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Understanding the assembly of interdisciplinary teams and its impact on performance

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Abstract

Interdisciplinary teams are assembled in scientific research and are aimed at solving complex problems. Given their increasing importance, it is not surprising that considerable attention has been focused on processes of collaboration in interdisciplinary teams. Despite such efforts, we know less about the factors affecting the assembly of such teams in the first place. In this paper, we investigate the structure and the success of interdisciplinary scientific research teams. We examine the assembly factors using a sample of 1,103 grant proposals submitted to two National Science Foundation interdisciplinary initiatives during a 3-year period, including both awarded and non-awarded proposals. The results indicate that individuals' likelihood of collaboration on a proposal is higher among those with longer tenure, lower institutional tier, lower H-index, and with higher levels of prior co-authorship and citation relationships. However, successful proposals have a little bit different relational patterns: individuals' likelihood of collaboration is higher among those with lower institutional tier, lower H-index, (female) gender, higher levels of prior co-authorship, but with lower levels of prior citation relationships.

Keywords

Team assembly; Social network analysis; Co-authorship network; Citation network; Scientific collaboration; Interdisciplinary collaboration; Project funding; Grant decision-making

1 Introduction

> "Discovery increasingly requires the expertise of individuals with different perspectives—from different disciplines and often from different nations—working together to accommodate the extraordinary complexity of today's science and engineering challenges." (National Science Foundation 2006)

There is a growing recognition of the importance of interdisciplinary teams in addressing contemporary societal and scientific challenges. Such teams bring together scientists from diverse fields (McCorcle, 1982) to create a common understanding of issues (Hall, Feng, Moser, Stokols, & Taylor, 2008; Huutoniemi, Klein, Bruun, & Hukkinen, 2010; Wagner et al., 2011) “whose solutions are beyond the scope of a single discipline or area of research practice” (National Academies, 2004, p. 26). While interdisciplinary scientific teams share some similarities to traditional teams, they operate in a more complex environment (Klein, 2005). Specifically, these teams are established to solve complex problems that homogenous or cohesive teams, which are traditional for individual disciplines, cannot (Younglove-Webb, Gray, Abdalla, & Thurow, 1999).

The increasing importance of interdisciplinary teams in science has prompted scholars to investigate the key factors behind effective collaboration among such team members (Fiore, 2008; Olson, Zimmerman, & Bos, 2008; Stokols, Hall, Taylor, & Moser, 2008). This research showed how interdisciplinary scientific teams benefit from understanding the importance of collaboration networks and proposed ways to efficiently collaborate within and across university boundaries (Cummings & Kiesler, 2008). Research has also demonstrated that team collaborations yielded publications with a higher intellectual impact than single researchers did (Wuchty, Jones, & Uzzi, 2007). And yet, consistently assembling teams that produce significant knowledge is a daunting task, for intellectual as well as logistic and technical reasons. As a result, while people form teams all the time, they often do so in a suboptimal manner, negatively impacting the scientific enterprise. Therefore, there is clearly a need for an understanding of 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).

Understanding the assembly of interdisciplinary scientific teams and the drivers affecting their success is important for at least two reasons. First, many teams in the workplace today are ad-hoc, agile, distributed, and transient entities, as they emerge from a larger primordial network of relationships within virtual communities. These teams are formed of researchers that made individual decisions on whether to collaborate or not. The scientific enterprise is one of the areas where this trend is particularly noteworthy (Bercovitz & Feldman, 2011). Therefore, interdisciplinary collaboration provides an appropriate context to study team formation and to understand individuals’ motivations to choose team members and engage in team work.

Second, interdisciplinary scientific teams also incorporate specialized expertise, concepts, and diverse methodological and theoretical approaches (National Academies, 2004). This requirement produces extreme heterogeneity across many attributes of an interdisciplinary team. And yet, these interdisciplinary teams must utilize the heterogeneous attributes of their members to successfully accomplish their goals (Börner, et al., 2010). Therefore, such teams serve as an excellent context to study the mechanisms that drive the formation of successful teams where members need to possess specialized and diverse expertise.

As we mentioned, prior research mostly examined the factors affecting team effectiveness without considering how these teams were formed in the first place (Acedo, Barroso, Casanueva, & Galán, 2006; Guimera, Uzzi, Spiro, & Amaral, 2005). Our study seeks to advance our understanding of team assembly processes. We believe this area of scholarly inquiry is especially important given the freedom individuals have in choosing team members and given the diverse and specialized expertise needed to successfully accomplish their goals. We draw upon theories on the formation of social networks (Contractor, Wasserman, & Faust, 2006), their extensions to the assembly of teams (Contractor, 2013) as well as the more extensive research on groups and teams (Levine & Moreland, 1998) to examine the factors leading to assembly of interdisciplinary scientific teams in general and successful collaborations in particular. Our hypotheses build on these theories to predict how individual level factors (i.e., gender, tenure, and university affiliation) and relational factors (i.e. prior collaboration and citation relationships) influence the formation of interdisciplinary scientific teams and to identify the factors influencing team success. We conclude with implications of our findings to research and policy on interdisciplinary scientific collaboration.

2 Theoretical background and hypotheses

National Academies (2004, p. 26) defines interdisciplinary research as “a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or area of research practice.” While this definition refers to both teams and individuals, Fiore (2008, p. 272) stressed the importance of the concept of the “team” in interdisciplinary research by emphasizing that interdisciplinary research is in fact team research because “it is infeasible to conduct interdisciplinary research independently.” Scientific interdisciplinary teams are made-up of scientists from diverse disciplines that are brought together to create a common understanding of complex issues or problems (Hall, et al., 2008; Wagner, et al., 2011).

