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Investigating the antecedents of general purpose technologies: A patent perspective in the green energy field

Abstract

This research analyzes the emergence of general purpose technologies. Specifically, we examine the relationship between how broadly organizations search across diverse knowledge domains in the invention process (i.e., their search breadth) and the technological generality of resulting inventive outcomes. Based on a sample of 88,748 patents belonging to the "Alternative energy production" and "Energy conservation" classes, we reveal that search breadth is curvilinearly related to an invention's technological generality. Furthermore, we assess if a geographically dispersed inventive team moderates the costs and benefits of searching broadly, showing that it makes organizations more able to benefit from a wider search breadth.

Keywords: general purpose technologies; search breadth; geographically dispersed teams; green energy technologies

1. Introduction

General purpose technologies (GPTs) refer to technologies “the exploitation of which will yield benefits for a wide range of sectors of the economy and/or society’’ (Keenan, 2003:132), such as the steam engine, nanotechnology, and the ICT (Banerjee and Cole, 2010; Bresnahan and Trajtenberg, 1995; Shea, 2005). This characteristic is ascribed to their high level of technological generality, which indeed favors their use and spread in a broad range of industries and market applications (Bresnahan and Trajtenberg, 1995; Gambardella and Giarratana, 2013; Keenan, 2003; Thoma, 2009). GPTs have gained more and more attention across both academics and practitioners in the last years. Nevertheless, as stated by Thoma (2009:108), “our understanding of GPTs is still somewhat limited", hence requiring more in-depth studies on how they work and emerge. Particularly, this article attempts to shed more light on the emergence of GPTs.

Previous research has argued that the ability to develop more generic technologies is associated to the use of diverse technological fields in the inventing activities (eg., Argyres and Silverman, 2004; Hicks and Hegde, 2005), which in turn increases the probability to make the resulting inventions applicable in diverse industrial contexts (Banerjee and Cole, 2010). This drives us to the research question of the present study, as what are the effects of a firm's strategy to search for knowledge across a broad range of technological domains on the creation of a GPT? Indeed, among other types of search strategy, such as search depth and search scope (eg., Katila and Ahuja, 2002), organizations can vary the diversity of knowledge to solve a specific technical problem, by deciding to expand the breadth of their search across diverse knowledge areas. We refer to this search strategy as search breadth (see also Capaldo and Messeni Petruzzelli, 2011), where the more different the knowledge areas searched across, the broader the breadth of search (Subramanian and Soh, 2010).

We argue that organizations can gain from search broadly in creating generic technologies and extend this logic by suggesting also that these benefits are subjected to decreasing and negative returns. Specifically, we draw on theories that support the assumption that searching in diverse technological domains improves recombination possibilities and avoids cognitive myopia (Fleming, 2001; Levinthal and March, 1993; Maggitti et al., 2013), which may lead to the creation of technologies that more easily span industry realms. However, when the number of knowledge fields searched across rises beyond a certain threshold, cognitive and managerial constraints related to the ability to link them together arise (Capaldo and Messeni Petruzzelli, 2011), hence suggesting an inverted U-shaped relationship between search breadth and technological generality. Furthermore, since people actually lie at the core of the recombinant process characterizing organizations' inventing activities (Fleming, 2001), we also claim that this curvilinear relationship is moderated by the degree of geographic dispersion of the inventive team, since it may alter the threshold level of search breadth at which decreasing and negative returns set in. Indeed, the past literature has argued that organizations' learning and recombination opportunities can be influenced by pursuing a R&D internationalization strategy, as reflected by the use of geographically dispersed teams (e.g., Gajendran and Joshi, 2012; Gassmann and von Zedtwitz, 2003; O'Leary and Mortensen, 2010; Susman et al., 2003). This, in turn, depends on the possibility to tap into unique bodies of knowledge that reside in specific geographic locations, and acquire new relational capital and problem-solving techniques (e.g., Doz and Wilson, 2013; Gajendran and Joshi, 2012; Kratzer et al., 2006; Singh, 2008).

The green energy sector is chosen as the research setting for the study. Indeed, related inventions often arise from the recombination of multiple technological areas (OECD, 2012), and their underlying knowledge is geographically dispersed (Albino et al., 2014), hence making search breadth and team dispersion relevant factors to be taken into account. This choice, more particularly, also follows the need to comprehend how to develop green GPTs, which has become more and more as an urgent issue (Cecere et al., 2014; Pearson and Foxon, 2012). Accordingly, to test our predictions, we collected 88,748 patents successfully filed at the U.S.PTO. from 1971 to 2009 and belonging to the "Alternative energy production" and "Energy conservation" green technological classes, as identified by the International Patent Classification (IPC) Green Inventory.

