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The mechanisms of collaboration in inventive teams: Composition, social networks, and geography

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ABSTRACT

This paper investigates the composition of creative teams of academic scientists engaged in inventive activity. Our data provides a unique opportunity to explore the links between team composition and commercialization outcomes. We find that there are coordination costs associated with reaching across academic departments and organizational boundaries to build teams. However, we also find evidence of benefits due to knowledge diversity, particularly in the cases of truly novel combinations. In support of internal cohesion arguments, we find that performance improves with the experience of the team. In line with arguments regarding the value of diverse external networks, we find that teams that are composed of members from multiple institutions – focal university, other research institution, and/or industry – are more successful in generating patents, licenses, and royalties. Finally, we find that the presence of prior social ties supporting links with external team members positively influences commercial outcomes. We find that there is no benefit to proximity in team configuration.

"Rita, you and I are good, but together we are wonderful."

Stanley Cohen to Rita Levi Montalcini talking about their work on Nerve Growth Factor, which was awarded the 1986 Nobel Prize in Medicine[1]

1. Introduction

Invention, in spite of the romantic image of lone genius, has increasingly become a team endeavor. Problem-focused creative teams involving individuals with varied backgrounds are a staple across organizations, including academic institutions, small entrepreneurial ventures, and large corporations (Reagans and Zuckerman, 2001; Roberts, 1991). Creative teams have become especially important in research and development, inventive efforts, and new product development as scientific activity is becoming more specialized (Wuchty et al., 2007). Creating valuable and novel solutions requires melding multiple types of individual expertise. One notable fact is that team size among American inventors, as witnessed by the number of inventors on U.S. patents, has been increasing at the rate of 17% per decade (Jones, 2009). Technical innovation is increasingly at the intersection of traditional domains of knowledge calling for greater use of interdisciplinary creative teams. Simultaneously with the growth in team size, there is also a trend towards including individuals from outside the focal organization in order to tap external expertise (Chesbrough, 2003).

Despite the pervasiveness and importance of teams, many open questions remain as to how to successfully configure effective teams. Issues of team configuration become even more salient when the task is complex and requires creativity and problem solving (Amibile, 1988). The desired outcome for commercially oriented R&D teams is the generation of an invention that is novel, valuable and non-obvious. While organizations have an interest in finding team configurations that increase the probability that scientific and economic value result, the relationships between combinations of individual expertise, expertise diversity and team performance have proven difficult to disentangle (Williams and O'Reilly, 1998). In addition, greater understanding of the social networks that underlie these combinations is needed as team learning capacity, and hence team performance, may be influenced by these social ties (Reagans et al., 2005). One vexing problem in evaluating team configuration is lack of systematic data on team performance outcomes.

The objective of this paper is to enhance our understanding of the links between team structure and outcomes. Our subject is academic teams of university scientists and other external members who engage in inventive activity. In the context we

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[1] http://www.hypothesis.it/nobel/ita/bio/montalcini_ext.htm, referenced December 27, 2005. As referenced in Stephan and Levin (1992, p. 15).

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study, team composition is internally managed rather than externally assigned or determined. This means that teams are able to self-organize, providing an ability to experiment with different configurations of individuals, including adding members from different departments or even other organizations. We have detailed data on the individuals that comprise the invention team. We are able to follow inventive teams from the initial reporting or disclosure of their invention and the progress the idea makes towards realizing commercial value. In this process there are a variety of outcome measures such as the granting of a patent based on the invention, the subsequent licensing of that intellectual property to a commercial firm, and finally, the generation of royalties from the license. Thus, we can test how different constructs of team composition affect team performance using econometric methods. This provides a unique opportunity to study how team composition affects outcomes and productivity.

The paper is organized as follows. Section 2 provides a review of the literature and develops hypotheses about creative team composition and effectiveness. Section 3 introduces our data and study context and develops our empirical measures. Section 4 presents results and Section 5 concludes.

2. Creative team composition and effectiveness: theory and predictions

A team is a collection of individuals who share responsibility for an outcome. Even within the same organization and performing the same task, different teams produce widely varying outcomes. The difference is believed to be attributable to the configuration of individuals on the team, specifically the blending of their expertise, access to multiple networks, and the experience of the team members learning to communicate and work together. In scientific labs, the context we study, the lead professor directs the team but the implementation of experiments requires a mix of graduate students, lab assistants and may include additional professors and external partners from other academic institutions, industries, government labs or other organizations. Each individual brings specific human capital and social capital to the task at hand. In the case of research teams, the expertise embodied in human capital is largely due to formal training or background domain knowledge. Social capital is largely derived from the team members' organizational affiliations and the associated network. Ideally, a creative team is more than the sum of its individual parts. However, delineating the precise configuration of the team needed to create high quality outcomes has proven elusive. In the discussion below, we draw on the theoretical literature to provide insights into team configuration and develop empirically testable hypotheses.

2.1. Knowledge combination novelty

Inventive teams differ in composition and level of heterogeneity. While there are multiple sources of heterogeneity, most salient is the combination of different types of expertise that individual team members bring to the creative task. More heterogeneous teams have greater opportunity to leverage the expertise of each individual team member and apply a wider range of information to the creative process (Cohen and Levinthal, 1990; Dahlin et al., 2005). When the members of the team draw on similar common knowledge their search space is circumscribed and together they run the risk of technological exhaustion and a lower chance of significant breakthroughs (Fleming, 2001, p. 120). When teams combine different types of knowledge and expertise, they are likely to approach problems from distinct perspectives prompting a broader search for possible solutions (Wiersema and Bantel, 1992; Rivkin and Siggelkow, 2003).

Innovation, at its core, is a process of recombination of different types of knowledge. Innovations arise from new combinations of previously unassociated components or from the development of new relationships between previously combined components (Schumpeter, 1939; Henderson and Clark, 1990). For example, Jones (2009) considers the invention of the microprocessor, which was the inspiration of Ted Hoff, an electrical engineer. However, the inventive team combined knowledge from physics (Frederico Faggin), and computer programming (Stan Mazer). The complexity of the invention required a blending of the inventors' different expertises to ultimately transform the design of computers. The cross-fertilization of ideas is associated with more creative outcomes (Perry-Smith and Shalley, 2003).

In configuring a team, the combined knowledge of the individuals may range from homogeneous where all members are grounded in a single common knowledge area, differentiated but with members drawn from multiple knowledge areas that are frequently deployed together, to very novel combinations with a high degree of differentiation with members drawn from multiple knowledge areas with little history of interaction between their source knowledge domains. In the first case, recombination possibilities are constrained. When individual team members have similar backgrounds and are in the same academic department, their performance as a team may be dampened by a tendency to search for solutions along the existing technology trajectory using a discipline-specific frame (Henderson, 1995). Moving along the continuum, producing a more significant advance requires a team with individuals who represent somewhat different perspectives that reflect different domains of knowledge. Expanding the team to incorporate multiple, but commonly coupled, knowledge components allows for greater *exploitation* (March, 1991) [which] "occurs when an inventor recombines from a familiar set of technology components or refines a previously used combination" (Fleming, 2001, p. 119). At the most creative end of the continuum is exploration, which requires delving into untried combinations. This third type of team embodies novel combinations of individual team members' heterogeneous knowledge components.

