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The Renaissance of the *Renaissance Man*? Specialists vs. Generalists in Teams of Inventors*

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Abstract

Is there a role for the multifaceted *Renaissance Man* in modern team-intensive innovation activities? This paper argues that researchers with broad knowledge, also known as generalists, make an especially valuable contribution to innovation teams. Given the re-combinative nature of technological progress, innovation results depend crucially on the skilful matching of different pieces of knowledge. The presence of generalists in innovation teams makes the knowledge recombination process more effective, even if this comes at the cost of reduced knowledge depth. Moreover, typical barriers in team processes become less acute with the presence of generalists. We analyze the role of generalists versus specialists in innovation teams by tracking the trajectories of inventors in the electrical and electronics industry through their patenting activity. Our findings suggest that innovation teams with the contribution of generalists outperform those that rely on a diverse set of specialists.

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 the patents nowadays are co-authored and co-invented, respectively. Jones (2009) argues that the increasing use of teamwork in innovation activities 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 ―Renaissance Men”, i.e. people who excel at multiple disciplines, are extremely scarce. In contrast, the majority of innovators are deep specialists in constricted areas, 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?

In this paper, we develop the idea of a ―new” Renaissance Man, i.e. an innovator who chooses to have broad instead of deep knowledge and who is crucially valuable in teams of inventors. We build our theory based on three arguments. First, given the re-combinative nature of innovation, we suggest that a researcher does not need to master the knowledge of any given area to be able to innovate (contrary to Jones (2009) assumption). Instead, he can trade off depth for breadth and become a generalist innovator who is knowledgeable in different areas without reaching the frontier of knowledge in all of them. Second, we posit that knowledge variety is a very valuable asset in the recombination of knowledge. Third, teams of inventors that gather field specialists to obtain the necessary knowledge variety suffer from a series of coordination and motivation problems during the innovation process. We argue that the presence of generalists in teams of inventors helps to attenuate or to avoid these problems. Hence, our main prediction is that, all else equal, teams of inventors that include generalists will outperform teams of inventors that combine only specialists. They will produce more relevant innovations and, because of their particular advantage in the knowledge recombination process, more original ones[1].

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. The innovation literature has typically examined innovation at the firm and, more recently, at the individual level—mainly from a network perspective—but not at the team level. To our knowledge, the only exception is Fleming and Singh (2010), who analyze the productivity of teams of inventors versus that of lone inventors. From the sociology literature, we have some insights on how the within-team interactions among members (i.e. a team's internal social capital) affect the productivity of R&D teams (Reagans and Zuckerman, 2001).

On the other hand, the organizational behavior literature has extensively analyzed the effect of *team-level* knowledge variety on team performance (Harrison and Klein, 2007)[2]. This literature associates high knowledge variety at the team level with the potential to recombine ideas that lead to highly creative results (Jackson et al., 1995; Paulus 2000; Taylor and Greve, 2006) but also with motivation and communication problems that damage team performance (Stewart and Stasser, 1995; Gigone and Hastie, 1997; Jehn et al., 1999). Nevertheless, this strand of literature has not dealt with the way in which team-level variety is achieved. Knowledge variety in teams may stem from two sources: either the team consists only of specialists from different technological areas or it includes one or more generalists. In the first case, each of the team members has a certain level of expertise in a field that is unfamiliar to the rest of teammates. In the second case, one or more of the

[1] Note that there are many aspects contributing to efficiency gains from the use of teams that do not relate to knowledge specialization. Therefore, the accurate way to test the performance of teams of specialized inventors is to compare them with similar-sized teams achieving a similar level of knowledge variety through the inclusion of some generalist member(s), not with lone generalist inventors.

[2] 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.

members of the team have a multidisciplinary background that accounts for a large part of the knowledge variety in the team. To our knowledge, this topic has been addressed only by Rulke and Galaskiewicz (2000), who looked at the composition of teams of MBA students performing business simulation games. The authors find that teams formed of students, each of whom has experience in several functional areas, outperform teams whose members are specialized in one functional area each[3]. The focus of Rulke and Galaskiewicz (2000) on (simulated) managerial decision-making, however, makes their findings difficult to extrapolate to teams engaged in knowledge generation.