The key contribution of this paper consists in empirically testing the impact of an organization's search breadth in the invention process on the level of an invention's technological generality, and how the internationalization of the inventive team alters the benefits of a wide breadth of search. In addition, we focus our attention on a novel research setting, as represented by the green energy sector, hence allowing us to shed more light on the factors favoring the development of green GPTs in that industry.

The reminder of the paper is structured as follows. First, we provide the theoretical framework and present the hypotheses. Then, we describe the sample and the research methodology.

Afterwards, we expose data analysis and results. Finally, we provide discussion and implications, as well as limitations and directions for future research.

2. Theoretical framework and hypotheses

2.1. General purpose technologies

The idea that a technical solution can be applied across multiple domains dates back to Smith (1776) in The Wealth of Nations and was further re-examined by Stigler (1951), who referred to it as “general specialities”. More recently, instead, the literature has focused on the concept of GPTs, which has captured the attention of many scholars and executives in the last two decades (e.g., Bresnahan and Trajtenberg, 1995; Gambardella and Giarratana, 2013; Keenan, 2003). With the term GPTs, they mainly refer to technologies characterized by diverse technological fields, forming a knowledge base “with high levels of innovative complementarities and an ever-expanding set of new applications in a wide variety of industrial contexts” (Arikan, 2009:666). Indeed, a GPT is a pervasive technology that allows economic agents to combine existing technical solutions of different sectors with it, or build new innovative activities upon the same GPT, hence acting as a platform for subsequent complementary technological developments (Bresnahan and Trajtenberg, 1995; Gambardella and McGahan, 2010). In turn, this complementary effect enhances the impact of the GPT and helps it to drive the overall technical progress and promote economic growth (Bresnahan and Trajtenberg, 1995; Helpan and Trajtenberg, 1998). Thereby, inventions can differ along a particular attribute, namely technological generality (Gambardella and Giarratana, 2013), which influences their breadth of impact (Argyres and Silverman, 2004; Banerjee and Cole, 2010), facilitating the recombination of an invention with technologically distant components and its consequent diffusion.

Recognizing the presumed role of GPTs as “engines of growth”, past studies have been long interested in the benefits and impacts of these technological solutions, thus revealing their important role in creating value at both the microeconomic and macroeconomic level (Bresnahan and Trajtenberg, 1995; Helpan and Trajtenberg, 1998; Rosenberg and Trajtenberg, 2004; Shane, 2004). However, the commercialization and diffusion of GPTs are not straightforward, being principally limited by the high adaptation efforts required to apply them in diverse industries (Gambardella and Giarratana, 2013). Thereby, in the recent past, the literature has delved into the invention commercialization strategies that should be adopted to make GPTs available and diffused on the market (Gambardella and Giarratana, 2013; Gambardella and McGahan, 2010; Maine and Garnsey, 2006; Majumdar et al., 2010; Rainer and Strohmaier, 2014; Thoma, 2009). Nevertheless, only few insights about the antecedents of GPTs have been offered (Thoma, 2009). Argyres and Silverman (2004) first dug into this topic, proving that organizations with a centralized R&D structure, rather than a R&D lab for each product division, create inventions that span industry realms. This is explained by arguing that these organizations are more likely to merge different knowledge areas into a single technology, since they manage diverse types of knowledge simultaneously (see also Banerjee and Cole, 2010). Further, looking at the types of organization embroiled in inventive activities, Hicks and Hegde (2005) suggested that serial technology suppliers are more able to create GPTs. Accordingly, since their aim is to sell their inventions to as many organizations as possible, these companies tend to create technical solutions whose knowledge base is highly diversified, so as to allow to a number of different downstream specialized companies, both in the same and other sectors, to understand the inventions' underlying knowledge and build on them. In line with this reasoning, it emerges that developing technologies embodying a diversified variety of knowledge may contribute to the emergence of GPTs. In other words, it increases inventions' technological generality.