When a task requires creativity and novelty, as in the case of explorative R&D, the potential benefits of novel combinations of expertise are particularly salient (Hambrick et al., 1996; Hamilton et al., 2003; Koestler, 1989; Nooteboom et al., 2007). Consider the team that discovered the Krebs Cycle. Hans Krebs was a medical doctor trained in biology, and his collaborator, Frederic Lawrence Holmes, was a conventionally trained chemist. Holmes notes that Krebs' lack of expert knowledge of organic compounds freed him from the biases that limited the inquiries of contemporary biochemists searching for plausible explanations for cellular respiration, an important and vexing scientific problem at the time. This unique grouping, the team's degree of knowledge combination novelty, conferred an advantage to their joint research (as noted by Kulkarni and Simon, 1988, p. 142).

A significant degree of novelty generates a wide-ranging search over a greater knowledge space to solve more complex problems. The commitment to search for more challenging adaptations and integration of knowledge from one discipline to another suggests a higher probability of generating real breakthroughs (Fleming, 2001; Taylor and Greve, 2006). Creative teams aim to achieve novelty sufficient to result in an invention that will yield intellectual property rights that provide a more marketable idea. Thus, we hypothesize

H1. Creative teams with more knowledge combination novelty will have a higher probability of commercialization success.

2.2. Coordination costs and learning

Achievement of project goals requires communication and coordination between team members (Kogut and Zander, 1992; Boland and Tenkasi, 1995; Nahapiet and Ghoshal, 1998). This can be challenging as innovation efforts often span both technological and organizational boundaries (Rosenkopf and Nerkar, 2001). While higher knowledge combination novelty can have a positive influence on team performance, diversity, particularly diversity that results in a team spread across organizational divisions, may also reduce internal team cohesion, increasing communication and coordination costs.

Consider first the coordination costs arising from the spanning of technological boundaries. Diversity in functional or educational background can increase the amount of discussion required to effectively communicate and reach consensus as individuals hold tightly to the "world-views" acquired during professional training (Dougherty, 1992; Pelled et al., 1999). Further, the team's ability to capitalize on variation in knowledge bases can be compromised by communication difficulties that exist due to different vocabularies and norms of practice (Zenger and Lawrence, 1989; Bunderson and Sutcliffe, 2002). Diverse teams may have trouble building the shared understanding needed to productively integrate disparate chunks of information (Dahlin et al., 2005).

The challenges of melding different knowledge bases is further complicated if there are organizational barriers to overcome as well. Inconsistent incentives, costly monitoring, and uncertain enforcement are three factors that may raise coordination costs when organizational (even intra-organizational) boundaries are crossed. First, given unique histories, the commercialization norms and cultures developed across institutions and across departments within institutions vary (Bercovitz and Feldman, 2008; Kenney and Goe, 2004). These variations give rise to differences in departmentally based incentives that may complicate coordination efforts. For example, negotiating costs can escalate when there are disagreements as to what constitutes "acceptable" publication outlets for faculty seeking tenure, promotion, and peer recognition (Cummings and Kiesler, 2007). Second, monitoring costs are expected to be greater when the team leader needs to supervise and manage team members across departments that are performing dissimilar, and perhaps unfamiliar, tasks (Coase, 1952; Masten et al., 1991). Finally, enforcement is arguably important in supporting team productivity as the ability to achieve coordination is enhanced when non-cooperative behavior can be sanctioned. Both economic and social sanctions can be adopted. Departmental diversity, however, limits the effectiveness of social sanctions as an enforcement mechanism as it is difficult to exert peer pressure if team members do not belong to overlapping social networks (Kandel and Lazear, 1992; Hamilton et al., 2004).

Coordination becomes more challenging whenever technological and/or organizational boundaries are crossed. "Further, the chances of a breakdown in production due to poor coordination of the tasks and functions performed by different members, or to the communication of misleading information among members, also tends to expand as the number of specialists grows" (Becker and Murphy, 1992, p. 1141). As such, we hypothesize:

H2. The higher coordination costs of a creative team that spans multiple disciplinary and/or organizational areas lowers the probability of commercialization success.

Bringing individuals together into a coherent team requires strong internal coordination processes to insure the efficient deployment of resources to identify and exploit opportunities. Both coordination capabilities and communication skills can be developed over time as team members interact, developing routines and an effective division of responsibilities. Time spent working together provides individuals with the opportunity to become familiar with the specialized language used by peers as well as to learn "who knows what" (Edmondson et al., 2003; Reagans et al., 2005; Uzzi, 1997). Learning where specific knowledge resides in a team is important for developing roles and responsibilities that support an effective division of labor (Liang et al., 1995). Further, with ongoing interactions, teams have the opportunity to ascertain, through trial and error and then refinement, better operational practices and to select more efficient governance arrangements (Mayer and Argyres, 2004; Nelson and Winter, 1982). There are expected benefits to having a history of working together as a team that will mitigate the coordination costs. Thus, we hypothesize:

H3. The greater the experience of creative team leaders working together, the greater the probability of commercialization success.

2.3. External networks, social ties and proximity

The effectiveness of a team is expected to be enhanced when its members provide links to multiple, diverse social worlds in the larger environment. Team members that have distinct organizational affiliations may themselves bring unique knowledge to the team offering different skills, experiences and perspectives. These ties may bring "horizontal" knowledge increasing the breadth of the team's scientific base as well as "vertical" knowledge extending the team's understanding of market needs and opportunities. Equally valuable, these external members can bridge structural holes providing an important conduit for knowledge and resources to and from their home organization, a second network cluster outside the team's own (Burt, 1992; Guimera et al., 2005).

Network range – the number of different external groups accessed by the team through bridging ties – is believed to promote knowledge dissemination and technology-transfer capabilities (Reagans and McEvily, 2003). Further, having ties to non-overlapping networks can expand the commercialization options for the team's technology through identification of, and introduction to, a broader array of potential licensing partners. As such, we predict that

H4. Creative teams with ties to external networks will have a higher probability of commercialization success.

While all bridging ties are expected to positively influence team performance, the magnitude of the effect will likely be linked to characteristics of the external group or network accessed. As a broad categorization, consider the distinction between bridges into external academic clusters versus bridges into external industry clusters. The traditional "open science" norm of academics supports the emergence of a *small world* social structure where the path between any two academic researchers in an epistemic community is relatively short (Newman, 2001; Guimera et al., 2005). Conversely, the "proprietary" norms of industry-based research leads to a more disconnected social structure with a large number of small, isolated clusters (Balconi et al., 2004). Given that the principal investigator and the other internal team members are likely to be members of the same small world network (or indivisible college) as team members drawn from other academic institutions, much of the information an external academic member brings to the team is likely to be, or quickly become, redundant. External industry members drawn from more isolated clusters are likely to bring unique information and resources to the team and thus may have a greater impact on performance.