The interdisciplinary scientific teams have only recently emerged as a distinct area of research. The few studies of interdisciplinary collaboration conducted thus far emphasize the importance of leadership, trust, and communication (Fiore, 2008), the need for time to develop common ground (O’Donnell & Derry, 2005), and the greater significance of individual characteristics over organizational factors in determining the shape of interdisciplinary networks (Rhoten, 2004; Rhoten & Parker, 2004).

More recently, scholars have examined the issue of distributed versus collocated collaboration in scientific research. Jones and colleagues showed that, while multi-university collaborations represent the fastest growing mode of co-authorship (Jones, Wuchty, & Uzzi, 2008; Wuchty, et al., 2007), the geographical dispersion of both researchers and universities continues to be challenging and not uniformly successful. The process of developing and maintaining the awareness of what is going on in their work environment (Kraut, Fussell, Brennan, & Siegel, 2002) is more difficult in dispersed teams than in collocated ones (Cramton, 2002). Research has begun to explore ways to resolve this issue. Prior experience in working together has been shown to diminish the negative impact of geographic and disciplinaryrelations (Cummings & Kiesler, 2008) and to increase the quality of team outcomes (Guimera, et al., 2005).

While advancing our knowledge of interdisciplinary scientific collaboration, prior research has done little to understand the factors affecting the assembly and success of interdisciplinary teams. We draw upon the literatures in social networks and groups and teams to fill in this research gap.

2.1 Assembly of interdisciplinary teams

Generalizing from the literature on groups and teams to interdisciplinary scientific teams presents two challenges. First, most prior research examined teams that were already formed and in which the team members had no discretion or decision-making power to affect the make-up of the team in the first place. In contrast, contemporary scientific teams are often assembled on an ad-hoc basis reflecting the autonomous and individual choices of potential team members. Individuals—members in such ad-hoc teams—have complete discretion over their behaviors. Therefore, individual or relational attributes that may affect the ad-hoc formation of interdisciplinary scientific teams are not likely to be considered in traditional research on groups and teams.

Second, in contrast to traditional teams, members of interdisciplinary teams are experts in different fields and are trained to use diverse tools and concepts (Luszki, 1958). Interdisciplinarity requires collaboration among researchers with disparate areas of specialization and the incorporation of specialized expertise, concepts, and diverse methodological and theoretical approaches (National Academies, 2004). Therefore, although research on traditional teams has showed, for example, that team members' similarity (Ancona & Caldwell, 1992; Newcomb, 1961) and proximity (Festinger, Schachter, & Back, 1950) leads to the natural formation of traditional teams through a maximization of their relationship potential (Gruenfeld, Mannix, Williams, & Neale, 1996), such factors would most likely have different effects, if any, in the context of interdisciplinary collaboration.

To overcome the challenges mentioned above, we leverage research on social psychology, teams, and social networks to investigate the different influences of researchers' individual attributes as well as their prior collaboration and citation relations in interdisciplinary scientific teams.

2.1.1 Gender—Research in gender psychology has long been interested in how gender differences affect behavior. Prior studies showed, for example, that women are more likely to collaborate (e.g., Hayes, 2001; Keashly, 1994) and are more inclined to work in teams than men (Severiens & ten Dam, 1994). Empirically, McDowell et al. (2006) examined the likelihood of collaboration for men versus women in scientific research settings and showed a changing trend: Although in the past men were more likely to collaborate, over time women have become equally likely to collaborate in research. In the context of interdisciplinary collaboration, Rhoten and Pfirman (2007) showed that women have more collaborators than men, especially when they engage in knowledge producing activities such as papers, articles, and presentations. There is evidence that female scientists are more inclined to step outside their disciplinary boundaries than their male counterparts. Using self-reported data, van Rijnsoever and Hessels (2011) also showed that women engage more than men in interdisciplinary research collaborations.

Overall, prior research suggests that women have a higher propensity to collaborate and even more so in interdisciplinary scientific contexts. However, prior studies have been based on researchers' self-reported statements about their "intention" to collaborate. Whether such future collaboration has indeed happened, has not yet been empirically tested. Hence we propose:

Hypothesis 1 Female researchers are more likely to collaborate with other researchers on interdisciplinary teams.

2.1.2 Tenure—There is very modest research examining the effect of tenure (i.e., number of years in academia) on the likelihood to collaborate. The few studies that examined this relationship suggest a higher inclination among senior researchers with longer tenure to engage in collaboration. Studies of scientific teams, for example, indicate that senior researchers are more often associated with larger research teams with high levels of consolidation and integration (Martín-Sempere, Garzón-García, & Rey-Rocha, 2008). This is consistent with the research showing that the longer a scientist has been active, the more opportunities he or she has had to build networks (S. Lee & Bozeman, 2005). Longer tenured researchers have developed scientific and technical human capital as well as social capital, which in turn makes them more likely to find collaborators (Bozeman & Corley, 2004). Further the social and human capital that senior researchers have built through their activities captures the attention of their colleagues who attempt to draw from their knowledge base thus making them even more likely to collaborate on teams (Rhoten, 2003). Finally, in the context of interdisciplinary scientific collaboration, tenure also affords senior researchers the job security and academic freedom needed to take on career risks that accompany this highly unpredictable type of scientific collaboration. Thus, we hypothesize:

Hypothesis 2 Researchers with high tenure are more likely to collaborate with other researchers on interdisciplinary teams.

