ASSEMBLY MECHANISMS OF EMERGING INTERDISCIPLINARY SCIENTIFIC TEAMS AND THEIR IMPACT ON PERFORMANCE

ABSTRACT

We use a multi-level multi-theory framework to study the influence of compositional, relation, and ecosystem mechanisms on the assembly and performance of scientific teams in interdisciplinary fields. Specifically, we test the effects of these mechanisms on the assembly of interdisciplinary scientific teams using a novel hybrid agent-based and systems dynamics computational model fitted using data collected from 533 teams and 1,696 researchers working in the scientific field of Oncofertility from its inception in 1996 until 2010. We further complement these simulation models with robust statistical linear regression techniques to assess the implications of assembly mechanisms on team performance. Our analysis offers new insights about the assembly of interdisciplinary scientific teams and for increasing the ability of such teams to take corrective actions under conditions of low performance.

Keywords: Interdisciplinary teams, Team assembly, Team performance, Computational Model, Team ecosystem, Social Networks

INTRODUCTION

There is a growing recognition of the importance of interdisciplinary teams in addressing contemporary societal and scientific challenges (Wagner et al., 2011). While interdisciplinary scientific collaboration has clear benefits and is encouraged and supported by many academic institutions, funding agencies, and private entities, the divergent and often conflicting researcher demographics and discrepant beliefs about methodologies and theoretical models raise many challenges for this type of collaboration (Cummings & Kiesler, 2008). Specifically, not only that the knowledge needed to perform team-based tasks has to be understood by all parties, but also the required effective interaction and coordination among researchers with heterogeneous scientific backgrounds (Malone & Crowston, 1994) is hard to achieve (Hara, Solomon, Kim, & Sonnenwald, 2003). As a result, although the importance of scientific interdisciplinary teams has grown consistently over time (Uzzi, Mukherjee, Stringer, & Jones, 2013; Wuchty, Jones, & Uzzi, 2007), the assembly and resulting performance of such teams is often suboptimal (Contractor, 2013; Cummings & Kiesler, 2008; Lungeanu, Huang, & Contractor, 2014). Clearly, there are benefits to consider more specifically how scientific teams are formed in the first place (Acedo, Barroso, Casanueva, & Galán, 2006; Guimera, Uzzi, Spiro, & Amaral, 2005).

There is a clear need to understand how interdisciplinary scientific teams form and how they can be "optimized for the knowledge and skills required for the science to be conducted" (Börner et al., 2010). This paper addresses these challenges and examines (1) the factors that affect the assembly of interdisciplinary teams and (2) how these assembly factors influence interdisciplinary team performance. Specifically, we draw upon theories on the formation of social networks (Contractor, Wasserman, & Faust, 2006) as well as on the more extensive research on groups and teams (Levine & Moreland, 1998), to examine the factors affecting the assembly and performance of interdisciplinary teams during the emergence of new scientific field. To meet collaboration challenges that are specific to innovative fields, recent research has suggested that collaboration should be based on diversity (Barkema, Baum, & Mannix, 2002; Lungeanu & Contractor, 2015), history of interaction (Bordons & Gómez, 2000), and ecosystem (Poole & Contractor, 2011), among other factors. Therefore, we examine how team compositional-level factors (i.e., seniority, expertise, gender, and university affiliation), relational factors (i.e., prior successful collaboration, friend of a friend, and elite homophily), and ecosystem factors (i.e., local ecosystem closure and global ecosystem closure) influence the assembly of interdisciplinary teams. We integrate these theoretical frameworks using a multi-level, multi-theoretical approach (Contractor et al., 2006) to answer the following core research question: *What are the compositional, relational, and ecosystem factors that affect the likelihood of interdisciplinary scientific team assembly and does their influence change over time?* We answer this question by developing an agent-based and system dynamics computational model fitted using empirical data from real interdisciplinary teams to capture the most common norms to form teams, which we conceptualize as "form-norms" teams. Our analytical method also captures the mechanism through which factors' influence may change in strength over time: Field growth affects the strength and influence of team-assembly factors, which in turn influence scientific field growth.

Our computational model approach allows us to further test the premise that teams often vary in their application of assembly norms and that the degree to which they depart from these norms impacts team performance. Team performance has been the subject of a large body of prior research. Evaluations of extant literature starting with Williams and O'Reilly's (1998) review of more than 40 years of research on diversity as well as the recent work by Joshi and Roh (2009) and Stokols et al. (2008) reveal inconsistent findings regarding the specific factors or mechanisms that improve team performance. This study seeks to help resolve these inconsistencies by examining whether there are differences between the team characteristics for specific observed teams and the average “form-norms” for teams and whether reducing these differences will improve (versus degrade) team performance. Consequently, we ask a secondary research question: *What are the performance consequences of the compositional, relational, and ecosystem assembly mechanisms and, what are the performance consequences for observed teams deviating from the norms of assembly?* The premise of the secondary research question is that while some factors may be more frequently observed in the assembly of interdisciplinary teams, other less frequently observed mechanisms may be associated with higher (or lower) team performance. We conceptualize the assembly mechanisms that are associated with higher team performance as “perform-norm” and we further assess the differences between the “predicted” team composition as predicted by the computational model and the “realized” team composition observed in the empirical data.

Specifically, this paper investigates the aforementioned research questions using data from collaboration patterns among 1,696 scientists who published 553 publications in the nascent scientific field of Oncofertility during the period from 1996 (i.e., the field’s inception) to 2010. In summary, our multi-theoretical multilevel model of team assembly and performance integrates prior research on compositional and relational factors that explain why teams form and how these factors impact how they perform. It extends prior research by considering the impact of structural characteristics of the ecosystem of overlapping teams on how teams form and perform. Finally, it examines how all of these assembly factors might influence the evolution of a new interdisciplinary field and how the coalescing of this field might in turn influence the assembly of teams at later stages in the lifecycle of the interdisciplinary field. The findings of this study have policy implications for the assembly of interdisciplinary scientific teams and for increasing the ability of teams to take corrective actions when performance is not satisfactory.

THEORY AND HYPOTHESES

Across domains of study, from molecular biology to women's studies to policy sciences, a consistent theme has emerged: The large problems these disciplines try to solve are like no other. It is not just that these large problems have major social implications, but they are also highly complex and thus require research design, technological, and theoretical approaches that are truly interdisciplinary in nature. However, while interdisciplinary scientific collaboration is critical and has clear benefits, challenges associated with such collaboration suggest that the assembly of interdisciplinary teams has remained a daunting task, with many teams likely suffering from a suboptimal grouping of constituent members (Cummings & Kiesler, 2008; Lungeanu et al., 2014).

Scientific innovation requires a strong combination of specialized expertise, concepts, and diverse methodological and theoretical approaches. As a result, past research also suggests that interdisciplinary teams must utilize the heterogeneous attributes of their members—such as specialized and diverse expertise—to accomplish their innovation goals (Börner et al., 2010). Yet, the mere requirement for heterogeneity may impede interdisciplinary teams' functioning, as it may result in clashing viewpoints and approaches (Cummings & Kiesler, 2008).

Furthermore, most prior research on groups and teams treated teams as well-defined, neatly circumscribed entities with a stable set of members who work interdependently toward a common goal (Cohen & Bailey, 1997; Offermann & Spiros, 2001). The reality of team-based scientific work, however, is that 65 to 90 percent of such knowledge workers hold membership in multiple teams simultaneously (O'Leary, Mortensen, & Woolley, 2011). Multiple team membership is especially common in knowledge-intensive environments, such as those related to information technology, new product development, and academic settings. Thus, membership in a broad ecosystem consisting of multiple teams is the rule, rather than the exception. Networks of collaboration are embedded within ecosystems of relationships, defined as dynamic and complex networks of prior collaborations and connections of both individuals and networks of individuals (Poole & Contractor, 2011) whose characteristics may shape future collaborative relationships and affect the assembly of future interdisciplinary teams, along with their performance. Despite acknowledgements that teams are embedded within an ecosystem of collaboration relations, no research has examined the role of the ecosystem in serving as a primordial soup from which teams assemble and how this impacts their performance. One reason for the paucity of studies examining overlapping teams is that such ecosystem-focused investigations entail multiple levels of analysis, which in turn requires the use of complex statistical analyses and tools.

