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Explorative and exploitative search patterns in the generation of green technologies: A patent-based analysis of inventors' and applicants' strategies

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Abstract

By exploiting the EPO universe of patent data, we investigate whether GTs emerge out of exploitative or exploitative knowledge-search strategies mastered by the focal actors involved in inventive processes: patent's applicant and inventor. Grounded on the knowledge recombination framework, results suggest the importance of exploitative strategies in driving the probability to observe the generation of a GT. Results also confirm that GTs seem to require the mastering of knowledge inputs stemming from heterogeneous sources. Technological differentiation is thus fundamental in their generation process, thus explorative patterns could emerge according to the maturity of firms' technological competences.

Jelcodes:O31,O32

Explorative and exploitative search patterns in the generation of green technologies: A patent-based analysis of inventors' and applicants' strategies

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[VERY PRELIMINARY DRAFT]

ABSTRACT

By exploiting the EPO universe of patent data, we investigate whether GTs emerge out of explorative or exploitative knowledge-search strategies mastered by the focal actors involved in inventive processes: patent's applicant and inventor. Grounded on the knowledge recombination framework, results suggest the importance of exploitative strategies in driving the probability to observe the generation of a GT. Results also confirm that GTs seem to require the mastering of knowledge inputs stemming from heterogeneous sources. Technological differentiation is thus fundamental in their generation process, thus explorative patterns could emerge according to the maturity of firms' technological competences.

JEL Classification Codes: O31 – O32

Keywords: Exploration; Exploitation; Green Knowledge; Knowledge Recombination

1 Introduction

Green technologies (GTs) have been the object of increasing interest in the last two decades, following the well-known argument set forth by Porter and van der Linde (1995) according to which the adoption of GTs is likely to yield a twofold positive effect for the economy, as they make it possible not only to improve the environmental performance of economic activities, but also their productive efficiency. In other words the so-called 'Porter hypothesis' maintains that GTs are key to the decoupling economic growth from environmental degradation (Ambec et al., 2013).

While the benefits from the adoption of GTs appeared straightforward, the economic analysis of the incentives leading to their generation had to account for a critical issue related to the 'double externality' problem. Like for any kind of innovation, economic agents are likely to underinvest in GTs because of the difficulties in appropriating the results of R&D activities. In addition, GTs engender positive external effects concerning the quality improvement of the environment. In this context, the analysis of the determinants of GTs has focused on the importance of the regulatory framework in inducing the commitment of resources to green R&D (Del Río Gozalez, 2009; Frondel et al., 2008; Horbach et al., 2012; Jaffe and Palmer, 1997; Johnstone et al., 2010; Newell et al., 1999; Lanjouw and Mody, 1996; Popp et al., 2010; Rennings and Rammer, 2011). Regulation can pull the demand for GTs and push the technological efforts towards their invention (Rennings, 2000).

The extant literature has much focused on the importance of environmental and innovation policies, as well as of their interplay, in setting up the incentives to the generation and adoption of GTs. Less attention has been paid instead to the very technological factors underpinning the invention of GTs. Some literature has pointed to the peculiarity of eco-innovative activities, as far as the related knowledge inputs are concerned. GTs seem indeed to require the mastering of knowledge inputs stemming from heterogeneous sources (Florida, 1996; Oltra and Saint Jean, 2005a, b; Rennings and Rammer, 2009; Horbach et al., 2013). Recently, Ghisetti et al. (2015) find evidence of a non-linear relationship between the breadth of the knowledge sourcing and the propensity to introduce GTs at the firm level. Eco-innovative activities are not likely to emerge in presence of too low diversification, but too much diversification can be equally harmful because of cognitive constraint.

This evidence is mostly based on data drawn from the Community Innovation Survey (CIS), and therefore focusing on the adoption of eco-innovative behaviors, rather than on the very generation of GTs. The extant contributions neglect the analysis of the characteristics of the knowledge base underpinning green inventions, and the corresponding search patterns. This paper aims at filling this gap, by investigating the extent to which the generation of GTs is driven by exploitative or explorative search behaviors. Drawing upon the recombinant approach to knowledge generation (Weitzman, 1998; Fleming and Sorenson, 2001), we focus the analysis on the characteristics of the knowledge base of the focal actors involved in the inventive process, i.e. patents' inventors and applicants, as fundamental drivers for the generation of GTs. More precisely, we investigate whether the generation of a green patent is driven by more explorative ("search scope") or by more exploitative ("search depth") patterns of knowledge recombination, or a mix of both.