2.1.3 Institution tier and H-index—The status of a researcher has been often measured using the researchers' institution affiliation or his/her H-index. When examining institutional affiliation, the status of the researcher is captured by the institution tier. Usually, a researcher affiliated with a university ranked among the top 10% in research, as defined by Jones et al. (2008), is considered of high status. The H-index captures the productivity and the impact of the researcher in his/her field of study and is represented by the maximum number *h* for which a researcher's *h* papers have at least *h* citations each (Hirsch, 2005).

There are two reasons to expect that an affiliation with a top-tier university or a high H-index will decrease their likelihood to engage frequently in interdisciplinary teams. First, from a substantive standpoint, researchers from top-tier universities or with higher H-indices have resource advantages (Jones, et al., 2008), such as more financial resources and the access to more PhD students. This enables them to develop a higher absorptive capacity in their own teams without relying on external collaborations. Absorptive capacity (Cohen & Levinthal, 1990), or the ability to accumulate external knowledge, is a necessary component of innovation and is reflected by the high impact papers published by researchers from elite schools (Jones, et al., 2008). Such researchers can absorb knowledge that is outside of their discipline and exhibit a lower need for collaborators. Second, from a symbolic standpoint, researchers affiliated with a lower tier university or with a lower H-index might feel the additional need to engage in collaborations so as to compensate for their perceived limitations by funding agencies and review panels. We therefore propose:

Hypothesis 3 Researchers from top-tier universities are less likely to collaborate with other researchers on interdisciplinary teams.

Hypothesis 4 Researchers with high H-index are less likely to collaborate with other researchers on interdisciplinary teams.

2.1.4 Co-authorship relation—When forming new teams, people prefer previous partners to reduce uncertainty in collaboration behavior (Goodman & Leyden, 1991; Gruenfeld, et al., 1996; Hinds, Carley, Krackhardt, & Wholey, 2000). Cummings and Kiesler (2008) investigated the effect of familiarity within teams and showed that greater past interaction reduces uncertainty about future behavior and that prior working experience increases the chances of working together again. Therefore, when selecting future team members, people are biased toward selecting collaborators with whom they have already developed strong working relationships (Hinds, et al., 2000). In the context of scientific collaboration, prior research showed that previous collaboration in knowledge creation increases the likelihood of future/further such collaboration. For example, Lee (2010) studied the collaboration network of U.S. biotech inventors between 1976 and 1995 and showed that previous co-authorship relations among these researchers increased their likelihood of patent collaboration. Further, working previously on a team helps overcome geographic and disciplinary hurdles to future team assembly and influences subsequent collaboration. Together, these findings suggest that, in the context of interdisciplinary scientific collaboration, researchers who collaborated in the past are more likely to collaborate in the future. Therefore, we propose:

Hypothesis 5 Team members that co-authored in the past are more likely to collaborate with each other on interdisciplinary teams.

2.1.5 Citation relation—The number of academic citations is arguably associated with higher quality research (Aksnes, 2006; Wuchty, et al., 2007). Citation analysis has often served to evaluate how the ideas and concepts of a publication influenced subsequent research, leading to cascades of influence and field advancement (Garfield, 1972; Lambiotte & Panzarasa, 2009). Citing each other's publications is a reflection of team members' growing familiarity with each other's work and expertise. According to transactive memory research, familiarity enhances team understanding by helping members be more aware of "who knows what" on the team (Hollingshead, 1998; Hollingshead & Contractor, 2002; Moreland, 1999; Su, Huang, & Contractor, 2011; Wegner, 1995) and by helping team builders identify others in a network who have the required expertise (Monge & Contractor, 2003). Therefore, we expect researchers that cite other researchers to easily identify them as possible collaborators in the network:

Hypothesis 6 Team members that cited each other's publications in the past are more likely to collaborate with each other on interdisciplinary teams.

Hypotheses 1 through 6 examine the factors influencing individuals to collaborate with one another on interdisciplinary teams. The following section posits mechanisms for the success of these collaborations.

2.2 Success of interdisciplinary scientific teams

Research on intra-organizational learning has examined the factors that help teams, groups, and firms to operate more efficiently and effectively. Low turnover in team membership has been associated with knowledge retention, whereas high turnover has been associated with knowledge creation (i.e. innovation) and transfer (Argote & Ophir, 2002). Clearly, low and high turnover in membership has different impacts on performance depending on the nature of tasks at hand. R&D departments, for example, thrive with high turnover (Gruenfeld, Martorana, & Fan, 2000), while law offices prosper under low turnover because the knowledge and technology necessary to operate efficiently changes little over long periods of time.

This paradox about membership also exists in research on scientific collaboration. On the one hand, Wells and Pelz (1966) found that high turnover among scientists and engineers improved the performance of research teams. On the other hand, research on transactive memory suggested that it is low turnover that helps their performance (e.g., Liang, Moreland, & Argote, 1995; Moreland & Myaskovsky, 2000). More specifically, studies showed that team members are able to specialize by relying on other members as their "external memory aids" (Wegner, 1987). Such specialization reduces the knowledge overlap in a stable team and leads to more task-related knowledge for the team. Clearly, the substantial body of research on intra-organizational learning at different levels of analysis, i.e. organizations, groups, and teams, has yielded inconsistent findings. This presents an opportunity to advance our understanding of the consequences of team assembly on performance. In this section we posit why prior experience, specifically co-authoring a paper or citing one another will influence the success of interdisciplinary teams.