This paper contributes to the literature on how team composition affects innovation results by suggesting that innovation teams including members with broad knowledge outperform those combining field specialists. We test our arguments using patent data. This data is useful to identify teams of inventors responsible for the creation of innovations and measure their performance. Moreover, in patent-intensive sectors such as the electrical and electronics industry (Hall, 2004), patent data also helps to characterize the extent to which each inventor is a generalist (or, as we will refer from now on, his knowledge breadth). Empirical results point out that variety generated by the presence of generalists has a positive impact on the relevance of the innovation and that this effect is mediated by an increased level of invention originality.

2. Theory and Hypotheses

[3] In a different strand of literature, and from a firm-level perspective, Gompers et al. (2009) make an analogous exercise by linking the performance of venture capital firms to their degree of specialization and that of their professionals. According to their findings, generalist venture capital firms obtain superior performance when the individual investment professionals that they employ are highly specialized.

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 depends crucially on the first two stages, when inventors try different ways of combining existing pieces of knowledge to create some 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; Stasson and Bradshaw, 1995; Jackson, 1996). In accordance with this idea, Singh and Fleming (2010) find that teams of inventors outperform solo inventors, partly because of their higher 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 (Maznevski, 1994), conflicts that may occur when members feel strongly committed to their diverse perspectives (Levine and Thompson, 1996), and free-riding problems that are specially 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. In the particular case of teams of inventors, we expect that the inclusion of generalist inventors in a team enhances the above-mentioned advantages and diminishes the malfunctions, leading to more relevant and more original innovations. Below we develop the arguments that support this thesis.

Relevance of the Innovation

Knowledge recombination. Innovations are often described as the result of a process where existing technologies are recombined in a novel way (Schumpeter, 1939; Henderson and Clark, 1990; Fleming, 2001; Fleming and Sorenson, 2001). By its very nature, this process of recombination is carried out more effectively 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 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 a generalist has in mind enables him to conduct a more effective search than that performed by different specialists stitching several small sections of this same landscape. Moreover, in a team setting, a broad individual knowledge background will entail more overlapping expertise among the inventors. Given that, 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 presence of generalists.

As Jones (2009) remarks, a broad-knowledge human capital background can only be built at the expense of knowledge depth[4]. Thus, generalists contribute less deep knowledge to their innovation teams than do specialist co-inventors with a comparable amount of experience. Nevertheless, the process of innovation by knowledge recombination does not require one to be 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 represents the frontier in their respective fields.

[4] Obviously, there is a minimum knowledge depth that an inventor must achieve in each area in order to be able to use it for recombination. We understand a generalist inventor as someone with knowledge depth above that minimum in each of the considered areas. In our empirical study, such minimum depth is guaranteed by the measure of an inventor's knowledge background, which is based on previous innovation experiences.

Therefore, broad knowledge is a more valuable asset for recombination than deep knowledge. This implies that teams including generalists can be expected to outperform teams of specialists in the use of knowledge variety to conceive high-potential ideas.

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 with the presence of generalists in the team. Since teams that include generalists in their ranks are more likely to have overlapping knowledge among their members, they will benefit from shared codes of communication. Not only will generalists have more fluent dialogues with overlapping co-inventors, but they will facilitate the dialogue between specialist team-mates by building communication bridges among them. The existence of a common language is an important enabling factor in order to share knowledge and harness the potential benefits of knowledge variety. Therefore, we expect that teams with generalist inventors 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; Levine and Thompson 1996). This is especially likely if members are field specialists. Firstly, generalist co-inventors are more likely to have some overlapping knowledge that makes it easier for them to understand the scope of co-inventors‘ critiques. Secondly, inventors with a more diversified 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 specialists are more likely to suffer strong, dysfunctional conflicts while teams including generalists 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 (Wageman, 1995; 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 it takes the form of field specialists, because they will not be able to evaluate each others‘ effort. In contrast, the presence of some generalist researchers makes it possible 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 the inclusion of some generalist members in their ranks are expected to perform better than those that include different field specialists only. The reason is that such teams are better at recombining knowledge and dealing with conflicts, communication, and free-riding problems.[5]

Hypothesis 1: Teams of inventors that obtain knowledge variety through the inclusion of generalist members generate innovations of greater relevance than teams that achieve variety through field specialists.

