Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

The Renaissance of the Renaissance Man? The Role of Broad Individual Knowledge in Teams of Inventors

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Abstract

This paper suggests that the way in which knowledge variety is achieved in innovation teams affects their performance. In particular, teams whose knowledge variety is based on high average individual knowledge breadth of their members outperform teams whose knowledge variety is based on specialized contributions. Given the re-combinative nature of technological progress, innovation results depend crucially on the skilful matching of different pieces of knowledge. For a given level of knowledge variety in an innovation team, greater knowledge breadth of the individual members will make the recombination process more effective. Moreover, typical barriers in team processes will be less acute. We analyze the effect of team knowledge variety and average individual knowledge breadth in innovation teams in the electrical and electronics industry by tracking the trajectories of inventors and the performance of the teams they work in through their patenting activity. Our findings are consistent with the propositions outlined above.

Jelcodes:M12,J24

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Abstract

This paper suggests that the way in which knowledge variety is achieved in innovation teams affects their performance. In particular, teams whose knowledge variety is based on high average individual knowledge breadth of their members outperform teams whose knowledge variety is based on specialized contributions. Given the re-combinative nature of technological progress, innovation results depend crucially on the skilful matching of different pieces of knowledge. For a given level of knowledge variety in an innovation team, greater knowledge breadth of the individual members will make the recombination process more effective. Moreover, typical barriers in team processes will be less acute. We analyze the effect of team knowledge variety and average individual knowledge breadth in innovation teams in the electrical and electronics industry by tracking the trajectories of inventors and the performance of the teams they work in through their patenting activity. Our findings are consistent with the propositions outlined above.

Keywords: teams of inventors; knowledge recombination; knowledge breadth; patents

1. Introduction

Modern research activities are mostly, and increasingly, organized in teams. As Wutchy et al. (2007) report, the majority of scientific papers and about half of patents nowadays are co-authored and co-invented, respectively. Jones (2009) argues that this trend is the consequence of the growing specialization of innovators. According to this view, the large stock of knowledge that has to be learnt in each discipline makes it increasingly costly to master several areas of knowledge. The result is that people who excel at multiple disciplines, the probervial "Renaissance Men", are extremely scarce. In contrast, the majority of innovators are narrow specialists, who frequently need to work in teams with other specialists to cover the relevant technological space needed to develop increasingly complex innovations. One question arises naturally as an objection to this perspective: to what extent are teams of specialists able to collaborate effectively in the development of innovations? Singh and Fleming (2010) suggest that part of the advantage of teams of inventors with respect to lone inventors is due to the higher knowledge variety encompassed by teams. This, however, does not necessarily imply that innovation teams obtain their variety advantage uniquely from the sum of specialized contributions. Team knowledge variety can also be based on team members with broad and potentially overlapping knowledge. The question, then, is left unanswered.

In this paper, we suggest that the internal distribution of knowledge variety among team members is relevant for the generation of innovations in teams of inventors. In particular, we propose that, in terms of relevance and originality, teams comprising inventors with greater knowledge breadth outperform teams that achieve the same level of variety by combining a range of narrow contributions. Our main argument is that individual knowledge breadth is particularly valuable for the recombination of knowledge and for attenuating the coordination and motivation problems that usually arise during the innovation process in teams. We do not suggest, however, that broader knowledge unboundedly leads to superior performance. As Jones (2009) points out, broad-knowledge human capital background can only be built at the expense of knowledge depth. An extremely generalist researcher with very superficial knowledge in many areas would lack a deep enough understanding of innovation problems and solutions. In the context of teams of inventors, we consider an inventor as knowledgeable in a given area only if he filed a patent in that area in the past. Consequently, although a trade-off between depth and breadth may still affect performance in our setting, we discard extreme shallowness and its negative effects. Taking into account these considerations, our main prediction is that teams of inventors that achieve a given level of knowledge variety through members with broader knowledge will produce more relevant and more original innovations, but at a marginally decreasing rate.

Even though teams of inventors are arguably the most relevant type of creative teams for social and economic development, very little is known about how they are organized at firms and how this affects their productivity. Only the abovementioned Singh and Fleming (2010) examine the productivity of teams of inventors versus that of lone inventors. The organizational behavior literature has extensively analyzed the effect of team-level knowledge variety on the performance of different types of teams (Harrison and Klein, 2007)[1], though not teams of inventors. This literature associates high knowledge variety at the team level with the potential to recombine ideas that lead to highly creative results (Jackson, 1996; Paulus, 2000; Taylor and Greve, 2006) but also with motivation and communication problems that impair team performance (Stewart and Stasser, 1995; Jehn and Mannix, 2001). Similar to our approach, Rulke and Galaskiewicz (2000) devoted attention to how team-level variety is achieved, i.e. either by specialized contributions or by broad and potentially overlapping contributions, and the effect on performance. By looking at the composition of teams of MBA students performing business simulation games, they find that teams in which each member has experience in several functional areas outperform teams whose members are specialized in one functional area each. However, their focus on (simulated) managerial decision-making makes their findings difficult to extrapolate to teams engaged in knowledge generation.

The literature on network analysis has studied individual creativity, including that of innovators, as a function of their position in the social or/and knowledge structure. This position determines their degree of access to new and redundant information and, thus, their ability to generate further creative output (Burt, 2004; Obstfeld, 2005). Applying this approach to inventors of patents, Fleming et al (2007) suggest that, in network structures characterized by redundant information, individual creativity depends on the set of personal characteristics of the inventor and their colleagues, including their knowledge diversity.

This article contributes to the literature on the management of innovation at the team level by enhancing our understanding of the impact on performance of the knowledge distribution among inventors in a team. We test our arguments using extensive data on technological innovations produced by teams and protected by patents. Patent data is useful to identify teams of inventors responsible for the creation of the underlying innovation as well as to measure the impact of the newly created technology. Moreover, in patent-intensive sectors such as the electrical and electronics industry (Hall, 2004), patents also make it possible to characterize the inventors' knowledge breadth. Empirical results partially support our hypothesis: teams that achieve a certain level of variety by combining inventors with broader expertise generate innovations that are more relevant and also (at a decreasing rate) more original.