The readiness of the transfer of knowledge and resources, however, likely depends on the degree to which the tie is embedded in a social attachment (Granovetter, 1985; Uzzi, 1997). Three attributes associated with social attachment – communication, cooperation, and motivation – are argued to promote the sharing of private knowledge and proprietary resources which can increase team productivity (Reagans and McEvily, 2003; Uzzi and Lancaster, 2003). Interpersonal connections are built through frequent communication, which in turn, can lead to more effective interactions (Uzzi, 1997). Attachment and the expectation of continued interactions can catalyze the emergence of cooperative norms which can then support performance (Bercovitz et al., 2006). Emotional involvement can motivate individuals to put forth substantial effort to meet the needs of significant individuals in their network (Granovetter, 1985). Further, and important for innovation teams, embedded ties are believed to be positively related to explorative learning (Uzzi and Lancaster, 2003).

H5. Creative teams with pre-existing social ties among team members will have a higher probability of commercialization success.

The challenge of leveraging the skills and resources of external team members may also be influenced by geography. The literature on localized knowledge spillovers and regional innovation suggests that research teams in close geographic proximity are likely to be more productive than more geographically dispersed teams (Jaffe et al., 1993; Audretsch and Feldman, 1996). Certainly, this belief motivates much economic development policy that attempts to encourage local university interaction and outreach with industry. While the literature on knowledge spillovers motivates this result there are multiple reasons to expect that geography matters in this context (Feldman and Kogler, 2010). First, if team members are in close proximity, the costs of communication and knowledge transmission are reduced and the difficulty of arranging direct meetings will generally be lower. Proximity is expected to result in greater frequency of interactions between internal and external team members. Through frequent, face-to-face interactions, team members can gain greater familiarity with one another, develop an enhanced understanding of the problem-solving processes of their partners, and build personal ties that result in both trust and more effective research routines (Allen, 1977; Gulati, 1995; Zaheer and Venkataraman, 1995; Zollo et al., 2002). Second, innovation often rests on the development and transfer of tacit knowledge and know-how. Teams in close geographic proximity are believed to have an advantage in such research activities as exchanging tacit knowledge across organizational boundaries arguably requires intimate personal interaction to be successful (Nonaka, 1994; Jensen and Thursby, 2001). Third, anchored in the core team's experience and reputation, much of the team's social capital – in terms of ties to financial providers and professional experts – is likely to be concentrated within the principal investigator's home region (Kenney, 1986; Stuart and Sorenson, 2003). The expectation is that creative teams with local external team members will have a higher probability of commercialization success:

H6. Creative teams with local external team members will have a higher probability of commercialization success.

2.4. Geography, prior work experience, social ties and reputation

Given the expected advantages of geographical proximity, a final question we consider is factors which might mitigate the disadvantages of distance and increase the likelihood that a team will include more geographically far-flung external members. The literature suggests three possible candidates: prior experience working together, strong social ties, and reputation. First, a team comprised of inventors who have experience working together in the disclosure process will establish common expectations about what makes a high quality invention (Hackman, 1987). Through their prior work experience, the individuals on this team may be able to better configure a team in subsequent rounds that is more capable of success. Specifically, team leaders have the authority to reconfigure the team. If, through prior experience, the team leaders gain a greater understanding of the relative effectiveness of alternative coordination processes, they can compel the current team to adopt these practices. Finally, individuals develop reputations based on their past activities. Leaders that have substantial experience in directing teams may engender confidence with current team members, which further enhances motivation and effort (Edmondson et al., 2001). Thus, we expect that

H7a. The distance spanned by a creative team will be positively related to the core team's experience working together.

Similarly, having an established social tie with an external player – either through previous co-location or previous collaboration – may diminish the costs of greater geographical dispersion. With pre-existing ties, norms of communication and coordination have likely already been developed, thus limiting the need for continuous and frequent face-to-face interactions. Most commonly, these prior social ties will reflect prior employment, prior training experiences or simply long-time collaborations. After all, when considering working together there must be some initiating event that establishes connections and raises the potential for future collaboration:

H7b. The distance spanned by a creative team will be positively related to presence of pre-existing social ties between the team members.

Finally, another mechanism for identifying potential team members is scientific reputation. It is possible that the benefits of associating with high-reputation individuals outweigh the costs of managing teams across distances. Specifically, it is feasible that what have become known in the literature as star scientists have the potential to add great value to the research endeavor (Azoulay et al., 2008). The reputation of the star scientist and their association with a particular expertise provides an incentive for other researchers to seek them out to form collaborations. Through their enhanced reputation, star scientists may attract more distant collaborators. Thus, we expect that

H7c. The distance spanned by a creative team will be positively related to the scientific reputations of the team members.

3. Data and methods

Our subject is academic research teams who disclose their invention to the university technology transfer office. We have detailed inventor and outcome data for the 2380 invention disclosures made at two prominent universities with well-known medical schools for fiscal years 1988–1999 (July 1, 1988 to June 30, 1999). Of these disclosures, 1425, or 60%, involved teams of multiple inventors. Our sample includes all 1425 team disclosures.[2] Both universities we studied did not have an organized technology transfer operation until the mid-1980s (see Bercovitz and Feldman, 2008 for more detail). By 1988, policies and procedures were in place and technology-transfer activities had reached significant levels, though both universities saw significant growth in these activities in the following decade. The end date of 1999 of our sample period is chosen to allow sufficient time for outcome measures to be negotiated and realized post invention disclosure.

Every invention disclosure represents the formal acknowledgement of the discovery of scientific results that may have commercial application. In tracking disclosures, our dataset includes those academics that seek to span the scientific and innovation boundary. As

[2] As this paper is focused on issues of team composition and performance, we have limited our sample to team disclosures. In earlier econometric analysis, we have found that teams are generally more successful than solo inventors in generating commercial outcomes – patents, licenses, royalties (Bercovitz and Feldman, 2006).

Gittelman and Kogut (2003, p. 380) note, “bridging the disconnect between scientific knowledge and innovation appears to depend on access to individuals who perform both activities, rather than on the ability to generate valuable scientific knowledge alone”. It is this capacity to operate under both scientific and innovation logics, they argue, that leads to more successful innovations.

The invention disclosure is the first step towards patenting and licensing the technology that is disclosed. The disclosure lists the names of the inventors in the order that would be used on a patent application in case the Office of Technology Licensing (OTL) deems that the invention should move forward from disclosure to patent. The statutory requirements for co-inventorship are described in the U.S. legal code and related case law (Ducor, 2000, p. 873), “[A] joint invention is simply the product of a collaboration between two or more persons working together to solve the problem addressed”. And, “to constitute a joint invention, it is necessary that each of the inventors work on the same subject matter and make some contribution to the inventive thought and to the final result”. Thus, the list of inventors constitutes a team.[3]

In contrast to the convention in economics of listing authors alphabetically, the order of inventors on a disclosure is determined by the contribution to the invention. The order of the listing of the members of the disclosure team matters, with the first name listed on the disclosure taking the lead and making the most significant contribution to the invention. We verified this assumption by examining the revenue share assigned to the inventors on a team. In every case the lead inventor received an equal or greater share than the other team member.

