6-2013

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DOI: https://doi.org/10.1002/sej.1154

Published in Strategic Entrepreneurship Journal, 2013, 7 (2), pp. 122-137.
https://doi.org/10.1002/sej.1154

COLLABORATIVE BENEFITS AND COORDINATION COSTS: LEARNING AND CAPABILITY DEVELOPMENT IN SCIENCE

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We examine the effects of team structure and experience on the impact of inventions produced by scientific teams. Whereas multidisciplinary, collaborative teams have become the norm in scientific production, there are coordination costs commensurate with managing such teams. We use patent citation analysis to examine the effect of prior collaboration and patenting experience on invention impact of 282 patents granted in human embryonic stem cell (hESC) research from 1998 to 2010. Our results reveal that team experience outside the domain may be detrimental to project performance in a setting where the underlying knowledge changes. In stem cell science, we show that interdepartmental collaboration has a negative effect on invention impact. Scientific proximity between members of the team has a curvilinear relationship, suggesting that teams consisting of members with moderate proximity get the highest impact. We elaborate on these findings for theories of collaboration and coordination and its implications for radical scientific discoveries.

INTRODUCTION

Scientists aspire for breakthrough inventions that will reshape their discipline. An emerging debate to explain why some breakthrough inventions emerge is the role of collaboration and the influence of diverse scientific backgrounds. Collaboration fosters integration of skills, ideas, and experiences across individuals; it also helps develop new insights through the recombination of relevant knowledge across subfields. Although scholars have analyzed collaboration in science, the analysis has primarily focused on the issues of teamwork dealing with the choice of collaboration partners and the trend toward joint research (Dahlander and McFarland, 2013; Guimera *et al.*, 2005). This line of thought has established that there is a trend toward cross-institutional collaborations (Jones, Wuchty, and Uzzi, 2008), as well as difficulties associated with such collaborations (Cummings and Kiesler, 2005, 2007; Kotha, George, and Srikanth, 2013).

Previous studies have shown a positive link between team-based organization and innovative performance (Gupta and Wilemon, 1996), but with limited specificity of its impact on dimensions of success in innovative projects (Hoegl and Gemuenden, 2001). The ability of the individuals taking part in a team to collaborate and the interdependencies among the team's members, as well as the diversity and depth of knowledge they bring to the project, determine the project outcomes (Bercovitz and Feldman, 2011; Taylor and Greve, 2006). A major problem with isolating the drivers of success in teamwork stems from the fact that team success depends on collaborative work of individuals, who bring different sets of knowledge and experience.

Keywords: scientific teams; collaboration; university; invention; knowledge
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In studying the benefits of collaborative work, scholars have analyzed how team-level learning takes place when teams adopt disruptive technologies (Edmondson, Bohmer, and Pisano, 2001) and how learning and improvisation processes occur in groups (Miner, Bassoff, and Moorman, 2001). At the firm level, the benefits of collaboration include enhanced connectivity to the environment, which stimulates innovative processes (Powell, Koput, and Smith-Doerr, 1996). Another literature stream has focused on the strategic development of collaborative capabilities that describe how firms capture, disseminate, and manage relationships across organizational boundaries and how the existence of such capabilities enhances performance outcomes (Dyer and Singh, 1998; Kale, Dyer, and Singh, 2002). Notwithstanding these rich studies, there is limited research on collaborative projects in scientific research teams with respect to the development of collaborative capabilities (Taylor and Greve, 2006; Tzabbar, 2009) and their attendant coordination costs (Kiesler and Cummings, 2002).

Although teams have taken a central role in the generation of knowledge and the development of inventions (Jones *et al*., 2008; Wuchty, Jones, and Uzzi, 2007), the best way to design a team—based on knowledge context, skills, and experience of individual team members and members' proximity in scientific and institutional domains—remains a tangled issue. And the question of organizing teams that can address potential coordination concerns while leveraging the benefits of collaborative work still maintains its importance. This question becomes even more pronounced when teamwork involves highly complex and novel approaches to knowledge generation (Amabile, 1988; Bercovitz and Feldman, 2011), as in the case of scientific discoveries in emerging fields (Kotha *et al*., 2013).

This study addresses the question of what factors influence the effectiveness of teams for scientific discoveries in emerging fields. We examine inventions and patenting activity in human embryonic stem cells (hESC), an area of research with the potential to solve numerous debilitating ailments, such as diabetes, Alzheimer's, and Parkinson's disease (McCormick, Owen-Smith, and Scott, 2009; Scott, McCormick, and Owen-Smith, 2009). Stem cell research is relevant as a context for this study because of its emergence as a technical field of study over the past two decades. Importantly, the cell lines themselves are fickle material that requires significant tacit knowledge on handling and propagation, which makes experience more relevant for success in discovery (Jain and George, 2007).

Two factors of theoretical and practical interest come into play when analyzing teamwork success in innovative projects: (1) collaboration benefits that arise from the enhanced ability of team members to work together effectively and develop routines and processes, possibly using their previous experiences with similar tasks as a lens and drawing on the diverse knowledge of team members to recombine knowledge for creative solutions; and (2) coordination costs that emerge as the team seeks to bridge the institutional, geographic, and scientific gaps across its members. Thus, collaboration is a double-edged sword in the context of radical, new science, as it brings both benefits and costs. Successful collaborations occur when the benefits from collaboration outweigh the costs of coordination that team members face. Hence, in this study, we systematically examine the effects of prior collaborative experience and the recombination ability among team members on invention impact in radical, new science.

The research setting offers an excellent opportunity to study factors affecting collaboration in geographically and institutionally separated scientific teams and the impact of their invention outcomes. Our data cover 12 years of patenting activity since the discovery of hESC and gives a comprehensive picture of collaborations in this field. Due to the recent emergence of the hESC field, the work in this area is concentrated among 648 scientists and dominated by collaborative work we are able to observe in our data. From this data, we draw a range of different variables to assess the effects of experience with a unique resource, experience in joint work within and outside the field, as well as team composition attributes while controlling for patent- and team-level characteristics.