Moreover, an invention can be considered as the result of "a process of recombinant search over technology landscapes" (Fleming and Sorenson, 2001:1019). Therefore, the diversity of knowledge that is searched in the inventive activities to solve a technical problem plays a key role in developing general technologies. In fact, it affects the variety of technological fields that will characterize the subsequent invention (Ejermo and Karlsson, 2006; Maggitti et al., 2013), hence influencing the probability that a technology further spans industry boundaries and market applications. Building on this argument, we more specifically analyze the costs and benefits of an organization's strategy to search broadly in the invention process for the development of technologically general inventive outcomes. Furthermore, we also investigate how these costs and benefits may change when organizations pursue a R&D internationalization strategy, as reflected by the decision to form a geographically dispersed inventive team. Indeed, relevant knowledge inputs that are required to innovate in many sectors are often dispersed among diverse geographical areas (Doz and Wilson, 2013; Singh, 2008). Thereby, distributed teams can favor the access and acquisition of this unique body of knowledge, hence increasing the variety of the exploitable knowledge (Chen et al., 2012; Hoegl et al., 2007). In addition, they are deemed to have better combination capabilities and act more creatively than co-located teams, since they also tap into foreign sources of know-how and relational capital (Gajendran and Joshi, 2012; Kratzer et al., 2006; O'Leary and Mortensen, 2010).

2.2. Search breadth

It has been suggested that the more diverse the technological domains upon which an invention is based, the higher its level of technological generality and subsequent breadth of impact (Argyres and Silverman, 2004; Banerjee and Cole, 2010). Thus, it is reasonable to assume a positive effect of a wide search breadth on the emergence of GPTs. Indeed, enriching the diversity of knowledge domains in the search process increases the number of technological pieces that will characterize an invention, as well as the potential linkages and associations between the diverse technological areas (Capaldo and Messeni Petruzzelli, 2011; Fleming, 2001; Kauffman, 1993; Maggitti et al., 2013; Maine et al., 2014). In addition, a broad search breadth provides stimuli for cross-fertilization of different knowledge fields, perspectives, and ideas (Björkdahl, 2009; Hargadon and Sutton, 1997), hence favoring the use of different knowledge pieces simultaneously and their integration into a comprehensive whole. In turn, this can raise the likelihood that future technological developments, independently from their specific industrial context, can be built on inventions arising from search efforts spanning multiple technological boundaries. Furthermore, a wide breadth of search also leads to the development of new problem-solving techniques (Ahuja and Lampert, 2001) and avoid cognitive myopia toward different types of commercial application (Levinthal and March, 1993; Novelli, Forthcoming; Rosenkopf and Nerkar, 2001). Thereby, this contributes to reduce the risks to focus on a single market, hence increasing the probability to pursue diversified objectives at the same time, as well as to recognize a wider variety of potential commercial opportunities that may unfold as the different knowledge areas are searched and combined. Finally, inventions resulting from search efforts directed toward multiple diverse technological fields can have more chances to be understood by organizations operating in different industries, hence making these technologies as more widely used in many sectors (Banerjee and Cole, 2010).

Although the benefits of enlarging the breadth of search across several technological domains for the development of GPTs can be considerable, there is a point where this search effort is subjected to diminishing or even negative returns. Searching across a wide range of knowledge domains extensively can in fact limit the creation of more generic solutions. At some point, organizations' cognitive capabilities required to find and create useful knowledge combinations drastically drop, due to the increasing probability to work with unfamiliar knowledge domains and the lack of the required absorptive capacity (Cohen and Levinthal, 1990; Laursen and Salter, 2006). Hence, also the organizations' ability to recognize the technological and market potential of the diverse knowledge diminishes (Lin and Chang, Forthcoming). This may thus reduce the likelihood to come up with a discovery of more generalizable impacts. In addition, as search breadth becomes wider, the probability to conceive too many ideas respect to organizations' ability to select and implement them grows (Capaldo and Messeni Petruzzelli, 2011; Koput, 1997). Thereby, they might then focus on a restricted set of more familiar knowledge pieces in order to limit the number and complexity of the potential knowledge combinations (Fleming, 2001), hence reducing the diversity of the knowledge base characterizing inventive outcomes. Furthermore, organizations tend to conduct their search processes in a path-dependent way, which are often characterized by a well-established modus operandi (Nelson and Winter, 1982; Peteraf, 1993). However, since expanding the search breadth needs the creation of new routines with the aim to integrate multiple knowledge areas, they often face managerial constraints in performing such a task, hence limiting the effective use and integration of a diversified knowledge stock (Capaldo and Messeni Petruzzelli, 2011; Nelson and Winter, 1982). Finally, searching broadly comes with uncertainties regarding the future value of the inventions (Messeni Petruzzelli et al., Forthcoming; Taylor and Greve, 2006). Thus, economic agents' capacity to assess their worthiness, which is a central prerequisite to make a technology exploited and applied across several economic sectors (Banerjee and Cole, 2010; Nelson and Winter, 1977), is hampered. Therefore, on the basis of the above reasoning, we posit the following hypothesis:

Hypothesis 1. An organization's search breadth has a curvilinear (inverted U) effect on the level of technological generality of the resulting invention.