We use the population of all team disclosures to test predictions about the effects of knowledge combination novelty, coordination costs, team experience and access to external networks on team performance. We use the subset of those disclosure teams with external members (a total of 286 teams) to investigate the effect of social ties and proximity for these boundary-spanning teams.

3.1. Dependent variables

The value of an invention may be considered in a number of different ways that follow the commercialization process. Disclosures are the basis for patents, licenses, and royalties. In our analysis, we measure commercialization success using two dummy variables. The dependent variable patent is equal to 1 if the disclosure yielded one or more patents. The next measure of value of the disclosure would be the licensing outcome. This may be measured by a dummy variable indicating that a license was signed. The probability of a disclosure converting to a patent or license is estimated using a PROBIT model (Maddala, 1983). Royalty dollars is our final dependent variable. Given a highly skewed distribution, we use a log transformation of this variable. The level of royalty dollars is estimated using a Tobit model to account for the large number of left-censored observations – disclosures that do not generate any royalties.

3.2. Independent variables

We tap the disclosure records from the technology transfer offices at the two universities for many of the variables used to characterize the composition of the invention team. Along with inventor names, the invention disclosure includes information about departmental affiliation for the academic inventors. We use a count of the number of different home departments for the inventors on a team plus the number of external organizations involved as a proxy for the coordination and communications costs associated with working across different types of expertise and across different organizational boundaries. For the teams of two or greater, more than one-third have inventors from multiple departments. Department structures are constant over the time period we study. We have created unified department names that eliminate differences in department titles between the two universities.

Knowledge domain expertise is an attribute that individuals bring to teams. We expect that team performance will be positively affected by the degree of novelty of the combination of individual knowledge domain expertise. While there are many sources of novelty, we follow Taylor and Greve (2006) to focus on the deep-level diversity or the less observable cognitive diversity that captures different frames of reference. To characterize knowledge combination novelty among team members, we use a hierarchical clustering method for categorical data to discern the relationship between distinct types of expertise on the team. We calculate the Euclidian distances associated with different combinations of academic departments. This provides a measure of how commonly different department combinations are observed. For example, we noticed that biomedical engineers frequently invent with surgeons. This common pattern makes sense as an example of user driven invention as surgeons often recognize opportunities for new surgical instruments and then work with engineers to design prototypes. This more common type of team would have a lower expertise distance. Another likely combination is medicine teaming with pharmacology on human therapeutics. The most distant collaborations include oncology with cardiology, ophthalmology with genetics and pharmacology and radiology. The larger the measure of expertise distance, the greater the novelty of combination among the members of the invention team. Teams with all members from the same academic department are given a novelty score of 0.

To test the effect of team experience on performance, we exploit the fact that our database includes the date of the disclosure. This allows us to keep a running count of the number of times the inventors on a team have disclosed together in the past. In reviewing the patterns of past collaboration, we noted that it was relatively rare for an entire team to engage in multiple disclosures. Team configurations frequently change with members both added and dropped from the team over time. However, we often saw a stable core of inventors who worked together repeatedly. Finding that much of the mobility in the sample could be attributed to the temporary presence of students, both post-docs and graduate students, we tracked the more permanent employees – faculty and staff – to operationalize core team experience. Specifically, the core experience count was increased by one for each time at least two of these more permanent members of the research community had disclosed together in the past. Core team experience was varied, ranging from 0, indicating no prior experience working together to a maximum of a pair of inventors that had worked together on 41 disclosures. The mean number of times that core teams worked together was 2.92.

To test for the effects of access to external networks on team performance, we use the number of individuals from industry or outside the focal university on the team. Overall, 20% of the teams in our data included external members. For teams with external members, close to two-thirds (63%) were working with academics from universities other than the home university of the team leader. Industry members, while clearly material, were less common as just over one-fourth (26%) of the teams having external members drew on industry players.

[3] It is useful to draw a distinction here as teams of academic inventors are the outcome of research projects and we do not have access to data on all ongoing research projects and who was working on the research project. Thus we are not able to consider who might possibly have contributed to the invention but did not and was thus not part of the invention team. Our point of departure is the realization of an outcome – the production of an idea with commercial potential. As such we are not measuring the output or productivity of all research projects.

We had personnel records for individuals who were employed at each of the universities. Information was less clear for the external inventors. Frequently, the technology transfer office records provided the current address for the inventor and not the place where the individual was employed at the time when the inventive work was undertaken – the data element that we were looking for. We conducted web-based searches for information on the external inventors to verify the affiliation listed in the disclosure database and to fill in missing information. We were able to find vitae or biographies for about half of the external inventors. If no background information was found, then we turned our attention to patent databases and the Institute for Scientific Information (ISI)'s Web of Science. When the disclosure resulted in a patent, we were able to confirm the affiliation of the external members from the inventor information provided on the patent documents. When no patent resulted, we used the ISI database to search for the author's name and identified articles submitted close to the date of the invention. We recorded the information that the articles list as the authors' affiliation. External inventors were then identified as either working for industry or working at other universities, government labs or other not for profit institutions. We coded dummy variables for each external inventor with respect to these categories, summing across all members to characterize the composition of the team.

To understand the relationship between internal team members and the external team member(s), we investigated the backgrounds of the external team members and the internal team members. Frequently, individuals appeared in the database multiple times with their affiliations changing over time. We were able to find individuals who had previously worked together at the focal institution or at another organization. The fact that many academic labs list alumni aided this identification. We also used UMI dissertation information to identify any possible advisor/advisee relationships between team members. Many of the inventors who were listed as external team members were determined to have been affiliated with the focal institution prior to the time of the inventive work. Dummy variables were created to designate these individuals as prior faculty members or students (doctorates, post-docs or residents) or, in the cases where prior co-location occurred at a site other than the focal institutions, as having a prior social relationship.

Next, there were teams where we were not able to identify any relationship based on available biographic information. We then used ISI to see if we could identify the team members as having worked together more than 3 years before the disclosure date. We identified these individuals as long-time co-authors. Although we could not identify the precise type of social relationship or its origins, it seemed clear that long time co-authors as members of the invention team had a prior working relationship. We coded a dummy variable equal to one if any of the external members on a team was identified as having a prior social relationship across the above categories – previous co-location, previous students, and long-time co-authors. We also segmented this variable to reflect whether the identified social tie supported an industry link or an external academic link.

To explore the role of geographic proximity in team performance, we calculated the distance between the home institution of the principal investigator (PI) and the employment location for each of the external team members. A dummy variable, local, was then created with local = 1 for teams in which all external members were located within 60 miles of the PI's institution, and 0 otherwise. The use of more or less 60 miles to define a geographic agglomeration is consistent with other studies, for example, Anselin (1995). For the teams with external members, just less than one-fourth (22%) were local, while three-fourths of the teams spanned greater distances, with 16% of the teams including non-U.S.-based players.