THEORY AND HYPOTHESES

Generalized experience (experience outside the hESC domain)

Experience can be thought of having two dimensions in relation to a given knowledge context: (1) specific experience, which stems from work done specifically in the context where the current work is taking place; or (2) generalized experience, which stems from work outside the domain of the current knowledge context. Although, scholars have focused on the benefits of specific experience (Argote and Epple, 1990; Cummings and Kiesler, 2005) and overall experience, there has been limited work on analyzing the differential effects of generalized experience in changing knowledge contexts (Bunderson and Sutcliffe, 2002; Huckman, Staats, and Upton, 2009).

Experience accrues two major benefits for a team. First, it provides the benefit of resource sharing, allowing researchers to combine knowledge, skills, and access to physical assets (e.g., labs). Experience helps in developing new routines that facilitate coordination and solve the mutual knowledge and task allocation problems. Improved knowledge codification and enhanced cooperation over collaborative activities results in more effective collaboration. Second, it helps to develop critical information about who knows what and who knows how; this aids in effective communication and task allocation (Cummings and Kiesler, 2005, 2007, 2008; Owen-Smith and Powell, 2003). Teams with individuals who have prior joint work experience are, therefore, more efficient in carrying out research than teams lacking such experiences (Katz, 1982). Experience also allows teams to adopt practices that increase their ability to coordinate their activities (Bercovitz and Feldman, 2011) and establish expectations about acceptable levels of performance. As individuals accumulate experience by working together in teams, they develop routines and practices that allow them to function more effectively as a team (Bercovitz and Feldman, 2011; Mayer and Argyres, 2004; Nelson and Winter, 1982).

However, the effectiveness of this adoption may work against the team when a change in context requires novel ways of approaching and solving problems, as in the case of work involving human embryonic stem cell lines. Previous work routines may no longer be applicable to the changing context of research, and they may become detrimental to project performance. Applying knowledge and routines from existing domains may be problematic when novelty arises because current routines and language may not adequately address the differences and dependencies that arise with novelty (Carlile, 2002). Not only do individuals who participate in similar activities produce shared meanings (Orr, 1996), but their knowledge is sticky in the situated knowledge context, making it harder to apply to novel domains (Carlile, 2002; Tyre and von Hippel, 1997).

Novelty, as in the case of radical discoveries, could also be disruptive to existing routines for scientific production, i.e., the task-oriented day-to-day processes, and reduce the relevance of prior generalized experience for the new context. For instance, how cell culture and propagation is carried out substantively differs between embryonic stem cells and other adult mature cells (Jain and George, 2007). Further, in radical discoveries, prior joint experience could hinder experimentation and focus team efforts along established lines of inquiry that apply to mature fields. Taken together, we expect that teams with generalized joint work experience may have a higher tendency to adopt tried-and-tested means to solve novel problems, thereby negatively affecting the quality of the invention. Hence, we posit that:

Hypothesis 1: The effect of generalized experience (prior joint work experience outside the hESC domain) of team members on the invention impact of the focal patent is negative.

Scientific proximity

Scholars have posited that new knowledge is created by unique recombination of existing knowledge repositories (Basalla, 1988; Henderson and Cockburn, 1994; Schumpeter, 1939). Though inventors can possibly combine any prevalent knowledge, what actually gets combined is constrained by the localness of their search and the social construction of what knowledge can be gainfully combined. Of particular interest is the way in which heterogeneous resources are brought together as determined by the cognitive distance across individuals who have different knowledge and perspectives (Nooteboom, 2000a, 2000b; Nooteboom *et al*., 2007). As a related concept, the extent to which scientists perceive the world differently from one another based on the development of their cognition stemming from their prior scientific work shapes the space over which useful combinations can occur. Scientific proximity, as measured by the degree of overall overlap in prior experience, decreases the stock of opportunities to which scientists have access in their joint work, since scientifically proximate individuals can perceive only a narrow spectrum of the paths available (Fleming, 2001; Fleming and Sorenson, 2004). Teams that recombine ideas from proximate technological niches are likely to have lower invention impact on their field (George, Kotha, and Zheng, 2008; Kotha, Zheng, and George, 2011).

In teams with lower scientific proximity, the difference in scientific expertise of scientists across multiple topics allows for a variety in problem-solving approaches, which increases the likelihood that novel solutions can be found for important technological bottlenecks. Recombination can also enhance the impact of the innovation on the technology domain itself. Indeed, it has been argued that breakthroughs result from recombining nonobvious technology components (Basalla, 1988). Hence, when the scientific proximity is low in a team, the inventing team could combine new knowledge with its existing knowledge to yield radical innovations (Ahuja and Morris Lampert, 2001; Katila and Ahuja, 2002) that can potentially influence both domains (Ethiraj and Puranam, 2004).

Though searching widely for technology solutions has positive implications in terms of the space for recombination and the consequent impact, the ability to effectively recombine this knowledge depends on the team's ability to coordinate their activities. As the scientific distance increases across inventors, a scientific language problem arises such that wider gaps lead to increased difficulty in communicating ideas across the team (Katz, 1982). Moreover, absorptive capacity of scientists is limited by their prior investments in knowledge domains, which in scientifically disparate teams reflects itself as a problem in the assimilation and implementation of external knowledge (Zahra and George, 2002). Consequently, we expect a curvilinear relationship between scientific proximity of an inventing team and the impact of inventions produced, such that moderate distance is better than low or high distance for the impact of inventions. Therefore, we posit that:

> *Hypothesis 2: The relationship between the scientific proximity across inventors of a focal patent, as measured by the degree of overlap in their prior work, and the impact of the focal patent is curvilinear (inverted U-shaped) such that moderate scientific proximity creates the highest impact.*

Coordination across departments

Coordination costs emerge when individuals or organizations engage in collaborations that involve anticipated complexity of disintegrated tasks among partners and require the ongoing coordination of activities to be completed jointly or individually across organizational boundaries (Gulati and Singh, 1998). Concerns about coordination costs are significant in settings that involve significant coordination of activities between the parties but have to be managed without the benefit of the structure and systems available in traditional hierarchies (Litwak and Hylton, 1962). Scientists working in teams can choose collaboration partners who are available and most suitable for advancing ideas together.

