Research Policy 44 (2015) 154–167

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

The *Renaissance Man* is not dead! The role of generalists in teams of inventors

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ARTICLE INFO

Article history:
Received 4 June 2012
Received in revised form 12 July 2014
Accepted 13 July 2014
Available online 6 August 2014

Keywords:
Teams of inventors
Generalists
Knowledge recombination
Patents

ABSTRACT

Is there a role for the multifaceted Renaissance Man in modern team-intensive innovation activities? This paper argues that generalist inventors, holding a broad knowledge set, make an especially valuable contribution to innovation teams in uncertain contexts. For a given level of team knowledge variety, the presence of generalists in an innovation team enables a more effective recombination of knowledge and attenuates the typical barriers affecting team-working processes. On the other hand, the lack of specialized contributions in such teams may hamper the process of adapting each recombined component in the search for an innovative solution. Thus, we expect teams including generalists to perform better than otherwise comparable teams in contexts where there is not a well-defined path to combine knowledge and the advantage of specialized contributions plays only a secondary role. We analyze the role of generalists in teams of inventors in the electrical and electronics industry by tracking the trajectories of individual members and the performance of their teams through their patenting activity. Our findings are consistent with the proposition outlined above.

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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 proverbial "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 process: 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 exclusively from a combination of specialists. Individual co-inventors may have deeper knowledge if their prior expertise is concentrated in a given technological area (specialized contributions) or broader knowledge if such expertise is distributed among different technological areas (generalist contributions). Team-level knowledge variety[1] can then be based on the contribution of some generalist inventor(s) or the combination of specialized contributions. The above question, therefore, has not yet been answered.

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 teams including generalist inventors outperform teams that achieve the same level of variety by gathering specialists in settings where the innovation process involves an especially high degree of uncertainty. Otherwise, the presence of generalists will have no effect or even a negative effect on the final outcome, measured in terms of the economic relevance of the innovation generated. Our

[1] Following Harrison and Klein (2007), we use the term "knowledge variety" in this paper to refer to the diversity in the pieces of knowledge held by a team. Whereas "diversity" is a general term that reflects the existence of differences with respect to the personal characteristics of the members of a group (age, gender, education, knowledge background, etc.), "variety" refers specifically to the diversity with respect to characteristics that are not one-dimensional but multi-categorical (knowledge background or type of education would fall within this definition).

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http://dx.doi.org/10.1016/j.respol.2014.07.005
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main argument is that the knowledge breadth of generalists is particularly valuable for the recombination of knowledge in contexts where the procedures for solving problems are not clearly established. Nevertheless, as Jones (2009) points out, broad-knowledge human capital background can only be built at the expense of knowledge depth. This lack of depth of generalists may negatively affect the efficiency of teamwork in certain settings, where deep knowledge facilitates problem solving.

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), 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 expertise in different technological sub-areas. Empirical results support our hypothesis on the moderating role of domain uncertainty on the relationship between the presence of generalists in a team of inventors and the economic relevance of the innovation they generate: the presence of generalists decreases the relevance of the team output in settings with low levels of uncertainty whereas their presence increases the economic relevance of the outcome in settings with high levels of uncertainty.

2. Theory and hypothesis

In a broad sense, innovation can be described as the result of a process where existing technologies are recombined in a novel way (Schumpeter, 1939). The quality of the result of any innovation effort, therefore, will depend crucially on the ability of the innovator(s) to select and combine existing pieces of knowledge (knowledge recombination) and adapt them to meet each other's requirements (adaptation of components). Additionally, the output produced by a team of inventors will also depend on how co-inventors deal with the usual team malfunctions that arise in the innovation process (inventors' teamwork processes). Prior research suggests that teams that combine a more varied knowledge set enjoy more room for recombination and more alternative paths to solve problems but they also risk suffering more from malfunctions (Paulus, 2000; Jackson, 1996). Below we develop the argument that the presence of generalists in a team of inventors affects the trade-off posed by knowledge variety. We also hypothesize that the role of generalists in this trade-off is moderated by the uncertainty of the setting where the team of inventors operates (domain uncertainty).

2.1. Knowledge recombination

This initial step in the development of an innovation can be understood as a procedure in which inventors identify and select the relevant pieces of knowledge and define the structure of the new combination in a way that offers a novel solution to an existing problem. As a problem-solving process, knowledge recombination will be more effective when at least one head can fit most of the relevant pieces of knowledge together (Simon, 1985). Conversely, if each of the different pieces needed for recombination is held by different co-inventors, the amount and 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 generalist inventors have in mind enables them to conduct a more effective search than that performed by different specialists stitching together several small sections of the same landscape. Understanding the general principles from different technological landscapes at the same time allows generalist researchers to make more informed choices about the combination of distant pieces of knowledge (Gruber et al., 2013). Because they are in a better position to evaluate the potential of alternative links connecting knowledge from different areas, they are expected to be better at identifying fruitful novel technological combinations.

Moreover, in a team setting, the presence of some generalist increases the expected amount of overlapping expertise (i.e., expertise in common areas) among the members of the team. Generalists, then, would play a "knowledge bridging" function that is particularly important for knowledge recombination because shared information is more likely to be retrieved than unshared information in team interactions (Stasser and Titus, 1985; Rulke and Galaskiewicz, 2000). Thus, the potential for both *individual* and *collaborative* knowledge recombination will increase with the presence of generalist inventors in the team.

2.2. Adaptation of components

Once the relevant pieces of knowledge are identified and the structure of the new combination is defined, teams of inventors have to adapt each component to the particular design of the new combination. As mentioned previously, teams including generalist inventors suffer the drawback of having less deep-knowledge contributions than do teams with equivalent amount and variety of expertise but including exclusively specialist inventors. This downside may particularly affect the task of adapting the different elements brought for recombination in a way that they effectively fit each other.

To the extent that the task of adapting individual technological components to the overarching entity can be modularized, the team of inventors will divide it up into independent sub-tasks in order to benefit from division of labor (Von Hippel, 1990; Ethiraj and Levinthal, 2004). Specialist inventors are expected to enjoy an advantage in performing each sub-task as an independent piece of work. They are particularly well suited to attack narrowly defined problems within their area of expertise and, consequently, they can offer superior local search for incremental improvements on particular components (Schmickl and Kieser, 2008). Thus, lacking specialized knowledge in some of the fields in play (in comparison with otherwise equivalent teams), teams with generalist inventors may suffer to tailor the different knowledge components in an effective and timely manner. This shortcoming may have an important impact on the technical quality of the innovation, the time-to-market of its specific applications and their economic value.

2.3. Inventors' teamwork processes

In addition to the effect that the presence of generalists has on the processes of knowledge recombination and adaptation of components, it may also have an impact on the organizational behavior of the team of inventors. Diversity has long been considered a source of both creativity potential and team-working obstacles (e.g., Jackson, 1996). In particular, knowledge variety generates a set of communication, conflict, and free-rider problems that we expect to be attenuated by the presence of generalist inventors.

