal ones $P(A_{ij}=1|Z_i, Z_j)$ for any Z_i, Z_j. Note that in the second block there is a high proportion of members seeking advice from each other and calling each other direct competitors. This proportion is provided

[8] Specialty codes are as follows:

- 10 Diagnostics-epidemiology-prevention
- 20 Clinical research without fundamental research (Surgery, Radiology)
- 21 Clinical research with fundamental research (Hematology-immunology)
- 22 Clinical research without fundamental research Others (Solid tumors, Chemotherapy)
- 30 Fundamental research – Pharmacology
- 40 Fundamental research – Molecular/cellular
- 50 Fundamental research – Molecular/Genetics.

[9] A four-block structure is very close in terms of fit and was duly scrutinized. In the four-block structure, the block of hematologists does not change in composition or in ties to other blocks. Block 3 breaks down into two blocks which does not change the interpretation of this structure from our perspective.

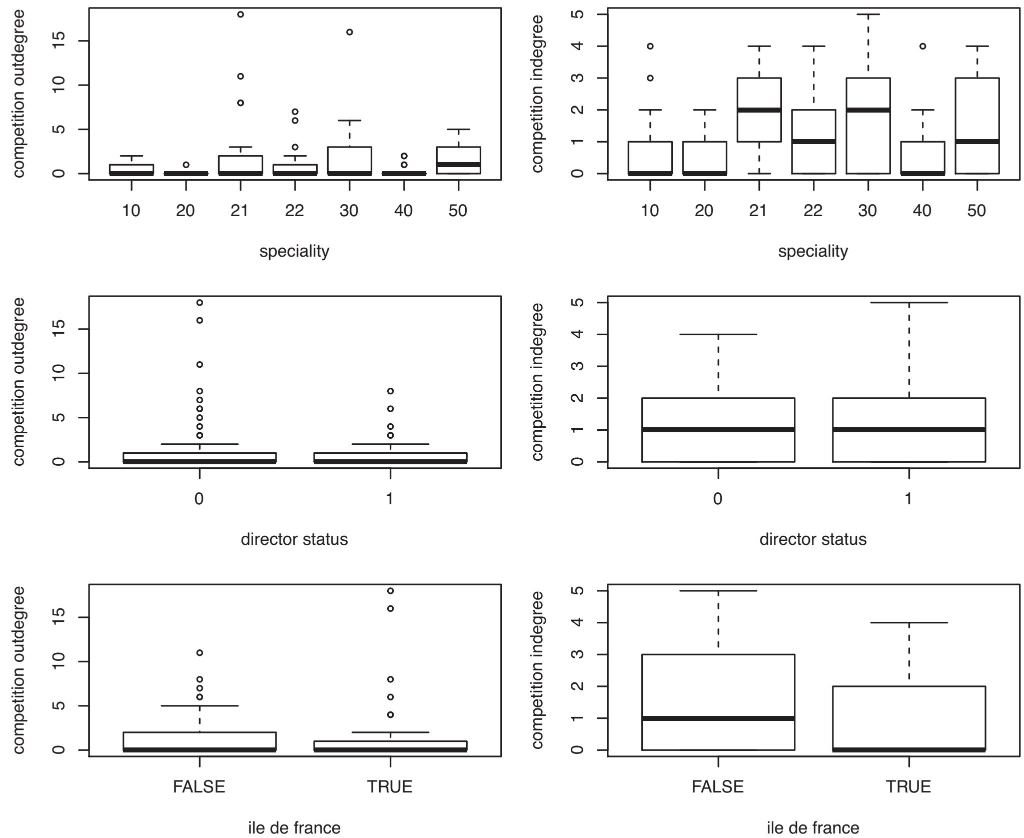


Fig. 3. Boxplots for the competition identification network. Specialty codes are given in Footnote 8.

by the conditional probability $P(A_{ij} = 1|C_{ij} = 1, Z_i, Z_j)$ (Fig. 4(e)). This shows that this is a dyadic-level effect as much as a niche-level effect. These are indeed mainly the same dyads that seek advice from each other and call each other direct competitors. SBM allows to conclude both at the dyadic and group level simultaneously.

Before studying precisely the groups, note that SBM has led to three blocks which corresponds to three levels of within connexion probabilities. We now study this composition of blocks more accurately. Table 1 describes this composition in terms of specialties, localization, fish/pond clustering (Lazega et al., 2008) and status (Fig. 6).