2.2.1 Co-authorship relation—We expect that prior experience of team members working together will positively affect the success of interdisciplinary scientific collaboration. By working together in the past, team members adapt to each other which eases communication (Katz, 1982). Teams with prior experience have often established efficient communication processes to utilize member diversity more effectively (Harrison, Price, & Bell, 1998; Harrison, Price, Gavin, & Florey, 2002), and are therefore more likely to attain creative goals (Gilson, Mathieu, Shalley, & Ruddy, 2005; Taylor & Greve, 2006).

Prior collaboration experience has, in fact, been found to increase the productivity of scientific collaboration (Abbasi, Altmann, & Hossain, 2011; Stipelman et al., 2010).

Since interdisciplinary teams are defined as “linkages between specialties of diverse subject matter” (Garfield, Malin, & Small, 1978, p. 189), they need to have good communication in order to produce creative and novel ideas. The National Science Foundation (NSF)’s statement on what is encouraged for research grant proposals is quite telling: “NSF […] encourages researchers to submit unsolicited interdisciplinary proposals for ideas that are in novel or emerging areas extending beyond any particular current NSF program” (National Science Foundation, 2011). Given prior findings suggesting that earlier collaboration may produce creative outcomes and given the NSF’s guiding principle to fund proposals that are novel and creative, we propose:

Hypothesis 7 Interdisciplinary teams where members have co-authored with one another are more likely to be successful than teams where members have not co-authored.

2.2.2 Citation relation—Why researchers cite one another has been previously studied across various scholarly domains. One framework proposes that researchers cite others in order to support their arguments. However, how and why they do it differ. Specifically, the constructivist approach argues that citations are overwhelmingly focused on big-name peers with the goal to gain credibility by association and persuade through rhetoric. The universalism approach, argues that citations are used to give credit for the use of intellectual property. Recent studies brought further evidence to the universalism approach (White, 2004). Closely related to the universalism approach to citation making, a second framework suggests that people cite one another because of similar research methods or common theoretical perspectives (Baldi, 1998; Van Dalen & Henkens, 2001). Therefore, citation relations are more relevant to the authors’ work from an intellectual rather than a personal point of view.

Taken together, both insights imply that citation may be “strongly associated with a common discipline and shared subject matter” (White, Wellman, & Nazer, 2004, p. 112). Citing literature from the same or overlapping research areas implies that the outcome of a scientific collaboration is likely to be intellectually contiguous to the knowledge leveraged and therefore at best represents an incremental advancement. We would not expect such a proposal to yield novelty. Therefore, we believe researchers in interdisciplinary teams that cite each other extensively to be less successful. We propose:

Hypothesis 8 Interdisciplinary teams where members cite one another are less likely to be successful than teams where members do not cite one another.

3 Data and methodology

3.1 Context

We tested our hypotheses using archival and bibliographic data about teams submitting research proposals to two interdisciplinary initiatives by the National Science Foundation (NSF). NSF proposals provide a particularly appropriate context to examine the factors affecting the assembly and the success of interdisciplinary scientific teams for two reasons. First, research proposals submitted to interdisciplinary initiatives provide a good opportunity to study the assembly of interdisciplinary teams and define a sample population of many applicants interested in the interdisciplinary research in related fields. Second, since some proposals were awarded and some were not, we have a fairly robust, albeit preliminary, measure of the outcomes associated with the assembly of interdisciplinary teams. It is only a preliminary measure of outcome because the team still needs to conduct the research proposed in the awarded grant. The data on awarded and un-awarded proposals offer the opportunity to better understand the factors that distinguish the assembly of successful teams.

3.2 Data and sample

We first identified two NSF initiatives that explicitly solicited proposals from multidisciplinary teams utilizing interdisciplinary approaches. We used the *NSF dataset* [1] to identify 1,103 grant proposals that were submitted to these two initiatives over the last three years of the initiatives' existence. A total of 2,186 researchers were identified as principal investigators or co-principal investigators (PIs/Co-PIs), of whom 1,741 did not have awarded proposals, 93 had both awarded and un-awarded proposals, and 352 had only awarded proposals only.

Demographic information and university affiliations of researchers were extracted from the *NSF proposal cover sheets*. Generally, the cover sheets include the names of the PIs/Co-PIs and their basic information, such as university affiliations, email addresses, the years of the highest degrees. We used the *Web of Science (WoS)* database provided by Thomson Reuters to construct PIs/Co-PIs' bibliometric information (including publications, co-authorship, and citation relations). Bibliometric analysis has been widely employed to evaluate the scientific output (for a review, see Wagner, et al., 2011). Author name disambiguation is a recognized issue when constructing bibliometric measures (Torvik, Weeber, Swanson, & Smalheiser, 2005). This is the problem of ensuring that we only consider, for instance, the publications by John Smith who submitted a proposal and not others with the same name. To overcome this limitation, we took a conservative approach in identifying an author's publications: We only considered the publications with identical author names, email addresses, and Digital Author Identification System (DAIS) numbers. DAIS is a unique internal ID used by Thomson Reuters to disambiguate authors.