First, communication problems are a concern for any working group, and innovation teams are no exception. 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., 2010). We expect inventors with a broad background to help reducing intra-group communication problems by serving as a communication node between co-inventors with different backgrounds or by generating a shared code of communication that allows direct pair-wise discussions at all levels. The existence of a common language is an important enabling factor for sharing knowledge and harnessing the potential benefits of knowledge variety (Brown and Duguid, 1998).

A second team-working problem 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). The presence of generalist inventors in a team helps to keep conflict intensity at the moderate level at which it may have a positive effect on performance. Their higher knowledge breadth allows them to better understand the scope of co-inventors' critiques and makes less likely to suffer from a "myopic" view that leads to inflexibility in discussions. These two qualities make generalists suitable to play the mediator role in team conflicts and direct them toward a constructive end.

Finally, the presence of generalists can also help to attenuate the *free riding* problem that occurs in working groups when individual members' contributions to the collective output cannot be measured separately. Group members may exert less effort because any expected reward to their contribution has to be shared with the rest of group members. 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, the presence of some co-inventor with broad knowledge background facilitates the use of peer pressure to counteract free-riding.

In sum, teams of inventors that include some generalist member enjoy some advantages but also suffer some drawbacks with respect to teams that base their knowledge variety exclusively on narrow contributions of their members. On the one hand, teams including generalist co-inventors are expected to recombine knowledge more effectively. They also enjoy an advantage in dealing with classical teamwork issues such as communication problems, conflicts and free-riding.[2] On the other hand, the presence of co-inventors with broad knowledge also involves fewer deep-knowledge contributions (for a given level of expertise and knowledge variety). This can put at risk the ability of the team to develop the adapted components of the innovation in an effective and timely fashion. Therefore, the presence of generalists in teams of inventors generates opposite effects on the value of their output. We argue below that the uncertainty of the particular technological context of the innovation in which the team works delimits the importance of the knowledge recombination process and, therefore, moderates the impact of generalist co-inventors.

2.4. The role of domain uncertainty

We understand *domain uncertainty* as the unpredictability faced by inventors working in a given technological domain with respect to the result of their inventive effort. This uncertainty is related to the (lack of) familiarity of the community of researchers with the particular combination of components that define that domain and is associated with more variable results, i.e., more failures and more breakthrough innovations (Fleming, 2001). Domain uncertainty is an important aspect to address the role of generalists in the process of invention generation. The reason is that generalists are expected to have a comparative advantage precisely in the job of combining the different knowledge elements in play and this comparative advantage is particularly valuable when the structure of such combination is not standard or clearly established.

Knowledge variety can be valuable to address innovation problems in both high and low-uncertainty environments, as long as innovations in both types of contexts need to incorporate elements from different fields. Domain uncertainty, however, reinforces the importance of being able to effectively combine these elements. Technological domains with low uncertainty will typically have well-defined and structured paths to solve technological problems. Furthermore, we expect the variety supplied by specialized contributions to be particularly valuable in these contexts, where low uncertainty makes it easier to break problems down into narrowly defined sub-tasks. This is the case because specialized inventors can provide enhanced local search and design suitable component adaptations associated exclusively with their subtasks (Schmickl and Kieser, 2008).

Conversely, in technological domains with high uncertainty, teams of inventors initially lack a clear road map to combine the different elements in play. This makes the participation of generalist inventors especially valuable. First, defining the structure of the solution to a given technological problem is of particular importance in this context, since the effect of the quality of this process spans to the rest of tasks. A good design of the structure of

[2] 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.

knowledge combination can lead to a very successful outcome as much as a bad decision can lead to absolute failure. As argued above, we expect that teams including generalist inventors are able to establish more and better-quality interconnections between separate pieces of knowledge. This enables them to design comparatively superior knowledge-recombination structures when a standard pattern for such structures does not exist. Secondly, there are limits on the degree to which innovation projects can be modularized, and these limits are tighter when there is more uncertainty in the field about the potential of the different knowledge recombination alternatives (Ethiraj and Levinthal, 2004; Schmickl and Kieser, 2008). Thus, domain uncertainty is associated with a more integral design of innovation projects, which in turn leads to a higher need for intra-team effective communication, giving a higher value to the facilitator role of generalists.

To sum up, we expect uncertainty to play a key moderating role in the effect of the presence of generalists in teams of inventors.

Hypothesis 1. For a given level of knowledge variety in a team of inventors, the presence of generalist inventors has an effect on the relevance of the innovation that is positively moderated by the domain uncertainty of the recombination process such that:

a. For low levels of domain uncertainty, the relevance of the innovation generated by the team decreases with the presence of generalists.
b. For high levels of domain uncertainty, the relevance of the innovation generated by the team increases with the presence of generalists.

3. Data, variables and methods

3.1. 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. They 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 1975 up to 1999. This dataset includes, for each patent, a set of information of interest to our analysis, mainly: (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) and (2) its classification into a technological domain (the primary technological class of the patent). By tracking any given inventor across patents and looking in which technological area they are classified, we are able to identify the knowledge background of each inventor who participates in a team innovation. In order to have a reliable historical record for each inventor, we only analyze team patents from 1985 to 1999. We also retrieve data from the "OECD Triadic Patent Families database", that allows us to identify whether the US patents are also filed in the European and Japanese patent offices. Finally, we use the Fleming Dataverse dataset (Lai et al., 2013) in order to retrieve the whole set of technological areas in which the patent is assigned to (primary and secondary classes).

We restrict our analysis to patents granted to private firms 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 1985–1999. 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[3] appears at least twice in the sample and contributes with some within-firm variation. These restrictions produce a final sample of 32,010 teams from 880 assignees.

Using patent data to analyze the composition and performance of teams of inventors has several limitations. First, 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 et al., 2013). These issues may generate some measurement error leading to an attenuation bias in the estimation of effects in our empirical analysis.

3.2. Key variables of the analysis

3.2.1. Economic relevance of the innovation

We measure the economic relevance of the innovation, the dependent variable of our analysis, with an indicator equal to 1 if the patent protecting the innovation is a triadic patent and 0 otherwise (variable *Triadic*). Triadic patents are patents jointly filed at the European, Japanese and US patent offices and therefore, granting protection to all these markets. Non-triadic patents in our sample are therefore patents only being filed in the USPTO. Given the substantially higher filing and maintenance costs of triadic patents with respect to patents applied only in the US, we expect that firms file for triadic patents only to protect economically relevant innovations (Guellec and van Pottelsberghe de la Potterie, 2008).

3.2.2. Presence of generalists

We capture the presence of generalists in the team with a dummy variable that equals to one if at least one member of the team can be considered a generalist inventor, and zero otherwise. In order to define generalist inventors, we compute, for each inventor, the diversification of his expertise across technological areas, and

[3] 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.