3.3. Control variables

We include several control variables in the estimations. First, disclosure behavior and the subsequent outcomes may be influenced by the research quality and the resource base of the team members. One measure of quality for academic scientists is the ability to attain research awards from NIH, as these awards are highly competitive and highly respected. To control for the potential effect of team research ability and resource availability, we include a dollar measure of total NIH awards across team members for the three-year period surrounding an invention disclosure. We log this variable given its skewed distribution. As a second measure of quality (or scientific reputation) of teams, we control for the number of "star scientists" on each team. Previous research has noted that a small subset of academic scientists both publish substantially more, and produce papers that have greater impact, than their peers. These stars are also believed to have pronounced effect on commercialization efforts (Zucker et al., 1998). Following Azoulay et al. (2008), we code an individual inventor as a star scientist if they have been designated as a Howard Hughes Medical Investigator (HHMI), if they have been designated as a "highly cited" author by ISI, or if they are in the top percentages in NIH grant generation.

It is feasible that outcomes may be tied to the type of research the team is conducting. We thus use the terminal degrees of the investigators – PhD or MD – as a proxy for project type. Team members holding a PhD degree are more likely to engage in basic research than members with the more applied MD degree. We also control for team size using the number of inventors listed on the invention disclosure. Teams varied in size from two members to the largest team with 15 members. Average team size was 2.89. A dummy variable for university is included to control for institutional differences. Finally, we control for the fiscal year of the disclosure and, using a dummy variable, whether the disclosure team includes individuals located at the medical school. Descriptive statistics and correlations are presented in Table 1. Correlations are generally low to moderate. Multicollinearity is not a problem for the estimations.

4. Results

Table 2 provides estimates of the probability that a disclosure generates any of the outcomes of commercial success: converting to a patent, providing the basis for a license with a company or generating a royalty stream. We run our model against each of these dependent variables and the results are provided in the columns of our tables. While these are sequential steps, our model considers how the composition of the team may affect the probability that a disclosure would convert to any of the relevant outcomes. This is the concern of the technology transfer office when first facing a disclosure to evaluate.

Consider first the Probit analyses in the first two columns of Table 2. Coordination cost, proxied by the number of intra- and inter-organizational boundaries crossed, is negatively and statistically significantly related to the likelihood of a disclosure successfully converting into a patent or a license. In line with H2, the evidence suggests that coordination challenges hinder team processes and reduce team effectiveness. On average, the benefits of building teams that span departmental and/or organizational boundaries to tap diverse knowledge appear to be swamped by the added communication and coordination costs of different groups working together. However, teams do seem to gain from diversity when the more original combinations of knowledge are brought together. Specifically, we find some support for H1 in that the coefficient on novelty is positive and significant for both patenting and licensing. For unique combinations of knowledge, the creativity

Table 1
Descriptive statistics and correlations. All teams: 1425 observations.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Patent	1.00																
2. License	0.79	1.00															
3. Royalty	0.47	0.58	1.00														
4. Royalty dollars (Ln)	0.46	0.56	0.97	1.00													
5. Novelty	0.04	0.04	−0.00	−0.00	1.00												
6. Coordination costs	0.06	0.08	0.05	0.05	0.50	1.00											
7. Core team experience	0.11	0.13	0.17	0.17	−0.01	0.01	1.00										
8. # of external academics	0.06	0.06	0.10	0.09	−0.01	0.41	0.01	1.00									
9. # of industry team members	0.11	0.11	0.07	0.08	−0.03	0.26	−0.04	0.00	1.00								
10. # of MDs on team	0.07	0.09	0.02	0.02	0.14	0.25	0.15	0.11	0.06	1.00							
11. # of PhDs on team	0.15	0.11	0.08	0.10	0.05	0.25	0.01	0.19	0.21	0.06	1.00						
12. # star scientists	0.20	0.22	0.21	0.22	0.03	0.13	0.24	0.18	0.02	0.25	0.19	1.00					
13. Total team NIH dollars (Ln)	0.15	0.18	0.12	0.12	0.02	0.08	0.19	0.11	0.00	0.20	0.15	0.39	1.00				
14. Team size	0.20	0.18	0.10	0.13	0.17	0.44	0.15	0.23	0.20	0.41	0.49	0.22	0.21	1.00			
15. Medicine	0.07	0.11	0.11	0.11	0.12	0.11	0.12	−0.01	−0.03	0.35	−0.14	0.24	0.21	0.08	1.00		
16. Year	0.01	−0.02	−0.09	−0.10	−0.00	−0.04	0.05	−0.03	−0.04	0.02	0.03	−0.12	−0.09	0.06	0.01	1.00	
17. University	−0.10	−0.12	0.12	0.14	−0.07	−0.04	0.05	0.08	0.02	−0.18	0.06	−0.08	−0.02	−0.01	−0.18	−0.08	1.00
Mean	0.49	0.37	0.18	1.73	11.20	1.58	2.92	0.16	0.07	1.22	1.70	0.53	11.68	2.89	0.87	1994	0.54
Standard deviation	0.50	0.48	0.38	3.85	22.26	0.72	6.03	0.47	0.35	1.22	1.24	0.78	5.72	1.21	0.34	2.96	0.50
Min.	0	0	0	0.0	0.0	1	0	0	0	0	0	0	0.0	2	0	1988	0
Max.	1	1	1	15.1	197.8	5	41	4	4	11	11	5	17.6	15	1	1998	1

Table 2
Analysis of commercialization success. All teams.

	Patent (Probit)		License (Probit)		Royalty $s (LN) (Tobit)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Independent variables						
Coordination costs (needs)	−0.247	0.074^{**}	−0.149	0.072^{*}	−1.261	1.028
Novelty	0.004	0.002^{*}	0.003	0.002^{+}	0.013	0.027
Core team experience	0.015	0.007^{*}	0.018	0.006^{**}	0.305	0.075^{***}
# of external academics	0.156	0.090^{+}	0.136	0.088	2.339	1.209^{+}
# of industry team members	0.577	0.144^{***}	0.483	0.126^{***}	3.066	1.420^{*}
Control variables						
# of MDs on team	−0.082	0.036^{*}	−0.070	0.035^{*}	−1.353	0.568^{*}
# of PhDs on team	0.064	0.035^{+}	0.018	0.035	0.323	0.564
# star scientists	0.222	0.054^{***}	0.200	0.052^{***}	3.284	0.724^{***}
Total team NIH dollars (Ln)	0.014	0.007^{*}	0.023	0.007^{**}	0.059	0.113
Team size	0.195	0.043^{***}	0.140	0.040^{**}	0.950	0.584
Medicine	0.146	0.114	0.220	0.122^{+}	8.847	2.161^{***}
Year	0.002	0.012	−0.009	0.012	−0.517	0.184^{**}
University	−0.292	0.072^{***}	−0.326	0.073^{***}	5.572	1.150^{***}
Constant	−6.300	23.427	17.374	24.269	1002.64	366.05^{**}
Number of observations		1425		1425		1425
Likelihood ratio		152.47^{***}		150.21^{***}		147.29^{***}
Pseudo R^2		0.077		0.080		0.050
Left-censored observations						1172
Uncensored observations						253

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
+ $p < 0.10$.

benefits appear to be high enough to overcome the added coordination costs.[4] Though the same pattern holds for when royalty dollars (in the natural log) is the dependent variable, the coefficients on coordination costs or novelty variables do not reach significance.