Finally, prior research on our understanding of team assembly and collaboration networks assume that these factors are time invariant with respect to the growth of scientific fields. The dynamic nature of these networks (e.g., new scientists join, while incumbents may depart), combined with the processes underlying the emergence of a new interdisciplinary field, presents a unique opportunity to shed light on how the factors affecting team assembly vary during the life-cycle of a specific field.

Most prior research has focused on examining the factors affecting team effectiveness after the team has been assembled rather than considering the formation of these teams in the first place (Acedo et al., 2006; Guimera et al., 2005). Recent research has suggested that the assembly of teams should be based on (i) *composition* level mechanisms that focus on the individual characteristics of team members (Barkema et al., 2002; Lungeanu & Contractor, 2015), (ii) *relational* level mechanisms that focus on members' relationships (for instance, prior collaboration, communication, trust) with one another (Bordons & Gómez, 2000), and (iii) the *ecosystem* level mechanisms that focus on the extent to which team members are embedded in multiple other teams that may have overlapping team membership (Poole & Contractor, 2011). These three sets of factors operate at different levels of analysis and incorporate different theoretical mechanisms prompting the development of a multi-theory, multilevel model of team assembly (Contractor et al., 2006).

In the next section, we theorize on the effect of these three sets mechanisms – compositional, relational, and ecosystem – on team assembly and performance. We will first present the mechanisms that affects team assembly, and then present hypotheses regarding the effects of these mechanisms on team performance. Finally, because one would expect observed teams to vary from their adherence to the form-norm, we also examine the degree to which the assembly of individual teams depart from the "form-norm" and use these discrepancies to conceptualize a "perform-norm" – the assembly mechanisms associated with high performance teams. Specifically, we will estimate the extent to which teams' positive and negative departure from the form-norms on specific assembly mechanisms impacted the performance of the teams.

Mechanisms for Team Assembly and Performance

Compositional-level mechanisms and Team assembly

Seniority and high performing researchers. Although research examining the effects of seniority on the likelihood to collaborate is scarce, the few studies that examined this issue showed that more senior researchers have developed scientific and technical human capital as well as social capital, and that these attributes are sought after by other researchers looking for collaboration opportunities (Bozeman & Corley, 2004). Senior researchers also enjoy a level of job security and academic freedom that makes them indifferent to the risks that accompany engagement in research in a new scientific field. Second, researchers that have already built a reputation of success in their field are also sought after because reputation can spill over to researchers just starting their careers. This natural tendency to associate with successful others results in gains ranging from benefitting from the taken-for-granted assumption that success breeds success to the spillover benefits mentioned above. Altogether, we propose two mechanisms:

M1: Researchers prefer to collaborate with senior researchers.

M2: Researchers prefer to collaborate with high performing researchers (H-index).

Gender and institutional affiliation inertia. Research shows that individuals exhibit inertial preferences towards homophilous but also heterophilous collaborations (Fu, Nowak, Christakis, & Fowler, 2012). On the one hand, homophilous collaborations reflect individuals' common interests which in turn heightens the ease of communication (Ibarra, 1992) and lowers the levels of emotional conflict (Pelled, Eisenhardt, & Xin, 1999). Therefore, such collaboration is more likely to attain creative goals (Gilson, Mathieu, Shalley, & Ruddy, 2005). On the other hand, heterophilous collaborations provide access to new and diverse information. When collaborators have different backgrounds, skills, abilities, information, and knowledge, they are more likely to search for solutions outside their own areas of expertise and to produce novel and creative ideas (Guimera et al., 2005). Given individual inertia towards homophily or heterophily demographic characteristics, such as gender or institution affiliation, we expect that individuals will maintain their preferences when choosing new collaborators. Therefore:

M3: Researchers' preferences for (or against) gender homophily when choosing new collaborators will remain the same as their preferences in choosing prior collaborators.

M4: Researchers' preferences for (or against) institution homophily when choosing new collaborators will remain the same as their preferences in choosing prior collaborators.

Compositional-level attributes and Team performance

Seniority. In the specific context of interdisciplinary scientific research, several mechanisms are at work. First, considering the average seniority of the team, the flexibility of less senior team members in considering alternatives (compared to the rigidity of older team members) likely results from their cognitive abilities such as learning ability, reasoning, and memory which have been shown to decrease with time (Burke & Light, 1981). Junior team members are more prone to taking-risks in the form of appreciating and considering radical ideas, an individual-level behavioral trait that can be useful in the context of interdisciplinary scientific teams. In the context of a new interdisciplinary scientific field, this suggests that teams that are less senior on average are likely to perform better than teams with a higher average seniority. This conclusion is supported by research on scholarly performance as measured through the number of citations (Hinnant et al., 2012). Therefore, we hypothesize that:

H1a: The higher the average seniority in interdisciplinary scientific teams, the lower the performance of the team.

The presence of a balanced mix of younger and more seasoned researchers should result in bold ideas being expressed (Horwitz, 2005) and also create a mechanism that can evaluate those ideas and push them forward to the community of researchers (Hinnant et al., 2012). This line of argument is congruent with work by Gingras, Lariviere, Macaluso, and Robitaille (2008), who found that productivity increases at a high pace between ages 28 and 40, increases at a slower pace between 41 and 50, and then decreases slowly after age 50. Therefore:

H1b: The higher the seniority diversity in interdisciplinary scientific teams, the higher the performance of the team.

H-index. The H-index provides a direct indication of the quality of future work of the researcher and offers an indirect indication of an author's reputation in the field. Merton (1968) associated this process with the Mathew effect and further suggested that scholars generally pay special attention to work published by highly-reputable colleagues while avoiding reading work by colleagues of lower established reputation, thus optimizing on the time and attention they allocate (Van Dalen & Henkens, 2001). Furthermore, teams with members with a high H-index results in recognition and rewards to flow by virtue of enjoying greater exposure and higher status (Gould, 2002; Merton, 1968; Van Dalen & Henkens, 2001). The symbolic meaning of a high H-index can increase the number of citations that the publication will receive. Therefore:

H2a: The higher the average H-index in interdisciplinary scientific teams, the higher the performance of the team.

Hinnant et al.(2012) also argue that the presence of renowned senior researchers on a team can directly impact the likelihood to publish a team's work because a team composed of more renowned researchers can more readily influence the editorial review process. As Skilton (2008) suggests, researchers with a lower H-index while able to produce quality-high research, lack the social capital to have their work more readily published or cited. To substitute for this weakness, researchers with a low H-index associate with researchers with a higher H-index in order to benefit from their social capital (Gould, 2002; Merton, 1968). As a result, team performance can benefit when some of its members with low H-index contribute ideas that get more exposure because of other more visible members who have a high H-index. Therefore:

H3b: The higher the H-index diversity in interdisciplinary scientific teams, the higher the performance of the team.