2.3. Team geographic dispersion and search breadth

We argue that organizations relying upon a geographically dispersed team of inventors have a better chance of benefiting from a wider search breadth. First, the diverse knowledge inputs and resource endowments that an organization can search across often reside and develop in different regional clusters, such as Silicon Valley for microelectronics and Detroit for automotive equipment (Doz and Wilson, 2013; Myles et al., 2000). Thereby, establishing dispersed teams lets organizations get closer to these different locations in order to actually understand and acquire the various specific bodies of knowledge (Gassmann and von Zedtwitz, 2003; Hsu et al., Forthcoming; Singh, 2008; Penner-Hahn and Shaver, 2005). In fact, these different knowledge is usually not easily transferable across geographic regions unless organizational R&D members "participate in locale-specific practices" (Sole and Edmondson, 2002:S17; see also Singh, 2008). Accordingly, dispersed teams may increase the organizations' absorptive capacity and reduce the extent of coping with unfamiliar knowledge when they search broadly. This may also alleviate the problems related to the recognition of the technological and market potential of the diverse knowledge searched across, hence favoring its integration and use for multiple commercial opportunities. Second, the internationalization of the inventive team can also help organizations to identify and implement potential relevant ideas, without reducing the diversity of the knowledge domains recombined to develop a given invention. Indeed, members at different sites, besides having a better chance to understand a particular piece of knowledge, acquire new problem-solving approaches and relational capital, which allow them to generate more higher quality solutions to address a technical problem (Edmondson and Nembhard, 2009; Gajendran and Joshi, 2012). In turn, this also helps them to perform more creatively, and so come up with more ideas for knowledge combination (Gajendran and Joshi, 2012; Polzer et al., 2006). Thereby, the cognitive limitations related to the integration of different technological domains can be mitigated. Third, in an internationalized context, interactions between team members are more spontaneous and characterized by variance in relational patterns (Hinds and Mortensen, 2005), which let organizations using dispersed teams develop "R&D capabilities through improvisational learning" (Parida et al., 2013:46). Thus, they are less subject to the managerial and coordination difficulties that arise from the need to create ad-hoc routines for favoring the exchange and integration of the various knowledge pieces in the invention process. According to the foregoing discussion, we hypothesize:

Hypothesis 2. Team internationalization moderates the relationship between search breadth and the level of technological generality of an invention, such that the threshold level of search breadth at which diminishing or negative returns arise will be higher for those organizations that use a geographically dispersed team.

3. Data and methods

3.1. Industry setting

The green energy sector serves as the research setting for the study. We believe this is an appropriate setting because, first, the need to favor the shift toward more efficient low-carbon energy systems in many sectors of the society, while promoting economic growth, is more and more recognized as a an urgent issue. Hence, the relevance of green GPTs in the energy field, such as the case of insulation technologies (Sorrell, 2007), have drastically risen (Cecere et al., 2014; Pearson and Foxon, 2012). Second, technological developments in the green energy sector include solutions having origins in diverse industries (OECD, 2012). Therefore, the extent of different technologies that can be potentially recombined within the invention process is various, thus making the search effort toward diverse knowledge domains as an important factor to be considered. Third, the technical knowledge underlying the development of green energy technologies is dispersed among many countries (Albino et al., 2014). Thereby, employing a R&D internationalization strategy is seen as an effective way to tap into new knowledge and skills to develop green technical solutions (Wagner, 2007). Finally, intellectual property protection is of foremost importance in the green energy sector (OECD, 2012). Thereby, patents serve as appropriate proxies to capture the technological inventions developed in this field.

3.2. Sample and data

Following previous studies (e.g., Albino et al., 2014; Kemp and Pearson, 2008; Popp, 2006), we use patent data in order to identify inventions developed in the green energy sector. In particular, we refer to the IPC Green Inventory for patent collection (Albino et al., 2014; Shapira et al., 2014). It is a well-defined classification that was developed by an IPC Committee of experts working for the World Intellectual Property Organization in 2008. Specifically, the IPC Green Inventory allows to search for patents related to the so called Environmentally Sound Technologies (ESTs), as defined in the Chapter 34 of the Agenda 21 (UN, 1992), by suggesting specific IPC codes for patent retrieval. Specifically, seven green technological classes were taken into account, in turn divided into a hierarchical set of subclasses[1]. For the purpose of this study, we limit our attention to the "Alternative Energy Production" and "Energy Conservation" classes. Hence, we collected all the patents successfully filed at the U.S.PTO. from 1971 to 2009 that refer to the two green technological classes above mentioned. For each patent we then gathered bibliographic information (i.e., backward, forward, and scientific-based citations, as well as information about the inventing team and assignees). Being primarily interested in the search efforts undertaken by a given organization, we limit our sample to those patents registered by just one assignee, leaving out patents owned by individuals working autonomously, as well as those granted to more than one organization in order to avoid network-specific effects. This procedure yielded a final sample of 88,748 patents.

