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Team formation and performance on nanoHub: a network selection challenge in scientific communities[1]

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This study proposes a rationale by which researchers can use network analysis tools to improve policies and guidelines for the formation of teams within a particular community. The study begins by defining voluntary collaborative project teams (VCPTs) as teams where members have semi-autonomous discretion over whether to join or participate. It is argued that, with reference to VCPTs, those making policies or guidelines appear to face both an information disadvantage and possess an information advantage relative to individual team members, stemming from differing positions regarding emergent qualities of teams. While team members have access to team-specific information, policy-makers can use information regarding norms within the community as a whole. It is then argued that network analysis is a useful tool for uncovering these community-wide tendencies. An example analysis is then performed using exponential random graph modeling of a network to uncover the underlying logics of team construction within nanoHub.org, an online community that fosters collaboration amongst nanoscientists. Results suggest that the technique is promising, as a normative tendency which undermines team performance is uncovered.

5.1 Introduction

As many industries migrate towards a network-based production implemented by short-term, fluid teams which are permeable, interconnected, and modular (Schilling and Steensma, 2001), the performance of teams where members relatively freely choose their collaborators is becoming increasingly important.

[1] The authors wish to acknowledge the following funding sources that contributed to the development of materials presented in this chapter National Science Foundation Grants: OCI-0904356, IIS-0838564.

Networks in Social Policy Problems, eds. Balázs Vedres and Marco Scotti. Published by Cambridge University Press

Settings in which semi-autonomous team assembly is particularly prevalent include the development of software in the open source movement, collaboration in large online multiplayer games, scientific co-authorship, and artistic collaborations (Amaral, 2005; Guimerà *et al.*, 2005; Uzzi and Spiro, 2005). Especially noteworthy for governmental funding agencies, research communities, and collaboration platform managers is the growth in the incidence and productivity of science conducted in teams, or "team science" (Fiore, 2008; Stokols *et al.*, 2008; Falk-Krzesinski *et al.*, 2010, 2011; Börner *et al.*, 2010). This growth has made investigations of the mechanisms of effective scientific teamwork and collaboration increasingly relevant. Moreover, recent research has found that many cross-institutional scientific teams fail to achieve their goals; but the few of them that did succeed, did spectacularly (Cummings and Kiesler, 2007; Huang *et al.*, 2010). Therefore, it is important to discover the mechanisms associated with more successful scientific collaborations so that an understanding of these mechanisms can inform policy-making processes for collaboration platform managers and governmental funding agencies. Such information can thus foster more effective scientific team collaborations and improve scientific productivity across communities.

Network research suggests that when organizational entities expand their collaborative activities and diversify their relationships, cohesive subnetworks characterized by multiple, independent logics of organization can emerge (Powell *et al.*, 2005). This self-organized emergence raises a set of important questions for makers of policy and institutions responsible for setting governance structures (Contractor, 1994). Can self-organization be improved? More specifically, can these emergent logics be evaluated from an external position for strengths and weaknesses? Can the introduction of incentives or governance structures guide the development of these logics toward the construction of more cohesive, sustainable, or productive wholes (Provan *et al.*, 2007)?

This study examines these self-organized collaborations in scientific teams. Many contemporary scientific teams can be seen as hybrid-project systems (Schwab and Miner, 2008). In these systems, team membership is neither dominated by organizational control nor fully the result of independent choices made by individuals. In this middle ground, scientists must balance autonomy and institutional constraints when assembling teams to optimize team performance (Huang *et al.*, 2010). As suggested by Schwab and Miner (2008), some hybrid systems tilt more toward the stand-alone end of the continuum, with more freedom of selection on the part of team members, such as research teams with members from different universities. Within this context, the question is how larger institutions might construct and implement policies to provide information, incentives, or guidelines which would improve these semi-autonomous choices.

5.2 Voluntary collaborative project teams

The current study focuses on these more freely assembled teams, which we refer to as *voluntary collaborative project teams* (VCPTs). We define voluntary collaborative project teams as those assembled for the purpose of accomplishing a task by a set of individuals who have freedom to choose their collaborators from a large set of potential candidates. VCPTs are what Hackman and Katz (2010) called *self-governing* groups – ones in which members are free to define goals, modify the structure of the team and aspects of its context, and manage their own performance. They go beyond self-governing groups in that individuals have the prerogative to choose who is included in the team.

These teams are distinct from other subjects of small group study. Unlike classic work teams assigned by a superior or an institution, VCPT members select one another and choose to participate on a voluntary basis. Yet unlike emergent groups that lack specific goals, such as social clubs, these teams have specific, finite goals that they intend to accomplish, such as the execution of a particular experiment, the construction of a piece of software, or the publication of an article or chapter. Given this definition, we suggest that performance is the primary goal of voluntary collaborative project teams (Fafchamps *et al.*, 2010), i.e. these teams form because individuals hope that by joining the team they might accomplish something that they might not otherwise be able to accomplish on their own.