TEAM WITHOUT GENERALISTS RESPONSIBLE FOR PATENT # 5925932					TEAM WITH GENERALISTS RESPONSIBLE FOR PATENT # 5895266				
INVENTOR A					INVENTOR A				
	Subcat	Freq.	Percent	(1-H)		Subcat	Freq.	Percent	(1-H)
	24	1	12.50			19	1	33.33	
	46	7	87.50			46	2	66.67	
				0.219					0.444
INVENTOR B					INVENTOR B				
	Subcat	Freq.	Percent	(1-H)		Subcat	Freq.	Percent	(1-H)
	19	1	16.67			19	2	100	
	46	5	83.33						
				0.278					0
INVENTOR C					INVENTOR C				
	Subcat	Freq.	Percent	(1-H)		Subcat	Freq.	Percent	(1-H)
	12	1	100.00			12	1	14.29	
						19	2	28.57	
						46	3	42.86	
						54	1	14.29	
				0					0.694

Fig. 1. Example of a team including a generalist inventor and one not including it (both teams have *Number of Inventors* = 3 and *Team Variety* = 4).

consider one minus the Herfindhal index (1-H).[4] We consider two alternative levels of aggregation to identify technological areas: class and subcategory. Innovations patented at the USPTO are classified into 416 primary (or main) technological classes (as of 1999) that Hall et al. (2001) group into 36 narrower subcategories. The narrow scope of patent-class grouping minimizes the chances of understating the real breadth of knowledge of individual inventors. On the other hand, the broader scope of the subcategory level avoids overstating it, but may fail to consider the technological heterogeneity that may exist within a given subcategory.

We code a team as including some generalist (*Presence of Generalist* = 1) if the inventor with the highest diversification (1-H) in this team falls within the top 10% of the distribution. This corresponds to (1-H) ≥ 0.756 using the measure based on classes and (1-H) ≥ 0.6938 using the measure based on subcategories. Fig. 1 presents two examples of comparable teams in our sample, one that includes a generalist inventor one that does not. As robustness checks, we present results for measures that set the threshold at the top 5% (corresponding to (1-H) ≥ 0.808 for classes and (1-H) ≥ 0.750 for subcategories) and the top 25% (corresponding to (1-H) ≥ 0.666 for classes and (1-H) ≥ 0.566 for subcategories).

3.2.3. Domain uncertainty

We operationalize the existing uncertainty in the knowledge recombination process in a given domain with a measure based on the variance of the importance of the past innovations in that domain. In particular, we use the dispersion index of the citations received by patents assigned in the past to the exact same combination of technological classes (primary plus secondary classes) to which the focal innovation is assigned:

$$\text{Dispersion index} = \frac{\sigma^2}{\mu}$$

where σ^2 and μ represent the variance and the mean of the standardized citations[5] received by previous patents assigned to the corresponding combination. We consider patents that were applied for during the previous five years before the focal patent was filed.

Thus, we use the index of dispersion of the citations received by previous patents in a given technological domain (i.e., a given combination of technological classes) to measure the uncertainty associated with knowledge recombination in that domain (variable *Uncertainty*). Because every patented innovation must cite the previous patents upon which it builds, patents with more citations tend to represent innovations that have contributed more to technological development. Consequently, domains where past patents tend to register more extreme values in number of citations (i.e., higher dispersion) are domains associated with higher uncertainty about how to re-combine the relevant knowledge in a valuable way, while in domains with less dispersion in citations there is less uncertainty in that sense. A high dispersion index suggests that there are effective paths for knowledge re-combination (as shown by the existence of a number of successful past innovations in that domain) but it is not obvious how to navigate them (as shown by the existence of a number of failed trials as well). Conversely, a low dispersion index indicates less uncertainty about the path to effective re-combination, either because such a path has proven ineffective (past innovations in the domain have none or a very low number of citations) or because it has proven to be effective and is readily available to inventors (they *all* tend to have a similar moderate or high number of citations).

3.3. Control variables

3.3.1. 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 (variable *Team Variety*). The larger the number of different areas in which at least one team member worked in the past, the greater the team knowledge variety. As with our measure of the presence of generalists in teams, we consider both the class and subcategory levels of aggregation to identify technological areas. Singh and Fleming (2010) also use the number of different technological classes in which team members patented in the past to capture knowledge variety.

3.3.2. Number of trials

We introduce as a control the number of times that the specific combination of technological classes in which the focal patent is assigned to has appeared in any previous patent during the last five years. In other words, this variable accounts for the frequency with which inventors have done research in the past in the specific

[4] An alternative measure of inventors' knowledge breadth that we could have used here is the simple count of areas in which the inventor has filed a patent. We follow Gruber et al. (2013) in considering that both the number of areas and the relative amount of experience that the inventor has in each area are important in determining whether an inventor is a generalist or not. Hence, we prefer the Herfindhal index.

[5] 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 domain of the focal patent. By controlling for this variable in the regression analysis, we are able to capture the effect of domain uncertainty while keeping constant the number of past re-combination trials in this domain.

3.3.3. 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.

3.3.4. 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.

3.3.5. 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 the presence of generalists. We capture the asymmetry in team members' expertise with the standard deviation of their number of previous patents.

3.3.6. 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. This allows us to improve our ability to control for the distribution of expertise within the team and therefore identify the effect of the presence of generalists.

3.3.7. Average quality of members' expertise

The quality of team members' past work may be related to the value of their subsequent work, since it may reflect the inventors' underlying ability. Therefore, we introduce a control variable that captures the average quality of the patented innovations created by co-inventors. In particular, we account for the average number of forward citations received by previous patents in which team members of the focal patent participated. More specifically, we use standardized citations received 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.

3.3.8. 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.

3.3.9. 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.

3.3.10. 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.

3.3.11. Technological area effects

There are differences in the propensity to be cited across different technological 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.

3.3.12. Time effects

We use a set of dummy variables to account for the year in which the patent is applied for. Controlling for time effects is important because there are technological and economic factors in the electrical and electronics sector that change over time and may be related to a firm's propensity to file a triadic patent.

3.4. Methods

We use a fixed-effects (conditional) logit regression model and a fixed-effects linear probability model to test our hypothesis. Given that our dependent variable is a dichotomous indicator -being a triadic patent or not-, logit regression is an appropriate model to approach the hypothesized relationship. Furthermore, there are potentially important unobserved firm-level attributes that could confound our analysis and need to be accounted for. Fixed-effects logit regression allows us to explore how within-firm differences in team composition relate to within-firm differences in the triadic status of the patents produced by these teams, allowing us to control for firm-level unobserved heterogeneity.

We also present a linear probability model with firm fixed-effects, so that we can provide a good and simple approximation to the average partial effects, something that we cannot do with the logit fixed-effects (see Wooldridge, 2010). Moreover, the linear model allows a neat and straightforward interpretation of the magnitude of interaction effects, which are needed for the analysis of the moderator role of domain uncertainty.

We present a series of tests of the robustness of our analysis. First, in order to check the sensitivity of our results to the measure of uncertainty chosen, we repeat our main analysis using the average lag of the citations made by the focal patent as an alternative indicator. Second, we check whether results are robust to the selection of *Triadic* as our main dependent variable by using the (standardized) number of forward citations received as an alternative indicator. Given the count-data format of this alternative dependent variable, we use a negative binomial regression model for this second robustness test. Finally, to address a potential endogeneity problem in the composition of teams of inventors, we present a robustness check where we use the relative availability of generalists in the focal firm and year as an instrument for the presence of generalists in teams. As recommended by Angrist and Pischke (2009), we use the linear probability model for the instrumental variable estimation.