3.3. Measures

3.3.1. Dependent variable

Technological generality. Following previous studies (e.g., Argyres and Silverman, 2004; Banerjee and Cole, 2010; Gambardella and Giarratana, 2013; Hicks and Hegde, 2005), in order to operationalize technological generality we refer to the generality index proposed by Hall et al. (2001). In particular, this refers to a Herfindhal-type index that measures the diversity of the technological classes assigned to patents that cite a focal one. The rationale behind this index is that the higher the variety of technological classes of the citing patents, the higher the focal patent's technological generality. On the contrary, if citing patents are concentrated in few technological fields, the focal patent's technological generality is low. However, this measure has been revealed to be biased downward when the number of forward citations is rather small (Hall, 2005; Hall et al.,

[1] See http://www.wipo.int/classifications/ipc/en/est/

2001). Hence, we correct this measure according to Hall (2005), who suggested to multiply the generality index by the ratio of the number of forward citations received by a focal patent (F_P) over F_P minus one. Therefore, our measure of technological generality is computed as follows:

$$Technological\ generality = \frac{F_P}{F_P - 1}\left[1 - \sum\left(\frac{F_{iP}}{F_P}\right)^2\right],$$

where F_{iP} stands for the number of citations received by the focal patent P in the three digit U.S. class i.

3.3.2. Independent and moderating variables

Search breadth. To compute this variable we follow the measure of originality, as defined by Hall et al. (2001) (see also Capaldo and Messeni Petruzzelli, 2011; Messeni Petruzzelli et al., Forthcoming). It is based on the same rationale of the generality measure, except for the fact that it refers to a focal patents' backward citations. Thus, the more diverse the extent of technological classes assigned to the patents cited by a focal one, the wider is assumed to be the breadth of search (Capaldo and Messeni Petruzzelli, 2011). Specifically, search breadth is operationalized as follows:

$$Search\ breadth = 1 - \sum\left(\frac{B_{iP}}{B_P}\right)^2,$$

where B_{iP} is the number of citations made by the focal patent P belonging to the three digit U.S. class i, and B_P is the total number of backward citations of the focal patent P.

Team dispersion. Patent documents report information about the team involved in the creation of a given invention. Particularly, for each inventor it is indicated the name and where he/she resides. Based on this data, according to previous studies (e.g., Lahiri, 2010; Nielsen, 2010), we operationalize the dispersion of the inventive team as follows:

$$Team\ dispersion = 1 - \sum\left(\frac{T_{cP}}{T_P}\right)^2,$$

where T_{cP} is the number of inventors being part the inventing team of the focal patent P that resides in the country c, and T_P is the total number of inventors of the focal patent P.

3.3.3. Control variables

Other factors can influence the level of technological generality of an invention. Therefore, control variables are also included in our model. First, we consider the size of the inventive team (*Team size*). It is measured by counting the number of people reported as inventors in the patent document (Singh, 2008). Second, we control for the total number of backward citations made by a focal patent (*Cited*) (Banerjee and Cole, 2010). Third, we include the number of claims, as reported in the patent document (*Claims*) (Tong and Frame, 1994). Fourth, the use of scientific knowledge in the invention process is also taken into account, by measuring the number of references made by a patent to non-patent literature (Narin et al., 1997). Fifth, to account for potential time effects, we include a set of three dummy variables to reflect four important time periods that have characterized the green energy sector (*dummy period*). Specifically, the first time period ranges from the 1971 to the 1987, year in which the Brundland report was published (WCED, 1987). The second one refers to the period between 1988 and 1997, which ends when the Kyoto protocol was signed. The third one goes from 1998 to 2002, when the Johannesburg Declaration on Sustainable Development was adopted at the World Summit on Sustainable Development (UN, 2002). The last one captures all the years after the 2002 till 2009. Sixth, we include three out of four dummy variables capturing the different types of patent assignee (*dummy assignee*), namely research centers, companies, financial institutions, and governmental organizations. Finally, in order to control for the patent's technological class, we add a dummy variable having value one if the patent belongs to the "Energy conservation" class, zero otherwise (*dummy class*).