Originality of the Innovation

Innovation can result either from exploitation of existing ideas or from exploration of new paradigms. The first approach to innovation is more likely to result in incremental ideas, whereas the latter is more likely to produce more original output. We argue that the presence of generalists in a team will favour exploration over exploitation and this will have consequences for the originality of the innovation. As mentioned earlier, generalists make the recombination of ideas in a team more effective. As we argue below, they also have the ability to manage recombination in a more creative way.

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 uniquely stored 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

[5] 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.

anchoring effect that leads to incremental, less original innovations (Ward, 1994, 2004). Conversely, the presence of generalists in a team makes it possible to consider more abstract pieces of knowledge in the recombination process. First, as individuals, their higher knowledge breadth provides them with more room for analogies and re-organization involving abstract elements. In this vein -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, teams with a greater presence of generalists enjoy more overlapping expertise, which enables researchers to exchange ideas in more abstract terms and avoid the aforementioned anchoring effect.

We also argue that originality is conducive to greater relevance of the innovation. By unlocking new ways of approaching technological solutions, original innovations open up a way for subsequent creative efforts and applications. Ahuja and Lampert (2001) find that, at the firm level, the originality of innovations is linked to the number of industry breakthroughs produced by the firm. This implies that original innovations generate an option value, allowing for the development of further innovations based on them. In a similar vein, Rosenkopf and Nerkar (2001) find that innovations that result from ―radical" exploration, i.e. that build upon knowledge that spans firm and technology boundaries, have higher impact on subsequent research. Thus, more original innovations are expected to be more relevant for the scientific community.

Since teams with a larger presence of generalist inventors engender more original innovations, and more original innovations are expected to be more relevant than less original ones, it follows that originality of the innovation is a mediating variable in the relationship between team composition and the relevance of the innovation. On the other hand, the lower communication, conflict and free riding costs that teams with generalists enjoy enhance the final quality of the innovation, independently of the originality of the idea behind it. Therefore, the argument that teams that harness knowledge variety through generalist inventors benefit from reduced costs of motivation and coordination holds for any level of originality of the new knowledge. In other words, originality only partially mediates the effect of the presence of generalists on the relevance of the innovation.

Hypothesis2: The positive effect of team knowledge variety obtained through the inclusion of generalist inventors on the relevance of the resulting innovation is partially mediated by the originality of such innovation.

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 form the team responsible for it (Jones, 2009; Singh & 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, one of the sectors in which firms are especially likely to patent every improvement they achieve (Hall, 2004). This sample restriction means that we 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[6] 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 firms.

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.

[6] We identify the firm employing each team of inventors by using the "assignee" code of each patent, which refers to the legal entity that applies for and owns it. The assignee code typically identifies the employer firm, although sometimes it identifies different subsidiaries or establishments of a larger firm separately.

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.

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 (Henderson et al., 1998; Jaffe et al., 2000; Hall et al., 2005).

Team knowledge variety. We measure team knowledge variety with the number of primary technological areas in which team members have patented in the past. Patents are assigned to technological categories. 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) use the number of different technological classes in which team members patented in the past to capture knowledge variety[7].

Average individual knowledge breadth. Analogously, in order to capture the breadth of the knowledge held by individual co-inventors, we average across team members the number of classes (and also the number of subcategories) in which each of them has experience. A large average number of areas of expertise indicates that the average inventor of the team has a broader knowledge background, i.e. that he is more of a generalist. Note that team knowledge variety and individual breadth are highly correlated (correlation coefficients are 0.87 and 0.89 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 specialized contributions or through the participation of generalists.

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:

$$\text{Originality}_i = 1 - \sum_j^J s_{ij}^2$$

[7] Marx et al. (2009), Gompers et al. (2009) and Grober et al. (2008) use Herfindahl concentration indexes to capture team 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 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.

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. Gompers et al., 2005; Palomeras, 2007; 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.

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 the focal patent), in order to reflect the amount of expertise of the average inventor in the team.

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 and individual knowledge variety. 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, we control for 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[8] 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.

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).

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.