The rest of the paper is organized as follows. Section 2 reviews the background literature and proposes our hypotheses. Section 3 describes the empirical strategy. Section 4 discusses the main results, and Section 5 concludes.

2 Exploration, exploitation and the generation of GTs

2.1 Exploration, exploitation and ambidexterity

Previous contributions in management science have proposed to classify innovations according to their relatedness degree with existing technologies, products and services, and with existing customers or markets (Abernathy and Clark, 1985; Benner and Tushman, 2003; Danneels, 2002).

Since the seminal contribution by March (1991), the tension "exploration of new possibilities" and "exploitation of old certainties" has been object of analysis in a wide range of contexts. These include organizational science and strategic management (Levinthal and March 1993, Vera and Crossan 2004), innovation studies (Danneels, 2002; Rothaermel and Deeds, 2004), and entrepreneurship (Shane and Venkataraman, 2000). Exploration implies firm's behaviors characterized by search, discovery, experimentation, risk taking and innovation; exploitation implies instead firm behaviors characterized by refinement, implementation, efficiency, production and selection.

Exploratory search behaviors are mostly conducive to the introduction of radical innovations, which are likely to meet the needs of emerging markets (Benner and Tushman, 2003; Danneels 2002; Abernathy and Clark, 1985). In this perspective, exploration requires the development of new knowledge, or moving away from the existing technological competences (Benner and Tushman, 2002; Levinthal and March, 1993).

On the contrary, exploitative search patterns are likely to lead to the introduction of incremental innovations, which are suited to meet the needs of customers in existing markets (Benner and Tushman, 2003; Danneels, 2002). As such, exploitation builds upon existing knowledge and competences and strengthen existing skills, processes, and structures (Abernathy and Clark, 1985; Benner and Tushman, 2002; Levinthal and March, 1993).

March (1991) suggested that exploration and exploitation should not be viewed as mutually exclusive strategies. Maintaining an appropriate balance between exploration and exploitation is critical for firm survival and prosperity. According to Levinthal and March (1993, p. 105), "The basic problem confronting an organization is to engage in sufficient exploitation to ensure its current viability and, at the same time, to devote enough energy to exploration to ensure its future viability". Tushman and O'Reilly (1996) have subsequently crystallized this tension in the concept of '*ambidexterity*', according to which firms need to achieve a "balance" between the two to achieve superior performances. Following Katila and Ahuja (2002), exploitation of existing capabilities often supports the exploration of new capabilities, while exploration of new capabilities is likely to enhance a firm's existing knowledge base. However, despite the theoretical relevance of the concept, only few studies have analyzed the effects of ambidextrous strategies, by focusing specifically on explorative and exploitative innovation activities (Jansen et al., 2006; He and Wong 2004; Benner and Tushman 2003).

2.2 Knowledge recombination in exploitative and explorative search for GTs

The debate about the kind of knowledge sources underpinning eco-innovative strategies has gained momentum in the last years. Ghisetti et al. (2015) summarize the discussion emphasizing that the extant literature agrees on the fact that the mastering of heterogeneous knowledge sources enables the adoption of eco-innovative behaviors. The authors themselves provide evidence of the importance of knowledge breadth in this respect. However, these studies focus on the demand side, *i.e.* on the adoption of any kind of innovation improving environmental performances, while somewhat less attention has been paid to the very dynamics underlying the generation of GTs, *i.e.* to the supply side.