We also find support for H3. Core team experience has a positive and statistically significant effect on all three commercial outcomes. The organizational and technical know-how generated from having worked together in the past, enhances the performance of the team. This measure indicates that a core group of individuals who have chosen to work together repeatedly can develop routines that mitigate coordination costs and enable the team to produce higher quality outcomes.[5]

[4] We also considered whether there might be an interaction effect between knowledge domain novelty and coordination costs. It can be argued that spanning a set number of boundaries could be more costly when novelty is high given the added complexity of communication and coordination in such situations. This supposition was not supported. The interaction term coordination costs × novelty showed no significance and adding this term did not significantly improve the fit of the model.

[5] It is possible that team experience could have a non-linear effect as, overtime teams that repeatedly engage may become increasingly isolated while simultaneously exhausting their valuable ideas (Katz, 1982; Berman et al., 2002). We investigated this possibility by including a squared core team experience term in the analysis and found no evidence of a non-linear effect – as the coefficient on this variable was insignificant. Similarly, we have also explored the potential team experience × coordination cost interaction. One can make the argument that having experience as a team can smooth coordination and thus damped the direct negative effect crossing technical and/or organizational boundaries. Again, the interaction term did not reach significance. We also investigated whether team size might have a non-linear effect, finding no significance.

The findings with respect to external network ties provide support for H4. Having a team member from industry significantly increases the probability that a disclosure will have a positive outcome with regards to patenting ($p < 0.001$), licensing ($p < 0.001$), as well as having a positive relationship with the level of royalties generated ($p < 0.05$). The inclusion of team members from other universities has a relatively small positive effect on the probability of either patenting or licensing with only the former reaching significance. However, inclusion of external academics on the team is positively and significantly related to the generation of royalties ($p \leq 0.053$). The value in linking to an industry-based external network seems to be one of identifying commercial options and accessing financial resources. Conversely, ties within the small world academic network are of limited assistance in opening commercial doors, but do add to the market value of the invention. Our findings suggest that in certain circumstances team members from other universities, though they may not bring the needed ties to potential licensees, may bring particularly valuable knowledge assets to the team. Additional work to examine how these external members are identified and recruited is needed to clarify this relationship.

Turning now to the control variables: We find that team performance, measured by patents, licenses, and royalty dollars, is negatively related to the number of MDs on the team. It appears that teams with a larger number of individuals trained with medical degrees are more likely to produce lower quality or non-commercial inventions. Team quality, as measured by total NIH dollars, increases the probability that a disclosure will have a positive outcome with regards to patenting and licensing, but does not significantly influence the generation of royalties. The presence of star scientists on the team, however, significantly increases the probability of success across all commercialization outcomes.

Team size is positively related to the probability of a disclosure moving to a patent or a license, though unrelated to the level of royalties generated. This finding further supports arguments regarding the growing complexity of research and the related response of a greater role for teams in the discovery process. Teams with members from the medical school show increased commercialization success. Finally, the university dummy variable is included to control for heterogeneity between the two institutions and their technology transfer offices. Interestingly, one university generates more patents and licenses while the other university's disclosures produce more licensing revenue. This suggests that the two universities are following different commercialization strategies.

The next set of analyses focus on those teams with external members. Table 3 summarizes the descriptive statistics and correlations for this subset of the data.

The models in Table 4 explore how the social ties underlying external ties influence patents, one measure of team performance. Model 1 includes two dummy variables designating whether any type of social tie – previous co-location, previous student, or long-time co-author – supports either an industry or an academic external relationship. The coefficients on these variables are positive and significant providing support for H5. In models 2 and 3, we disaggregate these social tie dummy variables into their most common component parts to investigate how performance is affected by type of previous relationship. We replicate this analysis with royalty dollars as the dependent variable in Table 5.

Interestingly, we find that for ties with external academics, those external team members that had previously been a student/Post-Doc or a long time co-author of an internal member of the team bring significant value to the team. This seems logical as previous students, particularly those prior students whom the faculty member chooses to continue to work with post-graduation, are likely to have a common knowledge base and a proven ability to communicate and coordinate with the internal faculty member. In addition to building on previous work, previous students are often early in their careers and have strong incentives to bring projects to successful completion. With respect to long-time co-authors, the value of having a history of working together also appears to improve performance. Though ties with both previous students and long-time co-authors significantly increase the likelihood of patenting, only ties with the latter group are associated with a significant increase in the amount of royalties generated. For industry externals, the social tie effects differ. The boost to performance is associated with including an external member that had been previously co-located with an internal member, though not at the current institution. Ties to such individuals increase both the likelihood of patenting a discovery and reaping financial rewards from commercialization.

Our results with respect to geographic proximity are intriguing and somewhat counter intuitive. In the models in Table 4 where the dependent variable is likelihood of generating a patent, the coefficient on the local dummy variable is negative, though not significant. We find no evidence that proximity increases the probability of generating valuable, non-obvious, and useful innovations. In the models in Table 5, where the dependent variable is royalty dollars, the coefficient on the local dummy variable is negative and significant – suggesting that geographical proximity is detrimental to commercial success when success is measured by royalty income. This is counter to expectations: geographic proximity does not increase the probability of a successful outcome. H6 is thus not supported.

There may be several reasons for this negative result. When building teams locally, potential partners may be identified through chance interactions and, because of the anticipated ease of future interactions, partnerships may be formed without thorough consideration of project promise. Due to the lower cost of participating in a team, there may be a greater number of lower quality inventions. That is to say, that the lower quality reflects the lower cost. Second, the two universities that we examine, while not geographically remote, are also not located in dense resource rich agglomerations. It may not be realistic to assume that the local area would have the appropriate capacity to benefit from proximity to the university. Third, local collaborations may reflect an economic development focus for the university and serve other organizational goals rather than licensing revenue generation. Finally, the idea of knowledge spillovers suggests that chance interactions and serendipity rather than the contractual arrangements we observe may be the operative mechanism for localization economies. Ideas gained from proximate relationships are likely to be informal and more open ended, in contrast to the more task oriented formation of an invention team.

Though our expectations regarding the benefits of proximity fail to find support, we do gain additional insight into factors supporting distant collaboration (Table 6). Core team prior work experience is material. Teams that have worked together in the past add more distantly located individuals when they expand than do teams with limited previous experience. Social ties are also important. Teams span greater distances when that distance is supported by a pre-existing social tie. This suggests that the most productive distant team collaborations are the result of prior socially mediated relationships.