[8] 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

Methods

We use the negative binomial regression model to estimate the effect of team composition on team performance. Given that our dependent variable (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 a fixed-effect 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, we apply the three-steps procedure established by Baron and Kenny (1986) to test mediation, which is particularly appropriate when analyzing large samples like the one studied in this article (Preacher and Hayes, 2008). To establish the mediating role of originality of the innovation on the relationship between team members' knowledge breadth and the relevance of the innovation, three conditions must hold. First, the presence of inventors with broad knowledge must have a positive impact on the originality of the innovation; second, the originality of the innovation must affect its relevance even when the members' knowledge breadth is controlled for; and third, the estimated effect of members' knowledge breadth on the relevance of the innovation is significantly smaller when originality is controlled for (with respect to the effect in the non-mediated model used to test Hypothesis 1).

4. Results

The descriptive statistics of the main variables corresponding to the sample used in the regression are presented in Table 1.

Table 2 presents the results of the **negative binomial regression model** with firm fixed-effects. 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 individual breadth) is necessarily associated with fewer specialized contributions. Columns (1) and (3) 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 positive and, for the number of classes, significant. According to Columns (2) and (4), the effect decreases to negative non-significant levels when the presence of generalists is taken into account. On the other hand, the effect of higher average individual knowledge 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 2.36% increase in expected citations received ($\exp\{0.0233\}=1.0236$). Similarly, a one-unit increase in members' average number of subcategories is associated with a 3.66% increase in expected citations received ($\exp\{0.0359\}=1.0366$). These findings provide support for Hypothesis 1. Furthermore, the fact that team variety does not have a significant impact on citations received once we control for average individual breadth suggests that only the variety contributed by members with some generalist background is beneficial for the relevance of the innovation. 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 and the mean tenure both have a negative effect. Surprisingly, the asymmetry in team members' expertise also has a negative effect on the citations received by the patent, questioning the idea that one superstar inventor is particularly relevant for the success of an innovation project (Gruber et al. 2008).

Tables 3 and 4 present the analysis on the mediating role of the originality of the innovation proposed in Hypothesis 2. The first part of the test intends to assess whether our relevant independent variable has an effect on the mediator (Table 3). The results of the fixed-effects regression analysis, which includes the same set of control variables used for testing Hypothesis 1, reveals that the originality of the invention increases with the inclusion of generalist members.[9]

Table 4 presents the results of the second step of the mediation analysis. Columns (1) and (3) replicate the results presented in Table 2 to test Hypothesis 1. Columns (2) and (4) in Table 4 present the same specification with the addition of Originality as an independent variable explaining the relevance of the innovation. As expected, the originality of the innovation has a significant positive effect on the number of citations received. Furthermore, the effect of team-members' average knowledge breadth—both in terms of technological classes and subcategories—drops by about 10% when we account for the originality of the innovation. We test the statistical significance of this change by bootstrapping the sample 500 times and directly estimating the distribution of the difference in coefficients. The results show that the difference in the estimated coefficient across specifications is statistically significant at the 1% level for both technological classes and subcategories. Therefore, we find support for Hypothesis 2, that is, the advantage of obtaining

[9] Since the Originality score used as dependent variable is bounded between 0 and 1, fractional response regression methods could seem more appropriate than the linear regression used here (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. However, the results of the fractional probit regression with correlated random effects suggested by Papke and Wooldridge (2008) yielded very similar results to those of Table 3.

knowledge variety with the contribution of generalists is partially mediated by the originality of the innovation. That the mediation effect is only partial is clear from the fact that the direct effect of members‘ average knowledge breadth remains significant after controlling for originality and still accounts for 90% of the total effect.

5. 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 variety based on generalists outperform those based on field specialists alone. The reason is that generalists are more effective in the recombination of knowledge and suffer less from some typical group process barriers such as communication problems, excessive conflict and free-riding issues. We test this idea using data on patents from teams of inventors.

In line with our predictions, the empirical analysis shows that innovations patented by teams with high knowledge variety receive more citations from subsequent patents if the average individual knowledge variety of its members is also high. High team knowledge variety has no statistically significant effect on the relevance of the innovation if combined with low average individual knowledge breadth. We also find that the effect of generalists is partially mediated by the originality of the innovation. This mediating role of originality, however, accounts for a relatively low share of the total effect of members‘ knowledge breadth. In our theoretical framework, we propose the originality of the innovation as a mediating variable because the presence of generalists is expected to enable better knowledge recombination across technological boundaries, hence overcoming local search and obtaining more radical innovations. Reversing the arguments, our results suggest that the added value of generalist members is to a larger extent a result of better communication, less free-riding and fewer conflicts and to a lesser extent the product of better recombination.