<u>Gender.</u> Recent research has found that women are more likely to have publications with higher impact then men in disciplines that require higher career risks (Duch et al., 2012). A study of 1,103 grant proposals submitted to two National Science Foundation interdisciplinary initiatives during a 3-year period showed that, while women are not more likely to collaborate on proposals in general, they were more likely to collaborate on proposals that were funded (an early sign of the potential quality of scientific research) (Lungeanu et al., 2014). Joshi (2014) showed that context

matters: (a) gender integrated teams with a higher proportion of highly educated women are more productive in disciplines with a greater female faculty representation; (b) teams with a greater proportion of highly educated women were significantly more productive in gender-balanced disciplines than in male-dominated disciplines. Given the above arguments, we hypothesize that:

> *H3: The higher the proportion of women in interdisciplinary scientific teams, the higher the performance of the team.*

Country affiliation. Collaboration among members from different nations may bring the added benefit of access to more (Watson, Kumar, & Michaelsen, 1993) or unique information (Choi, Nisbett, & Norenzayan, 1999) resulting from different worldviews. The unique and different information that these team members can add to the team (Choi et al., 1999), the different experiences that they have with various national contexts (Alderfer & Smith, 1982; Cox, 1994), their different cognitive orientations (Choi et al., 1999) can provide information-processing benefits that outweigh the limitations associated with social categorization processes that have been shown to occur in diverse teams (Dahlin, Weingart, & Hinds, 2005). Therefore:

> *H4: The larger the number of different countries present in interdisciplinary scientific teams, the higher the performance of the team.*

Institution affiliation. A large number of studies shows a negative impact of multi-institutional diversity on team outcomes. Scientific collaboration requires researchers to hold regular lab meetings and meet, advise, and direct the graduate students that spend many work hours on these projects. As Cummings and Kiesler (2007) note, this type of communication during projects is associated with greater trust, respect, and participatory norms, as it has been shown in the scientific field of particle physics (Chompalov, Genuth, & Shrum, 2002). It is possible that (a) resulting communication costs (Cummings & Kiesler, 2005; Hoegl & Proserpio, 2004), e.g., difficulties in intra-team communication, coordination, and conflict management, hindering teamwork processes (Hinds & Bailey, 2003) and (b) resulting time and effort required of the researcher to collaborate across institutions (Cummings & Kiesler, 2007; Hinds & Bailey, 2003), will outweighs the benefits provided by the enlarged resource base provided by inter-institutional collaboration. Therefore:

H5. The larger the number of different institutions present in interdisciplinary scientific teams, the lower the performance of the team.

Relational-level mechanisms and Team assembly

Prior successful collaboration experience. Prior research has studied the influence of relational mechanisms on the creation, maintenance, and dissolution of collaboration ties. A central finding of these studies is that prior collaboration is an important indicator for future collaboration ties. People prefer to work with those who share similar and familiar work practices, styles, and preferences. Such preference reduces uncertainty about how others will behave in the future (Hinds, Carley, Krackhardt, & Wholey, 2000). Studies on scientific collaboration have confirmed these findings as well (Lungeanu & Contractor, 2015; Lungeanu et al., 2014). Prior collaboration may be a necessary but not sufficient argument to suggest future collaboration. Theories of learning processes suggest that the likelihood of collaborating in the future is predicated on the joint existence of a prior collaboration and on its success (Cyert & March, 1963). Empirical research has also shown that prior successful collaboration increases the chance of similar future collaborations (Schwab & Miner, 2008). Therefore:

M5. Researchers are more likely to collaborate with prior successful collaborators proportional to the success of their prior collaboration.

Friend of a friend. While the studies mentioned above examined collaboration through direct ties, other scholars showed that prior collaboration influence future collaboration through indirect ties as well. According to the “friend-of-a-friend” mechanism, people tend to become friends with their friends’ friends (Heider, 1958). This tendency of clustering in a network is true not only in friendship networks, but also in professional networks such as those within academia or the banking industry (for a review, see Rivera, Soderstrom, & Uzzi, 2010). For example, Newman (2001) examined scientific collaboration in three scientific fields (i.e., biology, physics, and computer science) over a five-year period and showed that there is a "strong clustering effect in the scientific community: two researchers typically have a 30% or greater probability of collaborating if both have collaborated with a third scientist" (Newman, 2001, p. 408). Therefore:

M6. Researchers with prior common collaborators are more likely to collaborate.

Elite homophily. It is well know that individuals are more likely to preferentially form ties with well-connected (central or high-degree) individuals in a community than less well-connected (non-central or low-degree) individuals (for a review, see Rivera et al., 2010). This preferential attachment (Barabási & Albert, 1999; de Solla Price, 1965) to well-connected nodes has been found to occur in many social networks. When ties require effort to be maintained, highly connected individuals can only create forge ties up to a certain "carrying capacity." (Guimera et al., 2005; Uzzi & Spiro, 2005). In such circumstances, there is a preference for highly connected actors (the "elite") to assemble into teams with other highly connected actors. This preference for elite homophily results in a strong tendency for assortativity among elite actors. Therefore:

M7: Well-connected researchers are more likely to collaborate with other well-connected researchers.

Relational-level attributes and Team performance

Prior successful collaboration. As a substantive indicator of a relationship, prior successful collaboration is a reflection of good communication and coordination among the researchers, of the trust already built among them, and of their ability to use productively the different expertise these researchers hold (Stipelman, Feng, Hall, Moser, Stokols, & Nebeling, 2010). Consistent with this reasoning, research has found that individuals who are confident about their success perform better in audience settings than do those who hold negative expectations (e.g., Geen, 1979). In fact, a widely held view is that the probability of future success increases with achieved success: studies by Lewin et al. (1944) were probably the first to suggest that (student) confidence improves performance and further increases as the student achieves success.

H6: The higher the success of prior collaboration relations of the interdisciplinary scientific team's members, the higher the performance of the team.

Common collaborators. Both the benefits and the drawbacks of prior collaborations can be thought of trickling down through the network, such that collaborating with the collaborator of a prior collaborator would yield similar effects. Network cohesion is defined as "as the extent to which the focal dyad is surrounded by strong connections with common third parties" (Sosa, 2011). Although there are benefits to having network cohesion, the dyads surrounded by connections to common third parties are likely to also be presented with its numerous drawbacks as well. For example, if there is the case that the focal team depends on common third parties to obtain the knowledge they require to generate ideas, then the team will likely suffer from information redundancy (Amabile, 1996). Thus, while the team may possibly be productive, productivity does not necessarily mean that the team will generate creative and novel ideas because access to the necessary knowledge ingredients for these novel ideas does not exist.

H7: The higher the number of prior common collaborators in interdisciplinary scientific teams, the lower the performance of the team.

Team visibility. Finally, teams may be composed of members with various levels of visibility in their field. We define team visibility as the number of people within the large scientific community with which the members of the team have directly co-authored. Biscaro and Giupponi (2014) found that centrality measures significantly correlate with the article citation count. The mechanism these authors propose to predict this outcome is that the quality of ideas and knowledge work is given not just by the number of people who create it, but mainly by the knowledge diversity to which they are exposed. This mechanism is especially relevant in the context of interdisciplinary scientific research. As the authors argue, "establishing social connections with diverse groups enables the exposure to multiple and different intellectual domains, methods, perspectives and techniques and the inclusion of "whole domains of elements […] into the combinative hopper" (Simonton, 1995). Given these arguments, we propose:

H8: The higher the team visibility in interdisciplinary scientific teams, the higher the performance of the team.