The first block clusters together a very heterogeneous set of researchers with a variety of specialties. The second block brings together a strong majority of researchers from clinical hematology-immunology with relatively low formal hierarchical status (not many research directors among them) and carrying out fundamental research as well. The third block is also very heterogeneous but with a large minority of solid tumors researchers. Indeed, Block 3 is mostly composed of specialty 22 (solid tumors) in the Paris region; at the time, this collection of sub-specialties was not socially as organized as hematology-immunology, and certainly not as much as it is today (2015) with progress made by knowledge of the genome.

From Fig. 4, we notice that interblock advice relations are rare, whether or not the blocks are dense, i.e. block members tend not to seek advice from colleagues in other blocks. The marginal distribution of advice relationships between researchers shows that people in Block 1 seek less advice than others in general. In this structure, the density table (Fig. 4) shows that only one position exhibits both a strong density of advice seeking and a much higher frequency of mutual identification of co-members in the block as

Table 1
(a) Cross frequencies of blocks versus researcher specialties. (b) Cross frequencies of blocks versus the lab location (in Île-de-France (IdF) or not). (c) Cross frequencies of memberships given by the SBM with frequencies given by Lazega et al. (2008) Small/Big Fish in Small/Big Pond (NA not available memberships due to missing data). (d) Cross frequencies of blocks versus researcher's status (laboratory director or not).

(a)

	10	20	21	22	30	40	50
1	10	6	8	8	7	18	4
2	3	0	13	0	0	0	1
3	7	3	1	19	6	5	7

(b)

	Not	Idf
1	35	26
2	11	6
3	14	34

(c)

	NA	BF: BP/SP	SF: BP/SP
1	10	7/3	22/19
2	5	6/6	0/0
3	14	18/10	3/3

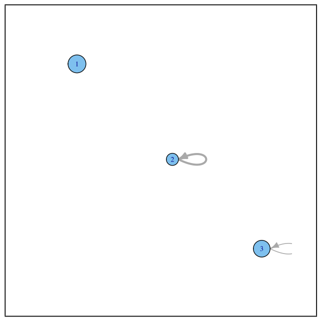
(d)

	Not director	Director
1	37	24
2	12	5
3	27	21

(a) $P(A_{ij} = 1|Z_i, Z_j)$

Z_i \ Z_j	1	2	3
1	0.02	0.02	0.03
2	0.04	0.46	0.05
3	0.04	0.04	0.18

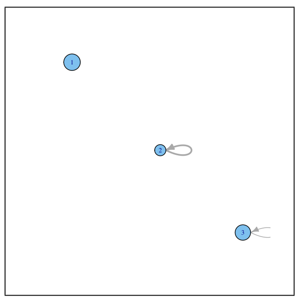
(b)



(c) $P(A_{ij} = 1|C_{ij} = 0, Z_i, Z_j)$

Z_i \ Z_j	1	2	3
1	0.02	0.01	0.02
2	0.04	0.41	0.04
3	0.04	0.04	0.17

(d)



(e) $P(A_{ij} = 1|C_{ij} = 1, Z_i, Z_j)$

Z_i \ Z_j	1	2	3
1	0.53	0.20	0.31
2	0.70	0.88	0.78
3	0.72	1.00	0.69

(f)

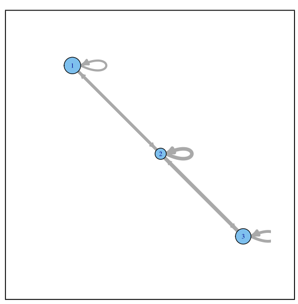
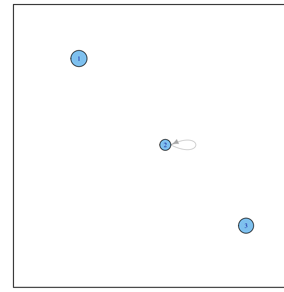


Fig. 4. Probabilities of advice relation between and within blocks. Marginal probabilities (top-left) and probabilities of advice connections between and within blocks conditionally to absence (middle-left) or presence (bottom-left) of competition connection. Corresponding graph on the right: vertex size is proportional to the block size. Edge width is proportional to the probabilities of connection; if this probability is smaller than 0.1, edges are not displayed.