Our 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 generalist-based teams 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 generalist 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 new type of ―Renaissance Man" is needed to extract the full potential of knowledge variety in innovation teams. Otherwise, the limited scope for knowledge recombination and the motivation and coordination problems that arise in a working group may result in knowledge variety being a liability rather than an asset.

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 some generalist members. More importantly, our investigation shows that, in the context of the generation of innovations, teams with generalist members actually outperform teams that combine specialists. The extent to which this result 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 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 attained by field specialists. On the contrary, teams involved in the generation of new knowledge, whose success strongly depends on how the existing building blocks are blended, will benefit most from the presence of generalist members.

To conclude, note that we frame our discussion of generalist versus specialist inventors at the group level, capturing it empirically with an aggregate indicator of mean individual knowledge variety. However, a single generalist 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 a ―Jack of all Technologies” (Gruber et al. 2008) 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 the knowledge recombination and coordinating and controlling group processes. Further research should address the particular effect of the existence of such a generalist coordinator and develop a methodology to measure the impact of his presence in a team of inventors.

6. References

Ahuja, G., C.M. Lampert. 2001. —Entrepreneurship in the Large Corporation: A Longitudinal Study of How Established Firms Create Breakthrough Inventions," *Strategic Management Journal*, 22, 521-543.

Ancona, D.G., D.F. Caldwell. 1992. —Demography and Design: Predictors of New Product Team Performance," *Organization Science*, 3, 321-341.

Arthur, W.B., —The structure of invention," *Research Policy* 36, 274-287.

Baron, R.M., D.A. Kenny. 1986. —The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategical and Statistical Considerations," *Journal of Personality and Social Psychology*, 51, 1173-1182.

De Dreu, C. K. W., L.R. Weingart. 2003. —Task versus Relationship Conflict and Team Effectiveness: A Meta-analysis," *Journal of Applied Psychology*, 88, 741-749.

Diehl, M., W. Stroebe. 1987. —Productivity Loss in Idea-Generating Groups: Toward the solution of a riddle," *Journal of Personality and Social Psychology*, 53, 497-509.

Fleming, L., O. Sorenson. 2001. —Technology as a Complex Adaptive System: Evidence from Patent Data," *Research Policy*, 30, 1019-1039.

Fleming, L., O. Sorenson. 2004. —Science as a Map in Technological Search," *Strategic Management Journal*, 25, 909-928.

Gigone, D., Hastie, R. 1997. —Proper Analysis of the Accuracy of Group Judgementes," *Psychological Bulletin*, 121 149-167.

Girotra, K., C. Terwiesch, K.T. Ulrich. 2010. —Idea Generation and the Quality of the Best Idea," *Management Science*, 56, 591-605.

Giuri, P., M. Ploner, F. Rullani , S. Torrisi. 2010. —Skills, Division of Labor and Performance in Collective Inventions: Evidence from Open Source Software," *International Journal of Industrial Organization*, 28, 54-68.

Gompers, P., A. Kovner, J. Lerner. 2009. —Specialization and Success: Evidence from Venture Capital," *Journal of Economics and Management Strategy,* 8, 817-844.

Gompers, P., J. Lerner, D. Scharfstein. 2005. —Entrepreneurial Spawning: Public Corporations and the Genesis of New Ventures, 1986 to 1999," *Journal of Finance*, 60, 577-614

Gruber, M., D. Harhoff , K. Hoisl. 2008. —The Jack of All Technologies: Knowledge Recombination across Technological Boundaries," *unpublished manuscript*, University of Munich.

Hall, B..2004. —Exploring the Patent Explosion", *NBER Working Paper 10605*

Hall, B., A. Jaffe, M. Trajtenberg, 2001. ―The NBER Patent Citations Data File: Lessons, insights and methodological tools," *NBER Working Paper 8498*.

Hall, B., A. Jaffe, M. Trajtenberg, 2005. ―Market Value and Patent Citations," *The Rand Journal of Economics,* 36, 16-38.

Harrison, D. , K. Klein. 2007, ―What's the Difference? Diversity Constructs as Separation, Variety or Disparity in Organizations," *Academy of Management Review*, 32, 1199-1228.