Involvement of multiple departments significantly increases coordination costs in scientific teams. Scientists who work in the same department are typically co-located, have similar educational training, and engage in shared decisions about hiring and promotion (Blau and Duncan, 1978). As a result, scientists within the same department typically conduct and evaluate research in similar ways. In contrast, teams that involve members from multiple departments have fewer opportunities to organize face-to-face meetings and exchange rich first-hand information. Interdepartmental teams often struggle to find common ground (Clark and Brennan, 1991), maintain awareness of what others are doing (Weisband, 2002), and adjust to surprises (Cummings and Kiesler, 2007).

Organizational theorists have defined several coordination activities as being important to integrate and utilize the knowledge of the team to the best level possible (Cummings and Kiesler, 2007). Assigning specialists to appropriate tasks is one of the important coordination activities that reduces overdependency and communication failures (Weick, 1985). Reducing efforts allocated to communication and information transfer through sharing resources is another coordination activity of importance, while learning and transferring knowledge across team members also brings about the synergistic benefits of knowledge sharing (Cummings and Kiesler, 2007). At the same time, direct communication is another critical coordination activity, which helps build trust, enhances participation, and develops respect among team members (Cummings and Kiesler, 2005, 2007, 2008). All these activities are important for integrating and utilizing knowledge across the members of a team, but they are difficult to achieve when the involvement of individuals from multiple departments increases the complexity of coordination (Cummings and Kiesler, 2007; Hobday, 2000). Consequently, we expect that:

> *Hypothesis 3: The effect of the number of unique departments represented on a patent team on the invention impact of the focal patent is negative.*

Scientific proximity and generalized experience

Of the two essential parts to the knowledge recombination problem taking place in a creative team (Taylor and Greve, 2006), *scientific proximity* determines the recombination space over which scientists can engage in diverse approaches to solving problems. It draws on sets of knowledge that are distant from one another. *Prior experience* helps develop the common knowledge across inventors and improves task allocation. However, when teams have prior experience from a context outside their current domain, this experience is reflected as formation of routines and processes that may not fit with the necessities of the changing environment.

Search for new knowledge is a path-dependent process (Song, Almeida, and Wu, 2003). Past success often reduces incentives to experiment with new ways of doing things (Sørensen and Stuart, 2000), and the development of routines becomes more standardized (Song *et al*., 2003). Existing routines stemming from successful collaborations in the past decrease the ability to adapt to the requirements of change. More specifically, we argue that the inverted U-shaped relationship between scientific proximity and impact is less pronounced for teams with high outside general experience than it is for those with low generalized experience. Outside general experience helps mitigate language and coordination problems. However, it correspondingly restricts the skills that can be brought to solve problems, so the benefit of moderate scientific proximity is reduced when outside general experience is high. Hence, prior recombination ability of a team may work against the team when a contextual change occurs, resulting in a shift in the fit of joint knowledge of scientists with the environment. Therefore, we posit that:

> *Hypothesis 4: The inverted U-shaped relationship between scientific proximity and impact is negatively moderated by generalized experience such that the relationship is less pronounced for teams with high generalized experience than for those with low generalized experience.*

Coordination across departments and generalized experience

Multidepartmental teams are known to suffer from problems of coordination and effective distribution of their joint work (Cummings and Kiesler, 2005, 2007). Supervising and monitoring joint work becomes particularly problematic when inter- and intraorganizational boundaries are crossed and when different incentive schemes and priorities have to be addressed in the project (Bercovitz and Feldman, 2011; Cummings and Kiesler, 2007). Teams with multidepartmental structures can better mitigate their coordination problems when they have prior joint work experience. Such experience may be an essential factor in helping bridge the coordination gap through development of transactive memory that allows team members to effectively communicate and distribute tasks across the team.

Experience with joint work in similar projects enhances the ability of team members to develop routines and skills specifically applicable to the domain. However, even when the experience stems from a domain that is outside the realm of the project work, having worked together in the past will allow for effective task allocation, building routines for enhanced communication and improving trust among team members. This will allow team members to effectively communicate and oversee the progress of the work in bridging multidepartmental team structures. Therefore, a team with prior generalized experience may be better able to overcome the coordination problems stemming from the involvement of multiple departments (Bercovitz and Feldman, 2011; Cummings and Kiesler, 2007; Taylor and Greve, 2006) and reap the benefits of interdepartmental collaboration. Hence, we posit that:

> *Hypothesis 5: In teams with high generalized experience, the relationship between the number of departments represented on a patent team and the invention impact of the focal patent is positive.*

Our model guiding our hypotheses is summarized in Figure 1.

METHOD

Sample and data

We use patent data to examine the effect of prior collaboration and patenting experience of teams on invention impact. Patents provide an excellent trail of codified knowledge and have been widely used in the context of innovation studies involving knowledge recombination and spillovers (Agarwal, Ganco, and Ziedonis, 2009; Ganco, 2013; Jaffe, Trajtenberg,

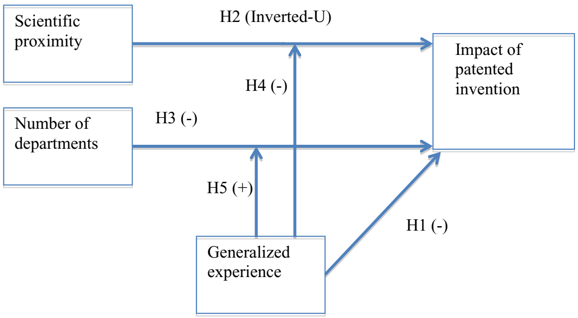

Figure 1. Theoretical model

and Henderson, 1993). We are interested in analyzing the collaboration benefits and coordination costs of a focal team on the technological impact of the team's work. The unit of analysis is the patent and the level of analysis is the patent team, consisting of individual inventors of a patent. In our analyses, each patent embodies a knowledge-creation effort by a team of designated individuals.