3.4. Analysis

Since our aim is to assess the influence of an organization's breadth of search on the level of an invention's technological generality, the single patent is used as the unit of analysis. Our dependent variable assumes values that range from zero to one. In this case, a Tobit regression model is more appropriate for hypothesis testing (Banerjee and Cole, 2010). Indeed, an OLS regression may lead to inconsistent parameter estimates, since predictions of related models can go outside the range between our dependent variable is defined (Long, 1997; Wooldridge, 2012), hence making OLS less than ideal. In other words, it does not approach the "true" population parameters (Long, 1997).

4. Results

Table 1 shows descriptive statistics and pairwise correlations, presenting values below the 0.70 threshold (Cohen et al., 2013), hence limiting multicollinearity concerns. Results of the Tobit regression models are presented in Table 2. Model 1 is the baseline model and includes the control variables only. Model 2 is used to test Hypothesis 1 and includes search breadth as linear and quadratic terms. Finally, Model 3 includes the moderator and its interactions with the linear and squared term of search breadth.

The baseline model shows that enlarging the dimension of the inventing team leads to more general solutions, being the coefficient of *Team size* positive and significant ($\beta = 0.021$, $p < 0.001$). Similarly, an invention's technological generality increases with the number of citations made to previous patents ($\beta = 0.002$, $p < 0.001$) and with the number of claims ($\beta = 0.002$, $p < 0.001$). On the contrary, it decreases with the reliance on basic research ($\beta = -0.001$, $p < 0.001$).

Hypothesis 1 posits an inverted U-shaped relation between the breadth of search and the level of technological generality of an invention. Our results support this prediction. Indeed, estimates of Model 2 show that the linear term of *Search breadth* is positive and significant ($\beta = 0.401$, $p < 0.001$), while its squared term is negative and significant ($\beta = -0.249$, $p < 0.001$). Using the coefficient estimates of Model 2 (Zelner, 2009) we also graph the search breadth against the predicted level of technological generality (Figure 1), providing further support to our hypothesis. The inflection point beyond which the impact of search breadth decreases technological generality corresponds to a value of 0.807.

Our second hypothesis refers to the moderation effect of *Team dispersion*. Consistent with Hypothesis 2, both the interaction terms with the linear and squared term of *Search breadth* are significant and in the expected directions ($\beta = 0.574$, $p < 0.001$ and $\beta = -0.567$, $p < 0.01$, respectively). To gain further insight into the interaction effects predicted by Hypotheses 2, we decompose the interaction terms and conduct simple slope analysis. We consider two levels of the moderating variables - low (one standard deviation below the mean) and high (one standard deviation above the mean) - and estimate the effect of *Search breadth* on *Technological generality* for both levels (Hoetker, 2007; Lahiri, 2010; Poppo et al., 2008). We plot search breadth against the predicted level of technological generality of an invention at both low and high level of *Team dispersion* (Figure 2), and compute the maximum of the two resulting inverted curves. Figure 2 shows that when the level of *Team dispersion* is low decreasing and negative returns to *Search breadth* set in if *Technological generality* is above the value of 0.757. Differently, at the high level of *Team dispersion* negative returns arise when *Technological generality* exceeds the value of 0.882. In other words, the maximum of the curve describing the relation between *Search breadth* and *Technological generality* shifts to the right if organizations tend to adopt a R&D internationalization strategy during inventing activities. This suggests that using R&D dispersed teams amplifies the benefits of a wider breadth of search.

<*Insert Table 1 about here*>

<*Insert Table 2 about here*>

<*Insert Figure 1 and Figure 2 about here*>

5. Discussion and conclusions

The previous literature has mainly focused on the advantages of GPTs in the economy (e.g., Bresnahan and Trajtenberg, 1995; Rosenberg and Trajtenberg, 2004), as well as on the commercialization strategies that should be set to enter and diffuse them within the market (Gambardella and Giarratana, 2013; Gambardella and McGahan, 2010). Yet, extant research has scantly analyzed the antecedents of GPTs (Thoma, 2009). In this study, we explore the impact of an organization's strategy to search widely across diverse knowledge domains on the level of the resulting invention's technological generality, thus providing a better comprehension of the emergence of GPTs. Furthermore, we also assess how a R&D internationalization strategy, involving the establishment of geographically dispersed teams, moderates the costs and benefits of a broad search breadth. Based on a sample of 88,748 patents belonging to the "Alternative energy production" and "Energy conservation" technological classes, results indicate that when organizations search across various knowledge domains technological generality increases, although up to a certain threshold, thus revealing an inverted U-shaped effect. Furthermore, when organizations' inventive activity is dispersed across R&D teams, they are in a position to derive greater benefit from a wider search breadth.