Ecosystem-level mechanisms and Team assembly

We define an ecosystem surrounding a focal team as the collection of teams that include individuals who share direct and indirect team membership with members of the focal team. The ecosystem shapes the likelihood of a focal team being assembled and also serves as a conduit for insights to flow between teams within the ecosystem. In the context of scientific interdisciplinary collaboration, these ecosystems of relationships are likely to develop as various members join new teams in search of new collaborators (Contractor, 2013; Guimera et al., 2005; Uzzi & Spiro, 2005). The structure of collaboration networks enables creativity and innovation by integrating members' diverse ideas, skills, and resources (Guimera et al., 2005; Wuchty et al., 2007), and thus influences the likelihood that specific actors will choose to collaborate in the future. Network mechanisms (such as homophily and balance) are drivers for team assembly, and group mechanisms (such as social identity) influence team functioning and performance after teams assemble (Poole & Contractor, 2011). Membership in multiple teams over time affects individual and team learning (O'Leary et al., 2011) and shapes relationships among teams within the larger ecosystem (O'Leary, Woolley, & Mortensen, 2011). In consequence, knowledge "flows through network ties via the individuals that connect different teams by virtue of co-memberships on teams" (Zaheer & Soda, 2009, p. 3). Thus it is possible that intellectual (i.e., knowledge) considerations, coupled with a scientist's prior interlocking relationships with other individuals in the collaborative community, will influence both the choice to join a scientific team and team performance.

Local ecosystem closure. The coherence of the scientific field in which researchers are embedded is necessary for team members to have their knowledge shared and understood. However, scholars have also pointed out that excessive closure might hurt creativity. Such extant research originates from the literature on diversity which postulates that diversity is a critical factor that drives the development of innovative ideas (Fleming, Mingo, & Chen, 2007; Guimera et al., 2005; Uzzi & Spiro, 2005).

As mentioned before, researchers have autonomy when deciding to join interdisciplinary teams and the nature of these teams is to share and build on the knowledge held by their individual members. Researchers may recognize immediate neighborhoods that are less cohesive and therefore more likely to provide collaboration opportunities with individuals holding diverse knowledge. An immediate intellectual neighborhood allows individuals to understand diverse knowledge while maintaining a cognitive structure that allows the transfer and combination of knowledge. Therefore, the first ecosystem mechanism we propose for team assembly is local ecosystem closure:

> *M8: Scientific teams are more likely to be assembled when they are brokering ties within the local neighborhood of their ecosystem.*

Global ecosystem closure. The closure of the ecosystem reflects the degree to which researchers have built a common socio-cognitive model to integrate the diverse sets of knowledge that they exchange. Such a cognitive model is necessary in order to recognize the knowledge held by others, understand current knowledge sharing practices, and understand the rules to identify new and useful knowledge and recombine prior knowledge in order to generate new knowledge (Murray & O'Mahony, 2007; Uzzi & Spiro, 2005). Since the knowledge held by a scientist joining a new team is largely tacit, its effective transfer requires the existence of strong (as opposed to weak) ties (Reagans & McEvily, 2003). Thus, the second ecosystem mechanism we propose is ecosystem closure (coherent intellectual neighborhood):

> *M9: Scientific teams are more likely to be assembled when their global scientific ecosystem represents a "coherent intellectual neighborhood."*

Ecosystem-level attributes and Team performance

Local and global ecosystem closure. At the *local ecosystem level*, a brokered social structure nurtures variety in ideas and information. In the context of interdisciplinary scientific fields, where innovation requires the combination of varied methodologies and theories that have not previously been combined, a brokered social structure provides needed exposure to such information flows (Fleming et al., 2007). At the *global ecosystem level*, a cohesive social structure signals coherence of ideas and methods available to the same members, as well as enhanced trust and uninterrupted knowledge exchange (Coleman, 1988). Prior work showed that a cohesive network allows the transfer of ideas more readily (Hansen, 1999; Reagans & McEvily, 2003). These benefits of cohesive network structures are particularly important when the evolution and growth of the field depends on the diffusion of ideas and innovations generated by teams embedded in the field to a larger audience. For example, Uzzi (1997) documented how cohesive networks supported richer information flows among New York garment designers and manufacturers. In the context of research and development engineers, Hansen (1999) and Reagans and McEvily (2003) demonstrated that cohesive social structures ease information and knowledge transfer, particularly for tacit and complex knowledge that is difficult to transmit. These benefits result in acceptance of ideas generated by the team by other researchers located in the broader global ecosystem and in an increase in the team performance (as expressed by the citations it receives).

> *H9: The lower the local ecosystem closure of interdisciplinary scientific teams, the higher the performance of the team.*

> *H10: The higher the global ecosystem closure of interdisciplinary scientific teams, the higher the performance of the team.*

Table 1 presents the correspondence between assembly and performance mechanisms.

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Outliers across mechanisms: How successful are they?

As mentioned, we proposed an integrated framework encompassing how three sets of mechanisms – compositional, relational, and ecosystem – simultaneously affect team assembly. We developed a theory-based computational model subsequently fitted with empirical data to estimate a set of parameters associated with the theoretical mechanisms which influence team assembly in interdisciplinary scientific teams. We further theorized on how the same mechanisms influence team performance and we conceptualized the latter as "perform-norms."

While the form-norms depict the most prevalent team assembly mechanisms, not all teams will strictly adhere to them. Likewise, while all these assembled teams resulted in publications, not all publications were equally successful. Therefore, we next want to explore the extent to which variance in the performance of these teams can be explained by their adherence to (or departure from) the form-norms. Since we do not theorize a priori why these deviations might impact performance, we pose the following research question:

RQ1a: For which assembly mechanisms is a team's departure from the form-norm associated with higher performance?

RQ1b: For which assembly mechanisms is a team's adherence to the form-norm associated with higher performance?

METHODS

Context, Data, and Variables

The dataset used in this study includes all teams that successfully published scientific articles in the Oncofertility field. The field of Oncofertility represents an appropriate context in which to examine the compositional, relational, and ecosystem mechanisms that may affect the assembly of interdisciplinary teams. Specifically, Oncofertility investigates fertility preservation for young patients with fertility-threatening diseases, reason why the field explicitly requires interdisciplinary collaboration among researchers from two fundamentally different research areas, oncology and fertility, to publish scientific articles. As a new scientific field, Oncofertility is emergent and allows the observation of team assembly and performance at multiple levels of analysis. Studies focused on Oncofertility[1] issues can be traced back to 1993 thus providing sufficient history to empirically test our hypotheses.

We first identified all scientific articles that were published in the Oncofertility field using the keywords *oncofertility*, or *cancer* and *ovarian tissue cryopreservation*, or *cancer* and *fertility preservation*. We used *Web of Science* and *PubMed* databases to construct researchers' bibliometric information. The dataset contained a total of 638 articles published from 1993 to 2010, with 1,708 unique authors. Since we model team assembly, we excluded 86 single authored publications. We also excluded years 1993 – 1995 because there was only one publication written in this interval. The final dataset used for this study spans years 1996 to 2010 for a total of 553 publications and 1,696 authors.

Dependent variables

The main variables assessed in this study are the emergent scientific collaboration relationships and teams, and team performance. First, for collaboration, researchers follow a process of initiating and accepting/rejecting invitations to collaborate and, through this process, teams are assembled. The steps of this process act as the generative mechanisms or antecedents that result in team assembly. Second, we define scientific team performance as research impact, which is operationalized as number of citations each team (i.e., publication) received after 5 years from publications, and we use natural logarithm to account for the skewed distribution. The

[1] The field was officially recognized in 2007 when the National Institutes of Health provided a $6.5 million dollar grant to fund the Oncofertility Consortium.

number of citations that a publication received is reflective of both visibility and quality of the paper, making this indicator a preferred mean for ranking a publication's value (Abbasi & Jaafari, 2013; Lehmann, Jackson, & Lautrup, 2006).