While an important strength of our dataset is to be able to conduct research that examines both successful and unsuccessful proposals, a limitation of our dataset is the fact that we are only able to observe proposals that have been submitted, and thus we might not include researchers who intended to collaborate, but never submitted proposals. Although we cannot measure the intention of researchers to contribute to the two fairly targeted and specific NSF initiatives (through observations of discussions these researchers might have held), the context allows us to be confident that if researchers recognized that this initiative was relevant to their research interests, they would have had ample opportunities to submit a proposal during the time-frame of our study: the final three years of each of the two well-publicized initiatives. Furthermore, the process of writing a proposal, while potentially less difficult than that of writing a paper for publication, entails significant sunk costs (such as mental effort, time, or overlooking parallel collaborations). A researcher starting such a process will therefore be incentivized to finish the proposal and submit it. Hence in the unlikely situation that a team of researchers began to collaborate, but did not submit the proposal in the first year, it is very probable that they would submit their proposal by the second or third year. In other words, the fact that our data include the three final years of these two NSF programs, reinforces our claim that our data comes close to capturing the population of researchers who were working within the substantive domains for which these two NSF programs solicited proposals. The limitation of not including in our sample those who did not submit proposals is further mitigated by the fact that our data includes those who submitted single-authored proposals. Thus, even though we may not have the

[1] The authors had secured access for a short period of time to NSF awarded and un-awarded grant proposal submissions as part of one of the author's participation on an NSF CISE/SBE Advisory Sub-Committee on Research Portfolio Analysis.

population of all researchers whose research was relevant to the two NSF initiatives, we do have data on several researchers (15% of proposals) who submitted single-authored proposals thus eschewing the opportunity to collaborate with others. To make sure that we overcome the limitations described above, we focus on predicting the likelihood to submit a collaborative proposal with a prior collaborator only amongst the pool of those who submitted collaborative proposals and excluding those who submitted single authored proposals.

3.2.1 Dependent variables

Proposal collaboration: We defined proposal collaboration as a relation between two researchers who submitted at least one grant proposal together to either of the two interdisciplinary NSF initiatives. This generated an undirected proposal collaboration relation network characterized by a 2,186 by 2,186 binary matrix. Each cell in the matrix represents the proposal collaboration relation between two researchers: 1 if two researchers collaborated on at least one proposal and 0 if not.

Proposal collaboration success: Based on the success outcome of the grant proposals (i.e. awarded vs. un-awarded), we constructed two additional proposal collaboration relation networks: (1) the awarded proposal collaboration network comprising the proposal collaboration relations among the 445 researchers who were on at least one awarded proposal and (2) the un-awarded proposal collaboration network comprising proposal collaboration relations among the 1,834 researchers who were not on any awarded proposals. The awarded proposal collaboration network was used to examine team success. Note that the number of researchers in the awarded and un-awarded networks do not add up to the 2,186 researchers because some researchers appear in both networks: awarded and un-awarded proposal collaboration.

3.2.2 Independent variables—Based on researchers' vitae and publication records, we constructed four variables to characterize their individual attributes: Gender, Tenure (i.e. years since Ph.D.), H-index, and Institution Tier (i.e. top 10% university affiliation). Except for gender, all measures were calculated for the year in which the proposals were submitted.

Gender: We manually coded each researcher's gender based on the first names and pictures available on their web pages. Females were coded as 1 and males were coded as 0.

Tenure (Years since PhD): We constructed the tenure measure by subtracting the completion years of researchers' Ph.D. degrees from the year in which they submitted the proposals. For example, the tenure of a researcher who graduated in 1964 and who submitted a proposal in 2011 was calculated as 2011 − 1964 = 47. If a researcher submitted proposals in multiple years, we considered the earliest submission year.

H-index: 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 was computed based on the publication and citation information available in the Web of Science database.

Institution tier: The institution tier measure is a binary variable indicating whether a researcher is affiliated with a university ranked among the top 10% in research, as defined by Jones et al. (2008). The authors ranked universities according to the total number of citations each school received from 1995 to 2005: Tier I (top 5% of the distribution), Tier II (6–10%), Tier III (11–20%), and Tier IV (the remainder). We coded Tier I and Tier II universities as 1 (top 10% of the distribution) and the remainders as 0.

In addition to researchers' attribute information enumerated above, we also computed their co-authorship and citation relations with one another. We used the Web of Science (WoS) database to extract the list of scientific articles published by each researcher prior to proposal submission.

Co-authorship relation: Based on the publication information, we considered a co-authorship relation between two researchers when they published a scientific article together. A 2,186 by 2,186 matrix was generated to measure co-authorship relations among the researchers. Each cell in the matrix represents the number of times a researcher co-authored with another researcher. Co-authoring a journal or conference publication is an important measure of researchers' prior collaborative relationship (Guimera, et al., 2005).

Citation relation: We used WoS to retrieve the list of publications cited by each researcher's publications. We then derived a citation network where one researcher has a citation link to another researcher if a publication (co-)authored by the first researcher cites a publication (co-)authored by the second researcher. This generated a directed 2,186 by 2,186 citation relation matrix. Each cell in the matrix represents the number of times one researcher cited the other's publications. We excluded self-citations, in which citing and cited papers have common authors. Prior research showed that the citation effect is constant whether or not self-citations are included (Wuchty, et al., 2007).

3.3 Analysis: Exponential Random Graph Models (p*/ERGM)

Hypotheses 1 through 4 predicted that individual attributes, such as gender, tenure, H-index, and institution tier, affect the likelihood that a researcher initiates a proposal collaboration relation. Hypotheses 5 through 8 predicted that previous relations, such as co-authorship and citation relations, affect the likelihood of a collaboration relation between two researchers.