The population of patents in the human embryonic stem cell area consists of 314 patents granted during the period from 1998 to 2010. However, as we are focusing on the team-level effects of experience and distance in our analysis, we use a restricted sample including 282 patents that have multiple inventors. We retrieved these patents by searching relevant key words (human and embryonic stem cells) in the United States Patent and Trade Office (USPTO) and European Patent Office (EPO). We then downloaded all the available information for each patent. We supplemented this data by retrieving inventor affiliations from the corresponding author institutions that were disclosed in scholarly article publications on or before the date at which the application for the focal patent was filed. We gathered additional information on the inventors from their designated Web pages and from their curriculum vitae (CVs) by going through each inventor manually. To further extend the dataset, we matched the patent data with publication data available in the ISI database. Different individuals may use different names, so we accounted for variations in spellings to ensure accuracy.

Measures

Dependent variable

Invention impact

To assess the impact of the patent and the underlying invention, we used the cumulative forward citations to an individual patent. Forward citations count the number of times a patent (the 'cited patent') is included in the prior art of subsequent patents. As an indicator of the impact of an invention, we recorded the total number of forward citations a patent received from the time it is granted until the end of the study period. These citations come from the entire population of patents in USPTO and EPO, which also includes the sample of patents used in this article.

Prior work has noted that patents in crowded technological fields may be cited more than patents in sparse fields simply because the population of citing patents is higher (Gittelman and Kogut, 2003). Our dataset is already limited by its focus on hESC patents and, thus, largely accounts for the effects of technological crowding. Each patenting activity by a team shows evidence of a collaborative activity. It is the responsibility of the inventor to cite appropriate prior art. Such citations need the approval of the patent examiner, and this approval helps in removing inventor bias from citation behavior to a considerable extent. As previous research suggests, forward citations to a patent can be considered a measure of technological impact (Albert *et al.*, 1991) and a proxy for economic value to the innovator (Hall, Jaffe, and Trajtenberg, 2005). Earlier research has suggested that in the life sciences, patents are a crucial means of appropriating returns to innovation and, hence, in this field, citation rates are more likely than in other fields to contain information about the technological and economic value of a given invention (Gittelman and Kogut, 2003; Powell *et al.*, 1996). We calculated two measures, forward citations and non-self-forward citations, which are closely related. We report the results for forward citations where self-cites are excluded, but the results are consistent when we also include self-cites.

Independent variables

Generalized experience (outside the hESC domain)

We calculated the cumulative number of times that a given team of individuals on a patent have worked together outside the hESC domain up to the time the focal patent was filed (Nerkar, 2003; Reagans, Argote, and Brooks, 2005; Rowley, Behrens, and Krackhardt, 2000).[1] Teams collaborating on multiple prior patents are likely to develop routines and pro-

[1] We also created an experience of core team that takes into consideration the generalized experience of not the whole team but the persistent dyads. Although the coefficient on this variable was negative, results were insignificant.

cesses to coordinate their work effectively (Nelson and Winter, 1982), yet the buildup of such routines may be detrimental when there is a change in knowledge context (Tyre and von Hippel, 1997). In our analysis, we use a log transformation of the generalized experience variable since this variable is heavily skewed.

Number of departments

Using information from our content coding of all inventors' affiliations, this variable refers to the total number of unique departments that are represented on a team. Each individual's departmental affiliation is compared with those of other members on the team, and the total number of unique departments is used as a measure of the dispersion resulting from having multiple departments being represented on the team. For instance, a team with five researchers from three different departments would receive a score of three (Cummings and Kiesler, 2007).

Scientific proximity

We measure scientific proximity among the patent inventors as calculated from the medical subject headings (MeSH) classifications of their previous publications. Using the *PublicationHarvester* program (Azoulay, Stellman, and Zivin, 2006) and the *Scientific Distance Report* application embedded, we gathered all publications for each inventor and calculated the propensity of overlap among inventors using MeSH terms assigned to each publication of each inventor in the PubMED database (http://www.ncbi.nlm.nih.gov/pubmed/). For any two inventors and using their published papers, this measure is calculated as follows: the number of total MeSH classifications that are used to classify both the focal inventor and the collaborator at year t-1, divided by the total number of unique MeSH classifications of both inventors' publications at year t-1. This is a continuous measure from 0 to 1; as the scientific proximity among patent inventors increases (i.e., the overlap across their MeSH classification increases), this value gets closer to 1. Using these values for all pairs of inventors in a team, we calculate the average scientific proximity for the team.[2]

[2] We calculated another variable using the minimum scientific proximity on a patent team, i.e., the proximity between the most distant pair. Using this variable, we found similar results at the $p < 0.10$ level. In our analysis, we opted to use the average distance across all pairs.

Control variables

In order to account for alternative explanations at the team and patent level, we include a series of control variables.

Time elapsed

The baseline of cumulative forward citations to a patent is influenced by its age and, therefore, it is necessary to control for the time elapsed between the granting of the patent and the date that the citation data was collected (Gittelman and Kogut, 2003; Podolny and Stuart, 1995). We develop a variable that counts the number of days between the granting date of the patent and the date that the citation data was collected.