2. Theory and Hypotheses

The innovation process can be divided into three consecutive phases: knowledge recombination, selection of ideas, and adoption (Simonton, 1999; Singh and Fleming, 2010). The quality of the result

[1] Following Harrison and Klein (2007), we use the term "knowledge variety" to refer to the diversity in the pieces of knowledge held by a team.

depends crucially on the first two stages, when inventors try different ways of combining existing pieces of knowledge to create a novel technology and select the best alternative. Past research on group diversity and creativity suggests that groups enjoy more room for recombination and more alternative paths to solve problems when they combine a more varied knowledge set (Paulus, 2000; Jackson, 1996). In accordance with this idea, Singh and Fleming (2010) find that teams of inventors outperform solo inventors, partly because of their greater knowledge variety. Nevertheless, knowledge variety may generate a series of team malfunctions, during both the recombination and the idea-selection phases. These obstacles include communication problems that arise when team members use different technical jargons, conflicts that may occur when members feel strongly committed to their different perspectives, and free-riding problems that are especially acute if teammates cannot easily evaluate their colleagues' contributions. The balance of advantages and difficulties generated by knowledge variety depends on how this variety is achieved in the group, as Rulke and Galaskiewicz (2000) suggest. Below we develop the arguments that analyze this balance in the case of teams of inventors, for two key dimensions of innovations: relevance and originality.

Relevance of the Innovation

Knowledge recombination. The seminal work of Schumpeter (1939) described innovation as the result of a process where existing technologies are recombined in a novel way. This process can be understood as a problem-solving procedure and, as Simon (1985) points out, problem-solving is more effective when at least one head can fit most of the relevant pieces of knowledge together. Conversely, if each of the different pieces needed for recombination is held by different co-inventors, the amount and the quality of the interconnections that can be established between these separate portions of information is limited by communication constraints. In terms of Fleming and Sorenson's (2001) technological landscape concept, the big picture of the landscape that individual inventors with broad knowledge have in mind enables them to conduct a more effective search than that performed by different specialists stitching together several small sections of that same landscape. Understanding the general principles from different technological landscapes at the same time allows the researcher to make more informed choices about the combination of distant pieces of knowledge (Gruber et al, 2012). Moreover, in a team setting, a broad individual background entails more overlapping expertise among the inventors. Since, in group discussions, shared information is more likely to be retrieved than unshared information (Stasser and Titus, 1985; Rulke and Galaskiewcz, 2000), the potential for *collaborative* knowledge recombination in a team will increase with the expertise breadth of its members.

One possible drawback of inventors with broad knowledge is that they contribute less deep knowledge to their innovation teams than do specialist inventors with a comparable amount of expertise. An important first step of the innovation process is to identify and properly understand the problem that needs to be solved. Additionally, combining existing knowledge to obtain a solution for that problem requires a good understanding of the particular concepts to be combined. At the extreme, having excessively shallow knowledge would result in researchers with a broad background being unable to identify the relevant problems to be solved and the particular concepts to be combined in the solution. Consistent with this rationale, Narayanan et al. (2009) find that individual productivity of software engineers is maximized when "there is a good balance between specialization and exposure to (task) variety". In the context of our research, we expect greater shallowness (associated with high levels of breadth) to cause decreasing returns to knowledge breadth, but not to the point of reversing the sign of the overall effect. The reason is that, by defining inventors' knowledge according to their past patenting history, we set a lower bound on the depth of knowledge that an inventor needs to master in order to be considered an expert in a given field. Thus, some lack of knowledge depth may erode the recombination advantage of inventors with broad background, but not to the extreme of rendering them unable to identify problems and solutions in their areas of expertise. As for the subsequent knowledge recombination, we assume that it does not require being at the frontier of knowledge in all the relevant areas. Recombination consists of mingling—for the first time or in a new way—old ideas or principles from different domains. That is, a novel combination of technologies A and B may be able to expand the frontier of knowledge even if neither technology A nor B represent the frontier in their respective fields[2].

Communication. Effective communication is a concern for any working group, and innovation teams are no exception. Communication issues are important for the processes of idea generation, enrichment and selection. Team members with different specialized knowledge often speak different jargons, hampering the gains from diversity (Maznevski, 1994). This argument has been frequently used to explain non-monotonic (inverted-U shape) effects of skill diversity on performance (Laursen et al., 2005; Giuri et al., 2009). Nonetheless, these communication problems are likely to lessen when team members have a broader background. Since those teams are more likely to have overlapping knowledge among their members, they benefit from shared codes of communication. Higher average knowledge breadth leads to more fluent dialogues among overlapping co-inventors and facilitates the dialogue between specialist team-mates by building communication bridges among them. The existence of a common language is an important enabling factor for sharing knowledge and harnessing the potential benefits of knowledge variety. Therefore, we expect that teams with higher

[2] Research by Gavetti et al. (2006) offer some support to this idea. In their simulation analysis of the effect of experience breadth and depth on the use of analogies for deciding strategies, the authors find that "beyond a modest level of depth, performance is not sensitive to depth", while experience breadth has a steadily positive effect on performance.

average knowledge breadth will suffer less from communication problems, one of the main obstacles that hinder the gains from knowledge variety.

Conflict. A related issue has to do with the conflicts that may arise among co-inventors in a team. Although some level of group conflict may stimulate creativity, high-intensity conflicts are strongly dysfunctional (De Dreu and Weingart, 2003; Jehn and Mannix, 2001). Groups that gather heterogeneous knowledge may have especially high levels of internal conflict if their members have strong feelings about their diverse perspectives (Paulus, 2000). This is especially likely if individual inventors lack knowledge breadth. Firstly, higher average knowledge breadth is likely to lead to some overlapping knowledge that makes it easier for co-inventors to understand the scope of each others' critiques. Secondly, inventors with broader background are less likely to suffer from a "myopic" view that leads to inflexibility in discussions. Both arguments suggest that teams of inventors whose knowledge variety is based on narrower contributions are more likely to suffer strong, dysfunctional conflicts while teams whose knowledge variety is based on broader contributions will be more likely to keep conflict intensity at the moderate level at which it may have a positive effect on performance (Jehn and Mannix, 2001).