(a) $P(C_{ij} = 1|Z_i, Z_j)$

Z_i \ Z_j	1	2	3
1	00.0	0 0.00	0.01
2	0.01	0.11	0.01
3	0.00	0.00	0.02

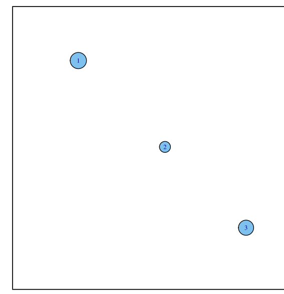
(b)



(c) $P(C_{ij} = 1|A_{ij} = 0, Z_i, Z_j)$

Z_i \ Z_j	1	2	3
1	0	0.00	0.00
2	0	0.03	0.00
3	0	0.00	0.01

(d)



(e) $P(C_{ij} = 1|A_{ij} = 1, Z_i, Z_j)$

Z_i \ Z_j	1	2	3
1	0.10	0.06	0.07
2	0.15	0.22	0.18
3	0.09	0.06	0.08

(f)

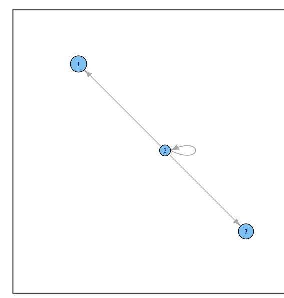


Fig. 5. Probabilities of competition identification between and within blocks. Marginal probabilities (top-left) and probabilities of competition identification connections between and within blocks conditionally to absence (middle-left) or presence (bottom-left) of an advice connection. Corresponding graph on the right: vertex size is proportional to the block size. Edge width is proportional to the probabilities of connection; if this probability is smaller than 0.1, edges are not displayed.

direct competitors. Fig. 4 shows that Block 2 is very dense (0.46) and Block 3 much less so (0.18) than Block 2. Block 2 is the only social niche in the system and it is precisely the block of hematologists that we described above. Block 1 members seek advice and are sought out for advice much less than Block 2 and 3 members. On average there are also more people identified as direct competitors in Block 2 than in the others. This does not vary with age, or performance, although performance levels during period 1 (1996–2000) and period 2 (2001–2005) are slightly higher on average for Block 2 members (see Table 1).

Specialties 21, 22, 30 and 50 have on average slightly more persons identified as direct competitors. Among these three blocks, Block 2 has the highest proportion of direct competition identifications by its own members (and by members of other Blocks). Identifying a direct competitor among hematologists is more frequent than in general in the network, especially more so when there is an advice tie than when there is no such a tie. Most members of this social niche are relatively young and ambitious MDs who are not yet directors of a research laboratory, who carry out research and write papers to get their PhD and become PU-PH (Professeur des Universités – Praticien Hospitalier) for which they need a doctoral dissertation in science, and therefore publications. They are clinicians maintaining a strong relationship with fundamental research, they are not in the Paris region, not directors of their laboratory, central in the network of cancer researchers (big fish), and in labs that are not the largest. Given that they will compete in the future for high level positions, seeking advice from each other could be delicate but it is not necessarily embarrassing or damaging when it is not systematic and when both benefit over time. Composition, structure and performance level of Block 2 are consistent with our knowledge of the reality of cancer research at the time, as presented above.

In that respect, our first hypothesis is confirmed. It is where there is a dense social niche, with the possibility to use homophily to select advisors based on similarity in scientific specialty, that members take the risk of seeking advice from colleagues whom they identify as direct competitors.

6. Status and the capacity to maintain the quality of advice in the social niche

Our second hypothesis requires a test of the extent to which there are members with high social status in the niche that will help