In this sense, VCPTs are similar to groups that form to accomplish collective actions, such as the execution of a political protest or the creation of a public good, such as a library or database (Flanagin *et al.*, 2006; Fulk *et al.*, 1996, 2004; Marwell *et al.*, 1988). Yet, unlike in the groups operating according to the classic collective action model, the project cannot be accomplished strictly through the accumulation of sufficient contributions or other a priori specifiable actions. Rather, the project's accomplishment is the result of the group's ongoing process of interaction and collaboration (Poole *et al.*, 1982; Seibold and Meyers, 2007). Thus, choosing the team members who are most likely to help and collaborate well in the successful completion of the project is a complex task. In addition to individual attributes that may suggest competence in tasks required by the project, team members must consider relational factors, such as the ability to communicate with one another, as well as team composition factors, such as the diversity of resources and opportunity for creative discussion (Huang *et al.*, 2010).

Consideration of these features of VCPTs suggests an interesting relationship between VCPT performance and the mechanisms by which VCPTs are assembled. On the one hand, it is in the interest of VCPT members to assemble into teams that achieve high performance. In the absence of institutional requirements which compel participation in particular teams or with particular individuals, team members should be free to volunteer their efforts only to those teams where they believe there will be a sufficient reward, that is, where they believe the team's project will be a successful and valuable one (Fulk *et al.*, 2004). Yet, as individuals subject to the constraints of bounded rationality, it is implausible to suggest that VCPT members choose their teammates perfectly every time (Simon, 1959). Rather, it seems more appropriate to suggest that VCPTs represent individuals' best efforts to construct effective teams. The question for policy-makers is then whether these best efforts can be improved through recommendations from an outside party.

Following this rationale, the goal of this inquiry is to uncover systematic imperfections or biases in individual best efforts. A policy is a systematic intervention in the processes by which a system develops (Ashby, 1960; Provan *et al.*, 2007). To suggest that policy changes that influence processes of VCPT assembly will improve team performance is therefore to suggest that the natural mechanisms of VCPT assembly are very likely to deviate from the ideal in a systematic way.

While there is already some evidence that such systematic biases exist (Guimerà *et al.*, 2005), scholars have not yet examined this proposition formally. In particular, research has not examined whether apparent deviations between observed mechanisms of team assembly and prototypical mechanisms of team assembly can be accurately attributed to systematic factors such as institutional diversity, gender composition, and expertise distribution. The rationale and procedure for conducting such an investigation is the focus of the remainder of this chapter.

5.3 Mechanisms associated with successful teams

Research on the assembly of effective teams has identified a number of mechanisms by which successful teams are likely to be formed. Notably, research suggests that teams perform best when they are the appropriate size – large enough to accomplish the necessary tasks, but small enough to minimize coordination costs and communication issues. For example, when new team members are added to an existing team, they are likely to bring three benefits – expertise, information processing ability, and diversity of perspectives. They will also bring a cost – an additional need for coordination (Amaral, 2005).

Teams are also more likely to be successful when they contain individuals with the relevant expertise. Expertise level is one of the most valued resources in scientific and other creative collaboration groups (Huang *et al.*, 2010). For instance, Van Der Vegt *et al.* (2006) examined the effects of expertise diversity on interpersonal helping and found that members will be more committed to and help those seen as having more expertise. Nonetheless, much about the effects of team expertise composition remains to be explained.

In addition, maintaining novelty and freshness in team composition appears to be an important factor influencing team creativity. Guimerà *et al.* (2005) find that teams where members have worked together before are less likely to be creative. However, previous collaboration history among team members can be a double-edged sword, in that prior knowledge reduces uncertainty (Hinds *et al.*, 2000). Huang *et al.* (2010) report that teams composed of individuals from different institutions are likely to provide more innovative products, but this effect is reduced when team members have worked together before. Successful team projects increase the social capital of their creators, which may in turn enhance the popularity of (and the community support for) the new collaborative endeavor (Amaral and Uzzi, 2007).

5.4 Translating findings into policy – an information problem

The previous review suggests that there are a variety of mechanisms associated with the assembly of successful teams. However, translating these findings into policy recommendations is not straightforward. While in many cases guidelines and incentives that encourage individuals to assemble teams according to the principles reflected in these findings will be helpful, in other cases they may mislead team members into a new set of problems. The risk of making counter-productive policy stems from the information problem faced by policy-makers: the absence of contextual information regarding a specific team's composition, activities, and internal relationships. Particularly in areas where teams assemble to create novel products or address new problems, recommendations drawn from findings regarding the most effective means by which the previous generations of inventions or solutions were discovered may be misleading. This section describes this problem and elaborates on its application to team assembly.

5.4.1 Emergent local dynamics – the information disadvantage of policy-making

At the core of policy-making is the construction of rules and guidelines for others to follow in pursing their activities. A primary challenge for policy-makers in any field is to justify these prescriptions to the individuals, groups, and institutions that they are guiding. In particular, there is a question of how policy-makers might contribute guidelines for performing an activity to those who are experienced experts in a particular domain. This concern is especially relevant in areas, such as scientific research, where the activities are highly sophisticated, often novel techniques performed by experts in a specialized field.