Free riding. Free riding is a problem of incentives that occurs in working groups when individual members' contributions to the collective output cannot be measured separately. Group members, then, may exert less effort because any expected reward to their contribution has to be shared with the rest of group members. Free-riding may particularly affect innovative teams by decreasing the quality of ideas they generate (Diehl and Stroebe, 1987; Girotra et al., 2010). The same rationale applies to the effort exerted in the other phases of the innovation process, i.e. screening and enriching teammates' ideas. One significant way to curb free riding is through peer pressure (Kandel and Lazear, 1992). If group members can mutually monitor their effort, they will put pressure on each other in order to keep performance high. Knowledge variety in teams of inventors may play against mutual monitoring -and therefore against peer pressure- if co-inventors are not be able to evaluate each others' effort. In that respect, a broader knowledge background enables co-inventors to exert the peer pressure needed to counteract free-riding.

In sum, teams of inventors that reach a high level of knowledge variety thanks to a high average knowledge breadth of their members recombine knowledge more effectively than those that obtain knowledge variety with narrow contributions of their members. This effect, however, is subject to decreasing returns because broad knowledge also involves to some extent less deep knowledge. The existence of teamwork issues such as communication problems, conflicts and free-riding problems reinforce the positive effect of knowledge breadth on the relevance of the innovation generated by the team.[3]

Hypothesis 1: For a given level of knowledge variety in a team of inventors, the relevance of the innovation generated by the team increases, at a decreasing rate, with the average knowledge breadth of team members.

Originality of the Innovation

Innovation can result either from exploitation of existing ideas or from exploration of new paradigms. Exploratory innovation is difficult to achieve, since it requires overcoming the local search that usually characterizes the innovation process at firms. In According to Nelson and Winter (1982), innovation at firms is path-dependent because they tend to rely on knowledge foundations from previous innovations. This favors exploitative innovation trajectories. In order to explore and produce original ideas, firms must gain exposure to different technological contexts (Rosenkopf and Almeida, 2003). For this, they need to have the capacity to identify, use and absorb outside knowledge (Cohen and Levinthal, 1990). As these authors argue, individual knowledge breadth conveys the advantage of enhancing knowledge absorption, since it increases the likelihood that useful external information is closer to what one already knows. This argument may also hold for knowledge variety at the team level (Taylor and Greve, 2006). However, as we discuss below, the process of integrating different technologies leading to exploratory innovations is enhanced if team variety arises from co-inventors' knowledge breath.

Original ideas often result from applying mental operations such as analogies or re-organization of categories to knowledge structures previously stored in memory (Ward, 2004). If a large part of the relevant key ideas and concepts are stored only in specialist team members' memories, the creation process is expected to be less fruitful in terms of originality. The reason is that the retrieval of information in knowledge-sharing meetings, on which teams of specialists rely crucially for knowledge recombination, usually takes the form of specific examples and applications rather than abstract concepts. This particular representation of information creates an anchoring effect that leads to incremental, less original innovations (Ward, 1994, 2004). Conversely, a team whose members have a broader knowledge background will be able to consider more abstract pieces of knowledge in the recombination process. First, at the individual level, higher knowledge breadth provides room for analogies and re-organization involving more abstract elements. In this vein —

[3] There are a number of factors that may affect team effectiveness in the innovation process but that have not been considered for the development of our hypothesis. These include cognitive and social issues such as production blocking, social apprehension and illusion of productivity. Despite the relevance that these processes have for creativity in innovation teams (Paulus, 2000; Girotra et al., 2010), we do not include them in the discussion because they do not clearly relate to team composition.

although in a different context— Shane (2000) shows that entrepreneurs with broad prior knowledge are more likely to conceive novel ways of representing the market and discover entrepreneurial opportunities than their narrow-knowledge counterparts. Second, high individual knowledge breadth tends to imply more overlapping expertise among co-inventors, enabling them to exchange ideas in more abstract terms and avoid the aforementioned anchoring effect. Both mechanisms suggest that teams of inventors with higher average knowledge breadth will be able to perform a more exploratory search for solutions and, therefore, to generate innovations that combine knowledge from different areas. Such innovations are expected to be more original because, by being based on a dispersed array of pieces of knowledge, they will tend to depart substantially from the existing technology.

As in the case of the importance of the innovation, the expected positive effect of co-inventors' average knowledge breadth on the originality of the innovation is subject to decreasing marginal returns. An exceedingly shallow background would hinder individual inventors' ability to identify potential cross-technological applications for a given piece of knowledge. It would also hinder inventors' ability to exchange knowledge in the form of abstract concepts. Both problems would lead, in the extreme, to a negative effect of average breadth on the originality of the resulting innovation. In the context of our research, as described earlier, inventors must have filed at least one patent in an area in order to be considered knowledgeable in that area. Therefore, we only expect these negative aspects to cause decreasing marginal returns in the positive effect of average knowledge breadth on originality.

Hypothesis 2: For a given level of knowledge variety in a team of inventors, the originality of the innovation generated by the team increases, at a decreasing rate, with the average knowledge breadth of team members.

3. Data, Variables and Methods

Data Overview

We use patent data to identify the creative output of teams of inventors. Patents are instruments used by firms to protect their innovations and are widely used in some industries, such as chemicals and electronics. Moreover, the majority of innovations patented in recent decades are the product of teamwork (Singh and Fleming, 2010).

In particular, we retrieve patent data from the NBER Patent Citations Data File (Hall et al., 2001), which contains data on all US patents granted from 1970 up to 1999. This dataset contains, for each patent, a set of information of interest to our analysis: 1) the names of the inventors who worked on the underlying innovation, which are considered to be the team responsible for it (Jones, 2009; Singh and Fleming, 2010), 2) its classification into a technological domain, and 3) the citations it received from subsequent patents, which is an indicator of the relevance of the patent (see next subsection). With all this information, we are able to identify the knowledge background of each inventor who participates in a team innovation (by tracking them across their previous patents) as well as the technological impact of this innovation. In order to have a reliable historical record for each inventor, we only analyze team patents from 1985 to 1999.