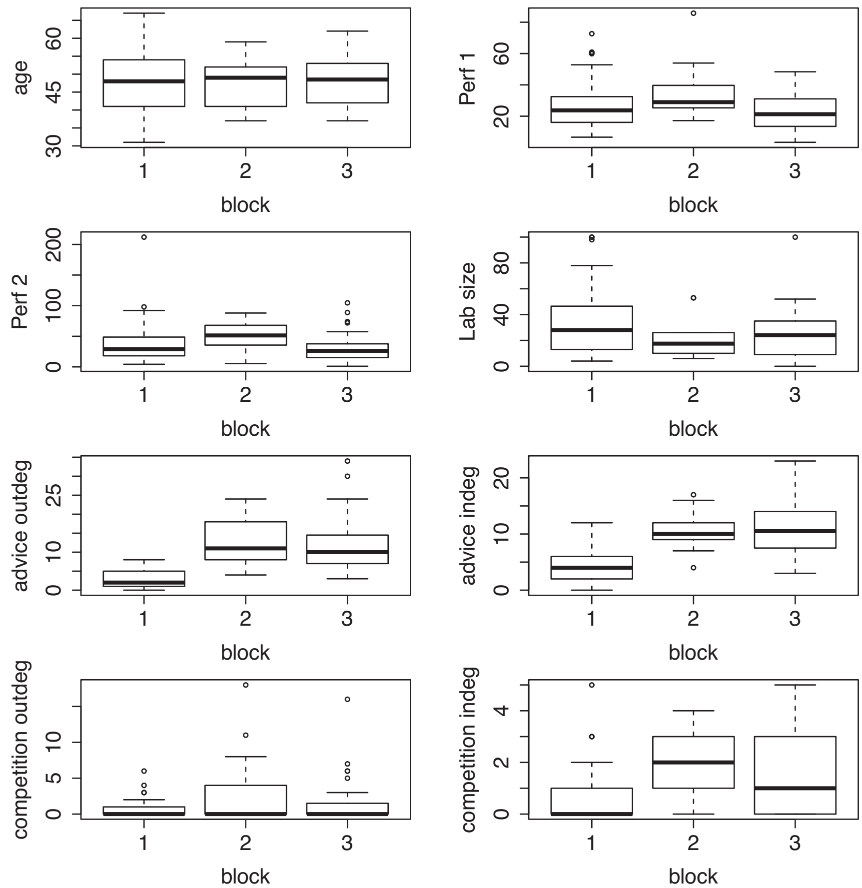


Fig. 6. Boxplot given the clusters.

guarantee that actors are in a context of friendly competition and legitimize this use of homophily and the quality of the knowledge shared in homophilous interactions. As flows of advice are shown to be consistently shaped by status competition and the pecking order in the system, it is important to check that this social niche is also endowed with enough members with relatively high status who can enforce the social discipline that facilitates risky advice seeking. It is therefore useful to look at the formal and informal stratification in this system.

This advice network has a high number of local epistemic leaders to seek advice from. Fig. 7 is a visual representation of the informal pecking order in the advice network examined here, i.e. of epistemic status differences between researchers in the system. Degree distributions presented in Fig. 7 show that this advice network is centralized but not very strongly. The degree distribution in the advice network shows that "centralization in" is relatively weak which means that there are many local epistemic leaders in this research system specialized in cancer. Many non-directors of laboratories are as central in the advice networks as the directors. In the French cancer research system at that time, high levels of status tend to be shared by many researchers with local forms of epistemic status. Part of local leaders' job is to make sure that members of their laboratories and collaboration networks respect the rules of friendly competition instead of creating a violent and pathogenic environment. There are many such colleagues who can enforce the social discipline when there is one. As we know, a formal hierarchy exists in laboratories in the sense that researchers work under the administrative responsibility of directors of laboratories who are also scientists with administrative responsibilities and who run the laboratory. But formal hierarchy matters less among scientists than among other professions. As shown by Fig. 1, there are many local leaders in this advice network. The latter is weakly centralized (centralization in: 11.87%; centralization out: 21.67%; average degree: 7.12).

In order to further identify these local epistemic leaders we introduce a multilevel covariate in the analysis of this multiplex blockmodel. This multilevel dimension of the dataset is based on the possibility of dual-positioning actors in this research ecosystem (Lazega et al., 2008), as well as in an extension of this approach in Bellotti (2012). This approach helps here in looking for combinations of niches and status as relational infrastructure facilitating the taming of direct, cut-throat competition. Using centrality of researchers in their aggregated advice network and centrality and size of the laboratories in the inter-organizational network, as well as affiliation of individuals in laboratories, researchers are defined as BFBP, BFSP, LFBP and LFSP. Using this variable Table 1 shows that Block 1 has a lot more little fish than big fish, equally in big ponds and small ponds. Block 2 has only big fish. Block 3 has mostly big fish equally in big and small ponds.

In sum, seeking advice from colleagues identified as direct competitors takes place mainly among hematologists – in their specific social niche with its own social discipline – who are all big fish, i.e. with indegrees higher than the median for that network. Big fish, being more senior scientists, also belong to boards of journals and to scientific advisory boards of charities distributing resources to this very population of researchers. They are assumed by others to have means to retaliate in case an advisor behaves too opportunistically and does not respect the social discipline of their scientific specialty – for example by hurting the advisor's status. This status-related retaliation capacity is used among Block 2 members and it is not directly available to the usually more junior colleagues (although tenured already, as all the members of these elite). Not one single