Both economists and small group researchers have pointed to the disadvantage of guiding local decisions, such as who should work with whom on what, by rules created by a central authority (Hayek, 1945; Poole *et al.*, 1996). The primary argument from these perspectives is that when actions are guided by centralized policy, they take into account a limited set of information. Specifically, prescriptions based on observations of similar situations that have occurred in the past often overlook important information that emerges *in situ*. As Hayek describes:

> The statistics which such a central authority would have to use would have to be arrived at precisely by abstracting from minor differences between the things, by lumping together, as resources of one kind, items which differ as regards location, quality, and other particulars, in a way which may be very significant for the specific decision. It follows from this that central planning based on statistical information by its nature cannot take direct account of these circumstances of time and place, and that the central planner will have to find some way or other in which the decisions depending on them can be left to the "man on the spot." (Hayek, 1945, p. 524)

In small groups, the new information often takes the form of emergent dynamics within a team itself (Poole *et al.*, 1982; Poole and DeSanctis, 1992). Of particular relevance to VCPTs is the emergence of relational factors within the team – the degree to which teammates get along, understand each other, or otherwise find it easy to communicate and cooperate.

In the extent to which these emergent factors influence the appropriate allocation of team resources to achieve team goals, policies imposed from outside and informed by observations of other teams can impede team success. For example, observations which associate team size with task complexity may suggest that individuals facing large tasks form large groups. Such a recommendation ignores the fact that teams may not know the nature of their task until they have been formed and discussion has begun (Weick, 1992). Once formed, however, group members may form relationships, shared understandings, and means of allocating knowledge and responsibility that make it difficult to jettison any particular group member (Hollingshead, 1997, 1998; Wegner, 1987). Thus, groups may become "locked-in" to task definitions which reflect their original size, rather than basing the team's size on a task that is selected by the best judgment of the group (Sydow *et al.*, 2009).

Similarly, the requisite expertise for a task is also contingent on emergent, team-specific factors. Poole and Contractor (2011) argue that assembly mechanisms vary based on the extent to which the teams are engaging in tasks that require exploration of new ideas, exploitation of existing resources, mobilization around a particular issue, bonding and building trust, and swarming in response to an emergency. In addition to factors based on task definition there are also rational factors that need to be considered within the team. The communication of complex knowledge often requires substantial shared understanding that creates absorptive capacity (Clark and Wilkes-Gibbs, 1986; Cohen and Levinthal, 1994). Group members may have an easy time communicating about certain topics or at a certain level of sophistication, but when the task demands the communication of more complex knowledge, communication breaks down (Sorenson *et al.*, 2006). To the extent to which team dialogue and norms of communication emerge through the team's work, it is possible that well configured teams suddenly become ill configured (Cohen and Bacdayan, 1994; Postmes *et al.*, 2000).

While much of the guidance offered by policy will, like team members' own best efforts, be only an approximation for best practices of team assembly, there is reason to believe that these recommendations may contain systematic biases. In particular, when teams are engaged in creative tasks which rely on novel, expert knowledge, repeating the team assembly processes that have led to success in the past may – like repetition of effective collaborations in the past – lead to outputs that are similar to what has been produced in the past (Guimerà *et al.*, 2005). Thus, as consistency with previously successful practices is enforced, novelty and diversity may be lost (Sydow *et al.*, 2009). For example, Gerstner (2002) suggests that IBM's stagnation emerged in part because it followed habits and routines that had brought it success.

Since policy-making is constrained to provide rules based on prior observations, these arguments suggest a limited role for the guidance of team formation based on findings from team assembly. The next section presents a counter-argument to the claim.

5.4.2 Emergent collective dynamics – the information advantage of policy-making

In the previous section it was argued that policy-makers are at an information disadvantage vis-à-vis team members in assessing appropriate team composition. Specifically, it was suggested that policy-makers have access to information that is more homogeneous than members of individual teams because these team members can combine best practices learned form historical observations with specific observations of emergent team dynamics. In this section, it is argued that team members are also burdened by their own yoke of conformity, and that policy-makers may be able to alleviate this burden through analyzing information that they are uniquely privy to. This information is in regard to a different set of emergent qualities, what can be called *emergent community norms*, rules or habits of team formation which are shared by a substantial portion of teams within a particular community (Meyer and Rowan, 1991 [1977]; Nelson and Winter, 1983).

As described above, team members can develop rules and norms that are specific to each team through the course of its operation (Poole and DeSanctis, 1992; Postmes *et al.*, 2000). Yet in many cases, team members are also members of higher-level institutions or communities (Lammers and Barbour, 2006). These higher-level institutions can also develop emergent norms which guide or constrain the behavior of team members (Monge and Contractor, 2003). For example, Huffaker (2010) reports a variety of tendencies that are shared across discussion topics and groups in an online community. Individuals are not likely to be aware of the fact that their individual sub-communities share common patterns with one another.

These norms can be helpful in guiding individuals to make better decisions. The generally accepted rule that researchers demonstrate competence through the achievement of a PhD is likely to be an effective rule. As research in neo-institutional theory argues, however, there is no guarantee that emergent norms correspond to performance enhancements (Meyer and Rowan, 1991 [1977]). That is, individuals or groups may consistently engage in a variety of routines, behaviors, or use logics of evaluation and inference simply because others also do so, or because these have been the rules that have been used in the past rather than because adherence to these rules provides any particular advantage.