We restrict our analysis to patents granted in the electrical and electronics industry. The electric and electronics industry is particularly interesting for the study because it is a sector in which firms are especially likely to patent every improvement they achieve (Hall, 2004). This feature means that we can capture a high fraction of all the innovations in this sector, greatly reducing the selection bias of considering only patented innovations. Moreover, it allows for a meaningful characterization of the inventors' background, since it is very likely that any work in this sector by a given inventor is captured in a patent. In order to further ensure that we meet these two objectives, we confine our analysis to patents filed by inventors located in the US (inventors located outside the US are likely to be more selective in patenting in the USPTO). Since we are interested in teams and their variety, we restrict our analysis to patents co-invented by a team, i.e. by at least 2 inventors, and assigned to a firm. This leaves an eligible sample of 60,242 teams of inventors, located in the US, who applied for a patent in the electrical and electronics category (as defined by Hall et al., 2001) during the period 1985 to 1999. Nevertheless, the final sample we work with is further restricted, for two reasons. First, in order to characterize the knowledge background of team members, we need that at least one of them has some previous experience. Second, since we rely on a firm fixed-effect approach for our estimations, we require that each firm[4] appears at least twice in the sample and contributes with some within-firm variation. These restrictions produce a final sample of 39,894 teams from 1,987 assignees.

Using patent data to analyze the composition and performance of teams of inventors has several limitations. First of all, tracking inventors' patenting history requires making some assumptions as to when two coincident names can be considered the same person (Trajtenberg et al., 2006). Our study relies on the most stringent criterion by which both inventor name and assignee affiliation must coincide, but results hold under more naïve matching criteria as well. Secondly, we do not have information regarding the exact contribution of each co-inventor to each innovation. Although all the individuals responsible for any significant contribution have to be included in the list of inventors to avoid legal problems (Klee, 1998), patents may occasionally include some "guest" author as well (e.g., the director of the lab) with no real contribution to the innovation (Lissoni and Montobbio, 2008). These issues may generate some measurement error leading to an attenuation bias in the estimation of effects in our empirical analysis.

[4] We identify the firm employing each team of inventors by using the "assignee" information of each patent, which refers to the legal entity that applies for and owns it. The assignee typically identifies the employer firm, although sometimes it identifies different subsidiaries or establishments of a larger firm separately. In particular, we use the standardized assignee code provided in the NBER dataset.

Key Variables of the Analysis

Relevance of the innovation. We measure the relevance of the innovation with the number of citations received by the focal patent from subsequent patents. The logic behind this measure is that that every patented innovation must cite the previous patents upon which it builds. Patents with more citations represent innovations that have contributed more to the technological development, and this is correlated with its economic performance in the market as well (Hall et al., 2005).

Originality. To determine how original a patented innovation is, we use the *Originality* index proposed by Trajtenberg et al. (1997) and implemented by Hall et al. (2001), which is a dispersion index of the citations made in the patent document to prior art across different classes. In particular, the index takes the following form:

$$\text{Originality}_i = 1-\Sigma_j^J s^2_{ij}$$

where s_{ij} is the percentage of the citations made by patent i that belong to patent class j out of J patent classes (J=416). Thus, the index takes high values when the focal patent cites prior art in a wide range of fields and low values otherwise. This originality measure has been widely used in studies using patent data (e. g., Lerner et al. 2011; Valentini, 2011). It is based on the idea that original innovations tend to synthesize knowledge from a number of different technologies that are used as building blocks. Arthur (2007) describes examples of inventions such as the xerography, the atomic bomb or the laser that meet this definition.

Team knowledge variety. We measure team knowledge variety using the number of different primary technological areas to which the patents held by team members are assigned.[5] The larger the number of different areas in which at least one team member worked in the past, the greater the team knowledge variety. Innovations patented at the USPTO are classified into 416 technological classes (as of 1999) that Hall et al. (2001) group into 36 narrower subcategories. We consider these two alternative levels of aggregation to identify technological areas: class and subcategory. The narrow scope of patent-class grouping minimizes the chances of understating the real knowledge variety. On the other hand, the broader scope of the subcategory level avoids overstating the team knowledge variety (if two or more classes actually represent the same technological area), but may fail to consider the technological heterogeneity that may exist within a given subcategory. Singh and Fleming (2010) also use the number of different technological classes in which team members patented in the past to capture knowledge variety[6].

[5] Patents are assigned to one primary (main) area and several secondary ones. In this paper we only make use of primary classes to develop our different measures.

[6] Other studies, such as Gruber et al. (2012) use Herfindahl concentration indexes to capture knowledge variety. Although Herfindahl-based measures are sensitive to the amount of experience held in each different field, they pose some problems that advise against their use in this study. First, the effect of a change in the Herfindahl index is relatively more difficult to interpret in the context of regression analysis than the effect of one

Average individual knowledge breadth. In order to compute this measure, we obtain the mean of the individual knowledge breadth of the inventors in the team. We measure individual breadth by the number of different primary technological areas in which each inventor has experience. We then average across team members this individual breadth measure at both the class and subcategory level. A higher average number of areas of expertise indicates that co-inventors have, on average, a broader knowledge background. Note that team knowledge variety and individual breadth are highly correlated (correlation coefficients are 0.87 and 0.86 for number of classes and number of subcategories, respectively). This correlation has a particular feature: average individual breadth is a lower bound for team variety. In other words, teams of inventors can attain knowledge variety either through narrow contributions or through a broad average background of their members. In order to capture non-linear effects and, in particular, to test for decreasing marginal returns to average knowledge breadth, we also consider the squared term of this variable.

Control Variables

Number of inventors. We control for the number of inventors who constitute the team responsible for the focal patent, since it may reflect the complexity of the underlying project as well as the amount of resources devoted to it, and both factors may affect the resulting output. We also introduce the square of this variable to account for non-linear effects.

Average members' expertise. We control for the mean number of previous patents filed by the inventors working in the team of the focal patent (up to the year they filed that focal patent), in order to reflect the amount of expertise of the average inventor in the team. Thus, this variable is computed by dividing all the past patents filed by team members in the previous ten years by the total number of inventors.

Asymmetry in members' expertise. We also control for the asymmetry in the distribution of expertise across team members, since the presence of one or more 'star inventors' may particularly affect the relevance of the innovation and could confound the effects of team variety and individual knowledge breadth. We capture the asymmetry in team members' expertise with the standard deviation of their number of previous patents.