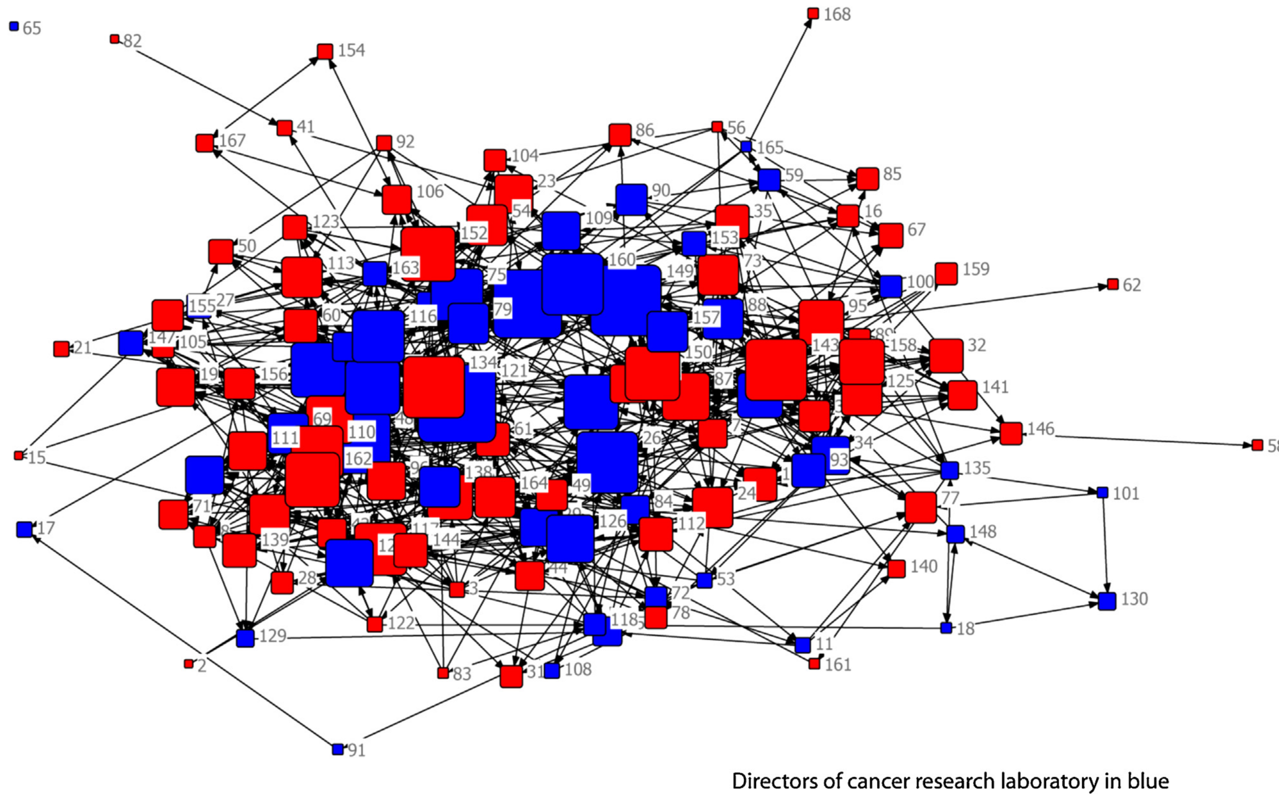


Fig. 7. *Many local epistemic leaders to seek advice from: Low centralization of a network in which local status matters as much as global status.* Status is measured here based on indegree centrality in the advice network among scientists. Researchers who are directors of their laboratory are represented in blue. The picture shows a large number of non-laboratory directors (in red) with high levels of indegree centrality in the network, i.e. with high levels of epistemic status in the learning process among peers, and thus with enforcement capacity in socially-disciplined status competition. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

little fish seeks advice from a declared direct competitor. Thus it is the combination of the existence of social niche membership with specialty homophily backed up by relatively high epistemic status among the members of the niche that helps the latter in seeking advice from peers whom they identify as direct competitors.

Thus, our second hypothesis is confirmed. It is not only specialty-based homophily that creates friendly competition in the social niche: it is homophily backed up by hierarchical authority and legitimacy of local epistemic leaders within the niche.

7. Discussion and conclusion

Seeking advice is a complex activity involving social exchange of appropriate information for deference and recognition of epistemic status of the advisor. We asked whether this kind of social exchange is disrupted when the advice seeker identifies the advisor as a direct competitor. In some ways it should terminate this exchange because competition makes this advice seeking quite risky. The worse risk is that advice provided is rotten, as in the example of Stalin and Mao. The neo-structural theory of cooperation among competitors predicts that competition is managed in a non-disruptive, even constructive way when competitors can build the relational infrastructure and social discipline that help them manage the dilemmas of their collective action. The elements of this relational infrastructure are social status and social niches. Previous empirical research in coopetitive milieux has identified their existence but it has always assumed, based on ethnographic evidence, that competitive behavior actually existed where it was detecting these elements. In this paper we were able to further confirm this theory using a previously unexploited variable in a dataset that measures who identifies whom as a direct competitor in a coopetitive milieu.