Team size

The size of the patent team is likely to influence both the benefits of collaboration and the coordination costs. Larger teams are likely to expend more effort in coordinating actions, whereas these larger teams also increase access to a broader set of skills and diverse knowledge. We use the number of inventors on a patent team to serve as a proxy for the resources invested in the research project, which may affect the research outcome (Gittelman and Kogut, 2003; Podolny and Stuart, 1995). Teams account for a larger proportion of science, and their work achieves a higher impact than lone inventors (Wuchty *et al*., 2007). Team size is measured as the total number of inventors that are working on a patent team.

Patent scope

USPTO and EPO use a classification system where each patent is assigned to relevant classes. The number of patent classes that a particular patent is assigned to is seen as a proxy for the breadth of the patent that influences the patent's subsequent impact (Lerner, 1995).

Team experience patenting in hESC

We constructed a count variable of the number of times that a team of inventors has worked together in hESC domain prior to their work in the focal patent. Literature shows that teams with relevant experience in joint work are better able to allocate tasks and effectively manage teamwork processes (Cummings and Kiesler, 2005, 2007). To account for the effect of joint experience, we include a team experience patenting in hESC variable.

Number of claims

Claims in a patent are argued to provide information about the intellectual space that the patent protects (Lanjouw and Schankerman, 2001). Thus, patents with more claims may have a higher likelihood of getting future citations. To control for this, we include a measure of the number of unique claims made in each patent.

Geographic distance

Individuals may find it harder to collaborate across departments because cross-departmental collaborations may involve a geographic distance component making it harder to bridge the space across individuals and allow for enhanced face-to-face communication and increased ability to engage in spontaneous discussions (Cummings and Kiesler, 2005, 2007). Hence, geographic distance may confound the effects of departmental differences in determining the coordination costs that the team faces. To control for this effect, we have created a distance variable, which calculates the geographic distance among the members of a scientific team using their affiliation information and the coordinates of their labs. The distance measure calculates the distance across inventors on Euclidean space (Stuart and Sorenson, 2003), with the final distance measure being calculated as an average of all distances across inventors.

Generalized publication experience

Teams with higher scientific capability may be better equipped to develop high impact inventions. This may be particularly pertinent in science-based industries such as biotechnology (Powell *et al*., 1996). At the same time, teams collaborating on multiple prior publications are likely to develop routines and processes to coordinate their work effectively (Nelson and Winter, 1982), yet the buildup of such routines may be detrimental when there is a change in knowledge context (Tyre and von Hippel, 1997). To control for the effect of joint work in publications taking place outside the realm of hESC, we matched all individuals represented on the patents with information in the Science Citation Index. We went through all names manually to account for different ways of spelling and to make sure we retrieved the full publication records for the individuals represented on the patents. We excluded those publications focusing on work in the hESC domain and measured the team's generalized publication experience by aggregating the number of publications on which inventors of a patent team are listed as coauthors. This variable captures the effect of joint work on all previous publications outside the hESC domain.

Analysis

The dependent variable is a count of (non-self) forward patent citations, which is heavily skewed, with many observations receiving a low number of citations. Such count data are usually estimated with one-parameter Poisson models, but because of overdispersion, Poisson estimates may be biased (Cameron and Trivedi, 1986). Therefore, we employ negative binomial regression models to correct for this potential bias. In our analysis, we run alternative specifications using zero-inflated negative binomial as well as Poisson models, and our results were stable across models. We report the negative binomial regression results in the following section.

RESULTS

In Table 1, we report the descriptive statistics and correlations of the variables. Although the correlations reported are relatively low, we derived the variance inflation factors (VIFs) as a control from the final model, and the average VIFs were well below the general accepted threshold of 10 (Greene, 1997). VIFs are typically made as a post estimation command for linear regressions, but as they make an assumption about the relationship between the independent variables, it is possible to use this technique for other functional forms as well (Menard, 2002). In testing our hypotheses, we included our variables stepwise to ensure that the signs of coefficients are stable across regressions. If multicollinearity would have been a major issue, signs and coefficients could have changed direction. In testing our interaction effects, we also mean centered our variables (Aiken and West, 1991). Taken together, these precautions minimized the problem of multicollinearity.

Table 2 shows the results of the negative binomial regression analysis where the dependent variable is the count of patent citations. Model 1 shows the baseline model, which includes controls for time elapsed since the patent was granted, team size, patent scope, team experience in patenting in hESC, number of claims, geographic distance across team members, and the team's scientific publication record. In Model 2, we introduce the first of our

Table 1. Descriptive statistics and correlations

	Variables	**Mean**	**S. D.**	**Min**	**Max**	1		2	3	4	5	6	7	8	9	10	11	12
1	Non-self-cites	3.51	16.93	0	260.00	1.00												
2	Time elapsed	1,750.3	827.2	110	4,529.00	0.28	1.00											
3	Team size	3.59	1.99	2	11.00	−0.06	−0.07	1.00										
4	Patent scope	6.20	5.15	1	24.00	0.24	0.56	−0.03	1.00									
5	Team experience patenting in hESC	7.97	7.07	0	39.00	−0.07	−0.17	0.42	−0.15	1.00								
6	Claims	35.59	38.69	2	372.00	0.03	−0.03	−0.04	−0.01	−0.07	1.00							
7	Geographic distance	869.14	2,685.77	0	16,929.53	−0.01	0.26	−0.02	0.20	−0.11	0.03	1.00						
8	Generalized publication experience	5.05	10.31	0	91.00	−0.05	−0.09	0.14	−0.07	−0.08	0.03	−0.01	1.00					
9	Generalized experience (log)	0.20	0.45	0	2.40	−0.04	0.02	−0.16	0.03	−0.04	0.11	−0.04	−0.02	1.00				
10	Scientific proximity	0.24	0.20	0	1.00	−0.08	−0.09	−0.07	−0.11	0.07	0.02	−0.09	0.29	0.05	1.00			
11	Scientific proximity squared	0.10	0.17	0	1.00	−0.05	−0.03	−0.15	−0.08	0.02	0.03	−0.08	0.25	0.11	0.92	1.00		
12	Number of departments	2.02	1.23	1	10.00	−0.03	−0.05	0.52	0.03	0.12	−0.08	0.13	0.04	−0.07	−0.16	−0.17	1.00	