4. Results

The descriptive statistics of the variables used in this study are presented in Table 1A. The average patented innovation in our sample has been developed by a team of 3 members, who jointly accumulate expertise on 3.6 different classes or 2.8 different subcategories. The individual with the highest dispersion in expertise per team has an average (1-H) index of 0.41 (if based on classes) or

Table 1A
Summary statistics.

Variable	Mean	Std. Dev.	Min	Median	Max
Triadic	0.3551	–	0	0	1
Presence of generalist:					
Based on classes	0.1091	–	0	0	1
Based on sub-categories	0.1098	–	0	0	1
Maximum individual dispersion in the team:					
Based on classes	0.4119	0.3007	0	0.5000	0.9534
Based on subcategories	0.3374	0.2860	0	0.4444	0.9066
Uncertainty	1.6348	1.3649	0	1.211	20.707
Team variety:					
Number of classes	3.575	3.1891	1	3	36
Number of sub-categories	2.7682	2.0811	1	2	16
Number of trials	1326	1594	2	802	7082
Number of inventors	2.9363	1.2771	2	3	23
Members' mean tenure	4.0578	3.3747	0.1	3	25
Members' mean expertise: mean number of previous patents	4.6403	7.4137	0.0909	2.3333	149
Asymmetry of expertise: standard deviation of previous of patents	4.2129	7.0537	0	2.1213	137.18
Mean number of past Co-inventors	2.7273	1.1757	1	2.5287	34
Members' mean quality: mean number of the citations received by the patents of team members	1.6539	1.6046	0	1.2830	48.11
Team tenure	0.1982	–	0	0	1
Number of inventors without expertise	0.9022	1.0589	0	1	11
(Average) Backward citation lag	9.0405	6.2419	0	7.5833	80
(Year-Class) Standardized citations received	1.3973	2.3298	0	0.7042	83.0189

$N = 32,010$.

0.34 (if based on sub-categories). This is the variable that we use to build our main independent variable, the presence of at least one generalist in a team. At the individual level, the members of the team have an average expertise of 4.6 previous patents. The probability that a patent in our sample is a triadic patent is 35.5%. Table 1B presents the correlation matrix of these variables.

Table 2 presents the results of the logit regression model with firm fixed-effects for the probability of being a triadic patent. In order to provide average marginal effects, we report as well linear regressions with firm fixed-effects (which yields qualitatively similar results). The table displays the effect of the presence of generalists 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 effect of the presence of generalists in a team. Given that we control for the total number of patents filed in the past by the co-inventors and for the number of areas in which the team has experience, the effect of presence of generalists in a team is necessarily associated with fewer specialized contributions (as illustrated by the differences between the knowledge structure of the two examples presented in Fig. 1).

All the different specifications in Table 2 suggest that having at least one generalist in the team has a negative and significant effect on the likelihood of a patent being triadic in domains of low uncertainty. According to columns (2) and (4), keeping team variety (and all other things) constant, the presence of a generalist in a team working in a domain with the lowest level of uncertainty (zero) decreases the probability of having a triadic patent by approximately 4% (3.8% if we use the class level to define generalists or 4.1% if we use the more aggregated level of subcategories). This negative effect is attenuated and turns to positive for domains with higher levels of uncertainty. Fig. 2 displays the effects (with 5% confidence intervals) of the variable *Presence of Generalist* on the probability of having a triadic patent across the range of values of *Uncertainty*. According to the estimates in column (2), for measures based on technological classes, the negative effect remains significant (at the 10% level) for values of domain uncertainty lower than 0.76 (16.6% of our sample). As shown by Fig. 2A, the effect turns to positive for uncertainty levels above 1.78, though it only has a positive significant effect for values of uncertainty higher than 2.86 (12.3% of our sample). For this particular level, the presence of a generalist increases the probability of having a triadic patent by 2.3% ($-0.038 + 0.021 * 2.86 = 0.023$). Results follow a very similar pattern when the presence of a generalist and team variety are measured according to the expertise at the more aggregated level of subcategories (Fig. 2B). In this case, the negative effect of the presence of a generalist in a team is significant for values of uncertainty lower than 0.9, which represents the lowest 28% of our sample. This effect turns positive when uncertainty equals 1.72 and it is positive and significant for values of uncertainty greater than 2.57 (top 15% of our sample). For this value of uncertainty, the presence of a generalist increases the probability of having a triadic patent by 2%.

Although the fixed-effects logit model does not allow us to obtain partial effects, we can interpret the estimated effect of the

Table 1B
Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) *Triadic*																
(2) *Presence of generalist (classes)*	0.0123															
(3) *Presence of generalist (subcats)*	0.0184	0.662														
(4) *Uncertainty*	−0.0369	0.0496	0.0211													
(5) *Team variety (classes)*	0.0116	0.6600	0.5868	0.1043												
(6) *Team variety (subcats)*	0.0147	0.6219	0.6316	0.0835	0.9434											
(7) *Number of trials*	−0.0606	−**0.0004**	−0.0258	0.3091	0.0486	0.0274										
(8) *Number of tnventors*	0.0721	0.0854	0.0983	0.0449	0.1834	0.1837	0.0255									
(9) *Mean tenure*	0.0221	0.2389	0.2026	−0.0351	0.4093	0.4002	−0.0213	−0.091								
(10) *Mean expertise*	−0.0337	0.2631	0.2076	0.197	0.5786	0.5393	0.1838	−0.071	0.3444							
(11) *Assymetry of expertise*	−0.0408	0.2476	0.1914	0.1823	0.5333	0.5028	0.1637	−0.0197	0.2313	0.8458						
(12) *Past Co-inventors*	0.0301	0.0734	0.0783	0.104	0.0918	0.0949	0.0735	0.3386	−0.0122	0.0308	0.0123					
(13) *Mean quality*	0.0539	0.02	0.017	0.2044	0.0613	0.0539	0.0242	0.0242	−0.0509	0.1011	0.0803	0.1058				
(14) *Team tenure*	0.0372	0.0723	0.0603	0.0735	0.1288	0.1215	0.0652	−0.1065	0.1842	0.2953	0.1221	**0.0034**	0.0589			
(15) *Inventors without expertise*	−**0.0053**	−0.0898	−0.073	−0.0418	−0.1872	−0.1821	−0.0408	0.5545	−0.3661	−0.2941	−0.1493	0.0330	−0.0363	−0.4236		
(16) *Backward Citation Lag*	−0.0219	−0.0221	−0.0306	−0.1479	−0.0676	−0.0654	−0.0545	−**0.0144**	0.0560	−0.0842	−0.0779	−0.0356	−0.1681	**0.0069**	0.0246	
(17) *Standardized citations received*	0.0718	**0.0056**	**0.0090**	0.0672	0.0333	0.0265	−0.0393	0.0399	−0.0372	0.0332	0.0154	0.0193	0.2513	**0.0032**	**0.0084**	−0.1503

Note: All correlations are significant at the 5% except for the bold values.