Independent variables

Compositional factors focus on characteristics of the individuals. Given the large number of international researchers, it was difficult to identify the researcher's age or researchers' PhD year. Therefore, to code *researcher seniority* (*M1*) we use a proxy measure: we subtracted the year of researchers' first publication from the year analyzed. Then, we computed *team average seniority (H1a)* and *team seniority diversity* (*H1b*) as the average, and variance respectively, of team members' seniority. H-index is the maximum number *h* for which a researcher's *h* papers have at least *h* citations each (Hirsch, 2005, 2007). H-index captures both the productivity and the impact of the researcher. Researchers' *H-index* (*M2*) was computed based on the publication and citation information available in the *Web of Science* database. Based on team members' H-index, we computed *team average H-index (H2a)* and *team H-index diversity* (H2b). Finally, we coded the *Percentage of females on team (M3 & H3),* the *number of countries (H4)* and *the number of institutions (M4 & H5)* with whom the team members are affiliated.

Relational factors focus on relations among the individuals. To code *Prior successful collaboration (M5 & H6)* we considered that a collaboration relation forms between two researchers when they published together. Co-authoring a publication is an important measure of researchers' prior collaborative relationship (Guimera et al., 2005). Next, we extracted all publications co-authored by at least two members of the team, and we extracted the number of citations these publications received before the team was assembled. Finally, the prior success of collaboration was operationalized as the average number of prior citations each team received.

The *number of prior common collaborators (M6 & H7)* was computed as the distinct number of researchers with whom any two researchers from the team collaborated before the team was formed. Finally, based on the co-authorship network, we also computed the measure *for the well-connected researchers (M7)* as researchers' number of unique collaborators (i.e., degree centrality) and *the team visibility* (*H8*) as the average team members' degree centrality in the Oncofertility field.

<u>Ecosystems factors</u> focus on characteristics of the ecosystem in which the potential team would be embedded. The ecosystem measures were computed for each team in the Oncofertility ecosystem. To compute these metrics we constructed the ecosystem network where the nodes were the teams associated with each publication and the links between two nodes are the team interlocks defined as the number of common coauthors between those two teams. *Local ecosystem closure (M8 & H9)* was computed as the focal team's local clustering coefficient in the Oncofertility ecosystem. The focal team's local neighborhood was defined as the total number of teams that were directly connected to the focal tam by at least one overlapping member. As such it was the focal team's egocentric network. The local clustering coefficient is defined as the amount of overlapping membership that existed among the teams that co-authored with members of the focal team. It is computed as the density of ties among the alters of the focal team. For instance, when there is no overlapping membership among the teams with which the focal team members coauthored the local clustering coefficient would be zero.

Finally, *Global ecosystem closure (M9 & H10)* was computed as the average clustering coefficient of the focal team's global neighborhood in the Oncofertility ecosystem. Focal team's global neighborhood was defined as the total number of teams three-steps away from the focal team in the ecosystem network. The global clustering coefficient is computed as the total number of closed triads in the ecosystem network relative to the number of possible triads. A closed triad represents a set of three teams all of which had overlapping membership.

Team Assembly: Computational Model Description

To test our hypothesized assembly mechanisms (M1 to M9) we use a hybrid agent-based system dynamics simulation. Although system dynamics models and agent-based models have been utilized separately to model the assembly of scientific teams and the evolution of new scientific fields (Bettencourt et al. 2008; Guimera et al. 2005; Sun et al.2013), a hybrid approach enables us to simultaneously examine the effect of heterogeneous individual attributes and relations on the assembly of teams in emerging scientific fields, as well as, in turn, the impact of systemic characteristics of the scientific field on subsequent team assembly. Therefore, a hybrid model has the potential to explore more realistically (and accurately) the assembly of teams in emerging scientific fields.

The implementation of the computational model relies heavily on empirical data and is focused on team level properties such as number of teams and distribution of team sizes. In order to simulate team assembly, we assume that the distribution of team sizes and an individual's participation in a certain set of team sizes in a given year are constant and equal to what was empirically observed. However, to preserve space, we do not describe here the model initialization and team assembly steps, but move on to implementation.

The model was implemented in the NetLogo ABM platform (Wilensky, 1999)and the model' parameters were fit using the BehaviorSearch tool (e.g., Stonedahl & Wilensky, 2010). BehaviorSearch is a powerful and robust tool that calibrates models implemented in NetLogo (Thiele, Kurth, & Grimm, 2014). The aim of calibration is to find the parameter combination that best fits the observational data (Railsback & Grimm, 2011). Basically, calibration describes the process of manipulating a model to get closer to a desired behavior. In this case, the desired behavior is matching the simulated teams to the empirical teams as closely as possible. The objective function used was to minimize the fit error. The fit error was computed mean squared error (MSE) between the average clustering coefficients of the simulated teams ($AvgCC_{SIM}$) and the empirical teams ($Avg\ CC_{EMP}$). By squaring the differences we make sure that negative errors do not offset positive errors, and that we emphasize larger rather than smaller errors (Railsback & Grimm, 2011)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(Avg\ CC_{EMP} - AvgCC_{SIM})^2} \quad (1)$$

where *n* represents the number of times the model is run with a specific set of parameters.

The optimization function was measured as the minimum objective function over 100 simulations. Each simulation contained 1,000 model runs with 100 replications of each previous best model obtained. The variables in the model were all weighted to fall between 0 and 1. Additionally, all parameters were specified to range between 0 and 1 because of the positive relationship hypothesized the model. This analytical strategy allows to compare directly the effect sizes of all parameters specified. The magnitude of the parameter is the effect size for each mechanism and describes how important each factor is relative to the others. Important effects are defined as effects that have larger effect sizes relative to the other factors assessed.

Two separate analyses were performed to empirically fit the model. First, the BehaviorSearch minimization was run across all years. This analysis yields one set of parameters. Additionally, the BehaviorSearch minimization was run for each year separately. This yields a distinct set of parameters for each year.

Team Performance: Statistical Model Description

The performance hypotheses (*H1* to *H10*) were tested using a generalized linear model regression. Furthermore, we used a spline function to determine the impact of the team's departure from the form-norm on performance (*RQ1* and *RQ2*). Spline functions incorporate the notion that preferences and behaviors can vary depending upon whether one's position is above or below a certain reference point or theoretical level (Greene, 1993). In this case the reference point is the form-norm based on the theory-driven computational model explained above.

Specifically, the reference point along each compositional, relational, and ecosystem mechanism is the mean values of team characteristics obtained from the computational model for the corresponding year (i.e., simulation). Therefore, for each independent variable described above (i.e., mechanism), we created two measures: *Characteristic above form-norm* and *Characteristic below form-norm.* In the next paragraphs we will present the methodology used to compute the teams' characteristics above and below the form-norm.

We ran the computational model using the year by year estimated parameters. Each model run was replicated 100 times. The teams created by the model with the minimum fit error were saved for the future analysis. After the last year model was run, we obtained 553 simulated teams. The simulated teams had the same size, the same distribution of team sizes, and the same individual's participation in a certain set of team sizes in a given year as the empirically observed teams. Next, for each of the 553 simulated teams, we computed the team characteristics used to predict team performance in the current study. The aspiration level, or the average simulated level is the mean value of each team characteristic for the corresponding year.

Then, for each factor we computed two measures: characteristic above the average simulated value and characteristic below the average simulated value. As an illustration, we will detail below the formula for the *percentage of females* on team characteristic.

$$\text{Percentage of females } \textit{above form} - \textit{norm}_{\,year_y, team_i} =$$
$$\begin{cases} \text{Percentage of females}_{\,team_i} - AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right), \\ if \text{ Percentage of females}_{\,team_i} \geq AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right) \\ 0, \\ if \text{ Percentage of females}_{\,team_i} < AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right) \end{cases} \quad (2)$$

$$\text{Percentage of females } \textit{below form} - \textit{norm}_{\,year_y, team_i} =$$
$$\begin{cases} \text{Percentage of females}_{\,team_i} - AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right), \\ if \text{ Percentage of females}_{\,team_i} < AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right) \\ 0, \\ if \text{ Percentage of females}_{\,team_i} \geq AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right) \end{cases} \quad (3)$$

where $team_i$ published in year $year_y$. $AVG\left(avg\ simulated \text{ Percentage of females}_{\,year_y}\right)$ is the average *percentage of females* for $year_y$ for the teams obtained in the computational model.