Average quality of members' expertise. The quality of team members' past work may be related to the quality of their subsequent work, since it may reflect the inventors' underlying ability. Therefore,

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additional area of expertise. More importantly, to compute unbiased Herfindahl indexes it is necessary to consider only inventors with two or more patents in their history (Hall et al. 2001), which can seriously bias the working sample.

we introduce a control variable that captures the average quality of the patented innovations created by co-inventors. In particular, we compute the average number of forward citations received by previous patents in which team members of the focal patent participated. In particular, we use standardized citations received[7] in order to take account of time effects that affect the number of citations received by a patent. The number of previous patents filed by team members and their average quality are especially important control variables. To the extent that they capture the quantity and quality of team members' human capital, they are potentially relevant confounding factors that must be taken into account in our analysis.

Number of members without previous expertise. We include the number of members in the team that have no previous patent in order to control for the presence of inventors without expertise. Inventors with no previous patenting experience drive the measure of average breadth of a team down without contributing any (narrow or broad) expertise to their teams. Thus, not controlling for their presence in the team could bias the results of the analysis.

Average number of past co-inventors. We average across team members the mean number of co-authors with which each of them worked in his previous patents, in order to adjust for the effect of their previous expertise.

Average tenure of team members. We take into account the mean tenure of team members, computed as the number of years in which each inventor has been patenting with the firm (based on the application year of their first patent and that of the focal patent). Inventors with no previous patents contribute to this measure with zero tenure.

Self-citations. We control for the percentage of citations that a patent receives from future patents applied by the same assignee than that of focal patent. This source of citations received may be not as informative as those coming from other assignees in terms of the importance of the innovation.

Team tenure. We control for the number of patents in which the team responsible for the focal patent worked together in the last ten years. This variable aims to control for communication and other coordination aspects that may affect the results of teams that have previously worked together.

Citations made. We control for the number of citations the focal patent made to previous patents in our analysis of the determinants of originality. The number of citations made is an important control variable in this context, given that the originality index builds on this information.

[7] The standardization, as proposed by Hall et al (2001), consists of adjusting the citations received by a patent by the mean citations received by the population of patents applied for in the same year and technological category

Technological area effects. There are differences in the propensity to be cited across different technological areas and sub-areas that could be related to differences in the structure of teams of inventors. We control for the technological class in which the patent falls within the Electrical and Electronics category, which is the focus of our analysis.

Time effects. We use a set of dummy variables to control for the year in which the patent is applied for, since time heavily affects the prospect for citations: as Hall et al. (2001) note, an older patent has a longer time span to be cited than a more recent patent.

Methods

We use a negative binomial regression model to test Hypothesis 1. Given that, in this case, our dependent variable - the number of citations received by subsequent patents- is a count variable presenting overdispersion, this is the most appropriate model to test Hypothesis 1 (Hausman et al, 1984). This model also allows for a fixed effects version to control for unobserved heterogeneity. This is something extremely appropriate for analyzing our data, which suffers from potentially important unobserved firm-level effects.

In order to test Hypothesis 2, where the originality index is the dependent variable, we use a firm fixed effects linear regression. Since the Originality score is bounded between 0 and 1, fractional response regression methods -in particular, the fractional probit regression- could seem more appropriate than the proposed linear regression (Papke and Wooldridge, 2008). We prefer the linear approach because it is the only way to eliminate firm fixed-effects without making assumptions about them. Nevertheless, the results of the correlated-random-effects fractional probit regression are qualitatively identical to that of the fixed effects linear model.

4. Results

The descriptive statistics of the variables used in this study are presented in Table 1A. The average patented innovation in our sample receives around 5 citations, it has been developed by a team of 3 members, who jointly accumulate expertise on more than 4 patented projects from 3.4 different classes and 2.7 different sub-categories. At the individual level, the members of the team average a knowledge breadth of 1.7 different classes and 1.4 subcategories. Table 1B presents the correlation matrix of these variables. Note that, given the high correlation coefficients between the key explanatory variables, a large sample like the one we have is necessary in order to separately identify their effects.

Table 2 presents the results of the **negative binomial regression model** with firm fixed-effects on citations received. The first four rows display the effect of team knowledge variety and average individual knowledge breadth for the two alternative levels of aggregation: technological classes and subcategories. The particular specification of our regression model has important consequences for the interpretation of the effects of team knowledge variety and average knowledge breadth. Given that we also control for the total number of patents filed in the past by co-inventors, the effect of an increase in the number of areas in which the team has experience (team variety), is also associated with a lower level of experience in some of them. Similarly, the effect of an increase in the average individual number of areas of expertise (average knowledge breadth) is necessarily associated with fewer specialized contributions. Columns (1) and (4) show the estimated effect of team variety on citations received when the average knowledge breadth of individual members is not controlled for. In both cases, the estimated impact is non-significant. According to Columns (2) and (5), the effect of team variety is significantly negative when the distribution of knowledge inside the team is taken into account. On the other hand, the effect of higher average individual breadth is positive and significant for both levels of field aggregation. Keeping all other things constant, a one-unit increase in members' average number of classes is associated with a 3.95% increase in expected citations received ($\exp\{0.0387\}=1.0395$). Similarly, a one-unit increase in members' average number of subcategories is associated with a 5.34% increase in expected citations received ($\exp\{0.0520\}=1.0534$). Results from columns (3) and (6), where we introduce the quadratic effect of individual breadth, indicate that the quadratic effect is not significantly different from zero. These findings, then, provide partial support for Hypothesis 1: the importance of the innovation increases with average inventors' breadth but not at a decreasing rate. Results suggest that an increase in team knowledge variety is beneficial for the relevance of the innovation when is due to an increase in the breadth of the inventors in the team. Actually, if a given level of team variety is achieved through very narrow contributions, the total effect on performance may be negative. Most of the important control variables in Table 2 show effects in the expected direction. Members' expertise in terms of quantity and quality of past patents has a positive effect on citations received, the number of inventors has a positive but decreasing effect, while the mean number of past co-inventors, the mean tenure of the current co-inventors, the presence of inventors without experience and the tenure of the team have a negative effect. The asymmetry in team members' expertise also has a negative effect on the citations received by the patent, countering the possibility that one superstar inventor is particularly relevant for the success of an innovation project.