The implications for theory that arise from these results are threefold. First, we corroborate findings of previous research on the emergence of GPTs, which argues that expanding the knowledge base charactering an invention increases its breadth of impact in diverse industrial contexts (Argyres and Silverman, 2004; Hicks and Hegde, 2005). Indeed, searching broadly across multiple technological domains helps organizations in creating a wider knowledge base (Capaldo and Messeni Petruzzelli, 2011; Maine et al., 2014). Moreover, it also provides advantages such as the reduction of cognitive myopia, increasing recombination possibilities, and the incentive to cross-fertilize different market ideas (e.g., Björkdahl, 2009; Maggitti et al., 2013). Furthermore, we add to previous research by arguing that there exists a threshold level, after which a wide search breadth comes with decreasing or even negative returns. In fact, the cognitive and managerial limitations related to the management of a too wide body of knowledge, as represented by the lack of absorptive capacity, the unfamiliarity with all knowledge domains, and the necessity to coordinate knowledge integration, cannot be underestimated (e.g., Capaldo and Messeni Petruzzelli, 2011). Second, our study further advances our understanding of how to create GPTs when organizations span multiple knowledge domains. Particularly, we demonstrate that in order to relieve the diminishing and negative returns of a wide search breadth a R&D internationalization strategy allows to alleviate organizations' cognitive and managerial limitations (Gajendran and Joshi, 2012). Accordingly, it favors a better understanding of the diverse knowledge pieces and the acquisition of new problem-solving techniques, which in turn enhances team members' creativity (Hinds and Mortensen, 2005). Furthermore, it also encourages spontaneous interactions between members, hence reducing the need to create ad-hoc routines for knowledge exchange. Third, ESTs in the energy sector have been deemed to play an important role for enhancing economic growth and environmental performance in several industries (Albino et al., 2014; Malek et al., 2014; Suzuki, Forthcoming). Nevertheless, while promising, these technological solutions faced several difficulties in diffusing on the market and failed to replace current carbon-based systems (Olson, 2014). Thereby, developing green energy technologies that can be more easily adopted and diffused in different industry domains has been recognized as a relevant issue (Suzuki, Forthcoming). Accordingly, our results contribute to this debate, revealing how it is possible to create green GPTs in the energy sector (Cecere et al., 2014; Pearson and Foxon, 2012).

Findings of this study inspire also some managerial implications. First, managers are advised of the double-edge word of a wide search breadth for the development of GPTs. Thereby, we suggest balancing the search efforts toward a wide range of knowledge domains, in order to avoid the risks to incur in the inability to gain returns from those efforts. Second, establishing dispersed teams may reduce the problems organizations face when they search broadly, being these useful to support the acquisition and integration of a diversified body of knowledge. Third, given the ever increasing need to develop more green general solutions (Cecere et al., 2014), our findings guide organizations to focus on the conditions that are most critical for creating green GPTs in the energy field.

Of course, this study presents some limitations that may however lead to new interesting lines of inquiry. We only consider organizations' search breadth. Other search strategies, such as search scope and search depth (Katila and Ahuja, 2002) may be investigated. Furthermore, additional characteristics of the inventive team, besides their internationalization, can be considered. For instance, future studies may take into account the presence of star scientists, whether team members have repeated experiences within the same group, and the set of norms characterizing team activities (e.g., Mathieu et al., 2013). We limit our attention to inventions developed by a single organization. Analyzing potential network-specific effects on the emergence of GPTs also require more in depth studies. Finally, this study has the green energy sector as its research setting. Further research considering other sectors may be useful to provide further support to our findings.

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Table

Table 1. Descriptive statistics and pairwise correlations

	Min	Max	Mean	S.D.	1	2	3	4	5	6	7
1-Technological generality	0	1	.360	.377	1	.258**	-.003				
2-Search breadth	0	.954	.334	.307	.258**	1	.033**				
3-Team internationalization	0	1	.017	.088	-.003	.033**	1				
4-Team size	1	27	2.300	1.684	.083**	.147**	.148**	1			
5-Scientific knowledge	0	858	5.460	22.088	-.050**	.011**	.062**	.122**	1		
6-Cited	0	1328	10.290	25.382	.094**	.177**	.011**	.080**	.311**	1	
7-Claims	1	900	11.040	16.074	.133**	.144**	.025**	.108**	.055**	.134**	1