We used Exponential Random Graph Models (ERGM, also known as p*) to simultaneously test our hypotheses (Frank & Strauss, 1986; Robins, Pattison, Kalish, & Lusher, 2007; Wasserman & Pattison, 1996). p*/ERGM techniques use a class of stochastic models that provide an appropriate analytic methodology to test multi-theoretical multilevel hypotheses, such as the ones described above (for details, see Contractor, et al., 2006; Monge & Contractor, 2003). In general terms, p*/ERGM estimates the likelihood of the observed network structures emerging out of all possible network configurations of that size generated by random assignment of the observed number of links. A key feature of p*/ERGM is the ability to control for purely structural effects (also called endogenous effects). For example, a researcher X may choose to collaborate with researcher Y simply based on the number of collaborators researcher Y already has. Preferential attachment hypothesis suggests that people tend to connect with the most popular actors in a network, i.e. nodes with high degree. While we did not hypothesize this phenomenon in the present study, p*/ERGM enables us to control for such an effect were it to occur. More generally, in order to control for such endogenous effects in the proposal collaboration network (our dependent measure), we used three network structures: isolates, edges, and the geometrically weighted degree distribution (Hunter, 2007). The number of isolates controlled for the number of single authored proposals. The number of edges controlled for the level of collaboration in the proposal collaboration network (i.e. network density). The geometrically weighted degree distribution controlled for researchers' tendency to collaborate with many others (i.e. preferential attachment). A positive estimate indicates a lack of preferential attachment. Similar to logistic regressions, positive and significant coefficients indicate that the corresponding structures are more likely to occur than random chance, and negative and significant coefficients indicate that the structures are less likely to occur than by chance alone. The effect size of one additional structure count can be measured by the odds ratio (OR), which equals to the exponential function of the corresponding coefficient (e.g. e^{β}).

Hypotheses 7 and 8 differentiated between factors that influence (1) the assembly of all teams and (2) the assembly of successful teams. To test these hypotheses, we estimated three independent models: the full model including all researchers (awarded and un-awarded), the awarded model including the researchers in the awarded proposal collaboration network, and the un-awarded model including the researchers in the un-awarded proposal collaboration network. The models were estimated using Statnet in R (Handcock, Hunter, Butts, Goodreau, & Morris, 2003).

As noted above, we tested the eight hypotheses by taking proposal collaboration networks as the dependent relations and taking co-authorship and citation relations as dyadic covariates, along with the four demographic attributes and three network control variables (p*/ERGM technique). We also considered an alternative method that used all three relation networks - proposal collaboration, co-authorship and citation relations - as multivariate ERGMs that better characterize the structures of the three networks and the influences among them. The current implementation of multivariate ERGMs only supports binary networks and dichotomizing co-authorship and citation relations resulted in a substantial loss of information about the magnitude of co-authorship and citations among the researchers. Therefore, in this study we relied on the approach that estimated the influence of researchers' co-authorship and citation relations on their proposal collaboration.

4 Results

Table 1 reports the means, standard deviations, and correlation coefficients for individual attributes of all researchers in the full model. Because of privacy issues, NSF precludes us from disclosing detailed separate descriptive statistics for the awarded and un-awarded models. For the same reason,we only report the density (number of existing links out of all possible links) for the three relation networks for all proposals (awarded and un-awarded): the density of the proposal collaboration network is 0.1%, the density of the co-authorship network is 0.02%, and the density of the citation network is 0.15%. All density measures are small because relations among researchers are quite sparse.

Table 2 presents the results of the p*/ERGM technique predicting the likelihood of proposal collaboration among awarded and un-awarded researchers (Full Model), among only awarded researchers (Awarded Model), and among un-awarded researchers (Un-awarded Model).

The focus of this study was to explain what motivates a researcher to choose a specific collaborator. Our analysis is based on only examining the population of researchers that submitted proposals to the two NSF initiatives and hence does not include possible collaboration opportunities with those who did not submit proposals. Hypothesis 1 predicted that female researchers are more likely than men to collaborate with other researchers on interdisciplinary teams. The results of the full model and the un-awarded model indicate that gender has no significant impact on an individual's likelihood of collaboration on interdisciplinary teams. The co-proposal links with at least one female PI are more likely to be observed in the awarded proposals than those between male PIs. ($\beta = 0.119$, $OR = 1.126$[2], $p < 0.05$). Thus, Hypothesis 1 is partially supported. Hypothesis 2 predicted that researchers with high tenure (i.e. more years since Ph.D.) are more likely to collaborate with other researchers on interdisciplinary teams. Tenure has a positive and significant effect in the

[2]This is the odds ratio and $OR = e^{\beta}$.

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fulland un-awarded models ($\beta = 0.002$, $OR = 1.002$, $p < 0.05$). The effect is not significant in awarded proposals. Thus, Hypothesis 2 is partially supported.

Hypotheses 3 and 4 posited that researchers from top-tier universities and with high H-index scores, respectively, are less likely to collaborate with other researchers on interdisciplinary teams. The estimate for institution tier is negative and significant in all three models ($\beta = -0.098, -0.098, -0.104$, OR=0.907, 0.907, 0.901, $p < 0.05$). In general, researchers from the top 10% of universities are less likely to collaborate on proposals: The odds of collaboration for top-tier researchers are only 90% of the odds for non-top-tier researchers. Similarly researchers with high H-index scores are less likely to collaborate than those with low H-index scores ($\beta = -0.018, -0.005, -0.009$, OR=0.982, 0.995, 0.991, $p < 0.05$). Both Hypotheses 3 and 4 are fully supported.