To summarize, results obtained with this dataset show that striking a fragile balance between advice giving and competition by playing with the (unspoken) social rules of status mitigation tends to be possible for some researchers, those belonging to a social niche, more than for others. Our empirical results confirm that members of the most successful segment of the profession at the time were socially organized in such a way (detected through this relational infrastructure) that it was possible for them to seek advice from colleagues whom they identified as direct competitors, much more than it was possible for members of different, less organized and less disciplined specialties.

We used a specific kind of multiplex stochastic blockmodeling to confirm that members of this successful segment were endowed at the time with these relational infrastructures and were socially organized in such a way. Indeed multiplex SBM identifies the only strong collective actor in this system, a block coming out of the discipline of hematology-immunology. In particular the combination of both dimensions of relational infrastructure is worth mentioning here because it sheds more light on the ways in which social discipline in the niche is backed up with more status-related retaliation power. Thus this dataset and this analysis provide support to the claim that actors find it socially rational, or at least reasonable, to seek advice from direct competitors when both focal actors and competitors belong to the same social niche and when they can use status-based homophily to signal the capacity to ruin the status of colleagues if they behave too opportunistically. Discourse by the members of this milieu attributes the organization of this collective actor to the top down efforts by one of their charismatic leaders, Jean Bernard; but as shown by our results this organization is as much a distributed relational construct by the members of an elite, a collegial oligarchy, in this scientific discipline.

Thus in this paper we provide support for the neo-structural theory of cooperation among competitors, at least in the sociology of science. The problem with Mao seeking advice from Stalin was that the former believed that the latter was part of a common niche, whereas the latter did not. When assumptions differ among actors about the strength of their common identifications and about the kind of competition that exists between them, friendly competitors stand to lose out. As in the prisonner's dilemma, knowing this, competitors are more easily driven to stop learning collectively, which can lower the capacity of a community to adapt and manage change.

Two limitations of this paper deserve to be explicitly mentioned for future research. First, we do believe, as explicitly mentioned in Section 1.2, that individuals know their position as members of a social niche. By assuming that, we run the risk of circular reasoning by explaining the choice of advisors using network positions based on the choice of advisors. This is due to the fact that we do not have longitudinal data: niche membership may very well be a strong constraint on selecting advisors and the level of recursivity in this effect should be specified with longitudinal data exposing the nature of these dynamics. Longitudinal data would thus be needed to better manage this risk. However from the perspective of a social rationality, using social niches as a predictor of advice relations is not necessarily based on pure circular reasoning: explaining the choice of advisors based on appropriateness judgments does not mean that network position is the only variable grounding these judgments, even if previous choices of advisors drive the perception of network position itself.

Second, a multilevel perspective should also be introduced to better understand the effect of competition on collective learning in advice networks. For example, relational strategies derived from overlaps between individual members' networks and their organizational networks show that collective learning by individuals is influenced by the organizational context. Therefore more can be done, for example, to read the blockmodels from a multilevel perspective (Žiberna, 2014). An organizational effect exists in this situation because researchers perceive each other as members of the same specialty but also as members of competing laboratories: the extent to which members of competing laboratories perceive each other as competitors at the individual level remains to be established. A multilevel approach also identifies extended opportunity structures (Lazega et al., 2013). Combined with the system of blocks, the friendly competition structure could provide actors without ties to the outside of their niche with opportunities to access other blocks through dual alters, and thus surprisingly to extend their capacity to learn from remote sources via direct competitors. Thus complex data structures using multilevel and longitudinal datasets should allow to further understand the effects of competition on learning.

Finally, the usefulness of stabilized relational infrastructure for collective learning could be taken into account by educational policies focusing for example on lifelong learning. We believe that based on insights such as that presented here, policies should not separate formal education institutions from informal learning taking place – as in our example – in structures of secondary socialization. Educational and research institutions as organized settings could perhaps be able to provide more systematically the context of friendly competition in which collective learning as an informal relational process takes place. Designing education policy, for example, would require more attention to the impossibilities of collective learning in a context of cut-throat competition, and to the conditions under which friendly competition can be fostered to make collective learning and adaptation to change possible. Whether in institutions of education or in the design and management of future knowledge commons (Lazega, forthcoming), the social discipline on which we just had a glimpse in this case can safeguard pupils and citizens from knowledge regimes that create, organize and spread ignorance by using and routinizing competition in purely bureaucratic ways, instead of carefully promoting relational infrastructures that foster cooperation among competitors in more collegial collective learning. Needless to say, in that area, much remains to be done.