In particular, institutional scholars point to the fact that consistent behaviors within a field or institutional setting often reflect the influence of information limitations (DiMaggio and Powell, 1983), rules for legitimate action (Hannan and Freeman, 1977; Meyer and Rowan, 1991 [1977]), as well as policy prescriptions (George *et al.*, 2006). When information regarding effective practices is limited, groups often engage in *follow-the-leader* behavior in which they imitate those groups which appear to be most effective (DiMaggio and Powell, 1983). In essence, these groups over-rule or over-ride their local, contextual information in favor of whatever the best performing group is doing. While this might bring an advantage, in many cases it does not. A single leader is a small sample size and many contextual factors which imitation ignores may be relevant. For example, Huffaker (2010) reports that group members are likely to imitate the language patterns of individuals that post frequently and respond regularly to others. Huffaker's results also show that the linguistic diversity of group leaders can foster further discussion within the team. It is thus possible that groups where certain individuals assert leadership through frequent posts and replies, but use a limited, homogenous vocabulary, may suppress further group discussion even when such discussion would be productive.

Legitimacy refers to degree to which a rule or practice is considered valid and worthy of resource investment by a community (Hannan and Freeman, 1977; Pfeffer and Salancik, 1978). When groups engage in legitimate practices, they are likely to continue to receive resources even if their actions fail (Baum and Oliver, 1991). Groups can also be guided by official rules and policy which do not correspond to performance (George *et al.*, 2006).

Research in these areas suggests that individuals, groups, and organizations are likely to continue to follow these practices, called *myths* by Meyer and Rowan (1991 [1977]), for at least two reasons. Firstly, there is evidence that individuals are not even aware that they follow these rules (Cohen and Bacdayan, 1994; Nonaka and Takeuchi, 1995; Zucker, 1991 [1977]). Secondly, the identification of myths requires information regarding the typical behavior of groups within a community. While in some cases this information is readily available, it is often distributed widely through the community. In particular, in cases where individual groups interact only with a small number of others, it may be difficult to observe broader tendencies within the community as a whole. It is unlikely, for example, that Google Groups participants are aware of the larger patterns in leadership and conversation that can only be observed through an analysis of thousands of posts (Lazer *et al.*, 2009). Such global knowledge is also unlikely in cases where groups share a common platform or technology but communicate on a limited basis. In particular, actions or decisions that appear novel and objective within a local area of a community may, in fact, be typical and normative within the community as a whole (Burt, 1987; Strang and Meyer, 1993).

The existence and systematic influence of these community-level myths or rules offer an avenue through which policy-makers may make a contribution to team assembly practices. In particular, policy-makers are a potential source of information regarding the biases that individuals may not be aware of. In many cases, policy-makers have access to information regarding the community as a whole. Particularly in digital communities, administrators or other policy-makers can observe the behavior of the whole community in a way that individual members cannot (Lazer *et al.*, 2009). As such, they can observe individuals embedded in a multidimensional network where some of the nodes are individuals, but others are technological artifacts such as documents and databases, as well as conceptual artifacts such as keywords and tags (Contractor *et al.*, 2011). More importantly, policy-makers have incentives to access and analyze this information that is not shared by individual teams. As beneficiaries of the aggregate of performance across all teams, policy-makers gain from any insight that can be gleaned from the analysis of this community-wide information (Easley and Kleinberg, 2010; Lazer and Friedman, 2007). More specifically, policy-makers stand to gain from any insight that can be used to improve *any* team over which they have policy-making authority. Individual teams do not necessarily share in this reward. Individual teams only benefit if analysis of the aggregate, community-wide information improves *their own* performance. Thus, the analysis of community level norms as potential myths is likely to fall prey to collective action failures (Fulk *et al.*, 1996, 2004).

5.5 Using network analysis to assist policy

5.5.1 Network analysis and community norms

Network analysis offers a powerful tool for identifying emergent norms within a community. Collective network structures have been shown to be important predictors of a variety of individual behaviors through processes of diffusion (Rogers, 2003). That is, the position of an individual in a network is often an important predictor of that individual's behavior. Yet individuals generally lack information regarding their position (Krackhardt, 1987). Networks are thus an important, hidden influence on behavior. The individual, or individual group, may experience network influences as changes in the salience or relevance of particular cues or values (Strang and Meyer, 1993; Strang and Soule, 1998). Without access to information about the network as a whole, however, the degree to which these changes are recognized as emergent norms is likely to be limited. More specifically, what individuals experience as novel may, through network analysis, be revealed to be normative (Coleman *et al.*, 1957; Burt, 1987).

For example, Barabási and Albert (1999) have shown that the citation of scientific papers suggests a normative logic called *preferential attachment*. Preferential attachment is a form of institutional imitation. According to preferential attachment, papers that receive many citations are more likely to be cited by new papers, strictly because they have received other citations in the past. The result of preferential attachment is a highly skewed distribution of citations where few papers receive a large number of citations and most papers receive very few. As Evans (2008) shows, it is quite likely that this habit does nothing to increase the quality of scientific research and may even harm it by limiting the diversity of ideas.

In spite of its potential for limiting scientific performance, evidence suggests that preferential attachment is an emergent rule rather than one that is consciously evaluated and chosen by researchers (Barabási, 2003; Powell *et al.*, 2005). As Barabási remarks, the mechanism appears to have operated in a variety of fields both in science and outside of science without anyone's knowledge. It was only through the analysis of large collections of citations that this norm was uncovered.

5.5.2 Network signatures of emergent norms of team assembly

Based on the preceding arguments, we suggest that policy-makers can use network analysis to identify community norms of team assembly. This section will explain the rationale by which these analyses can be used to make new rules and guidelines for the formation of teams. An example of such an analysis using data from nanoHub.org is then provided.