N = 282 hESC patent team observations.

theory variables of interest, generalized experience (experience outside hESC). Model 3 adds the scientific proximity as a measure of overlap across inventors' knowledge space and the squared term for scientific proximity. Model 4 includes the number of departments as a proxy for coordination costs incurred by a team. Model 5 adds the interaction terms between scientific proximity and the generalized experience variables. In Model 6, we introduce the interaction term between the number of departments and generalized experience variable. Model 7 includes a model of all the main effects without interaction terms, where Model 8 is a full model including all variables of interest and the interaction terms tested across previous models. Each model represents a significant improvement over the baseline model, with the log likelihood value improving from −458.1 for the base model ($p < 0.001$) to −446.6 ($p < 0.001$) in Model 8.

The baseline model is generally consistent with prior research findings for patent variables. In line with previous research, the number of days in between variable, which accounts for the age of a patent, has a positive effect on the citations received by the patent (Gittelman and Kogut, 2003). Patent claims also have a significant positive effect on the impact, as measured by citations (Lanjouw and Schankerman, 2001). Moreover, we observe a positive yet not significant effect for team experience in patenting in hESC domain, which concurs with previous studies on the effect of prior experience in team performance (Taylor and Greve, 2006). The overall experience in publications variable, however, is consistently negative, which may be due to the fact that this variable is driven heavily by joint work outside the human embryonic stem cell domain.

Hypothesis 1: generalized experience outside hESC

We predicted that the generalized experience, which is defined as the number of times that the members of a focal team worked outside the hESC domain, will have a negative effect on the impact of the invention. In Model 2, the coefficient for experience outside variable was statistically significant. The main effect of the experience outside variable was negative (b = −0.734, $p < 0.01$); this effect remains significant in Models 5, 6, 7, and 8 as well (b = −1.208, $p < 0.01$; b = −2.086, $p < 0.05$; b = −0.621, $p < 0.05$, b = −2.746, $p < 0.01$). This result lends

Table 2. Negative binomial models of impact

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Time elapsed	0.00174***	0.00174***	0.00181***	0.00178***	0.00171***	0.00179***	0.00185***	0.00175***
	[0.000178]	[0.000173]	[0.000184]	[0.000179]	[0.000177]	[0.000178]	[0.000180]	[0.000180]
Team size	–0.140**	–0.158***	–0.164***	–0.0499	–0.0572	–0.165***	–0.0977	–0.0617
	[0.0618]	[0.0608]	[0.0619]	[0.0713]	[0.0703]	[0.0616]	[0.0706]	[0.0705]
Patent scope	0.0310	0.0307	0.0263	0.0303	0.0353*	0.0269	0.0241	0.0321
	[0.0220]	[0.0215]	[0.0222]	[0.0220]	[0.0214]	[0.0216]	[0.0218]	[0.0215]
Team experience in patenting in hESC	0.0304*	0.0350**	0.0291	0.0279	0.0328*	0.0299*	0.0315*	0.0273
	[0.0180]	[0.0178]	[0.0179]	[0.0182]	[0.0177]	[0.0179]	[0.0178]	[0.0178]
Claims	0.00784***	0.00899***	0.00807***	0.00801***	0.00904***	0.00903***	0.00953***	0.00905***
	[0.00276]	[0.00294]	[0.00275]	[0.00295]	[0.00315]	[0.00289]	[0.00315]	[0.00310]
Geographic distance	–5.22e-05	–5.93e-05	–6.49e-05	–3.10e-05	–3.48e-05	–6.51e-05	–5.02e-05	–3.95e-05
	[4.21e-05]	[4.15e-05]	[4.18e-05]	[4.35e-05]	[4.17e-05]	[4.15e-05]	[4.26e-05]	[4.14e-05]
Generalized publication experience	–0.0581*	–0.0463	–0.0597*	–0.0586*	–0.0460*	–0.0597*	–0.0492*	–0.0593*
	[0.0315]	[0.0282]	[0.0331]	[0.0311]	[0.0271]	[0.0341]	[0.0293]	[0.0328]
Generalized experience (log)		–0.734***			–1.208***	–2.086**	–0.621**	–2.746***
		[0.257]			[0.421]	[0.833]	[0.256]	[0.947]
Scientific proximity			2.650**		1.554		2.287*	1.412
			[1.349]		[1.441]		[1.330]	[1.446]
Scientific proximity squared			–4.241**		–2.720		–3.819**	–2.734
			[1.828]		[2.046]		[1.772]	[2.065]
Number of departments				–0.270**		–0.386***	–0.236**	–0.397***
				[0.107]		[0.136]	[0.103]	[0.136]
Gen. exp. X departments						1.108*		1.191*
						[0.622]		[0.630]
Gen. exp. X proximity					4.185			4.630*
					[2.673]			[2.646]
Gen. exp. X proximity squared					–4.104			–4.241
					[2.809]			[2.778]
Log likelihood	–458.1	–454.3	–455.5	–455.0	–450.8	–450.2	–449.4	–446.6

*$p < 0.1$, **$p < 0.05$ ***$p < 0.01$; two-tailed tests. Robust standard errors are in brackets.
N = 282 hESC patent team observations.

support to our hypothesis that generalized experience may be detrimental in situations where knowledge context changes.

Hypothesis 2: scientific proximity

We argued that scientific proximity will have a curvilinear (inverted-U shaped) effect on the impact of inventions generated. In Model 3, we include the scientific proximity (b = 2.650, $p < 0.05$) and scientific proximity squared (b = −4.241, $p < 0.05$) terms and observe that there is a diminishing effect of scientific proximity on impact. This result lends support to Hypothesis 2. We have graphed this effect to have a better visualization of the relationship between scientific proximity and impact. Figure 2 illustrates this effect.