Hypothesis 5 stated that previous co-authorship increases the chance of subsequent collaboration. All three models show significant positive effects of co-authorship relations (β = 2.431, 1.386, 0.914, OR=11.37, 3.999, 2.494, $p < 0.05$). This suggests that researchers that published papers together previously are more likely to collaborate on interdisciplinary teams. Furthermore, the impact of co-authorship among the researchers on un-awarded proposals is smaller than among the researchers of awarded proposals. Among awarded proposals, the odds of a proposal collaboration between researchers with one previously co-authored paper are almost 4 times higher than among researchers without a prior co-authorship relation ($\beta = 1.386$, $OR = 3.999$, $p < 0.05$). Among un-awarded proposals, the odds of a proposal collaboration between researchers with one previously co-authored paper are only 2.5 times higher than among researchers without a prior co-authorship relation ($\beta = 0.914$, $OR = 2.494$, $p < 0.05$). Hence, consistent with Hypothesis 7, prior co-authorship raises the chance of a successful collaboration.

The citation relation has a significant positive effect in the full model ($\beta = 1.132$, $OR = 3.102$, $p < 0.05$), but the effect is significant and negative in the awarded model ($\beta = -0.147$, $OR = 0.863$, $p < 0.05$). This indicates that researchers who cited each other are more likely to collaborate on grant proposals (supporting Hypothesis 6), but they are less likely to have a successful proposal (supporting Hypothesis 8).

As mentioned earlier, we controlled for the endogenous effects of proposal collaboration relations using three network structures: isolates (single-researcher proposal submission), edges (proposal collaboration), and geographically weighted degree distribution (preferential attachment). In all models, isolates have a significant positive impact, whereas edges have a significant negative impact on forming proposal collaboration relations. These results suggest that we observed more single-authored interdisciplinary proposals and less proposal collaboration relations than we might have anticipated by random chance. More researchers than we might expect tend to submit interdisciplinary proposals by themselves (perhaps reflecting their belief that they individually embody interdisciplinarity). Further, they do not collaborate with others randomly because establishing collaboration relations is costly. Geometrically weighted degree distribution, a negative measure of preferential attachment, has a significant and positive effect suggesting that the number of collaborators (i.e. node degrees) is similar among the researchers. This indicates the absence of any researchers serving as "hubs" in the network with collaboration ties to a disproportionate number of other researchers. This suggests that, after accounting for all other effects, the marginal benefit of collaboration decreases when a researcher already has many collaborators (i.e. is working in a big team).

5 Discussion and conclusion

Interdisciplinary teams bring together different disciplines or areas of scientific discovery. Despite their growing importance for scientific research, however, we have only started our inquiry into what makes these teams "tick." Our study seeks to contribute to this body of research on interdisciplinary teams by investigating the factors that influence the genesis and the success of interdisciplinary research teams. Specifically, we examine whether researchers' attributes such as gender, tenure, H-index, institution tier, and prior experience such as co-authorship and citation relations influence the formation of interdisciplinary teams. We then inquire into the factors influencing the success of the team and focus on the prior relations of researchers making up the interdisciplinary teams. We discuss our findings below but begin by cautioning that all findings need to be qualified by an important limitation.

5.1 Limitations

An important limitation of this study is that it only sought to explain the motivations for a researcher collaborating with some other researcher who had also submitted a proposal in the last three years of these two interdisciplinary initiatives. As such it does not investigate what might have motivated a researcher to collaborate (or not) with someone on an un-submitted proposal. As we acknowledge in the methodology section, this limitation is less dire in our context, since our data include all proposals submitted in the last 3 years of a well publicized and fairly targeted NSF research initiative. This context encourages us to be confident that researchers who had an intention to contribute to the NSF initiative would have done so during the last 3 years of the two initiatives. The process of writing a proposal, we mentioned, entails sunk costs that incentivizes the researcher to finish the submission process. We also include individual proposals in our sample, thus capturing those situations in which researchers decided to go it alone.

5.2 Effect of researchers' attributes

Among the NSF grant applicants, our results add an interesting twist to the research using self-reported data that argued that women engage more in interdisciplinary research collaborations than men (van Rijnsoever & Hessels, 2011). Women are indeed more likely to collaborate, but this behavior holds only for awarded proposals (Hypothesis 1). This finding is important for organizations such as NSF that focus especially on proposals having a higher chance of knowledge production, a domain in which women researchers have previously been shown to excel (Rhoten & Pfirman, 2007). An alternative explanation for this finding might be that review panels are aware of the well documented gender disparity in scientific research and therefore might be unconsciously tipping their evaluations in favor of proposals that included women collaborators.

We also found that researchers with higher tenure are more likely to collaborate on research proposals (Hypothesis 2). Interestingly, the results are also significant for un-awarded proposals. This suggests that even though more senior researchers have more collaborators, it is not necessary that these collaborations will generate good interdisciplinary outcomes. The lack of success in this collaboration could be explained by the Apollo Syndrome (Belbin, 1981), which suggested that teams composed of highly capable individuals can collectively perform badly. Our results also revealed that NSF appears to reward researchers with lower tenure. This might reflect the fresh and innovative ideas which junior researchers bring to the research arena.

Our results showed that researchers from top tier universities or with high H-index collaborate less, while researchers from lower tier universities and with lower H-index collaborate more (Hypotheses 3 and 4). The results are significant in both the awarded and un-awarded models. This suggests that researchers from non-elite universities or with lower H-index scores might signal the quality and novelty of their proposals by including more collaborators. Alternatively, or in addition, our results suggest that researchers from elite universities or with higher H-index scores have a greater ability to absorb and leverage intellectual and materials resources thereby reducing the need for additional collaborations.

Compared to tenure, H-index has an opposite but dominant impact with almost five times bigger effect sizes. Although H-index and tenure have a positive correlation (0.35) since H-index incorporates paper productivity which increases over years, the two measure different aspects of academic status: tenure is a linear measure of time as a base line and H-index measures the quantity and quality of the research outcomes. For successful scientists, the value of H-index is usually bigger than tenure (Hirsch, 2005). Therefore, as the overall effect, researchers with a longer tenure and higher H-index are less likely to collaborate on proposals.