Interestingly, we find no evidence that reputation drives distant collaborations. Star scientists show no propensity to collaborate across greater distances than non-star scientists. Two factors may be behind this unexpected result. First, star scientists, given their strong skills, may have multiple partnering opportunities and select to work locally to avoid the added travel and coordination demands of distant collaborations. Second, the results may be confounded by the start-up activities associated with the star scientists. The data may be skewed by the partnerships star scientists form with exter-

Table 3
Descriptive statistics and correlations. Teams with external members: 286 observations.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. Patent	1.00																							
2. Royalty dollars (Ln)	0.51	1.00																						
3. Novelty	0.01	−0.04	1.00																					
4. Coordination costs	0.14	0.06	0.52	1.00																				
5. Core team experience	0.14	0.29	0.26	0.27	1.00																			
6. Ext. academic, prior ties	0.09	0.04	−0.04	0.16	−0.06	1.00																		
7. Ext. acad., former student	0.11	0.10	0.01	0.10	0.13	0.39	1.00																	
8. Ext. acad., LT co-author	0.13	0.03	−0.00	0.12	−0.10	0.52	−0.03	1.00																
9. Ext. acad., prior co-location	−0.05	−0.01	−0.10	0.04	−0.08	0.53	−0.14	−0.05	1.00															
10. Ext. industry, prior ties	0.19	0.02	−0.02	0.19	−0.05	−0.09	−0.08	−0.01	−0.02	1.00														
11. Ext. ind., former student	0.05	0.07	−0.01	0.04	−0.02	−0.04	0.07	−0.05	−0.05	0.32	1.00													
12. Ext. ind., LT co-author	0.09	−0.02	0.07	0.18	−0.05	−0.07	−0.08	0.09	−0.07	0.69	−0.03	1.00												
13. Ext. ind., prior co-location	0.14	0.06	−0.07	0.11	0.00	0.04	−0.06	−0.04	0.18	0.52	−0.02	0.08	1.00											
14. Local	−0.13	−0.21	0.06	−0.10	−0.10	−0.23	−0.05	−0.06	−0.19	−0.10	−0.06	−0.04	−0.07	1.00										
15. # of MDs on team	0.13	0.00	0.10	0.13	0.17	0.06	−0.01	0.14	0.01	0.07	−0.03	0.19	0.02	−0.03	1.00									
16. # of PhDs on team	0.20	0.07	0.11	0.16	−0.02	0.00	0.01	−0.02	0.02	0.12	−0.06	0.20	0.11	−0.01	0.32	1.00								
17. # star scientists	0.22	0.23	0.09	0.13	0.10	0.15	0.07	0.20	0.01	−0.03	0.06	0.05	−0.08	−0.12	0.23	0.17	1.00							
18. Total team NIH dollars (Ln)	0.19	0.10	0.06	0.12	0.14	0.09	0.02	0.16	−0.01	−0.12	0.04	0.03	−0.24	−0.13	0.27	0.11	0.40	1.00						
19. Team size	0.27	0.14	0.16	0.27	0.10	0.01	0.02	0.07	−0.04	0.05	−0.08	0.11	0.01	0.03	0.31	0.56	0.21	0.22	1.00					
20. Medicine	0.10	0.16	0.07	0.14	0.11	0.12	0.05	0.15	0.01	−0.02	0.06	0.08	−0.20	−0.26	0.35	−0.08	0.33	0.49	0.04	1.00				
21. Year	−0.13	−0.15	0.08	0.16	0.08	0.04	0.11	0.02	−0.04	0.02	−0.16	0.08	0.01	0.11	0.06	0.08	−0.08	−0.02	0.13	−0.03	1.00			
22. University	−0.07	0.19	−0.04	−0.03	0.17	−0.10	−0.07	−0.25	0.15	−0.21	−0.04	−0.26	0.04	−0.03	−0.25	−0.03	−0.11	−0.14	−0.03	−0.16	−0.15	1.00		
23. Prior social tie	0.12	0.02	−0.10	−0.08	−0.11	0.70	0.27	0.37	0.37	0.32	0.10	0.22	0.17	−0.21	0.14	0.05	0.11	0.04	−0.02	0.08	−0.03	−0.24	1.00	
24. Distance (Ln)	0.06	0.22	−0.02	0.03	0.13	0.21	0.04	0.08	0.14	0.07	0.08	0.04	0.01	−0.87	0.05	0.00	0.12	0.11	−0.01	0.25	0.00	0.03	0.21	1.00
Mean	0.55	2.56	9.85	2.26	2.59	0.40	0.09	0.15	0.16	0.12	0.01	0.06	0.04	0.22	1.43	2.29	0.77	12.55	3.49	0.82	1994	0.64	0.58	5.97
Standard deviation	0.50	4.51	19.36	0.73	5.79	0.49	0.29	0.36	0.37	0.33	0.12	0.24	0.22	0.42	1.63	1.67	1.00	5.34	1.48	0.38	2.87	0.48	0.49	2.29
Min.	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1988	0	0	0
Max.	1	13.8	117.8	5	38	1	1	1	1	1	1	1	1	1	11	11	5	17.22	15	1	1998	1	1	9.19

Table 4
Probit analysis – social ties, location, and commercialization success. Patents: teams with external members.

	Patent Model 1		Patent Model 2		Patent Model 3	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Independent variables						
Coordination costs	0.015	0.150	0.003	0.150	0.039	0.150
Novelty	−0.006	0.005	−0.006	0.005	−0.006	0.005
Core team experience	0.044	0.019*	0.041	0.020*	0.043	0.019*
External academic: prior social ties	0.263	0.179+			0.190	0.179
Ex. academic: former student			0.619	0.314*		
Ex academic: long time co-author			0.446	0.247+		
Ex academic: prior co-location			−0.066	0.239		
External industry with prior social ties	0.918	0.301***	0.961	0.301***		
Ex. industry: former student					0.327	0.692
Ex industry: long time co-author					0.427	0.394
Ex industry: prior co-location					1.643	0.656*
Local	−0.233	0.210	−0.281	0.208	−0.250	0.209
Control variables						
# of MDs on team	−0.055	0.063	−0.051	0.064	−0.058	0.064
# of PhDs on team	0.066	0.064	0.080	0.065	0.062	0.064
# star scientists	0.171	0.100+	0.156	0.101	0.157	0.101
Total team NIH dollars (Ln)	0.022	0.019	0.025	0.019	0.024	0.019
Team size	0.282	0.084***	0.256	0.085**	0.290	0.084***
Medicine	−0.035	0.268	−0.069	0.270	0.066	0.273
Year	−0.090	0.030**	−0.096	0.030**	−0.092	0.030**
University	−0.188	0.188	−0.101	0.195	−0.300	0.187
Constant	177.79	58.84**	190.45	59.93**	182.91	59.69**
Number of observations		286		286		286
Likelihood ratio		68.86***		73.98***		69.44***
Pseudo R^2		0.175		0.188		0.176

Significance is one-tailed for hypothesized variables and two-tailed for control variables.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
+ $p < 0.10$.

Table 5
Tobit analysis – social ties, location, and commercialization success. Royalty dollar: teams with external members.