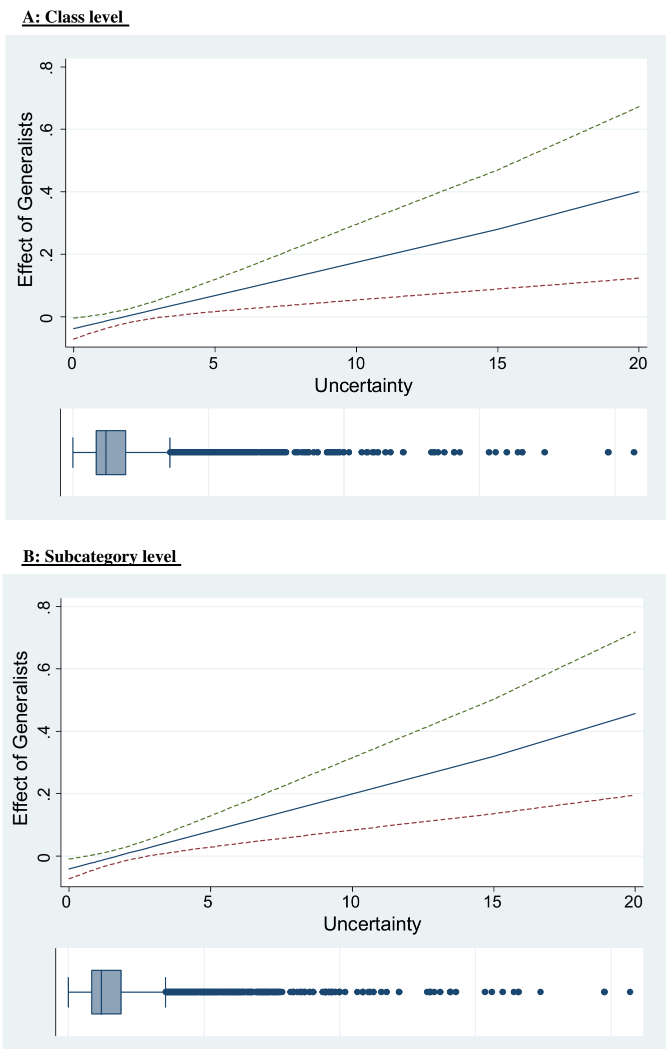

Fig. 2. Change on the probability that a patent is Triadic caused by the presence of generalists for different levels of uncertainty (with box-plot of uncertainty).

presence of a generalist in columns (1) and (3) in terms of odds-ratio (the magnitude by which the odds of being a triadic patent is multiplied when the team includes at least one generalist member). For the class level specification, for instance, the odds of being a triadic patent is multiplied by $\exp(-0.224) = 0.799$ when the team includes at least one generalist member in the lowest-uncertainty context. The value of such odds-ratio increases with domain uncertainty and takes values above one for uncertainty levels above 1.76.

These findings provide support for our Hypothesis: the presence of generalists in a team has a negative effect on the relevance of the resulting innovation when uncertainty is low, whereas it turns to positive for high levels of uncertainty. Most of the important control variables in Table 2 show effects in the expected direction. Although our theoretical analysis does not provide a clear prediction with respect to team variety, prior research by Singh and Fleming (2010) suggests that the effect should be positive. In our study, team variety has a positive and significant effect on the relevance of the innovation for low levels of uncertainty, which drops to non-significant levels for high-uncertainty contexts.[6]

Regarding the rest of control variables, members' mean tenure and their expertise (in terms of quality of past patents) and the tenure of the team have a positive effect on the likelihood of producing a triadic patent, the number of inventors has a positive but decreasing effect, while the mean number of past co-inventors, the presence of inventors without experience and the number of times the same recombination of areas appears in previous patents have all a negative effect.

Results are robust to changes in the way that we define our key variables. First, our initial definition of generalist inventors considers as teams with a generalist only those teams whose highest-breadth member is within the *top 10%* of the distribution of the knowledge-breadth measure (1-H). Table 3 shows the results for the most relevant variables when the threshold is set at the top 5% or the top 25%. They are qualitatively similar to those of Table 2. Secondly, our *Uncertainty* variable is based on the dispersion index of citations received by the patents filed in the same domain (combination of technological classes) in the *last 5 years*. We replicated our analysis for alternative measures of uncertainty that either extend this window to the previous 10 years or shorten it to the previous 3 years. The results (available upon request to the authors) are also qualitatively similar to those of Table 2.

5. Robustness checks

This section addresses three issues that could question the results presented previously: the reliability of our indicator of domain uncertainty, the robustness of our results to the use of an alternative measure of the importance of the output, and the potential endogeneity of the relevant independent variables.

5.1. Uncertainty

In the previous section, we capture domain uncertainty with an index of dispersion of the citations received by patents belonging to the same combination of technological classes in the last 5 years. To the best of our knowledge, this measure is novel to the innovation literature and has the advantage of being directly based on the actual spread of the distribution of value of past patents in the technological domain. An alternative approach, in the context of the available data, is to use some patent characteristic that can be reasonably assumed to be associated with the technological uncertainty of the corresponding project.

Therefore, in order to check the robustness of the results to the selection of our measure of uncertainty, we exploit a patent attribute that has previously been used in the literature: the average lag of the citations made by the focal patent (*Backward Citation Lag*). This variable captures the average difference (in years) between the grant year of the patent and the grant year of the previous patents it cites to. Prior research suggests a link between this variable and the degree of uncertainty of the associated technology. Gans et al. (2008) and Fabrizio (2009) relate longer citation lags to lengthier technological cycles and, therefore, shorter lags to more rapidly changing technological conditions. Similarly, Lin and Chen (2005) point out that the citation lag may capture to which extent the technological field is mature. All this suggests that inventors working in innovations that cite more recent prior art are likely to be facing projects in less mature domains where uncertainty about possible ways to combine knowledge is more prevalent.

[6] Note that we introduce the interaction of team variety with uncertainty in order to be able to neatly capture the interaction effect of uncertainty with our variable of interest (*presence of generalists*). Otherwise, the estimate of the hypothesized moderating effect of uncertainty on presence of generalists could pick up a confounding interaction effect of team variety and uncertainty.

Table 2
The presence of generalists (top 10% knowledge breadth) in teams of inventors and value of innovations. Logit and linear regressions (robust standard errors), firm fixed-effects.