n= 88,748; *p<0.05; **p<0.01

Table 2. Results of the Tobit regression models

	Model 1	**s.e.**	**Model 2**	**s.e.**	**Model 3**	**s.e.**
Technological breadth			.401***	.014	.411***	.014
Technological breadth^2			-.249***	.019	-.258***	.020
Team internationalization					.037	.023
Technological breadth x Team internationalization					-.574***	.158
Technological breadth^2 x Team internationalization					.567**	.209
Team size	.021***	.001	.015***	.001	.015***	.001
Scientific knowledge	-.001***	.000	-.001***	.000	-.001***	.000
Cited	.002***	.000	.001***	.000	.001***	.000
Claims	.002***	.000	.002***	.000	.002***	.000
dummy class	.203***	.003	.168***	.003	.168***	.003
dummy period	Included		Included		Included	
dummy assignee	Included		Included		Included	
Constant	.006***	.003	-.041***	.003	-.042***	.003
Log likelihood	-38341.23		-36715.66		-36699.20	
Observations	88,748		88,748		88,748	

*p<0.05; **p<0.01; ***p<0.001

Figure

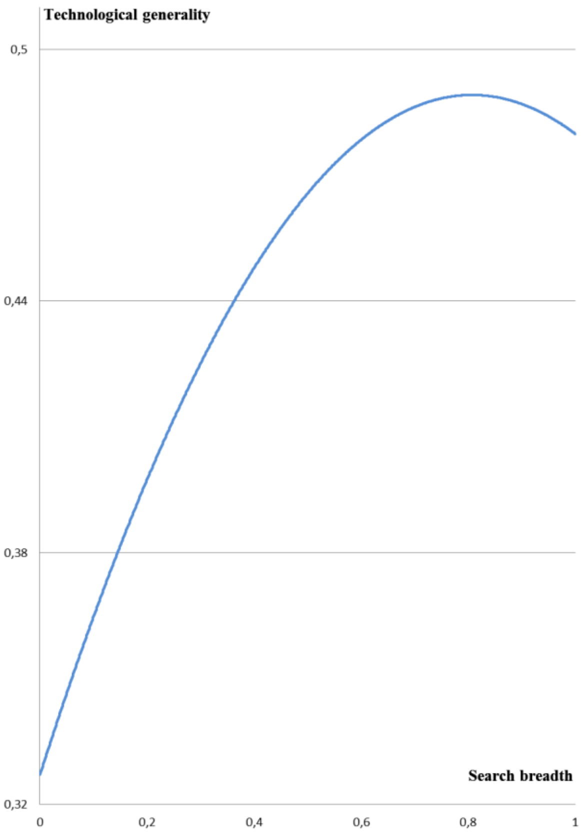

Figure 1. Predicted effect of *Search breadth* on *Technological generality*

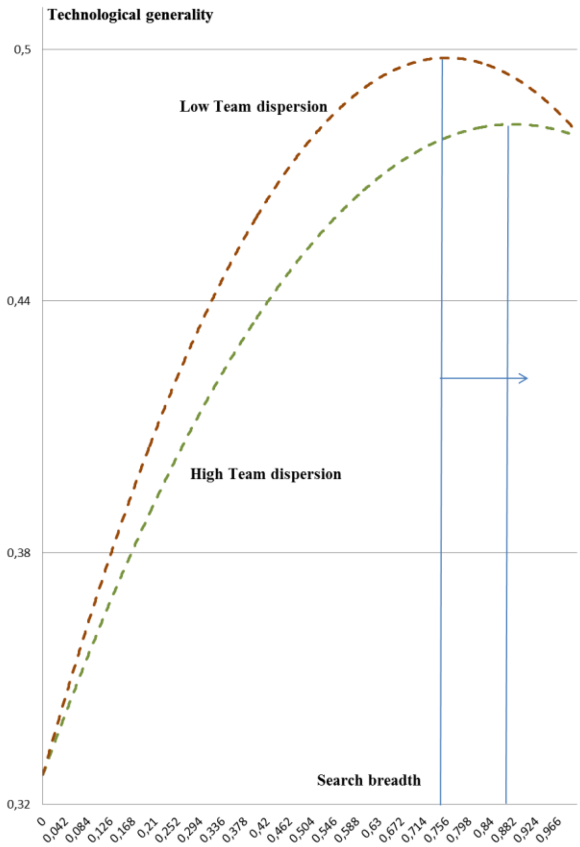

Figure 2. Moderation effect of *Team internationalization*