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References

Agneessens, F., Wittek, R., 2012. Where do intra-organizational advice relations come from? The role of informal status and social capital in social exchange. Soc. Netw. 34 (3), 333–345.
Argyris, C., Schön, D.A., 1978. Organizational Learning: A Theory of Action Perspective, vol. 173. Addison-Wesley Reading, MA.
Barbillon, P., Donnet, S., Lazega, E., Bar-Hen, A., 2015. Stochastic Block Models for Multiplex Networks: An Application to Networks of Researchers, arXiv:1501.06444***.
Barley, S.R., 1990. The alignment of technology and structure through roles and networks. Admin. Sci. Q., 61–103.
Bellotti, E., 2012. Getting funded. multi-level network of physicists in Italy. Soc. Netw. 34 (2), 215–229.
Blau, P.M., 1955. The Dynamics of Bureaucracy: A Study of Interpersonal Relations in Two Government Agencies. Chicago, U.P.
Blau, P.M., 1964. Exchange and Power in Social Life. Transaction Publishers.
Borgatti, S.P., Cross, R., 2003. A relational view of information seeking and learning in social networks. Manag. Sci. 49 (4), 432–445.
Brass, D.J., 1984. Being in the right place: a structural analysis of individual influence in an organization. Admin. Sci. Q., 518–539.
Brown, J.S., Duguid, P., 2000. The Social Life of Information. Harvard Business Press.
Burt, R.S., 2004. Structural holes and good ideas1. Am. J. Sociol. 110 (2), 349–399.
Burt, R.S., 2005. Brokerage and Closure: An Introduction to Social Capital. Oxford University Press.
Cerne, M., Nerstad, C., Dysvik, A., Škerlavaj, M., 2013. What goes around comes around: knowledge hiding, perceived motivational climate, and creativity. Acad. Manag. J., amj-2012.
Crane, D., 1972. Invisible Colleges: Diffusion of Knowledge in Scientific Communities.
Cross, R., Borgatti, S.P., Parker, A., 2001. Beyond answers: dimensions of the advice network. Soc. Netw. 23 (3), 215–235.
Daudin, J.J., Picard, F., Robin, S., 2008. A mixture model for random graphs. Stat. Comput. 18 (June (2)), 173–183.
De Laat, M.F., Simons, P., 2002. Collective learning: theoretical perspectives and ways to support networked learning. Eur. J. Vocat. Train. 27 (3), 13–24.
Doreian, P., Batagelj, V., Ferligoj, A., 2005. Generalized Blockmodeling, vol. 25. Cambridge University Press.
Favereau, O., 1994. Règles, organisation et apprentissage collectif: un paradigme non standard pour trois théories hétérodoxes. Anal. Econ. Conv., 113–137.
Gueneau de Mussy, T., 2011. Reading and Writing: Advice Ties and Scientific Collaboration among Elite French Cancer Researchers from 1989 to 2010, Master 2 Project Report.
Hagstrom, W.O., 1965. The Scientific Community, vol. 304. Basic Books, New York.
Hansen, M.T., 2002. Knowledge networks: explaining effective knowledge sharing in multiunit companies. Organ. Sci. 13 (3), 232–248.
Harrison, M., 1985. Primary accumulation in the soviet transition. J. Dev. Stud. 22 (1), 81–103.
Kaple, D.A., 1993. Dream of a Red Factory: The Legacy of High Stalinism in China: The Legacy of High Stalinism in China. Oxford University Press.
Keeble, D., Lawson, C., Moore, B., Wilkinson, F., 1999. Collective learning processes, networking and 'institutional thickness' in the Cambridge region. Reg. Stud. 33 (4), 319–332.
Kilduff, M., Tsai, W., 2003. Social Networks and Organizations. Sage.
Krackhardt, D., 1987. Cognitive social structures. Soc. Netw. 9 (2), 109–134.
Krackhardt, D., 1990. Assessing the political landscape: structure, cognition, and power in organizations. Admin. Sci. Q., 342–369.
Lam, A., 2000. Tacit knowledge, organizational learning and societal institutions: an integrated framework. Organ. Stud. 21 (3), 487–513.
Lazega, E., 1992. The Micropolitics of Knowledge. Communication and Indirect Control in Workgroups, New York.
Lazega, E., 2001. The Collegial Phenomenon: The Social Mechanisms of Cooperation among Peers in a Corporate Law Partnership. Oxford University Press.