Hausman, J., B.H. Hall, Z. Griliches. 1984. ―Econometric Models for Count Data with an Application to the Patents-R&D Relationship," *Econometrica*, 52, 909-938.

Henderson, R., K. Clark. 1990. ―Architectural Innovation: The Reconfiguration of Existing Product Technologies and Failure of Established Firms," *Administrative Science Quarterly*, 35, 9-30.

Jackson, S.E. 1996. ―The Consequences of Diversity in Multidisciplinary Work Teams," in M. West (Ed.), *Handbook of Work Group Psychology*. Chichester (UK): Wiley.

Jackson, S.E., K.E. May, K. Whitney. 1995. ―Understanding the Dynamics of Diversity in Decision Making Teams" in R.A. Guzzo, E. Salas. and Associates (Eds.), *Team Effectiveness and Decision Making in Organizations*. San Francisco: Jossey Bass Publishers.

Jehn, K.A., E.A. Mannix 2001. ―The Dynamic Nature of Conflict: A Longitudinal Study of Intragroup Conflict and Group Performance," *Academy of Management Journal* 44, 238-251.

Jehn, K.A., G.B. Northcraft, M.A. Neale. 1999. ―Why Differences make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups," *Administrative Science Quarterly*, 44, 741-763.

Jones, B.F. 2009. ―The Burden of Knowledge and the ―Death of the Renaissance Man": Is Innovation Getting Harder?" *Review of Economic Studies*, 76, 283-317.

Kandel, E., E.P. Lazear. 1992. ―Peer Pressure and Partnerships," *Journal of Political Economy*, 100, 801-817.

Klee, M. 1998. ―The Case of the Omitted Inventor," *IEEE Engineering in Medicine and Biology*, 17 (3), 110.

Kline, S. J., N. Rosenberg. 1986. ―An Overview of Innovation" in R. Landau and N. Rosenberg (Eds.), *The Positive Sum Strategy: Harnessing Technology for Economic growth*.Washington (D.C.): National Academy Press.

Laursen, K., V. Mahnke, P. Vejrup-Hansen. 2005. ―Do Differences Make a Difference? The Impact of Human Capital Diversity, Experience and Compensation on Firm Performance in Engineering Consulting," *Druid Working Paper 05-04*, Copenhagen.

Lazear, E. P. 2004. ―Balanced Skills and Entrepreneurship", *American Economic Review*, 94, 2, 208-211.

Lerner, J., M. Sorensen, P. Strömberg. 2011. ―Private Equity and Long-Run Investment: The Case of Innovation," *Journal of Finance*, 66, 445-477

Levine, J.M., Thompson, L. 1996. ―Conflict in Groups," in E.T. Higgins and A.W. Kruglanski (Eds.): *Social Psychology: Handbook of Basic Principles*. New York: The Guilford Press.

Levinthal, D., J.March, 1993. ―The Myopia of Learning", *Strategic Management Journal*, 14, 95-112.

Lissoni, F., F. Montobbio. 2008. ―Inventorship and Authorship as Attribution Rights: An Enquiry in the Economics of Scientific Credit," *CESPRI Working Paper 224*, Università Bocconi.

Maznevski, M.L. 1994. ―Understanding our Differences: Performance in Decision-Making Groups with Diverse Members," *Human Relations*, 47, 531-552.

Marx, M, Strumsky, D and Fleming, L., 2009. ―Mobility, Skills, and the Michigan Noncompete Experiment", *Management Science*, 55 (6), 875-889.

Palomeras, N. 2007. ―An Analysis of Pure-Revenue Technology Licensing," *Journal of Economics and Management Strategy*, 16, 971-994.

Paulus, P.B. 2000. ―Groups, Teams, and Creativity: The Creative Potential of Idea-generating Groups," *Applied Psychology: An international Review,* 49(2), 237-262.

Preacher, K.J., A.F. Hayes. 2008. ―Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models," *Behavior Research Methods*, 40, 879-891.

Rosenkopf, L. and A. Nerkar. 2001. Beyond Local Search: Boundary-Spanning, Exploration and Impact in the Optical Disk Industry, *Strategic Management Journal*, 22, 287-306.

Rulke, D., J. Galaskiewsz. 2000. ―Distribution of Knowledge, Group Network Structure, and Group Performance," *Management Science*, 46, 612-625.

Schumpeter. J. 1939. *Business Cycles*. New York: McGraw Hill.