Results: Team Assembly (Parameter Estimation)

The computational model shows that, of the four compositional mechanisms influencing team assembly, H-index was the most important factor (0.99), followed by seniority (0.79). Gender inertia and institution affiliation preferences are not important when deciding collaboration relationships (0.12 and 0.19 respectively). Out of the three relational mechanisms for team assembly, friend of a friend is the most important factor (0.88), followed by elite homophily (0.64), and prior successful collaboration (0.44). Out of the two ecosystem based team assembly mechanisms, global ecosystem closure is more important (0.45) than low local ecosystem closure (i.e., high number of brokering ties within the local ecosystem neighborhood).

As expected, the results show that the importance of the parameters for the four compositional mechanisms vary greatly at the beginning of a new scientific field with three of the factors recording a peak in year 2007 (i.e., seniority, H-index, and institution affiliation inertia). Out of the three relational mechanisms, the factor recorded for prior successful collaboration factor is stable in time with a very small change after 2007. The elite homophily factor, in particular, has an interesting trend: while its importance is very low at the beginning of the field, it increases gradually, and then decreases after 2006-2007. Both ecosystem mechanisms proposed show parameters that decrease in time. This trend suggests that the growth of the field is accompanied by a decrease in the risk associated with involvement in the field. Therefore, the need to have a common language and to pursue radically new ideas decreases.

It is noteworthy that the changes that appear around 2006-2007 coincide with NIH funding the creation of the Oncofertility Consortium. This illustrates the impact of external events such as funding on the motivations of individuals to assemble into teams. Furthermore, the overall parameters are close to those estimated in 2010 (except, M7- Elite homophily and M9 – Global ecosystem closure). This shows that year 2010 is important in the fit of the model. The reason could be that year 2010 has the highest number of teams 151 (27% of total teams).

Results: Factors Predicting Team Performance

Table 2 presents the results of the regression models predicting team performance. Model 1 presents the effects of the compositional factors. Model 2 presents the effect of both compositional and relational factors on team performance and Model 3 adds the effect of the ecosystem factors on team performance. Finally, Model 4 contains the squared term for institutions since it has been argued that, under some conditions, the number of institutions can have a positive effect on team performance (Jones, Wuchty, & Uzzi, 2008).

--- Insert Table 2 about here ---

Hypotheses 1 to 5 predict the effect of the compositional mechanism on team performance. Hypotheses 1a for *Average seniority* (negative and significant effect at $p < 0.001$), Hypotheses 1b for *Seniority diversity* (positive and significant effect at $p < 0.001$), and Hypotheses 2a for *Average H-index* (positive and significant effect at $p < 0.001$), Hypotheses 2b for *H-index diversity* (negative and significant effect at $p < 0.01$), Hypotheses 3 for *Percentage of females* (positive and significant effect at $p < 0.01$), and Hypotheses 4 for *Number of countries* (positive and significant effect at $p < 0.001$) were supported. Hypothesis 5 which predicted a negative effect of the *number of institutions* on performance is not supported.

As mentioned, although research has shown a negative effect for the number of institutions on team performance (see Cummings & Kiesler, 2007; Cummings, Kiesler, Zadeh, & Balakrishnan, 2013), Jones et al. (2008) argued for a positive effect when certain conditions are met (i.e., association with a top-tier university). Since Hypothesis 5 is not supported we investigated the possibility that there may be some conditions in which the number of institutions has a positive effect on performance. Therefore we provided a post-hoc analyses in which we added the institution's squared term to the regression. When a team has between 1 and 5 institutions represented, the effect on performance does not vary widely. However, each new institution added over 5 increases performance significantly.

Hypotheses 6 to 8 predict the effect of the relational mechanism on team performance. Hypotheses 6 for *Prior successful collaboration* (positive and significant effect at $p < 0.01$) and Hypotheses 7 for *Prior common collaborators* (negative and significant effect at $p < 0.05$) are supported. Hypothesis 8 which predicted a positive effect of *Team visibility* on team performance is not supported.

Hypotheses 9 for the effect of *Local ecosystem closure* (negative and significant effect at $p < 0.05$) on team performance and Hypotheses 10 for the effect of *Global ecosystem closure* (positive and significant effect at $p < 0.001$) on team performance were both supported.

One novelty that this study brings is that it shows the simultaneous combination of three different levels of influence on team performance. To determine whether the addition of the relational and ecosystem factors in the model improves the model fit in robust regression analyses, we conducted the Wald tests which calculate whether or not the coefficients of the added variables at each step are simultaneously zero. The results show that the addition of the relational factors increases the percent of variance in team performance. Furthermore, the added ecosystem measures explain more variance in team performance than the compositional and relational factors together.

Results: Factors Predicting Team Performance (Above and Below Form-Norms)

Tables 3 and 4 present the results of the effect of deviation across each proposed mechanisms from the form-norms (i.e., using the spline function procedure) on performance. Each model includes the variables above and below the form-norm while controlling for all the other observed team characteristics.

--- Insert Tables 3 and 4 about here ---

The results obtained through the spline function procedure show that when there is a positive relationship between a mechanism and the performance of team, *the observed teams fare better when their parameters associated with these mechanisms are already at levels higher than the form-norms*. This finding applies to *Seniority diversity, Average H-index, Number of countries, Prior successful collaboration,* and *Global ecosystem closure*. The same pattern applies to *Number of institutions* and *Team visibility*, although in those cases the overall effect of these mechanisms on team performance is not significant.

Further, when there is a positive relationship between a mechanism and team performance, *teams fare worse when their parameters associated with these mechanisms are already at levels lower than the form-norms*. Our analyses provided statistically significant relationships when parameters were below those of form-norms in three cases: *Average H-index, Percentage of female,* and *Number of countries*.

In cases where the mechanism has an overall negative effect (i.e. as the parameters associated with the mechanism increase, the performance of the team is decreasing), the split function reveals a distinct relationship for cases when the parameters are above those of the form-norms and a less distinct relationship when parameters are below those of form-norms.

Specifically, when there is an overall negative relationship between a mechanism and the team performance, *teams fare worse when their parameters associated with these mechanisms are already at levels higher than the form-norms*. This finding applies to *Average seniority, H-index diversity, Prior common collaborators,* and *Local ecosystem closure*.

The relationship between assembly mechanisms and team performance is less distinct when their parameters are already lower than those of form-norms. Specifically, we find that teams fare better when the empirical parameter for *Average seniority* is below that of the form-norms, and fare worse when the empirical parameter for *Prior common collaborators* is below that of the form-norms.

So far, we interpreted the results with a primary focus on the overall relationship between a particular mechanism and team performance, and a secondary focus on the location of the parameter for observed teams above or below that of the simulated teams. The results we obtained can also be interpreted with a sole focus on the location of the parameter, above or below the form-norms. Results show that when the empirical parameter is below the form-norm (in other words when observed teams have a parameter value for an assembly mechanism that is lower than the form-norm), an increase in the *Average H-index, Percentage of females on team, Number of countries,* and *Prior common collaborators* will improve team performance. For only one mechanism, *Average seniority*, an increase in its parameter leads to a performance decline.