Table 3 presents a firm fixed-effects **linear regression** on the originality of the innovation. Results reveal a significant positive effect of the average knowledge breadth of team members and a significant negative effect of the quadratic term of breadth on originality. That is, as proposed in Hypothesis 2, the originality of the innovation increases with the average knowledge breadth of the inventors in the team, but at a decreasing rate. The overall effect turns to negative for the highest values of breadth in our sample, which represent less than 0.1% of our observations (i.e. for values greater than 15 technological classes and 11 subcategories).

5. Robustness Checks

Relevance of patents

The number of citations received is probably the best available indicator of patent relevance. Nonetheless, survey evidence by Gambardella et al. (2008) shows that the number of citations received is a poor measure of relevance in absolute terms as long as it only explains small amount of the variation in *actual* relevance. For this reason, we test the robustness of our results with an alternative measure of relevance. We use the information on whether a patent is jointly filed at the European, Japanese and US patent offices. Given the high filing and maintenance costs, we expect that triadic patents, as they are named, only protect economically relevant innovations (Guéllec and van Pottelsberghe de la Potterie, 2008). Innovation scholars, though, have only recently begun to use this measure as an alternative measure for value (van Zeebroeck and van Pottelsberghe de la Potterie, 2011). We retrieve this data from the "OECD Triadic Patent Families database".

By using this data, the sample is restricted to 35.500 observations and 954 assignees, since many assignees lack of intra-assignee variability in the dependent variable. The dependent variable is a dichotomic variable equal to one if the patent is a triadic patent and zero otherwise. Results of a logit fixed-effects regression analysis are presented in Table 4 in the form of odds ratios. Columns (2) and (5) reflect the effect of the average individual breadth on the odds that a given patent is a triadic patent –for the two alternative measures of the independent variable. A breadth increase of 1 technological class multiplies by 1.08 the odds to be a triadic patent while an increase in 1 subcategory increases them by 1.1. The quadratic effect of breadth does not show significant. Therefore, results are in line with those obtained with citations received as our measure for importance.

6. Discussion and Conclusion

In this article, we argue that the source of knowledge variety in teams of inventors has an effect on their performance. In particular, we propose that teams that achieve a given level of variety based on a broader knowledge background of co-inventors outperform those based on inventors with narrower profiles along two dimensions -relevance and originality of the innovation. The reason is that a team whose members tend to have a broad background is more effective at recombining knowledge, suffers less from group process barriers and, consequently, it is able to generate more relevant innovations. Additionally, such a team is better at generating more original innovations, since it is more able to explore new domains for solutions.

We test these ideas using data on patents from teams of inventors. In line with our predictions, the empirical analysis shows that innovations patented by teams with a given knowledge variety are more relevant the higher the average individual knowledge breadth of its members. We measure the relevance of the innovation underlying the patent application with the number of citations it receives from subsequent patents – and, alternatively, with an indicator of whether the patent is applied for in different countries. Although we hypothesize a decreasing marginal effect of breadth on importance, the evidence suggests that its impact is rather steady. One possible reason is that a positive and non-decreasing effect of breadth attributable to team processes is high enough to compensate the decreasing effect resulting from the use of shallower knowledge. Another possibility is that co-inventors' knowledge depth in their areas of expertise is bounded by our definition of expertise at levels that are high enough to ensure effective recombination. Another interesting result is that team knowledge variety has no statistically significant effect on the relevance of the innovation if the distribution of this variety among the team members is not taken into account. Once we control for average knowledge breadth, however, team variety has a negative effect on the importance of the innovation, which is only compensated when this variety comes from inventors with a broad enough background. Therefore, the performance increases with team variety only if the latter is obtained by combining team members with sufficient knowledge breadth. Regarding our second hypothesis, the results of the regression analysis confirm that a broader knowledge background of co-inventors has a marginally decreasing positive effect on the originality of the innovation.

Our study has several implications. First of all, it pinpoints that knowledge variety in teams is not necessarily obtained by gathering different field specialists, but it can also be reached with the inclusion of co-inventors with broad background. More importantly, our investigation shows that, in the context of the generation of innovations, teams whose knowledge variety is based on broad contributions generate more relevant and more original innovations. These findings are apparently in conflict with the thesis of Jones (2009), who claims that the increasing use of teams in scientific research is the consequence of narrowing expertise which, in turn, is the consequence of the increasing complexity of knowledge. This "death of the Renaissance Man" argument is not easy to reconcile with our findings that teams with higher average knowledge breadth generate innovations of greater relevance than do specialist-based teams. One possible reason behind this paradox can be found in the cost function: if investing in a broad background is costly enough to cancel the benefits from the expected increase in the value of the output, it would be more economical to base team knowledge variety on specialized contributions. In any case, our results suggest that a more "Renaissance Men"-like background of researchers is particularly helpful to obtain the full potential of knowledge variety in innovation teams. Without it, the limited scope for knowledge recombination and the motivation and coordination problems that arise in a diverse working group may result in knowledge variety being a liability rather than an asset.

The extent to which these results can be generalized to teams in other contexts crucially depends on the interconnections between the different pieces of expertise that the team task requires. Teams involved in the generation of new knowledge, whose success strongly depends on how the existing building blocks are blended, will benefit most from high average breadth. We expect the intensity of these benefits to differ across technological domains according to characteristics such as the modularity and complexity of their structure of knowledge. Outside the knowledge generation realm, the advantages of breadth are expected to be less prevalent. Teams in which members' pieces of expertise are applied in isolation or are connected in a standard way (e.g. the cabin crew of an airplane), may profit more from the deep knowledge and narrow focus of field specialists. For intermediate situations that encompass both routine procedures and specific problem-solving exercises, as in Narayanan et al.'s (2009) case of software-developers, we expect the trade-off between narrow focus and knowledge breadth at the team level to be more complex and context-specific.

This study is not without limitations. First, the use of patent data implies that we only capture projects that are to some extent successful– i.e. we do not capture teams that were formed and failed to generate any innovation. In order to minimize this problem, we focused on a heavily patenting sector, where firms have incentives to patent even marginal contributions. Second, teams are not randomly assigned to projects, so it could be that projects with an expected higher payoff would be assigned ex-ante to a particular type of inventors. Thus, while we observe that teams with broad-based knowledge variety perform better, we have to be cautious in interpreting a causal relationship.