Variables	Class level		Subcategories level	
	Logit	Linear regression	Logit	Linear regression
	(1) Triadic	(2) Triadic	(3) Triadic	(4) Triadic
Presence of generalists	−0.224**	−0.0378**	−0.234***	−0.0414**
	(0.0907)	(0.0186)	(0.0861)	(0.0192)
Uncertainty	0.0412**	0.0084**	0.0498**	0.00995**
	(0.0201)	(0.0037)	(0.0212)	(0.0041)
Presence of generalists × uncertainty	0.127***	0.0212***	0.140***	0.0240***
	(0.0405)	(0.0068)	(0.0387)	(0.0075)
Team variety	0.0293***	0.0054**	0.0422***	0.0080*
	(0.0104)	(0.0023)	(0.0150)	(0.0042)
Team variety × uncertainty	−0.00718*	−0.0013	−0.0122**	−0.0023*
	(0.00414)	(0.0009)	(0.0058)	(0.0012)
Number of trials	−0.00002***	−0.00001**	−0.00005***	−0.00001**
	(0.00001)	(0.00000)	(0.00001)	(0.0000)
Members' mean tenure	0.0203***	0.0038***	0.0209***	0.0039***
	(0.00515)	(0.0012)	(0.0051)	(0.0012)
Member's mean expertise	−0.00699	−0.0012	−0.0062	−0.0011
	(0.00445)	(0.0011)	(0.0044)	(0.0012)
Assymmetry of members' expertise	0.00224	0.0005	0.0026	0.0006
	(0.00412)	(0.0006)	(0.0041)	(0.0006)
Members' mean quality	0.0876***	0.0161***	0.0875***	0.0161***
	(0.0104)	(0.0031)	(0.0105)	(0.0031)
Team tenure	0.248***	0.0464***	0.2473***	0.0464***
	(0.0392)	(0.0070)	(0.0392)	(0.0081)
Members without expertise	−0.0666***	−0.0138***	−0.0675***	−0.0140***
	(0.0187)	(0.0048)	(0.0187)	(0.0049)
Mean number of past-coinventors	−0.0266**	−0.0053	−0.0268**	−0.0053
	(0.0135)	(0.0033)	(0.0135)	(0.0032)
Number of inventors in this patent	0.228***	0.0436***	0.230***	0.0439***
	(0.0335)	(0.0070)	(0.033)	(0.0071)
Number of inventors squared	−0.00777**	−0.0013**	−0.0077**	−0.0013**
	(0.00335)	(0.0006)	(0.0033)	(0.0006)
Observations	32,010	32,010	32,010	32,010
Number of assignees	880	880	880	880

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

Table 4 displays the results of our different specifications with this alternative measure of uncertainty. Note that *Backward Citation Lag* measures the (lack of) uncertainty associated with the project. Thus, we expect that (1) if the backward citation lag is very short (high uncertainty context), the presence of generalists will have a positive impact, and (2) this effect will decrease and turn to negative as the citation lag increases. Results are generally consistent with the main findings of the previous section, although they are less robust across the different definitions of generalists and levels of aggregation of knowledge. In all but one model, the effect of the presence of generalists on the economic relevance of the innovation is, as expected, positive when the citation lag is very short and decreases as the citation lag increases. These effects, however, are only statistically significant for two of the six models considered.

5.2. Economic relevance of the innovation

In the previous section, we measure the economic relevance of the innovation with an indicator of whether the patent that protects it is triadic. To the extent that the firm's decision to invest in obtaining triadic protection for the innovation is driven by the balance of costs and benefits of that action, *Triadic* is a variable particularly linked to the economic relevance of the innovation. Past research, however, has heavily relied on the number of *forward citations received* as indicator of patent value, provided that there is some evidence that such indicator is correlated with the actual economic value of the patented innovation (Trajtenberg, 1990). Thus, a natural check to test the robustness of the results with respect to alternative measures of our dependent variable is to replicate the analysis using the number of forward citations received instead of *Triadic*.

Table 5 shows the results (for the main variables of interest) of the proposed replication using the *Standardized Number of Citations Received* as dependent variable.[7] Given the count data nature of the variable, we present the results from a negative binomial model with firm fixed-effects (Wooldridge, 2010). Similar findings, though, were obtained with a linear approach (results are available upon request). The coefficients presented in Table 5 tell a similar story than those of Tables 2 and 3 with respect to the role of generalists in teams of inventors. The main effect of *Presence of Generalist* on *Standardized Number of Citations Received* is negative and significant and its interaction with *Uncertainty* is positive and significant for the different definitions of generalist and levels of aggregation considered (except for the “top 25”

[7] We address the right-side truncation bias in citations received by standardizing each patent's citations with respect to the citation distribution of its primary class in the corresponding application year (as Hall et al., 2001 propose and as we do with our measure of uncertainty). The use of this particular dependent variable implies that we do not have to include the application year of the patent in the right-hand side of the equation.

Table 3
The presence of generalists in teams of inventors and value of innovations. Alternative measures for generalists (Top 5% & Top 25% knowledge breadth). Logit and linear regressions (robust standard errors), firm fixed-effects.

Variables	Class level		Subcategories level	
	Logit	Linear regression	Logit	Linear regression
	(1) Triadic	(2) Triadic	(3) Triadic	(4) Triadic
A. Generalists as top 5%				
Presence of generalists	−0.284**	−0.0524**	−0.0938	−0.0138
	(0.115)	(0.0229)	(0.106)	(0.0224)
Uncertainty	0.0383*	0.0079**	0.0450**	0.0091**
	(0.0201)	(0.0039)	(0.0212)	(0.0041)
Presence of generalists × uncertainty	0.127***	0.0219**	0.126***	0.0227***
	(0.0483)	(0.0102)	(0.0486)	(0.0087)
Team variety	0.0274***	0.0053***	0.0243*	0.0045*
	(0.0098)	(0.0023)	(0.0141)	(0.0039)
Team variety × uncertainty	−0.0042	−0.0009	−0.00724	−0.0015
	(0.0038)	(0.0009)	(0.00549)	(0.0014)
Observations	32,010	32,010	32,010	32,010
Number of assignee	880	880	880	880
B. Generalists as top 25%				
Presence of generalists	−0.171***	−0.0309**	−0.136**	−0.0241**
	(0.0630)	(0.0139)	(0.0654)	(0.0110)
Uncertainty	0.0265	0.0062*	0.0371*	0.00818**
	(0.0195)	(0.0036)	(0.0207)	(0.0040)
Presence of generalists × uncertainty	0.0878***	0.0153**	0.103***	0.0179***
	(0.0289)	(0.0068)	(0.0296)	(0.0051)
Team variety	0.0297***	0.0057**	0.0377**	0.0073*
	(0.0102)	(0.0026)	(0.0158)	(0.0042)
Team variety × uncertainty	−0.00611	−0.0013	−0.0128**	−0.0025*
	(0.00393)	(0.0009)	(0.00607)	(0.0013)
Observations	32,010	32,010	32,010	32,010
Number of assignee	880	880	880	880

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

definition of generalist with the measures calculated at the class level). In other words, for low levels of domain uncertainty, having at least one generalist in the team has a negative effect on citations received that turns to positive when domain uncertainty is high. Furthermore, the magnitude of the estimated coefficients suggest that the effect of the presence of generalists on citations received turns to positive for levels of uncertainty that are similar to the ones described in the previous section for the *Triadic* measure.