Results also show that when the empirical parameter is above the form-norm an increase in the *Seniority diversity, Average H-index, Number of countries, Number of institutions, Prior* *successful collaboration, Team visibility,* and *Global ecosystem closure,* increases team performance. On the other hand, an increase in the *Average seniority*, *H-index diversity*, *Prior common collaborator,* and *Local ecosystem closure* leads to a performance decline.

Several mechanisms record significant relationships for values of the empirical parameters above and below the form-norms. For example, the results suggest that when the parameter for *Percentage of females on team* is below that of the form-norm, one unit increase in the percentage of female will increase team performance by 69.3%. The results also suggest that when the parameter for *Number of countries* is below that of form-norm, one unit increase in parameter value will increase team performance by 31.1%. Finally, when the parameter for *Local ecosystem closure* is above that of form-norm, a 0.1 unit increase in the parameter value decreases team performance by 37.9%.

DISCUSSION

This study started with an investigation of the compositional, relational, and ecosystem mechanisms affecting interdisciplinary team *assembly* using a hybrid agent-based and system dynamics computational model fitted with empirical data. The computational model was used to investigate which of the mechanisms affect interdisciplinary team *performance*. Our premise was that while some mechanisms may be more frequently observed in the assembly of interdisciplinary teams assembly, other less frequently observed mechanisms may be associated with higher (or lower) team performance. Finally, we estimated the extent to which specific teams' positive and negative departure from the form-norms on specific assembly mechanisms impacted the performance of the teams.

Effects of Compositional, Relational, and Ecosystem Mechanisms on Team Performance

The overall effects of the compositional, relational, and ecosystem mechanisms on interdisciplinary team performance support the main hypotheses of this study, with the exception of team visibility and number of institutions. Teams with high visibility members (i.e. who have a larger number of co-authors) were not more likely to perform better and the number of institutions on a team does not have a linear effect on performance. When a team has between 1 and 5 institutions represented, the effect on performance does not vary widely. However, our post hoc analyses revealed that each new institution added, after 5 are represented on a team, significantly increases performance.

An important contribution of this study is the introduction of ecosystem mechanisms as factors influencing team performance. While the notion that teams are formed of individuals that have worked before is intuitive, this study is the first to show that the embeddedness of teams in prior relationship via multiple team memberships are consequential for team performance. Further, our study distinguishes between the types of ecosystem embeddedness – the structural characteristics of the local versus the global ecosystem. Specifically, we found that the performance of teams is higher when the local ecosystem (that is the ecosystem which is in the immediate neighborhood of the team) has low closure, but the global ecosystem (the ecosystem of teams that are up to three steps removed from the focal team) has high closure.

Cases where teams' assembly mechanisms are below the "form-norms"

The examination of specific teams with assembly parameters deviating from the form-norms for interdisciplinary teams provides interesting insights. Results suggest that increases in H-index, women and country representation, and working with more prior collaborators improve the performance of the team. However, an increase in the average age of the team to conform to normative expectations for team assembly leads to a performance decline.

Cases where teams' assembly mechanisms are above the "form-norms"

Results also show that teams perform better when their parameter values for assembly mechanisms are higher than the form-norms for diversity in team age, the average H-Index of the team, the number of countries and institutions represented on the team, prior successful collaboration, team visibility, and global ecosystem closure. On the other hand, teams perform worse when their parameter values are lower than the form-norms for average age of the team, H-index diversity, number of prior common collaborators, and local ecosystem closure. These results suggest that when the average H-index and number of countries represented on the team are below those expected based on form-norms, a further increase will increase performance.

To summarize, this study attempts to advance our understanding of the factors that influence the assembly of teams in an emerging scientific discipline. It found that team assembly factors that led to the nascent field receiving a large amount of external funding in 2010 were different from team assembly factors post-funding. Further, factors that explain why teams form, were not always predictors of how well they would perform. Finally, our analyses of the departure of specific teams from the general form-norms provide a foundation for developing and testing interventions to enhance the impact of team assembly on performance.

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TABLES AND FIGURES

TABLE 1. Summary: Team assembly mechanisms vs. Hypothesized performance mechanisms

Assembly	Performance
Compositional mechanisms	
M1: Researchers prefer to collaborate with senior researchers.	H1a: The higher the average seniority in interdisciplinary scientific teams, the lower the performance of the team. H1b: The higher the seniority diversity in interdisciplinary scientific teams, the higher the performance of the team.
M2: Researchers prefer to collaborate with high performing researchers (H-index)	H2a: The higher the average H-index in interdisciplinary scientific teams, the higher the performance of the team. H3b: The higher the H-index diversity in interdisciplinary scientific teams, the higher the performance of the team.
M3: Researchers' preferences for (or against) gender homophily when choosing new collaborators will remain the same as their preferences in choosing prior collaborators.	H3: The higher the proportion of women in interdisciplinary scientific teams, the higher the performance of the team.
M4: Researchers' preferences for (or against) institution homophily when choosing new collaborators will remain the same as their preferences in choosing prior collaborators.	H4*: The larger the number of different countries present in interdisciplinary scientific teams, the higher the performance of the team. H5: The larger the number of different institutions present in interdisciplinary scientific teams, the lower the performance of the team.
Relational mechanisms	
M5: Researchers are more likely to collaborate with prior successful collaborators proportional to the success of their prior collaboration.	H6: The higher the success of prior collaboration relations of the interdisciplinary scientific team's members, the higher the performance of the team.
M6: Researchers with prior common collaborators are more likely to collaborate.	H7: The higher the number of prior common collaborators in interdisciplinary scientific teams, the lower the performance of the team.
M7: Researchers prefer to collaborate with well-connected researchers. Well-connected researchers are less likely to accept collaborations with less well-connected researchers.	H8: The higher the team visibility in interdisciplinary scientific teams, the higher the performance of the team.
Ecosystem mechanisms	
M8: Scientific teams are more likely to be assembled when they are brokering ties within the local neighborhood of their ecosystem.	H9: The lower the local ecosystem closure of interdisciplinary scientific teams, the higher the performance of the team.
M9: Scientific teams are more likely to be assembled when their global scientific ecosystem represents a "coherent intellectual neighborhood."	H10: The higher the global ecosystem closure of interdisciplinary scientific teams, the higher the performance of the team.

*Note: * While the computational model does not contain country as a mechanism, the effect of country can be relevant given the globalization of scientific research and the given the different institutional environments for scientific endeavors created in different countries.*

TABLE 2. Effect of team characteristics on team performance

	Model 1 Compositional	Model 2 Relational	Model 3 Ecosystem	Model 4 Post-hoc
H1a: Average seniority	-0.275***	-0.275***	-0.284***	-0.284***
	(0.01)	(0.01)	(0.01)	(0.01)
H1b: Seniority diversity	0.136***	0.133***	0.132***	0.133***
	(0.00)	(0.00)	(0.00)	(0.00)
H2a: Average H-index	0.485***	0.485***	0.485***	0.464***
	(0.01)	(0.01)	(0.01)	(0.01)
H2b: H-index diversity	-0.198**	-0.203**	-0.195**	-0.181**
	(0.00)	(0.00)	(0.00)	(0.00)
H3: Percentage of female on team	0.126**	0.116**	0.115**	0.115**
	(0.15)	(0.15)	(0.15)	(0.15)
H4: Number of countries	0.165***	0.168***	0.148***	0.137***
	(0.07)	(0.07)	(0.07)	(0.08)
H5: Number of institutions	0.002	0.003	-0.005	-0.281*
	(0.04)	(0.04)	(0.04)	(0.11)
Number of institutions (square)				0.295**
				(0.02)
H6: Prior successful collaboration		0.069**	0.066**	0.070**
		(0.00)	(0.00)	(0.00)
H7: Prior common collaborators		-0.058	-0.135*	-0.123*
		(0.01)	(0.01)	(0.01)
H8: Team visibility		0.018	0.086	0.079
		(0.01)	(0.01)	(0.01)
H9: Local ecosystem closure			-0.206**	-0.195**
			(1.78)	(1.75)
H10: Global ecosystem closure			0.208***	0.214***
			(1.62)	(1.60)
Team size	0.164***	0.161**	0.126*	0.126*
	(0.02)	(0.02)	(0.02)	(0.02)
Publication Year (ref. categ. 1996-2006)				
2007	-0.075	-0.079+	-0.088+	-0.086+
	(0.16)	(0.16)	(0.16)	(0.16)
2008	-0.045	-0.050	-0.055	-0.053
	(0.14)	(0.14)	(0.14)	(0.14)
2009	-0.092+	-0.087+	-0.111*	-0.118*
	(0.13)	(0.14)	(0.13)	(0.13)
2010	-0.225***	-0.221***	-0.257***	-0.261***
	(0.12)	(0.13)	(0.13)	(0.13)
Log lik.	-740.2	-738.2	-730.5	-727.7
AIC	1506.4	1508.5	1496.9	1493.4
BIC	1562.0	1576.9	1573.9	1574.7