Finally, note that we focus our discussion on the extent to which a team's knowledge variety is based on members with broad knowledge and we capture it empirically with an aggregate indicator of mean individual knowledge breadth. However, this broad-based knowledge can be achieved in different ways. For instance, a single inventor with a broad background in the team may be enough to centralize the process of knowledge recombination, to effectively monitor teammates or to facilitate the solution of conflicts and communication problems. Such an inventor may have an analogous function to that of the "Jack of all Trades" manager in the business environment (Lazear, 2004), with special emphasis on managing knowledge recombination and coordinating and controlling group processes. More generally, further research should develop a methodology to identify the way in which broad-based knowledge is achieved and its impact on the performance of the team. This will shed light into the separate importance of each of the mechanisms that we suggest are behind the advantages of combining broad-knowledge co-inventors in a team. We view our research as a first step in the understanding of how the knowledge distribution in teams of inventors affects different dimensions of team performance. More generally, the paper contributes to the understanding of the management of innovation at the lowest subunit in the firm.

7. References

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Appendix

Table 1A. Summary statistics

Variable	Mean	Std Dev	Min	Median	Max
Citations Received by the focal patent	4.9631	8.1647	0	2	158
Triadic patent	0.3344	0.4718	0	0	1
Originality of the focal patent	0.4038	0.2732	0	0.449	0.93
Team Variety:					
Number of classes	3.4576	3.1079	1	2	44
Number of sub-categories	2.7047	2.0356	1	2	17
Members' Breadth:					
Mean number of classes	1.7371	1.5917	0.0833	1.333	29.67
Mean number of sub-categories	1.4392	1.1407	0.0833	1	13.66
Number of Inventors	2.9238	1.2695	2	3	23
Members' Mean Tenure	3.9342	3.3210	0.1	3	25
Members' Mean Expertise: Mean number of previous patents	4.3136	6.9652	0.0833	2	149
Asymmetry of Expertise: Standard deviation of previous of patents	3.9062	6.6092	0	2	137.18
Mean number of past Co-inventors	2.6952	1.1746	1	2.5	34
Members' mean Quality: Mean number of the citations received by the patents of team members	1.6318	1.6154	0	1.261	48.12
Self-citations received	0.1297	0.2575	0	0	1
Team Tenure	0.2057	0.4042	0	0	1
Number of inventors without expertise	0.9912	1.0636	0	1	11
Citations made	10.265	10.264	1	7	430

N=39894

Table 1B. Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Citations																
(2) Triadic	0.1236															
(3) Original	0.0040	0.0315														
(4) Number of classes	0.0007	0.0284	0.1262													
(5) Mean number of classes	-0.0038	0.0153	0.0964	0.8748												
(6) Number of sub-categories	-0.0056	0.0277	0.1349	0.9425	0.8186											
(7) Mean number of sub-categories	-0.0093	0.0190	0.1021	0.8338	0.9577	0.8571										
(8) Number of inventors	0.0163	0.0792	0.0717	0.1835	-0.0851	0.1823	-0.0943									
(9) Mean tenure	-0.0266	0.0271	0.0138	0.4176	0.4775	0.4089	0.4855	-0.0872								
(10) Mean expertise	-0.0310	-0.0166	-0.0085	0.5886	0.7088	0.5471	0.6668	-0.0654	0.3572							
(11) Assymetry of expertise	-0.0386	-0.0255	-0.0081	0.5354	0.5118	0.5118	0.4923	-0.0138	0.2451	0.8438						
(12) Past co-inventors	-0.0440	0.0455	0.0622	0.0990	0.0518	0.1000	0.0580	0.3464	-0.0030	0.0382	0.0175					
(13) Mean quality	0.2625	0.0741	0.0623	0.0562	0.0687	0.0480	0.0601	0.0401	-0.0522	0.0933	0.0730	0.1071				
(14) Self-citations	0.0936	0.0787	-0.0035	0.0383	0.0278	0.0391	0.0292	0.0348	0.0446	0.0272	0.0210	0.0058	0.0283			
(15) Team tenure	-0.0352	0.0390	0.0280	0.1123	0.3226	0.1076	0.3471	-0.1114	0.1779	0.2740	0.0974	0.0025	0.0544	-0.0214		
(16) Inventors without expertise	0.0200	-0.0050	0.0229	-0.1817	-0.4177	-0.1780	-0.4648	0.5610	-0.3609	-0.2877	-0.1393	0.0285	-0.0263	-0.0004	-0.4363	
(17) Citations made	-0.0196	0.0817	0.3012	0.0339	0.0356	0.0334	0.0352	0.0860	0.0075	0.0260	0.0126	0.0581	0.1052	0.0118	0.0708	-0.0020

Note: Correlations significant at the 5% except for the shaded values

Table 2: Distribution of knowledge in teams and the Value of innovations. Negative binomial regression, firm fixed-effects

	NUMBER OF CLASSES			NUMBER OF SUBCATEGORIES		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Citations received count	Citations received Count	Citations received count	Citations received count	Citations received count	Citations received count
Team Variety	0.0025	-0.0122***	-0.0117**	-0.0001	-0.0211***	-0.0222***
	(0.0025)	(0.0047)	(0.0049)	(0.0036)	(0.0067)	(0.0069)
Members' Breadth		0.0387***	0.0359***		0.0520***	0.0611***
		(0.0103)	(0.0134)		(0.0141)	(0.0192)
Members' Breadth squared			0.0002			-0.0012
			(0.0005)			(0.0017)
Members' mean tenure	-0.0122***	-0.0126***	-0.0124***	-0.0117***	-0.0122***	-0.0125***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Member's mean expertise	0.0092***	0.0045**	0.0045**	0.0097***	0.0055***	0.0060***
	(0.0017)	(0.0022)	(0.0022)	(0.0017)	(0.0021)	(0.0021)
Assymmetry of members' expertise	-0.0067***	-0.0040**	-0.0039**	-0.0064***	-0.0039**	-0.0042**
	(0.0016)	(0.0018)	(0.0018)	(0.0016)	(0.0018)	(0.0019)
Members' mean quality	0.0872***	0.0871***	0.0871***	0.0871***	0.0871***	0.0871***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Selfcitations received	0.526***	0.527***	0.527***	0.526***	0.527***	0.526***
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)
Team tenure	-0.0715***	-0.0856***	-0.0848***	-0.0732***	-0.0877***	-0.0892***
	(0.0146)	(0.0150)	(0.0152)	(0.0145)	(0.0150)	(0.0152)
Members without expertise	-0.0330***	-0.0309***	-0.0316***	-0.0345***	-0.0278***	-0.0257***
	(0.0070)	(0.0070)	(0.0073)	(0.0070)	(0.0072)	(0.0078)
Mean number of past-coinventors	-0.0382***	-0.0395***	-0.0395***	-0.0384***	-0.0396***	-0.0397***
	(0.0051)	(0.0052)	(0.0052)	(0.0051)	(0.0052)	(0.0052)
Number of inventors in this patent	0.0716***	0.0815***	0.0813***	0.0737***	0.0824***	0.0825***
	(0.0126)	(0.0129)	(0.0130)	(0.0126)	(0.0129)	(0.0129)
Number of inventors squared	-0.0023*	-0.0025*	-0.0025*	-0.0023*	-0.0026**	-0.0027**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Observations	39,894	39,894	39,894	39,894	39,894	39,894
Number of assignee	1,987	1,987	1,987	1,987	1,987	1,987