The preceding arguments suggest that the logics by which teams are assembled can be categorized in one of three general categories. Firstly, there are logics of team assembly which are typical in a community because they improve performance. These logics represent knowledge the community has gained. These may include some of the logics that have been discovered by team assembly researchers, and they may also include logics which have been uncovered within the community but are not yet known to team assembly researchers. Given that VCPTs involve voluntary contributions of team members' time and resources in order to accomplish goals, it is likely that many of these performance enhancing logics are present.

H1: For some logics of team assembly that are typical in a community, conformity to this logic will be associated with positive performance.

At the same time, the arguments from institutional theory presented above suggest that some logics may not have any performance benefit. In particular, these arguments suggest that logics which are difficult to observe from individual positions, such as preferential attachment, are not likely to be associated with performance. This is due to the fact that these logics may take hold without being evaluated by individuals for their performance benefit. Thus:

H2: For some emergent logics of team assembly that are typical in a community, conformity to this logic will be associated with negative performance.

While there is good reason to believe that preferential attachment will be such a logic, other network logics, such as imitation through structural equivalence (Burt, 1987) and repeat collaboration (Guimerà *et al.*, 2005) are also candidates. A third possibility is that team assembly logics are idiosyncratic or experimental, that is, that they are not typical within a community. These can be thought of as undiscovered by researchers or un-diffused within the community. These experimental logics may be performance enhancing, or they may be performance undermining. Policymakers may be interested in finding the experimental logics that are performance enhancing. Thus we ask:

RQ1: Are any atypical, experimental logics of team assembly performance enhancing?

5.6 Method

Sample

nanoHub is a major NSF-funded cyberinfrastructure-enabled collaboration environment hosted at Purdue University. It allows scientists and engineers to develop software tools and perform simulations for nanotechnology research. The online platform is a global resource for nanoscience and technology, created by the NSF-funded Network for Computational Nanotechnology. The software tools on nanoHub are hosted and run on computer clusters equivalent to 100 personal computers. Researchers around the world can access the platform to run simulations and perform experiments. This can be done through a regular Web browser run on personal computers or even a cell phone. Thus nanoHub provides researchers with the resources to do more scientific work without having to spend the time and money to build their own simulation environment.

nanoHub facilitates software tool collaboration in a number of ways. It provides a platform for software simulation, reducing development costs and creating a global scientific community of software developers and users working in the area of nanotechnology. Through shared virtual workspaces, nanoHub allows groups of users to collaborate, share results, and do collective troubleshooting. nanoHub facilitates the formation of virtual teams of scholars working on software development projects.

An explicit goal of the nanoHub online platform is to foster interorganizational and international collaboration. Combined with the ease of use and virtual nature of the workflow, we expect this to alleviate constraints based on structural opportunities for social contact (described in Ruef *et al.*, 2003). At least in theory, all who are interested in launching a project should have the means to contact the desired potential team members through the online service. This idea is, furthermore, in keeping with the definition of voluntary collaborative project teams that this chapter employs.

The sample used in this study consisted of 124 teams (size ranging from 2 to 8) with a total of 170 researchers who collaborated on the development of software tools published on the nanoHub. The researchers were distributed across 32 organizations (96% were universities) located in 10 countries. Ninety percent of the researchers were in the USA, with the rest located in Australia, Canada, China, Britain, Italy, Malaysia, Spain, and South Korea.

5.6.1 Inferring community logics

To infer the logics of team assembly within the nanoHub community we employ an Exponential Random Graph Model (ERGM) for bipartite networks. Through Monte Carlo Maximum Likelihood Estimates (MCMLE), the exponential random graph modeling approach identifies parameters which, if used as guides for the construction of the network, would make the observed network likely (Robins *et al.*, 2007). If the assembly mechanisms of a large number of teams can be explained by the operation of a small number of parameters as guides, this suggests that these parameters are close approximations to the tendencies by which team members come to work together.

Importantly, this technique involves an analysis of network outcomes, not individual intentions. The parameters that guide network construction may not be the rules by which individuals choose to form teams. Rather, these parameters describe the tendencies of team formation which emerge through the combination of individual motivations, inferences, and their interaction with contextual information. As such, ERGMs provide an excellent tool for identifying the emergent logics in a system or community.

For the purposes of this study, we constructed a two-mode network of 170 nanoHub researchers and their affiliations with the 124 tool projects on the platform. Using the BPNet software (Wang *et al.*, 2009) we created a model of the observed network which included the following potential underlying logics of team assembly.

Individual attributes

The knowledge, skills, and other individual characteristics of researchers affect their chances of being on a team. Previous research has shown, for instance, that gender, status, and expertise are important in the selection process (Hinds *et al.*, 2000). Factors like individual and aggregate team member expertise are also expected to be important for productivity (Balthazard *et al.*, 2004).

Additionally, particular individual characteristics specific to the nanoHub platform may play a role in team formation. Researchers belonging to the Network for Computational Nanotechnology (NCN), the founding organization of nanoHub, can be expected to play a more active role on the platform, starting and joining a large number of development teams.