Shane, S. 2000. Prior Knowledge and the Discovery of Entrepreneurial Opportunities. *Organization Science*, 11, 448-469

Simonton, D. K. 1999. *Origins Of Genius: Darwinian Perspectives On Creativity*. Oxford University Press, New York.

Singh, J., L. Fleming. 2010. ―Lone Inventors as Sources of Breakthroughs: Myth or Reality," *Management Science*, 56, 41-56.

Stasser, G., W. Titus. 1985. ―Pooling of Unshared Information in Group Decision Making: Biased Information Sampling during Discussion," *Journal of Personality and Social Psychology*, 48, 1467-1478.

Stasson, M. F., S.D. Bradshaw. 1995. “Explanation of Individual-Group Performance Differences: What Sort of “Bonus” Can Be Gained through Group Interaction?,” *Small Group Research*, 26, 296-308.

Stewart, D.D., G. Stasser. 1995. “Expert Role Assignment and Information Sampling during Collective Recall and Decision-Making,” *Journal of Personality and Social Psychology*, 69, 619-628.

Taylor, A., H. Greve. 2006. “Superman or the Fantastic Four? Knowledge Combination and Experience in Innovative Teams,” *Academy of Management Journal*, 49, 723–740.

Trajtenberg, M., R. Henderson, A. Jaffe. 1997. "University versus Corporate Patents: A Window on the Basicness of Invention," *Economics of Innovation and New Technology*, 5 (1), 19-50.

Trajtenberg, M., G. Shiff, R. Melamed. 2006. “The “Names Game”: Harnessing Inventors‘Patent Data for Economic Research”, *NBER Working Paper 12479*.

Valentini, G. 2011. “Measuring the Effect of M&A on Patenting Quantity and Quality”, *Strategic Management Journal*, 33, 336-346.

Ward, T.B. 1994. “Structured Imagination: The Role of Conceptual Structure in Exemplar Generation,” *Cognitive Psychology*, 27, 1-40.

Ward, T.B. 2004. “Cognition, Creativity and Entrepreneurship,” *Journal of Business Venturing*, 19, 173-188.

Wageman, R. 1995. “Interdependence and group effectiveness,” *Administrative Science Quarterly*, 40, 145-180.

Webber, S.S., L. Donahue. 2001. “Impact of Highly and Less Job-related Diversity on Work Group Cohesion and Performance: A Meta-analysis,” *Journal of Management*, 27, 141-162.

Wutchy, S., B. F. Jones, B. Uzzi. 2007. “The Increasing Dominance of Teams in Production of Knowledge,” *Science*, 316, 1036-1039.

Tables and Figures

Table 1. Summary statistics

Variable	Mean	Std Dev	Min	Max
Citations Received by the focal patent	4.9631	8.1647	0	158
Originality of the focal patent	0.4038	0.2732	0	0.93
Team Variety:				
Number of classes	3.4576	3.1079	1	44
Number of sub-categories	2.7047	2.0356	1	17
Members' Breadth:				
Mean number of classes	1.7371	1.5917	0.0833	29.67
Mean number of sub-categories	1.4392	1.1407	0.0833	13.66
Number of Inventors	2.9238	1.2695	2	23
Members' Expertise: Mean number of previous patents	4.3136	6.9652	0.0833	149
Asymmetry of Expertise: Standard deviation of previous of patents	3.9062	6.6092	0	137.18
Mean number of past Co-inventors	2.6952	1.1746	1	34
Members' Quality: Mean number of the citations received by the patents of team members	1.6318	1.6154	0	48.12

N=39894

Table 2: Team composition and the value of innovations. Negative binomial regression, firm fixed-effects