Note: Year and technological class dummies included as controls in all specifications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Distribution of knowledge in teams and the Originality of innovations. Linear regression, firm fixed-effects

	NUMBER OF CLASSES			NUMBER OF SUBCATEGORIES		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Originality index	Originality index	Originality index	Originality index	Originality index	Originality index
Team Variety	0.0115***	0.0074***	0.0060***	0.0186***	0.0115***	0.0104***
	(0.000601)	(0.0012)	(0.0012)	(0.0009)	(0.0017)	(0.0018)
Members' Breadth		0.0106***	0.0209***		0.0171***	0.0264***
		(0.0026)	(0.0034)		(0.0035)	(0.0049)
Members' Breadth squared			-0.0007***			-0.0012***
			(0.0002)			(0.0004)
Citations made	0.0064***	0.0064***	0.0064***	0.0064***	0.0064***	0.0064***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Members' mean tenure	-0.0013***	-0.0015***	-0.0020***	-0.0015***	-0.0017***	-0.0019***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Member's mean expertise	-0.0028***	-0.0037***	-0.0035***	-0.0026***	-0.0036***	-0.0033***
	(0.00039)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)
Assymmetry of members' expertise	-0.0004	0.0003	-1.40e-05	-0.0005	0.0002	2.38e-06
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Members' mean quality	0.0031***	0.00311***	0.0031***	0.0031***	0.00308***	0.0031***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Team tenure	0.0177***	0.0134***	0.0109***	0.0177***	0.0126***	0.0112***
	(0.0037)	(0.0039)	(0.0039)	(0.0037)	(0.0039)	(0.0039)
Members without expertise	0.0069***	0.0076***	0.0103***	0.0077***	0.0100***	0.0121***
	(0.0018)	(0.0018)	(0.0019)	(0.0018)	(0.0019)	(0.0020)
Mean number of past-coinventors	0.0013	0.0010	0.0009	0.0015	0.0011	0.0011
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Number of inventors in this patent	0.0040	0.0069**	0.0072**	0.0031	0.0062*	0.0062**
	(0.0031)	(0.0032)	(0.0032)	(0.0031)	(0.0032)	(0.0032)
Number of inventors squared	-0.0010***	-0.0010***	-0.0011***	-0.0009***	-0.0010***	-0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	39,425	39,425	39,425	39,425	39,425	39,425
R-squared	0.131	0.132	0.132	0.133	0.133	0.134
Number of assignees	1,985	1,985	1,985	1,985	1,985	1,985

Notes: Year and technological class dummies included as controls in all specifications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Robustness check: Triadic data.
Logit regressions, Firm fixed-effects. Odds Ratios Reported.

	NUMBER OF CLASSES			NUMBER OF SUBCATEGORIES		
	(1)	(2)	(3)	(4)	(5)	(6)
	Triadic	Triadic	Triadic	Triadic	Triadic	Triadic
Team Variety	1.019***	0.990	0.988	1.022**	0.981	0.983
	(0.0060)	(0.0113)	(0.0116)	(0.0088)	(0.0162)	(0.0167)
Members' Breadth		1.078***	1.095***		1.107***	1.083*
		(0.0278)	(0.0361)		(0.0386)	(0.0525)
Members' Breadth squared			0.999			1.003
			(0.0014)			(0.0044)
Members' mean tenure	1.020***	1.019***	1.018***	1.021***	1.020***	1.021***
	(0.0050)	(0.0050)	(0.0051)	(0.0050)	(0.0050)	(0.0051)
Member's mean expertise	0.993*	0.984***	0.985***	0.994	0.986***	0.986***
	(0.0041)	(0.0051)	(0.0051)	(0.0041)	(0.0049)	(0.0050)
Assymmetry of members' expertise	1.002	1.007	1.006	1.002	1.007	1.007*
	(0.0039)	(0.0044)	(0.0044)	(0.0039)	(0.0043)	(0.0044)
Members' mean quality	1.092***	1.092***	1.092***	1.092***	1.092***	1.092***
	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)
Selfcitations received	1.803***	1.804***	1.803***	1.803***	1.804***	1.804***
	(0.0891)	(0.0891)	(0.0890)	(0.0890)	(0.0891)	(0.0891)
Team tenure	1.308***	1.271***	1.266***	1.303***	1.266***	1.270***
	(0.0487)	(0.0490)	(0.0492)	(0.0485)	(0.0488)	(0.0493)
Members without expertise	0.937***	0.941***	0.945***	0.935***	0.947***	0.942***
	(0.0165)	(0.0167)	(0.0175)	(0.0165)	(0.0172)	(0.0186)
Mean number of past-coinventors	0.977*	0.974**	0.974**	0.976*	0.974**	0.975**
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Number of inventors in this patent	1.225***	1.251***	1.252***	1.230***	1.253***	1.253***
	(0.0374)	(0.0391)	(0.0392)	(0.0375)	(0.0390)	(0.0390)
Number of inventors squared	0.994**	0.994**	0.994**	0.994**	0.993**	0.994**
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Observations	35,500	35,500	35,500	35,500	35,500	35,500
Number of assignees	954	954	954	954	954	954

Notes: Year and technological class dummies included as controls in all specifications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.