5.3. *Endogeneity*

The fact that our analysis controls for firm fixed effects allows us to capture a wide range of potential confounding factors. Still,

Table 4
The presence of generalists in teams of inventors and the value of innovations. Robustness checks using backward citation lag as a measure of (lack of) uncertainty. Linear regression (robust standard errors), firm fixed-effects.

Definition of generalist:	TOP 10%		TOP 5%		TOP 25%	
Variables	Class level	Subcategory level	Class level	Subcategory level	Class level	Subcategory level
	Triadic	Triadic	Triadic	Triadic	Triadic	Triadic
Presence of generalists	0.0440**	−0.0039	0.0026	0.0362	0.0202	0.0239*
	(0.0210)	(0.0228)	(0.0230)	(0.0442)	(0.0125)	(0.0136)
Backward citation lag	−0.0023***	−0.0011	−0.0018**	−0.0014	−0.0019**	−0.0015*
	(0.0009)	(0.0009)	(0.0008)	(0.0010)	(0.0008)	(0.0009)
Presence of generalists × backward citation lag	−0.0050**	0.0006	−0.0016	−0.0012	−0.0029**	−0.0020
	(0.0023)	(0.0024)	(0.0025)	(0.0027)	(0.0014)	(0.0014)
Team variety	0.0007	0.0066	0.0037	0.0036	0.0017	0.0027
	(0.0028)	(0.0054)	(0.0031)	(0.0054)	(0.0029)	(0.0050)
Team variety × backward citation lag	0.0003	−0.0003	0.0000	−0.0002	0.0002	0.0000
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Observations	31,714	31,714	31,714	31,714	31,714	31,714
Number of assignees	880	880	880	880	880	880

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

Table 5
The presence of generalists in teams of inventors and the value of innovations. Robustness checks using standardized citations received as dependent variable. Negative binomial regression, firm fixed-effects.

Definition of generalist:	TOP 10%		TOP 5%		TOP 25%	
Variables	Class level	Subcategory level	Class level	Subcategory level	Class level	Subcategory level
	(1) Std. citations received	(2) Std. citations received	(3) Std. citations received	(4) Std. citations received	(5) Std. citations received	(6) Std. citations received
Presence of generalists	−0.1333***	−0.0851*	−0.2618***	−0.0973*	−0.0729**	−0.0902**
	(0.0484)	(0.0468)	(0.0592)	(0.0566)	(0.0337)	(0.0358)
Uncertainty	−0.1601***	−0.2048***	−0.1498***	−0.2016***	−0.1673***	−0.2098***
	(0.0107)	(0.0121)	(0.0107)	(0.0120)	(0.0103)	(0.0119)
Presence of generalists × uncertainty	0.0699***	0.0856***	0.1822***	0.1356***	0.0224	0.0550***
	(0.0248)	(0.0248)	(0.0282)	(0.0297)	(0.0178)	(0.0190)
Team variety	0.0052	0.0073	0.0078	0.0047	0.0038	0.0137
	(0.0055)	(0.0080)	(0.0052)	(0.0075)	(0.0054)	(0.0085)
Team variety × uncertainty	−0.0049**	−0.0095**	−0.0090***	−0.0102**	−0.0024	−0.095**
	(0.0025)	(0.0038)	(0.0024)	(0.0036)	(0.0024)	(0.0040)
Observations	31,915	31,915	31,915	31,915	31,915	31,915
Number of assignees	880	880	880	880	880	880

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

within-company differences in the presence of generalists in teams of inventors may not be exogenous to the relevance of the innovations that these teams generate. The reason is that team design may be to some extent the result of some unobserved feature of the initial idea that is correlated with the final output. R&D managers may tend to assign, for example, inventors with broad knowledge to projects with particularly high or low initial potential. A similar argument can be made for the knowledge variety of the team. Our analysis up to now assumes that the value of a patented innovation is generated during the team-working process. But if such assumption fails, the presence of a generalist or the knowledge variety of the team of inventors may be endogenous variables and, thus, the estimated coefficients resulting from our previous analysis could be biased.

To address this potential problem, we use an instrumental variables approach. The idea behind the instrumental variables estimation is that there may be some factors affecting the potentially endogenous variables that have no direct relationship with the dependent variable and can be exploited as sources of exogenous variation ("instruments"). In our particular setting, the proposed instruments are the respective aggregated measures at the firm-year level: (i) the relative availability of generalists in the firm in the focal year (the number of generalists in the firm relative to the total number of patents filed by the company in that year) and (ii) the knowledge variety available in the firm in the focal year (the number of different areas in which the inventors who patent in the firm that year have worked in the past). Since the test of our hypothesis requires including in the analysis the interaction of the potentially endogenous variables with domain uncertainty, such interactions have also been instrumented.[8]

The rationale for using these instruments is that, even if R&D managers want to design innovation teams according to the potential of the project, their actions are constrained by the human resources available in their company in a given moment of time. Thus, teams of inventors will be more likely to include a generalist in their ranks when there are relatively more generalists available in their firms. More generally, teams will tend to have a more varied knowledge set in companies whose R&D workers have expertise in a more varied pool of technological areas in the corresponding year. Firm-year relatively availability of generalist and aggregated knowledge variety are potentially useful instruments because, unlike their team-level counterparts, they are not likely to be endogenously determined by the potential of a given innovation project. However, there is an additional requirement that they need to meet: the instruments can only affect the dependent variable through their effect on the instrumented factors. This means that differences across years in firm-level relative availability of generalists and aggregated knowledge variety can only lead to differences in the economic importance of the patented output through their effect on team-level variety and presence of generalists in teams. In other words, we need to assume that there are not important spillovers across teams working simultaneously in a given firm (or, at least, that if those spillovers exist, they are not related to firm-level availability of generalists and knowledge variety). As long as this last assumption is weaker than the assumption that assignment of inventors to projects is unrelated to potential project value, the instrumental variables estimation is a useful test of the robustness of our results.

Table 6 shows the results of estimating the effect of the presence of a generalist in the team on the probability of a triadic patent with the instrumental variables described above. The presented estimates are the partial effects corresponding to a linear probability model with firm fixed-effects estimated through two-stage least squares.[9] The table shows estimation results that are qualitatively consistent with those of Tables 2 and 3: a negative effect of the presence of a generalist in contexts of low uncertainty that turns to positive as uncertainty grows. This pattern is robust across the different definitions of generalists. In quantitative terms,

[8] In particular, we have included as additional instruments the natural candidates in this context: (i) the interaction between the firm-level relative availability of generalist and the uncertainty of the domain of the project and (ii) the interaction between firm-level aggregated knowledge variety and the uncertainty of the domain.

[9] We follow Angrist and Pischke's (2009) suggestion and use a linear model instead of logit for the instrumental-variables analysis, even if our dependent variable and one of our instrumented variables are dichotomous. The reason is that we want to make sure that the variations generated in the instrumented variables in the first stage truly come from variations in the instruments and not from non-linearity of the model. Estimating the second step with logit regression, however, produced qualitatively similar findings (results available upon request).

Table 6
The presence of generalists in teams of inventors and the value of innovations. 2SLS instrumental variable estimation of linear regressions, firm fixed-effects (2nd stage results).