In-depth investigations of the characteristics of GTs production processes have attempted to provide answer to question as to what extent GTs emerge out of exploitative or explorative innovation modes, by stressing the key role of deployment policies. Following the inducement hypothesis, most of these studies conclude that deployment polices, by creating new market niches, are likely to foster exploitative learning due to the necessity for suppliers of GTs to meet rapidly increasing demand. These policies are therefore likely to favor the lock in mature technological trajectories, rather than to stimulate the search for radically new technological solutions (Nemet, 2009; Menanteau, 2000; Sandén, 2005; Sartorious, 2005; van den Heuvel and van den Bergh, 2009). Hopmann et al. (2013) refine the analysis by showing that deployment policies are likely to yield differential effects according to the maturity of firms' technological competences. Firms with relatively lower stock of technological competences are likely to undertake explorative strategies, due to the lack of existing competences to be exploited. Still, knowledge is a cumulative process affected by dynamic irreversibility, making explorative behaviors less likely to emerge the longer the cumulated technological experience is.

H1. GTs emerge out of exploitative search patterns.

H2. Exploitative search patterns are more evident for innovating agents that have previous experience in producing GTs.

While these works shed an interesting light on the understanding of the search patterns of technology producers, they appear to be focused on specific sectors, mainly providing qualitative evidence of these phenomena. The so-called recombinant knowledge approach can instead provide in this context the theoretical background to systematic empirical analysis of explorative vs. exploitative search patterns, based on patent documents. According to this stream of literature the creation of new knowledge – hence, any kind of novelty – can be represented as a search process across a set of multiple existent components (e.g., Fleming, 2001; Gavetti and Levinthal, 2000; Katila and Ahuja, 2002). New combinations of different pieces of knowledge, or new relationships between previously combined pieces of knowledge, arise within the evolution of the prior generated knowledge stock. Simultaneously, novelties, once introduced, modify both the qualitative composition and the direction of the stock itself. Either reinforcement of previous trajectories or technological breakthroughs consequently emerge.

If knowledge stems from the combination of different inputs, the knowledge base behind an innovation can be represented as a network, the nodes of which represent the elements of the knowledge space that could be combined, while the edges represent their actual combination. The observed frequency with which specific technologies are combined is useful to characterize the internal structure of the knowledge base. Such characterization takes account of the average degree of similarity and complementarity of the technologies comprising the knowledge bases, as well as the variety of the observed pairs of technologies. Three measurable properties of the knowledge structure can be identified in this respect:

- Knowledge Variety is related to technological differentiation within the knowledge base, in particular with respect to the possible different combinations of pieces of knowledge, from the creation of radically new types of knowledge to more incremental recombination of already existing types of knowledge. It can be decomposed between Related and Unrelated Variety, providing useful information about the space distance from which technological differentiation comes from.
- Knowledge Coherence can be defined as the extent to which the pieces of knowledge that agents combine to create new knowledge are complementary.
- Cognitive Distance refers to the extent to which the pieces of knowledge used are distant in the technology space.

These measures capture the design complexity of the knowledge structure. In this perspective, knowledge variety is likely to increase when new combinations of knowledge are introduced into the system. An increase in coherence and a decrease of cognitive distance are likely to signal the change to an exploitation strategy, while the opposite evidence is likely to be linked to an exploration strategy (Krafft et al ., 2014).

The grafting of the recombinant knowledge approach onto the discussion on innovation modes in the production of GTs allows us to refine our working hypotheses as it follows.

H1a. The production of GTs is based upon the combination of previous knowledge inputs exhibiting high degree of coherence and low degree of cognitive distance. Due to the reliance of GTs upon heterogeneous knowledge, GTs are associated with increasing variety, and in particular increasing unrelated variety.

H2a. The patterns related to knowledge variety, coherence and cognitive distance are amplified by previous experience in producing GTs.

3 Empirical application

3.1 Data and econometric strategy

Data refer to all the patents filed in at the European Patent Office (EPO), from 1980 to 2010.[1] The main dataset we exploit comes from PATSTAT and is maintained by CRIOS, which provides us – by applying the so-called Massacrator© Algorithm (Pezzoni et al., 2012) – the precious capability to disambiguate the names of all the EPO patents' inventors, and thus to uniquely identify them.

The theoretical arguments and the hypotheses proposed in Section 2 are tested with a probit regression model where the dependent variable is the probability to observe a patent with green content.