N= 532. 21 teams were excluded from the final analyses because they were outliers either in the first or second model. Standardized beta coefficients; Standard errors in parentheses. Two-tail effect: + p < .10, * p < .05, ** p < .01, *** p < .001

TABLE 3. Effect of team characteristics above or below form-norms on team performance (Compositional)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Average seniority	Seniority diversity	Average H-index	H-index diversity	Percentage of female on team	Number of countries	Number of institutions
Above Average Simulated	-0.143**	0.121***	0.311***	-0.162**	0.035	0.033*	0.055+
	(0.01)	(0.00)	(0.02)	(0.00)	(0.31)	(0.16)	(0.10)
Below Average Simulated	-0.112*	0.016	0.274***	0.017	0.085+	0.150***	-0.017
	(0.01)	(0.00)	(0.02)	(0.00)	(0.29)	(0.08)	(0.05)
Average seniority		-0.273***	-0.296***	-0.263***	-0.281***	-0.285***	-0.285***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Seniority diversity	0.095*		0.136***	0.120**	0.131***	0.131***	0.134***
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average H-index	0.419***	0.481***		0.424***	0.477***	0.485***	0.477***
	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)
H-index diversity	-0.162*	-0.186**	-0.199**		-0.192**	-0.193**	-0.189**
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Percentage of female on team	0.115**	0.114**	0.114**	0.108*		0.115**	0.114**
	(0.15)	(0.15)	(0.15)	(0.15)		(0.15)	(0.15)
Number of countries	0.157***	0.148***	0.145***	0.144***	0.147***		0.136***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
Number of institutions	-0.005	-0.005	-0.004	-0.004	-0.004	-0.007	
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Prior successful collaboration	0.065**	0.068**	0.065**	0.064**	0.068**	0.066**	0.068**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prior common collaborators	-0.138*	-0.136*	-0.142*	-0.138*	-0.137*	-0.135*	-0.128*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Team visibility	0.092	0.087	0.088	0.089	0.090	0.089	0.082
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Local ecosystem closure	0.206***	0.209***	0.210***	0.207***	0.209***	0.207***	0.208***
	(1.64)	(1.61)	(1.61)	(1.62)	(1.63)	(1.63)	(1.62)
Global ecosystem closure	-0.192*	-0.212**	-0.217**	-0.218**	-0.206**	-0.208**	-0.203**
	(1.78)	(1.79)	(1.81)	(1.78)	(1.77)	(1.77)	(1.78)
Team size	0.123*	0.131*	0.119*	0.115*	0.119*	0.130*	0.119*
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Publication Year (ref. categ. 1996-2006)							
2007	-0.097*	-0.087+	-0.044	-0.088+	-0.082+	-0.102*	-0.083+
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
2008	-0.046	-0.050	-0.044	-0.059	-0.046	-0.033	-0.053
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
2009	-0.096+	-0.121*	-0.119*	-0.105*	-0.098*	-0.074	-0.112*
	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.14)
2010	-0.304***	-0.246***	-0.149*	-0.262***	-0.245***	-0.216***	-0.254***
	(0.13)	(0.13)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)
Log lik.	-733.5	-730.3	-729.2	-730.4	-731.0	-729.7	-729.7
AIC	1505.1	1498.7	1496.4	1498.8	1499.9	1497.4	1497.4
BIC	1586.3	1580.0	1577.6	1580.0	1581.2	1578.7	1578.6

N= 532. 21 teams were excluded from the final analyses because they were outliers either in the first or second model. Standardized beta coefficients; Standard errors in parentheses. Two-tail effect: + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

TABLE 4. Effect of team characteristics above or below form-norms on team performance (Relational and Ecosystem)

	Model 8 Prior successful collaboration	Model 9 Prior common collaborators	Model 10 Team visibility	Model 11 Local ecosystem closure	Model 12 Global ecosystem closure
Above Average Simulated	0.052*	-0.179**	0.086*	-0.176*	0.210***
	(0.00)	(0.01)	(0.02)	(1.88)	(2.26)
Below Average Simulated	0.064	0.095+	0.014	-0.092	-0.038
	(0.03)	(0.09)	(0.02)	(8.17)	(7.79)
Average seniority	-0.284***	-0.284***	-0.281***	-0.284***	-0.283***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Seniority diversity	0.132***	0.136***	0.129***	0.134***	0.132***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average H-index	0.478***	0.469***	0.480***	0.479***	0.474***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
H-index diversity	-0.193**	-0.190**	-0.195**	-0.194**	-0.190**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Percentage of female on team	0.116**	0.117**	0.122**	0.118**	0.127**
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Number of countries	0.147***	0.141***	0.152***	0.151***	0.156***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Number of institutions	-0.004	0.001	-0.004	0.001	-0.001
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Prior successful collaboration		0.059*	0.069**	0.069**	0.071**
		(0.00)	(0.00)	(0.00)	(0.00)
Prior common collaborators	-0.138*		-0.125*	-0.128*	-0.120*
	(0.01)		(0.01)	(0.01)	(0.01)
Team visibility	0.091	0.097		0.105	0.107
	(0.01)	(0.01)		(0.01)	(0.01)
Local ecosystem closure	0.207***	0.208***	0.223***		-0.197**
	(1.62)	(1.62)	(1.66)		(1.75)
Global ecosystem closure	-0.207**	-0.219**	-0.209**	0.230***	
	(1.79)	(1.76)	(1.76)	(1.79)	
Team size	0.120*	0.102+	0.148*	0.113*	0.117*
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Publication Year (ref. categ. 1996-2006)					
2007	-0.039	-0.068	-0.090+	-0.109*	-0.090+
	(0.24)	(0.17)	(0.17)	(0.17)	(0.17)
2008	-0.057	-0.041	-0.053	-0.075	-0.061
	(0.14)	(0.14)	(0.16)	(0.14)	(0.15)
2009	-0.117*	-0.112*	-0.099	-0.146**	-0.110*
	(0.13)	(0.13)	(0.17)	(0.14)	(0.14)
2010	-0.273***	-0.258***	-0.232*	-0.330***	-0.261***
	(0.13)	(0.13)	(0.23)	(0.17)	(0.16)
Log lik.	-730.3	-728.0	-729.4	-729.7	-730.1
AIC	1498.5	1494.0	1496.8	1497.3	1498.2
BIC	1579.8	1575.3	1578.0	1578.6	1579.5

N= 532. 21 teams were excluded from the final analyses because they were outliers either in the first or second model. Standardized beta coefficients; Standard errors in parentheses. Two-tail effect: + p < .10, * p < .05, ** p < .01, *** p < .001