The model proposed here looks into the impact of the following characteristics:

- **Gender**: nanoHub teams are mostly composed of male researchers. While there are a small number of female tool developers on nanoHub ($N = 9$); those women researchers seem to play an active role: out of 124 teams, 30 have at least one female member. The gender parameter included in our model addresses the possibility that women are in general more likely to join teams.
- **Expertise**: knowledge and expertise are important qualities of a team member. We expect individuals with high observable level of expertise to be more likely to appear on many teams. For the purposes of this study, expertise is assessed based on each researcher's number of academic publications. The scholars who ranked in the top 25% for number of published papers were considered experts ($N = 49$).

- **NCN**: as members of the Network for Computational Nanotechnology are more invested in the nanoHub platform, they are likely to be particularly active members of the software development community. We expect individuals belonging to NCN to be more likely to participate in teams.

Structural parameters

In addition to individual attributes, the bipartite exponential random graph model developed here involves a number of structural properties of the researcher–team network. Parameters for alternating k stars are used to control for team popularity effects (the presence of a few large teams that many people have decided to join) and individual member attractiveness or extroversion (researchers likely to create, be invited onto, or volunteer to join a large number of projects). Additional structural parameters control for network density (number of links) and the propensity of researchers to work with the same collaborators on multiple teams (alternating k two-paths).

5.6.2 *Dependent/performance variables*

As community logics are assessed in terms of their impact on project outcome, we consider a number of measures related to the popularity, attractiveness, and quality of the software tools produced by each team in our sample. Since nanoHub software tools run on the platform's own computer clusters, nanoHub has accurate logs describing user ratings, tool tagging, and software citations. We take advantage of this rich source of information to construct a composite measure of team performance. The following five indicators are used for this purpose, as their combination captures both the academic impact and the user satisfaction with a particular software project.

(1) **Tool rating**: users of the nanoHub platform can rate the quality of each software tool. The scores given to the projects in our sample serve as an indication of the usefulness and quality of the software.
(2) **Number of times rated**: since the rating score of each tool is computed as an average, the number of people who opted to rate the project is another important measure. Popular, well-used tools are more likely to be rated by a large number of users.
(3) **Number of times cited**: nanoHub teams produce software that is used and cited in the academic community. As academic citations are often used to assess the originality, quality, and influence of the work produced by university research groups (Wuchty *et al.*, 2007), the number of citations (collected from published academic papers) is a good way to assess the impact of team output.

(4) **Number of times tagged**: both users and team members on nanoHub can tag software tools in order to make them easier to discover and categorize. Popular projects, as well as complex or interdisciplinary instruments, are likely to have a large number of tags applied to them by community members.
(5) **Number of taggers**: as tags can be generated by the creators of a software tool themselves, another relevant measure here is the number of nanoHub members who added a tag description to each project. Software tagged by a large number of people can be expected to be both popular and complex in nature.

The outcome variable used for hypothesis testing in the study is therefore computed taking into account all of the aspects mentioned above. Performance is operationalized as the sum of the standardized scores of five indicators: rating, times rated, number of citations, tags, and taggers.

5.6.3 Hypothesis testing

Hypotheses 1 and 2 are tested using the following procedure. Firstly, an ERGM is fitted to the network of teams. This model reveals the dominant parameters guiding team assembly in nanoHub. Next, these parameters are used to identify the degree to which teams conform to these dominant logics. As described above, some teams will conform to dominant logics whereas others will be idiosyncratic or experimental. The degree of conformity to a particular logic is then included as a predictor in a regression on the various team performance measures.

Calculating conformity

The degree to which a team conforms to a logic can be calculated in a number of ways. For individual logics, those that relate to structural features or attributes of particular individuals, the count of individuals included on the team that display those features is used. For example, if the ERGM suggests that teams favor the inclusion of members with a certain level of expertise, then the conformity of a team is based on the number of members with that level of expertise that it contains.

For more complex, collective logics, specific measurements related to the level of the parameter can be devised. For example, if a parameter showing that teams of a certain critical size tend to become very large, then a team's size relative to this threshold can be used. For the purposes of this study, five underlying logics were selected and explored in terms of their importance for team assembly and their impact on performance. Those are:

- **Gender-related**: (1) preference for selecting females on a team and (2) impact of number of female team members on performance.

- **Expertise-driven**: (1) preference for selecting experts on a team and (2) impact of number of experts on team outcome.
- **NCN-driven: nanoHub specific**: (1) tendency to include NCN members on a team and (2) impact of number of NCN members on performance.
- **Star-related**: (1) the propensity of a few popular/extraverted individuals to participate in a large number of teams and (2) the effect of the number of star members on team outcome. For the purpose of this study, star members are those whose number of team affiliations is more than one standard deviation larger than the mean for individuals in the sample ($M = 2.32$, $SD = 2.92$).
- **Team size**: team size was included as a control variable in both models. The number of members has a complex role in patterns of team assembly and performance. While more detailed inquiry into the dynamics of different team sizes is possible, for the purposes of this study the aspects of size controlled for were (1) propensity of select teams to attract a large number of members and (2) effect of team size on project outcome.

Regression on performance

After conformity measures were calculated for each logic, Hypotheses 1 and 2 were tested with a regression of team performance on these measures. According to Hypothesis 1, for at least one dominant logic, conformity to the logic will be associated with improved performance. In other words, teams with a higher degree of conformity to the logic will show a higher performance. Thus, the beta coefficient for conformity for at least one dominant logic will be positive. According to Hypothesis 2, at least one dominant logic will be associated with depressed performance. Thus, the beta coefficient for conformity for at least one dominant logic will be negative. In other words, teams with a higher degree of conformity to the logic will show lower performance.