Hypothesis 3: coordination across departments

We predicted that the number of departments represented on a patent team could have a negative effect on the impact of the invention due to the increased coordination problems stemming from having to bridge departmental differences. Given Model 4's improvement over the base model, we inspect the coefficient of number of departments variable, which is significant (b = −0.270, $p < 0.05$). The result holds consistently in Models 7 and 8 (b = −0.236, $p < 0.05$; b = 0.397, $p < 0.01$); this variable does indeed point to the negative effect of coordination problems stemming from having multiple departments represented on a patent team, thereby supporting Hypothesis 3.

Hypothesis 4: interaction between generalized experience and scientific proximity

We argued that in the existence of prior experience, scientific proximity has a smaller effect on the impact of inventions. In Model 5, we include the interaction effects between generalized experience and scientific proximity and the interaction between the generalized experience and scientific proximity squared variables. Unlike our expectations though, the interaction effects were not significant. Hypothesis 4 is, therefore, not supported and we elaborate on this finding in the Discussion session.

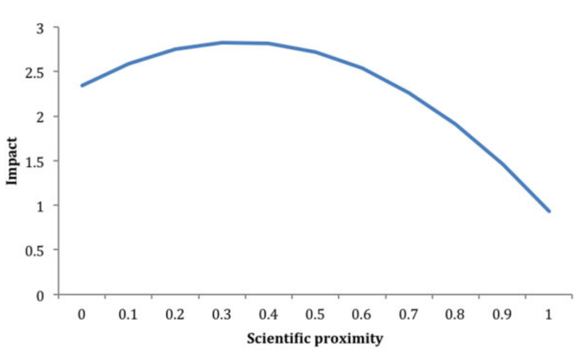

Figure 2. The effect of scientific proximity on invention impact

Hypothesis 5: interaction between generalized experience and number of departments

We argued that having generalized experience would reduce the potential coordination problems that teams having inventors from multiple departments may face in terms of communication and task allocation. In Model 6, we include the interaction effects between generalized experience and the number of departments. The interaction effect was positive and significant, lending support to our hypothesis (b = 1.108, $p < 0.1$). In order to interpret this interaction effect, we followed the suggestions of Aiken and West (1991) and visually graphed the effect. Figure 3 illustrates the effect.

DISCUSSION

The role of teams in the discovery process is understudied, even though recent studies systematically document that collaborative teamwork in science has increased substantially over the past few decades (Guimera *et al*., 2005; Jones *et al*., 2008). The primary issue is one of harnessing the benefits of collaboration (by knowledge recombination and sharing experience) while reducing the costs of coordination (by reducing costs associated with managing interdisciplinary and geographically dispersed teams). If one could enhance collaborative benefits and reduce coordination costs simultaneously, the value created from collaboration through discovery would likely be enhanced greatly. This study documents how the benefits of collaborative experience make a difference on invention impact. Further, we find evidence that prior experience has diverse effects on mitigating coordination costs stemming from scientific distance (measured as an overlap of knowledge across areas where individuals have previously worked) and departmental distance. We next explain the implications of these findings.

First, we find evidence that having prior experience does not always bring about benefits and, in

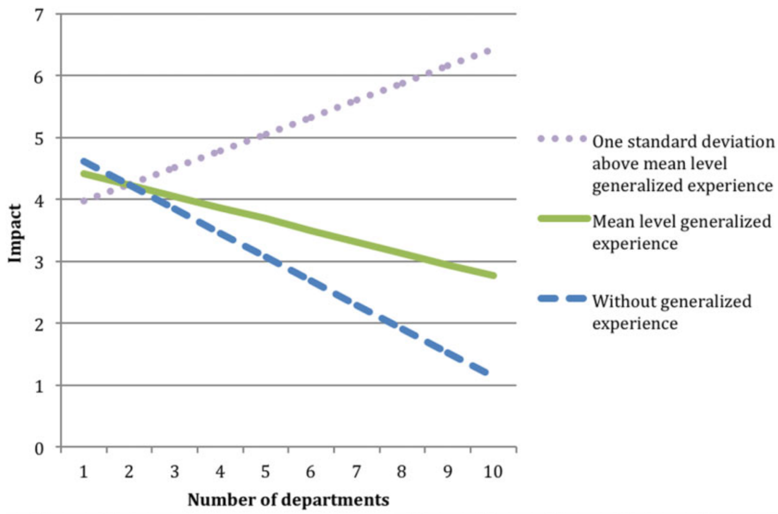

Figure 3. The effect of number of departments and generalized experience on impact

situations where the underlying knowledge of the field changes, having prior experience may hamper efforts to produce breakthrough work. It is important to think about this effect in terms of how individuals may leverage their knowledge in changing contexts: not just from a teamwork perspective, but also from an organizational design and task allocation perspective. Team composition in creative teams has been an issue studied by various scholars (Bercovitz and Feldman, 2011; Carlile, 2002; Cummings and Kiesler, 2005, 2007; Taylor and Greve, 2006), however, the potentially detrimental effect of experience and novel work mismatch has not been brought to the fore. Our primary contribution is that in radical and emerging science, experiential learning can have harmful effects when the experience is outside the focal domain. We show this through studying the effects of experiential learning in both inventions and publications.

Second, we provide empirical evidence for the effects of joint collaborative experience and its attendant coordination problems on invention impact in a radical science such as stem cells. Our contribution lies within the emphasis of coordination costs that constitute an important barrier on the effectiveness and efficiency of joint work in innovative settings. A plethora of research has documented the benefits that accrue from collaborating with partners (Cummings and Kiesler, 2005, 2007; Fleming, 2007; Guimera *et al*., 2005; Jones *et al*., 2008; Powell *et al*., 1996; Powell *et al*., 1999). A much less attended issue that we attempt to bring to the fore is the coordination costs that emerge when there are geographical, institutional, and scientific barriers to bridge that require ongoing dialogue and negotiation (Grant, 1996; Kotha *et al*., 2013). By combining the collaborative benefits and coordination costs, one can reach a more fine-grained understanding of the conditions under which collaborations may succeed.