	Royalty $ (Ln) Model 1		Royalty $ (Ln) Model 2	
	Coef.	S.E.	Coef.	S.E.
Independent variables				
Coordination costs	−0.101	1.591	−0.071	1.591
Novelty	−0.116	0.073+	−0.117	0.073+
Core team experience	0.562	0.152***	0.562	0.148***
External academic with prior social ties			0.906	1.952
Ex. academic: former student	3.880	3.073		
Ex academic: long time co-author	4.737	2.691*		
Ex academic: prior co-location	−0.228	2.449		
External industry with prior social ties	3.898	2.966+		
Ex. industry: former student			4.077	6.397
Ex industry: long time co-author			1.243	4.381
Ex industry: prior co-location			6.309	3.996+
Local	−7.115	2.981**	−6.727	2.974*
Control variables				
# of MDs on team	−1.114	0.774	−1.240	0.758
# of PhDs on team	0.396	0.817	0.307	0.801
# star scientists	2.433	0.988*	2.819	0.982**
Total team NIH dollars (Ln)	−0.212	0.215	−0.165	0.220
Team size	1.133	0.790	1.172	0.786
Medicine	6.751	3.404*	7.656	3.518*
Year	−1.048	0.340**	−0.984	0.343**
University	7.611	2.504**	6.039	2.353*
Constant	2067.69	677.49**	1940.02	682.85**
Number of observations		286		286
Likelihood ratio		77.65***		75.37***
Pseudo R^2		0.100		0.097
Left-censored observations		214		214
Uncensored observations		72		72

Significance is one-tailed for hypothesized variables and two-tailed for control variables.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
+ $p < 0.10$.

Table 6
Distance of external members.

	Distance (Ln) Model 1		Distance (Ln) Model 2	
	Coef.	S.E.	Coef.	S.E.
Independent variables				
Core team experience	0.042	0.023*	0.041	0.023*
Prior social tie	1.041	0.270***		
External academic with prior social ties			0.944	0.269***
External Industry with prior social ties			0.886	0.404*
# star scientists	0.080	0.141	0.080	0.142
Control variables				
Team size	−0.054	0.090	−0.069	0.090
Medicine	1.356	0.361***	1.328	0.362***
Year	0.020	0.464	0.007	0.046
University	0.536	0.288+	0.494	0.289+
Constant	−36.401	92.439	−9.494	92.520
Number of observations		286		286
F-stat		5.72***		5.11***
R^2		0.126		0.129

Significance is one-tailed for hypothesized variables and two-tailed for control variables.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
\+ $p < 0.10$.

nal individuals working at these starts-ups, which are generally located close to the spawning university.

5. Discussion

Scientists, particularly those in the medical and life sciences fields, rarely work alone (Wuchty et al., 2007). Rather, research activities are generally conducted in teams that bring together numerous individuals across knowledge domains and organizational boundaries. Teams, however, are not homogenous, differing on many dimensions including team size, team experience, knowledge combination characteristics, organizational diversity, as well as social grounding. An open and important question is, what factors differentiate more successful innovation teams from less successful innovation teams? In this paper, we probe the composition of academic research teams, developing and testing a set of theoretically derived hypotheses that link team attributes to performance. Our results provide insights into how to configure creative teams to increase the likelihood of a successful outcome.

We first explore two knowledge-based considerations argued to influence team composition choices – recombination potential and ability to span scientific and innovation logics. With respect to the first factor, we find that there are benefits associated with knowledge combination novelty. Exploration, a broad search that leads to the integration of knowledge in rarely tried combinations, offers a higher probability of generating significant breakthroughs. The likelihood that an invention is patented and licensed increased with the degree of novelty in the combination of knowledge expertise on the team. While the results for licensing income were not statistically significant, this may be due to the fact that truly novel inventions require more time to realize their commercial potential (Rosenberg, 1974). The data also show that there are gains to including individuals from external organizations on the team, particularly if these links offer access to market-related as well as science-related knowledge. Specifically, having a team member from industry significantly increases the probability that a disclosure will have a positive outcome with regards to patenting and licensing, as well as having a positive relationship with the level of royalties generated. The value in linking to an industry-based external network seems to be one of identifying commercial opportunities and accessing financial resources, as well as extending scientific knowledge. The benefits of ties with external academics appear to be narrower – contributing mainly to the latter (scientific advances), but not necessarily the former.

Though technological and knowledge-related issues may catalyze team formation and shape team composition, understanding coordination issues and the social relationships associated with these combinations are equally important. Progress towards a goal in a team environment requires the coordination of effort. We find that the challenge of achieving such coordination increases, and the likelihood of innovative success decreases, the greater number of departmental and organizational boundaries spanned by the team. Two socially based attributes – experience and embeddedness – provide means to meld a set of diverse individuals into a coherent and productive team. The data suggest that through repeated interactions, teams develop coordination capabilities, communication mechanisms, and task routines that enhance commercial performance. Relatedly, an external team member's initial willingness to cooperate in the transfer of knowledge appears to be a function of the level of attachment, or embeddednesss, in his ties to others on the team. The data shows that for both external academic scientists and external industry scientists, having a pre-existing social tie increases the innovation performance of the team. Perhaps most interesting, we find that the type of pre-existing tie is also material. Further, the existence of a prior social tie provides a foundation for collaboration across distances.

The academic teams that we study provide a transparent context to investigate the relationship between the team composition and team innovative performance. The teams we observe are self-organizing as there is no administrative assignment of individuals to participate in inventive activity. Team membership on an academic invention disclosure is dictated by the contribution of the individual to the effort and all individuals listed as a member of the inventive team will have made material contributions. The examination of teams that are more organic in organization and more selective in their membership allows a better comparison of how different configurations of individuals perform.

We believe, however, that the results we find are generalizable to other settings. Though academic inventive teams have more freedom in choosing with whom they collaborate, the knowledge-based factors that drive composition choices along with the coordination challenges associated with these choices are similar to those faced by other research-intensive teams in private companies and government labs. In particular, many firms that conduct research in emerging fields find themselves operating within Pasteur's quadrant and dealing with significant pressures to integrate science and market logics (Gittelman and Kogut, 2003). In such environments, the ability to access knowledge from external players and to integrate knowledge from multiple disciplines in novel ways is valued as it has been shown that such capabilities are positively associated with research outcomes and competitive performance (Henderson and Cockburn, 1994; Rosenkopf and Nerkar, 2001; Chesbrough, 2003). Less hierarchical organizations tend to be similarly fluid to universities in the organization of inventive activity. More hierarchical organizations who prescribe how this activity will be organized may benefit by adding domain novelty and by encouraging repeat interactions.

Further work will explore in more depth the different types of team configurations. Our results suggest that academic scientists learn how to organize and work with teams that are more likely to generate commercial success. We expect that inventive teams follow more or less archetypical patterns as it appears that some faculty members like to work with subordinates while other faculty members prefer to work with their peers. The patterns suggest that some inventors are more or less monogamous and work with the same individuals while other scientists reconfigure their teams more frequently. It may be that these patterns affect performance or that certain individuals are most productive once they find their type of team. In future work, we hope to examine how team structure evolves over time in order to increase the probability of a positive outcome.

Innovation is increasingly becoming a team sport. And like all team sports, success is a function of the expertise of the individual players, a solid roster enabling coverage of the key positions with the potential of a few stellar combinations, and an integrating set of social ties that enables the individuals to function smoothly as a unit.

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