5.7 Results

5.7.1 Identifying community logics

To test conformity to community logics, an exponential random graph model of the observed bipartite network was generated. A BPNet estimation of the goodness of fit confirmed that the model was satisfactory, with all of the parameters having t-statistics lower than 0.1 in absolute value.

The converged model (Table 5.1) suggested that, on a community level, there is a high degree of conformity with the logic that increases the probability of NCN members joining teams ($Estimate = 4.9,\ SE = 1.47$). No such patterns can be observed for females ($Estimate = 0.18,\ SE = 0.27$) and experts ($Estimate = 0.11,\ SE = 0.13$). A significant negative team star parameter ($Estimate = -0.86,\ SE = 0.28$)

Table 5.1. *Team assembly ERG model – community logics ($* = t < 0.1$, ratio of estimate to standard error > 2).*

Parameter	Effect estimate	Stdandard error	t-ratio	Significant
Density	−2.737	0.476	−0.003	*
Member stars	0.162	0.268	−0.010	-
Team stars	−0.860	0.275	0.004	*
Concurrent collaboration	−0.205	0.118	−0.026	-
Experts on teams	0.107	0.133	0.008	-
Females on teams	0.177	0.267	0.053	-
NCN members on teams	4.903	1.471	−0.035	*

Table 5.2. *Regression model: community logics – impact on performance; the relative strength of individual predictors ($*p < 0.05$).*

Predictors	Standardized regression coefficients β	Zero-order correlation with performance	Partial correlation with performance
Team size	0.176	0.397*	0.161
Number of females	0.183*	0.296*	0.182*
Number of experts	0.236*	0.401*	0.207*
Number of stars	0.424*	0.341*	0.260*
Number of NCN	−0.457*	0.165*	−0.286*

indicates that large sized teams are improbable and the variance in team sizes is not very big (Robins *et al.*, 2006).

5.7.2 Performance regression

Multiple regression analysis was conducted to evaluate the relationships of team performance on conformity measures including the team size and the number of females, experts, stars, and NCN members. The linear combination of those five factors was significantly related to team performance, $R^2 = 0.29$, $adjusted\ R^2 = 0.26$, $F(5, 118) = 9.54$, $p < 0.001$. Even though the explanatory power of the regression model could be improved by removing some of the predictors, all of them were retained. This was done to allow for a look at the team assembly logics listed in the previous section and their effect on project outcomes. The relative strength of individual predictors is presented in Table 5.2.

Table 5.3. *Correlations between predictor variables* ($*p < 0.05$, $**p < 0.001$).

Predictors	Team size	Number of females	Number of experts	Number of stars	Number of NCN
Team size	1	0.302*	0.569**	0.494**	0.389**
Number of females		1	0.385**	0.452**	0.486**
Number of experts			1	0.519**	0.494**
Number of stars				1	0.821**
Number of NCN					1

Four of the five predictors in the regression model were statistically significant ($p < 0.05$), team size being the only exception ($p = 0.79$). Three of the indicators – number of females, experts, and stars – had a significant positive zero-order and partial correlations with the performance variable. Number of NCN members had a significant positive zero-order correlation with team outcome, $r(124) = 0.165$, $p < 0.05$, but a negative partial correlation, $r(124) = -0{,}286$, $p < 0.05$, when controlling for all other indicators. The strong correlation between the number of stars and the number of NCN members may account for this ($r(124) = 0.891$, $p < 0.001$, see Table 5.3). This information suggests that NCN members are helpful to performance, because most NCN members that appear on teams are also stars. Controlling for stars, however, NCN members place a drag on performance.

5.8 Discussion

5.8.1 Review of findings

Results of the hypothesis tests, as summarized in Table 5.4, suggest that this method is promising. In particular, Hypothesis 2 is supported. That is, one logic, the inclusion of NCN members, is typical in the community but is performance suppressing. Evidence regarding Hypothesis 1 and the research question is a bit more complex. Hypothesis 1 is technically not supported, as no logic that is typical of the community is associated with increased performance. The three logics which are associated with improved performance – the inclusion of women, the inclusion of experts, and the inclusion of "stars" – do, however, each have a positive effect estimate in the ERGM. As the estimates are not statistically significant, the logics cannot be deemed typical of the community. They do, however, appear to be somewhat commonplace.

Thus, while Hypothesis 2 receives stronger support, the evidence from an analysis of the nanoHub community as a whole does suggest that nanoHub participants are using a combination of effective and ineffective team assembly mechanisms. Many members appear to be following useful logics by including women, experts,

Table 5.4. *Hypothesis testing.*

Team attribute	Typical community logic? (based on ERG model)	Effect on performance? (based on regression model)	Hypothesis testing (logics and outcomes)
Team size	(Control variable)	N/A	N/A
Gender	NO	POSITIVE	RQ1 Tentative Yes
Experts	NO	POSITIVE	RQ1 Tentative Yes
Stars	NO	POSITIVE	RQ1 Tentative Yes
NCN members	YES	NEGATIVE	Supports H2

and stars, though these habits are not dominant. Some of these benefits are suppressed, however, by the general tendency for nanoHub teams to include members affiliated with NCN institutions. This tendency is likely to reflect the degree to which NCN members are more familiar with the platform or with one another. It may also reflect policies or pressures from their institutions which encourage their participation.