5.3 Effect of researchers' network structures and prior relations

We found that prior collaboration or familiarity, measured by co-authorship and citation, leads to a greater likelihood of future collaboration. In line with the theory of transactive memory system and learning theories, our findings suggest that people who co-authored or cited each other previously are more likely to collaborate on interdisciplinary grant proposals. The positive effect of co-authorship relationships for the awarded model is in line with prior research on learning in teams, wherein low turnover improves the efficiency and performance of a team in particular situations (Liang, et al., 1995). On the other hand, the positive effect for the un-awarded model is also explained by research on learning: Low turnover (working with the same individuals) among scientists and engineers lowers performance in research teams (Wells & Pelz, 1966). These results have also been supported by Guimera et al. (2005) in their study of teams from artistic and scientific fields. The authors showed that teams composed only of people who have worked together in the past are less likely to have innovative ideas (Guimera, et al., 2005). However, while there is a theoretical rationale for each of these results, we would have expected to find a positive and a negative effect for awarded and un-awarded proposals, respectively, or vice versa. Given the lack of alignment in these effects, future research could explore whether there, in fact, is a curvilinear relationship between the extent of prior collaborations and success. At the beginning, prior collaboration may have initial benefits until it reaches a tipping point where the knowledge base of the collaboration is depleted and the success rate spirals down.

We obtained two unexpected but important results. First, our control variables revealed that single-authored proposals (Isolates) have a positive and significant effect in the awarded model. It appears that interdisciplinarity of a proposal does not necessarily require the need for a team. This finding might reflect the prevalence of individual scholars who have received interdisciplinary training within a growing number of interdisciplinary research and education programs in some universities. These scholars, by nature of their training, are able to tap into different pools of knowledge and produce interdisciplinary research without coming across the challenges of forming an interdisciplinary team. This finding contradicts Fiore's (2008, p. 272) argument that interdisciplinary research is an outcome of teams and not individuals. Our results indicate that individuals did propose interdisciplinary research, and they were successful in grant applications. This insight provides us with an important policy implication: Important scientific discovery may well depend on setting up interdisciplinary research and education centers that train interdisciplinary individual researchers rather than interdisciplinary teams.

Second, when analyzing the effect of citation relations on collaboration, we found a negative relationship for successful grant proposals. Thus, the more researchers cite each other, the more likely they are to generate an unsuccessful proposal. This suggests that researchers that do not cite one another may come from different areas of research and they have access to diverse knowledge sources (J. Lee, 2010). In line with the literature on structural holes which emphasizes that novel ideas come from non-redundant ties (Ahuja, 2000; Burt, 2004) and the brokerage network position of the researchers will lead to innovation (e.g., J. Lee, 2010). However, our results suggest that in order for a proposal to be successful, researchers need to have a history of prior collaborations (co-authorship) as well. Thus, it seems that not all structural holes lead to innovation: Innovation also requires researchers to have collaborated before while continuing to draw upon distinct intellectual bodies of knowledge.

From a practical perspective, researchers are more likely to be successful if they worked together before and therefore show successful collaboration records. However, they also need to come from different research areas, and draw upon different areas of expertise. As such our results offer empirical evidence that provides specific practical guidelines to enable the assembly of successful interdisciplinary teams.

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Highlights

- We investigate the assembly and success of interdisciplinary scientific teams
- People with lower H-index or from lower-tier institutions team up more
- Higher tenure and prior co-authorship/citation increase likelihood of collaboration
- More co-authorship but less mutual citations among members leads to team success
- Having females in teams increases the chance to get NSF grants

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TABLE 1

Descriptive statistics (Full model)-to check it again

Variables	N	Mean	Std. Dev.	1	2	3	4
1 Gender (Female)	2186	0.26	1.97E-09	-			
2 Tenure (Years since PhD)	2186	16.54	4.72E-08	−0.13	-		
3 Institution Tier (Top 10% University)	2186	6.16	3.96E-08	−0.10	0.04	-	
4 H-index	2186	0.38	2.17E-09	−0.01	0.35	0.15	-

TABLE 2

Explaining Collaboration Relation on Grant Proposals (p^*/ERGM results)

		Full Model	**Awarded Model**	**Un-awarded Model**
	Isolates (single author)	5.447* (1.108)	10.138* (2.516)	4.477* (1.197)
	Edge (proposal collaboration relation)	−6.751* (0.041)	−5.341* (0.115)	−6.571* (0.044)
	Weighted degree (negative measure of preferential attachment)	4.623* (1.082)	8.908* (2.472)	3.779* (1.171)
	Individual Attributes			
H1	Gender (*Female*)	0.021 (0.012)	0.119* (0.024)	−0.009 (0.013)
H2	Tenure (*Years since PhD*)	0.002* (0.000)	0.001 (0.001)	0.002* (0.000)
H3	Institution tier (*Top 10% University*)	−0.098* (0.009)	−0.098* (0.019)	−0.104* (0.011)
H4	H-index	−0.014* (0.001)	−0.005* (0.001)	−0.009* (0.001)
	Relations			
H5 & H7	Co-authorship relation	2.431* (0.076)	1.386* (0.055)	0.914* (0.035)
H6 & H8	Citation relation	1.132* (0.049)	−0.147* (0.014)	−0.008 (0.007)
	Observations	*2,186*	*445*	*1,834*

Standard errors in parentheses

*Indicates $p<0.05$