Lazega, E., 2009. Theory of cooperation among competitors: a neo-structural approach. Sociologica 1, 1–34.

Lazega, E., 2016. Networks and commons: organizational morphogenesis in the struggles to shape new sharing/taxing institutions. In: Archer's, M.S. (Ed.), Human Flourishing and Social Morphogenesis, Vol. V. Springer Verlag (forthcoming).

Lazega, E., Jourda, M.-T., Mounier, L., 2013. Network lift from dual alters: extended opportunity structures from a multilevel and structural perspective. Eur. Sociol. Rev., jct002.

Lazega, E., Jourda, M.-T., Mounier, L., Stofer, R., 2008. Catching up with big fish in the big pond? Multi-level network analysis through linked design. Soc. Netw. 30 (2), 159–176.

Lazega, E., Lemercier, C., Mounier, U., 2006. A spinning top model of formal organization and informal behavior: dynamics of advice networks among judges in a commercial court. Eur. Manag. Rev. 3 (2), 113–122.

Lazega, E., Mounier, L., Stofer, R., Tripier, A., 2004a. Discipline scientifique et discipline sociale: réseaux de conseil, apprentissage collectif et innovation dans la recherche française sur le cancer (1997–1999). Rech. Sociol. 35 (3), 3–28.

Lazega, E., Van Duijn, M., 1997. Position in formal structure, personal characteristics and choices of advisors in a law firm: a logistic regression model for dyadic network data. Soc. Netw. 19 (4), 375–397.

Lazega, E., Mounier, L., Stofer, R., Tripier, A., 2004b. Discipline scientifique et discipline sociale: réseaux de conseil, apprentissage collectif et innovation dans la recherche française sur le cancer (1997–1999). Rech. Sociol. 35 (1), 3–27.

McDonald, M.L., Westphal, J.D., 2003. Getting by with the advice of their friends: Ceos' advice networks and firms' strategic responses to poor performance. Admin. Sci. Q. 48 (1), 1–32.

McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. Annu. Rev. Sociol., 415–444.

Mulkay, M., Edge, D., Lemaine, G., 1976. Perspectives on the Emergence of Scientific Disciplines.

Nowicki, K., Snijders, T.A.B., 2001. Estimation and prediction for stochastic blockstructures. J. Am. Stat. Assoc. 96 (455), 1077–1087, http://dx.doi.org/10.1198/016214501753208735.

Pina-Stranger, A., Lazega, E., 2010. Inter-organisational collective learning: the case of biotechnology in France. Eur. J. Int. Manag. 4 (6), 602–620.

Porac, J.F., Thomas, H., Baden-Fuller, C., 1989. Competitive groups as cognitive communities: the case of Scottish knitwear manufacturers. J. Manag. Stud. 26 (4), 397–416.

Rulke, D.L., Galaskiewicz, J., 2000. Distribution of knowledge, group network structure, and group performance. Manag. Sci. 46 (5), 612–625.

Snijders, T.A., Nowicki, K., 1997. Estimation and prediction for stochastic blockmodels for graphs with latent block structure. J. Classif. 14 (1), 75–100.

Stofer, R., 2001. Gestion de la concurrence dans un système d'échange semi-collégial. les réseaux de conseils, de copublication et de citation au sein de l'élite des chercheurs français en cancérologie de 1996 à 1998 (Ph.D. thesis). Thèse de Doctorat de sociologie, Université des Sciences et Technologies de Lille.

Tsai, W., 2002. Social structure of "coopetition" within a multiunit organization: coordination, competition, and intraorganizational knowledge sharing. Organ. Sci. 13 (2), 179–190.

Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications, vol. 8. Cambridge university Press.

Wenger, E., 1998. Communities of Practice: Learning, Meaning, and Identity. Cambridge, New York.

White, H.C., Boorman, S.A., Breiger, R.L., 1976. Social structure from multiple networks. I. Blockmodels of roles and positions. Am. J. Sociol., 730–780.

Žiberna, A., 2014. Blockmodeling of multilevel networks. Soc. Netw. 39, 46–61.

Zuckerman, H., 1977. Scientific Elite: Nobel Laureates in the United States. Transaction Publishers.