Yet whatever the cause, the favoring of NCN members as teammates appears to be weakening performance. That is, individuals would be better served by searching more broadly within the nanoHub community for potential collaborators, potentially increasing both the diversity of interactions and the diversity of approaches to working with the platform.

It is also possible that NCN membership is interacting with team size to suppress team performance. As articulated in the theory section, once formed, teams may experience a lock-in to their size. The evidence from the ERGM further suggests that, in nanoHub, teams are on average smaller than could be expected by chance. Taken with the significance of the NCN parameter, this suggests that nanoHub users may be prematurely "filling" the limited roles in teams with fellow NCN members when, in fact, members of non-NCN institutions may make better collaborators.

Returning to the other helpful logics that are not typical, experts and stars present an interesting case. It is not surprising that the usefulness and scarcity of experts is a significant predictor of performance. Presumably, individuals that have a strong record of publication in the field of nanotechnology have access to knowledge and skills that are useful to other teams in the production of new nanotechnology tools and ideas. Interestingly, however, this effect does not explain away the additional contribution of stars. That is, individuals who are not experts, in terms of publication, but are stars, meaning they work with many individuals in nanoHub, also provide performance benefits to teams. It is possible that these individuals are "up-and-coming" experts who have not yet built a publication record and are thus making a contribution on a similar basis to that made by established experts. It is also possible, however, that these individuals are making a nanoHub-specific contribution. That is, these individuals may possess knowledge regarding the effective construction of new tools or other products within the nanoHub platform.

The significant, positive contribution of women to teams within nanoHub is also interesting. One possible explanation is that women are simply superior team players. That is, because of their ability to facilitate communication and teamwork (Metcalfe and Linstead, 2003), teams with women are more successful. Another explanation is that this finding reflects the residual evidence of gender discrimination in science. More specifically, because women find it more difficult to establish themselves in sciences such as nanotechnology, those women that do make it in the field tend to be disproportionately talented.

5.8.2 *Policy implications*

These arguments suggest that nanoHub administrators may wish to consider the following policies or guidelines to improve team performance within nanoHub:

(1) Set a quota of NCN members per team, based on team size. For example, teams could be required or encouraged to use no more than two NCN members unless they were at least five members in size. The evidence suggests that a quota would be helpful for two reasons. Firstly, a quota will encourage the inclusion of non-NCN members in teams, potentially improving performance. Secondly, such a rule will not force teams to necessarily abandon helpful NCN partners, as teams can also increase diversity by increasing team size.

(2) Make information and opportunities to collaborate with experts and stars more available. While it is possible that experts and stars are at their personal capacities for collaboration, it is also possible that teams do not include a sufficient number of experts and stars, because many teams do not know which experts and stars are available to work within nanoHub. Asking experts or stars who are willing to take on more projects to provide a form of contact or invitation might be helpful.

(3) Provide gender-disguising searches for collaborators. More work needs to be done in this area, but the preliminary evidence suggests that women were not statistically more likely to be on teams than men, given the number of women in the sample, but that team performance significantly improved performance when women were included as members of a team. This suggests that there may be some discrimination based on gender. In particular, it is possible that the women in the sample represent better overall performers than the men. In this case, the observed effects show a bias towards choosing men. That is, a

woman has to be of higher quality to be chosen at the same rate as a man, but once she is chosen, this higher quality is reflected in better team performance. One way to reduce the traditional unfair and performance limiting bias towards females would be to provide information about potential team members that is stripped of gender markers, such as photos and first names. The small, non-significant parameter favoring the inclusion of women may also be due to the small number of women in the sample. If more women were present, it is possible the effect would have been significant and positive, showing that, as predicted by H1, a typical logic of team assembly (choosing women as team members) is associated with higher team performance.

5.8.3 *Limitations and further research*

The research reported here is preliminary in many respects. Firstly, the data reflect only a sample of 124 teams taken from a particular time window. A more thorough analysis would include many different time slices and identify parameters whose significance was robust within the community. Secondly, further interrogation of relevant ERGM parameters should be considered. The parameters chosen here were largely those based on previous findings in team assembly research. However, there is no reason to believe that nanoHub members have not uncovered a variety of distinct logics, some performance enhancing, some performance neutral or undermining, that are unique to this platform or to online communities in general.

Thirdly, it is important to consider the influence of selection effects (Heckman, 1976, 1979). In particular, the data here are extant teams – those which were not only assembled, but performed sufficiently well to produce an observable output. However, to the extent to which the production of this output is correlated with variables that influence team performance, it is likely that teams assembled according to ineffective logics simply were not observed. Thus, there may be other logics which might support H2. Conversely, as Heckman (1979) shows, the exclusion of selection effects can suppress significant effects in the final regression. That is, many teams may be assembled by typical logics which provide them with a requisite level of performance enhancing resources. Having achieved this requisite level, these teams vary widely in their performance. Having failed to achieve this level, teams are not observed. In this case, the beta coefficient associated with this logic would be non-significant even though the logic is helpful to performance.

Further research should address these limitations. The method proposed here can also be extended to other communities where team assembly is likely to occur in a shared technological or normative environment. Such areas include scientific collaboration within particular disciplines or sub-fields, collaboration in particular industries, and voluntary task groups that form in various online communities.