VARIABLES	(1) Citations received count	(2) Citations received count	(3) Citations received count	(4) Citations received count
Team Variety:				
Number of classes	0.0060**	-0.0029		
	(0.0024)	(0.0045)		
Number of sub-categories			0.0053	-0.0096
			(0.0035)	(0.0063)
Members' Breadth:				
Mean number of classes		0.0233**		
		(0.0097)		
Mean number of sub-categories				0.0359***
				(0.0128)
Number of inventors	0.0653***	0.0727***	0.0669***	0.0761***
	(0.0124)	(0.0128)	(0.0124)	(0.0129)
Number of inventors squared	-0.0029**	-0.0030**	-0.0029**	-0.0031**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Members' expertise: Mean number of previous patents	0.0075***	0.0044**	0.0082***	0.0047***
	(0.0016)	(0.0021)	(0.0016)	(0.0020)
Asymmetry of members' expertise: S.D. of number of previous patents	-0.0060***	-0.0040**	-0.0057***	-0.0034*
	(0.0016)	(0.0018)	(0.0016)	(0.0018)
Members' quality: Mean number of citations received by their patents.	0.0861***	0.0861***	0.0860***	0.0862***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Mean number of past co-inventors	-0.0323***	-0.0334***	-0.0322***	-0.0339***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Mean tenure	-0.0098***	-0.0102***	-0.0093***	-0.0100***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Constant	0.3060***	0.2887***	0.299***	0.278***
	(0.0475)	(0.0481)	(0.0474)	(0.0480)
Observations	39,894	39,894	39,894	39,894
Number of firms	1,987	1,987	1,987	1,987

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 3: Mediation Analysis I: Does members' average knowledge breadth affect originality of the innovation? Firm fixed-effects Linear regression.

VARIABLES	(1) Originality index	(2) Originality Index
Team Variety:		
Number of classes	0.0064***	
	(0.0012)	
Number of sub-categories		0.0110***
		(0.0017)
Members' Breadth:		
Mean number of classes	0.0127***	
	(0.0026)	
Mean number of sub-categories		0.0166***
		(0.0033)
Number of inventors	0.0121***	0.0119***
	(0.0032)	(0.0032)
Number of inventors squared	-0.0007**	-0.0007**
	(0.0003)	(0.0003)
Members' expertise: Mean number of previous patents	-0.0035***	-0.0033***
	(0.0004)	(0.0005)
***Asymmetry of members' expertise*: S.D. of number of previous patents**	0.0003	0.0002
	(0.0004)	(0.0004)
Members' quality: Mean number of citations received by their patents.	0.0051***	0.0051***
	(0.0010)	(0.0010)
Mean number of past coinventors	-0.0003	0.0004
	(0.0013)	(0.0013)
Mean tenure	-0.0010**	-0.0012**
	(0.0005)	(0.0005)
Constant	0.2890***	0.2778***
	(0.0130)	(0.0130)
Observations	39,425	39,425
Number of firms	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: Mediation Analysis II: Does controlling for originality affect the effect of members' average knowledge breadth on the value of the innovation?
Negative binomial regression with firm fixed-effects

VARIABLES	(1) Citations received count	(2) Citations received count	(3) Citations received count	(4) Citations received count
***Team Variety*:**				
Number of classes	-0.0029	-0.0030		
	(0.0045)	(0.0045)		
Number of sub-categories			-0.0096	-0.0095
			(0.0063)	(0.064)
***Members' Breadth*:**				
Mean number of classes	0.0233**	0.0208**		
	(0.0097)	(0.0098)		
Mean number of sub-categories			0.0359***	0.0322**
			(0.0128)	(0.0128)
Originality		0.0659***		0.0672***
		(0.0189)		(0.0189)
Number of inventors	0.0727***	0.0703***	0.0761***	0.0735***
	(0.0128)	(0.0128)	(0.0129)	(0.0128)
Number of inventors squared	-0.0030**	-0.0029**	-0.0031**	-0.0029**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
***Members' expertise*: Mean number of previous patents	0.0044**	0.0049**	0.0047***	0.0052***
	(0.0021)	(0.0021)	(0.0020)	(0.0020)
***Asymmetry of members' expertise*:** S.D. of number of previous patents	-0.0040**	-0.0040**	-0.0034*	-0.0034*
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
***Members' quality*: Mean number of citations received by their patents.	0.0861***	0.0861***	0.0862***	0.0861***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Mean number of past coinventors	-0.0334***	-0.0330***	-0.0339***	-0.0335***
	(0.0050)	(0.0050)	(0.0050)	(0.0051)
Mean tenure	-0.0102***	-0.0100***	-0.0100***	-0.0976***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Constant	0.2887***	0.2733***	0.278***	0.263***
	(0.0481)	(0.0486)	(0.0480)	(0.0485)
Observations	39,894	39,417	39,894	39,417
Number of firms	1,987	1,978	1,987	1,978

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