Third, we were able to analyze the effects of coordination costs on the research outcomes of collaborative work in human embryonic stem cells. Having inventors from different departments on a patent team increases the costs of coordination as it increases the complexity and difficulty of communication, task allocation, and effective management of a joint work project. It is harder for teams with inventors from multiple departments to bridge institutional gaps and have a shared social setting or maintain awareness of what others are doing. However, in the existence of prior experience, coordination problems are overcome and departmental diversity contributes to the knowledge-creation activity of the team. Our findings build upon previous literature and further tease out the effects of coordination problems that hamper interdepartmental collaborations (Cummings and Kiesler, 2005, 2007).

Attending to such problems is important, as the number of interdepartmental teams has increased steadily over the last 25 years (Jones *et al*., 2008). This trend is driven by several different motives, including access to new instrumentation (de Solla Price, 1986), reduced communication costs enabled through new communication technologies (Agrawal and Goldfarb, 2008), complementarities of knowledge and experience to generate new scientific insights (Basalla, 1988), and solving increasingly complex problems that would be intractable for a single individual to solve. Despite these important observations, scholars have paid significantly less attention to the potential coordination costs that emerge from such interdepartmental teams and its effect on invention impact. Given the results of our study, we believe this is an unattended issue of importance for understanding the conditions under which interdepartmental teams will be successful.

Finally, we find evidence that heterogeneity among the inventors on a patent team has an inverted U-shaped effect on the impact of the resulting invention. This is because the ability of the team to recombine knowledge peaks when there is enough absorptive capacity across the team: members can understand each other's work while being distant enough to bring in new perspectives to the solution domain (Owen-Smith and Powell, 2003). The results show that the scientific proximity among assignees of a patent has an inverted-U curvilinear shape. Teams that combine members with the right mix of different knowledge and experience produce inventions of higher impact, but at some point, too much scientific distance can dampen invention impact.

Limitations

In spite of our study's contributions, limitations exist. We follow the tradition of learning curve research in studying the actual outcomes of learning and prior experience rather than measuring directly intermediate processes and mechanisms (Arrow, 1962; Yelle, 1979). In our study, we measured experience outcomes related to learning on the impact of patents produced. Due to data limitations, we could not access intermediate-level data to measure the development of collaboration routines during joint work at the team level. While we do control for joint work outside and inside the hESC domain in patenting and in publishing, we are unable to control for joint work in labs that are not converted into publications. Future research could make use of self-reported research endeavors to mitigate the concerns related to the structure of teams whose joint work is not documented in patents or publications.

Data on licensing and revenue generation are not available in our context primarily because of the early stage of developments involving therapeutic applications using stem cells. Hence, our measure of patent impact remains the only major determinant of invention success. At the same time, an important attribute of our context is the existence of and dependence on cell lines, the use of which requires expertise particular to these lines. In settings where such platforms are not necessary or where the knowledge of their operation is orthogonal to changes in the system, it would be possible to observe dissimilar effects of prior expertise on the success of focal work. Moreover, our data are limited by the nature of reporting in patent databases of USPTO and EPO, in that we do not have a conclusive picture of all patent applications or all potential projects leading toward a patent. We can observe only patents that were granted and cannot elaborate on processes that lead to a failure. Although we can clarify characteristics and composition of a patent team whose work has relatively more impact, to the extent that one believes that the same composition and/or processes may lead to a failure, we are unable to access the necessary data to empirically prove that this may not be the case. Future work in this area can disentangle this effect more clearly through the use of data on teamwork disclosures where available.

Lastly, we are observing a very unique setting, a novel one that started after a radical innovation, where prior experience can be deemed obsolete or even detrimental. Although our theory and data match perfectly, given the characteristics of our setting, one needs to be cautious about generalizing our findings. As human embryonic stem cells is a relatively new and highly specialized area of research, future work could potentially extend this study's findings by looking at multiple areas of radical innovations to have a broader picture of how the effect of team composition and characteristics on the impact of joint work changes when the underlying knowledge is disrupted.

Conclusion

Taken as a whole, our results evidence that team-level joint production experience and team structure in terms of scientific and departmental distance are important determinants of patent impact. Having scientists from multiple departments reduces the impact of the patented invention as coordination costs increase; however, prior experience in patenting moderates this relationship such that for multidepartmental teams, those with prior generalized experience create higher impact inventions. We also show that having a medium level of scientific proximity across inventors enhances the positive effect of recombination on patent impact by allowing for the right match of knowledge diversity and absorptive capacity. At the same time, learning from experience appears to be an important factor determining the patent outcomes.

More importantly, although much enthusiasm surrounds interdepartmental collaborations, an issue that has been somewhat neglected was the coordination costs that constitute the downside of collaboration. This study offers a test of when the benefits from collaborations may outweigh the costs of coordination in research leading to patented inventions. Further research should focus on the dynamic processes that are involved in the initiation of joint work and how collaborations develop despite coordination problems. Another thread of work is needed to uncover the underlying mechanisms by which the different ownership structures governing the patents influence the coordination activities and affect the impact of the resulting patents as well.

ACKNOWLEDGEMENTS

The manuscript has benefitted from constructive comments of Rajshree Agarwal and two reviewers, as well as Phanish Puranam, Lourdes Sosa, and seminar participants at London Business School. Gerard George gratefully acknowledges the support of Professorial Fellowship of the U.K.'s Economic and Social Research Council (RES-051-27-0321) and the Rajiv Gandhi Centre at Imperial College London.

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