Definition of Generalist:	TOP 10%		TOP 5%		TOP 25%	
Variables	Class level	Subcategory level	Class level	Subcategory level	Class level	Subcategory level
	Triadic	Triadic	Triadic	Triadic	Triadic	Triadic
Presence of generalists	−0.4271***	−0.4002***	−1.1020***	−0.5959***	−0.3319**	−0.1843**
	(0.1565)	(0.1134)	(0.1742)	(0.1450)	(0.1398)	(0.0818)
Uncertainty	0.0688***	0.0596**	0.0541**	0.0798***	0.0651***	0.0575***
	(0.0123)	(0.0129)	(0.0128)	(0.0195)	(0.0139)	(0.0114)
Presence of generalists × uncertainty	0.1389**	0.0747**	0.0823*	0.1309*	0.2642***	0.1005***
	(0.0609)	(0.0357)	(0.0477)	(0.0735)	(0.0883)	(0.0323)
Team variety	0.0849***	0.0644**	0.0995***	0.0748**	0.0124	0.0846***
	(0.0222)	(0.0315)	(0.0197)	(0.0321)	(0.0308)	(0.0361)
Team variety × uncertainty	−0.0199***	−0.0205***	−0.0122***	−0.0266***	−0.0359***	−0.0269***
	(0.0045)	(0.0054)	(0.0038)	(0.0078)	(0.0097)	(0.0063)
Observations	32,010	31,963	32,010	31,963	32,010	31,963
Number of assignees	880	880	880	880	880	880

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

however, the estimated coefficients are considerably larger than those of the previous analysis. This suggests that the results from Tables 2 and 3 may suffer, if anything, from some attenuation bias leading to underestimation of coefficients. This would be the case, for example, if teams including a generalist tend to be matched with projects belonging to high-uncertainty domains and they are only assigned to a given project from a low-uncertainty domain when they have some particular (unobserved) characteristic that makes them especially suitable for that project.

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 knowledge variety based on the presence of generalist inventors tend to generate a different innovative outcome (in terms of its economic relevance) than those based on inventors with narrower profiles. This difference is moderated by the level of uncertainty faced by inventors when solving a problem in a particular technological domain. For settings with low levels of domain uncertainty, the presence of generalist inventors in the team tends to reduce the relevance of the innovation (with respect teams with no generalists), whereas in domains with high uncertainty, the effect is reversed to positive. The main reason behind this result is that a team with some generalist inventor is more effective at recombining knowledge in domains with no clear path for recombination.

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 at least one generalist inventor within their ranks are less economically relevant in settings of low uncertainty and more economically relevant when produced in contexts of high uncertainty. We measure the economic relevance of the innovation underlying the patent application with an indicator of whether the patent is applied for in different countries, although the results also hold if we use the (standardized) number of forward citations received by the patent as alternative dependent variable.

Our study has several implications. First, it pinpoints that knowledge variety in teams is not necessarily obtained by gathering field specialists, who have individually deeper knowledge, but it can also be reached with the inclusion of generalist co-inventors, who have individually broader knowledge. More importantly, in the context of the generation of innovations our investigation suggests that teams whose knowledge variety is based (at least to some extent) on generalists generate more relevant innovations when they have to solve technological problems that involve no standardized routines. On the contrary, when facing a technological problem that can be effectively solved in a standard way, the presence of generalists will make the team underperform a specialist-based team.

Our findings are apparently in conflict with the thesis of Jones (2009), who interprets the increasing use of teams in scientific research as a consequence of narrowing individual expertise, which, in turn, is the consequence of the increasing complexity of knowledge. Jones (2009) documents a decreasing prevalence of generalist inventors contemporaneous with a steady increase of the use of teams of inventors, which jointly suggest a “death of the Renaissance Man” caused by the increasing complexity of knowledge. Our analysis takes a different perspective by addressing the role of generalists in teams of inventors. In that sense, our findings indicate that generalists are valuable when working in teams that tackle problems in contexts of high uncertainty: in such settings, these teams produce innovations of greater relevance than do specialist-based teams in settings of high uncertainty. One possible way to reconcile these two findings is to make a distinction between complexity and uncertainty. An innovation problem may have a complex solution but also a well-defined path to reach it. This is the case when many pieces of knowledge need to be combined but there is a clear map describing how to mingle them. In that context, generalist inventors may result redundant. Note that, according to our results, the variable *Presence of Generalist* has a positive significant effect only for the highest values of *Uncertainty* (which represent 12–15% of all the projects in our sample). For the majority of projects generalists do not have a statistically significant effect and, for the 15% of projects belonging to the least-uncertain domains, their effect is negative. Thus, our study suggests that the decline in the frequency of generalist inventors detected by Jones (2009) may not be associated to the “death of the Renaissance Man” but to “his” confinement to high-uncertainty settings where the ability to open new paths is particularly valuable.

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. A second external-validity problem arises from the fact that we are only analysing projects carried out by teams. To the extent that R&D managers may assign projects to teams and individuals that differ in unobserved characteristics, we cannot make inference about the role of generalist inventors for the type of projects that are being assigned to individuals. Finally, teams are not randomly assigned to projects either, so it could be that projects with an expected higher payoff would be assigned ex-ante to a particular type of teams of inventors. We address this problem with an instrumental variables approach. Although the instrumental variables estimation provides consistent results, the validity of our instrument relies on the assumption that generalists working in a team do not generate important spillovers to other teams of the same firm. Thus, while we observe that teams including at least one generalist perform better in uncertain technological domains, we have to be cautious in interpreting a causal relationship.

In sum, we view our research as a first step in the understanding of how the allocation of knowledge in teams of inventors affects one of the main dimensions of their performance, i.e., the economic relevance of their output. In a general sense, the paper contributes to advance our knowledge in the management of innovation at the lowest subunit of the firm, a realm quite unexplored by this stream of literature. We suggest that the role of generalist inventors does not need to be analyzed in opposition to the use of teams, but as a key part of those teams. We also show that characteristics of the technological context where the team is working (such as its uncertainty) are of particular importance to define the added value of generalists to their teams. We open a space for further research in this direction, which should primarily address what other structural features of the technological environment shape the trade-off associated with the inclusion of generalist inventors in innovation teams.

Acknowledgments

We are grateful to editor Asish Arora and two anonymous referees for their valuable suggestions. We also thank Ayfer Ali, Manuel F. Bagüés, Andrea Fosfuri, Marco Giarratana, Keld Laursen, Peter Mueser, and seminar participants at the Conference Knowledge in Organizations in Ascona, Universidad Carlos III de Madrid, CSIC-Madrid, Temple University, University of Missouri at Columbia, 1st SEI Workshop at ETH Zurich, Barcelona GSE Summer School 2013 and the 4th Madrid Work & Organizations Workshop for their comments on earlier drafts of the article. We acknowledge financial support from Grants ECO2012-333012 and ECO2012-33427 from the Spanish Ministerio de Economía y Competitividad. The usual disclaimers apply.

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