3.2 Dependent variable

Patents are classified as environmentally-related on the basis of the two main worldwide existent classifications: 1) The World Intellectual Property Organization "WIPO IPC green inventory", an International Patent Classification that identifies patents related to the so-called "Environmentally Sound Technologies" and scatters them into their technology fields, with the caveat that it is not the only possible classification of green technologies and, as with other available classifications, it presents some drawbacks (Costantini et al., 2013); 2) The OECD Indicator of Environmental Technologies (OECD, 2011), based on the International Patent Classification (IPC), which features seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting.

3.3 Independent variables

3.3.1 Patent-based knowledge-search indicators

In order to define the patterns of knowledge recombination search which characterize

[1] We are aware about traditional pros and cons of using patent data.

previous innovative strategies showed by the patent's applicant and the patent's inventor at the time in which the focal patent is filed in (patent's priority year), we assign to each team of inventors and to each applicant listed in the patent document the average degree of, respectively, RKV, UKV, COH and CD they accumulated in their previous patenting activities. For each applicant and inventor i we thus define:

$$RKV_{i,t-1} = \frac{\sum_p RKV_p}{N}$$

$$UKV_{i,t-1} = \frac{\sum_p UKV_p}{N}$$

$$COH_{i,t-1} = \frac{\sum_p COH_p}{N}$$

$$CD_{i,t-1} = \frac{\sum_p CD_p}{N}$$

where the numerators are the sums of the observed levels of, respectively, RKV, UKV, COH and CD, measured over all the patents where inventor and/or applicant i are listed, up to time $(t-1)$; N is the total number of patents filed by inventor and/or applicant i up to time $(t-1)$.[2]

The interpretative combination of these indicators, both within and between applicants and inventors involved in the inventive process, allows us to capture the complexity of the knowledge search strategy behind the generation of an invention. The way how we build the knowledge indicators is described as follows.

First, in order to measure the level of *technological-knowledge variety* a patent reveals, we apply the Information Entropy Index to the co-occurrences of IPC classes contained in the backward citations of any observed patent.[3] The index was introduced to economic analysis by Theil (1967). Its earlier applications aimed at measuring the degree of diversity of industrial activity (or of a sample of firms within an industry) against a uniform distribution of economic activities in all sectors, or among firms (Attaran, 1985; Frenken et al., 2007; Boschma and Iammarino, 2009). Compared with common measures of variety and concentration, information entropy has some interesting properties (Frenken and Nuvolari, 2004). An important feature of the entropy measure, which we exploit in our analysis, is its

[2] If the number of applicants and/or the number of inventors is > 1, we take the mean level of, respectively RKV, UKV, COH and CD for each applicants' team and inventors' team.

[3] Backward citations have been collected on the basis of the patent's DOCDB family. The IPC classes have been truncated at the 4 digits level.

multidimensional extension. Consider a pair of events (X_j, Y_m), and the probability of their co-occurrence p_{jm}, a two-dimensional (total) entropy measure can be expressed as follows (patent and time subscripts are omitted for the sake of clarity):

$$H(X,Y) = \sum_{j=1}^{q}\sum_{m=1}^{w} p_{jm} log_2\left(\frac{1}{p_{jm}}\right)$$

If p_{jm} is assumed to be the probability that two technological classes j and m, contained in the backward citations of a patent, co-occur within the same patent, then the measure of multidimensional entropy focuses on the variety of co-occurrences of technological classes within patents' backward citations portfolio.

Moreover, the total index can be decomposed in a "within" and a "between" part whenever the events to be investigated can be aggregated to form smaller numbers of subsets. Within-entropy measures the average degree of disorder or variety within the subsets, between-entropy focuses on the subsets measuring the variety across them. It can be easily shown that the decomposition theorem also holds for the multidimensional case. Hence, if one allows $j \in S_g$ and $m \in S_z$ $(g = 1, \ldots, G;\ z = 1, \ldots, Z)$, we can rewrite $H(X,Y)$ as follows:

$$H(X,Y) = H_Q + \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz}\, H_{gz}$$

where the first term on the right-hand-side is the between-group entropy and the second term is the (weighted) within-group entropy. In particular,

$$H_Q = \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz}\, log_2\left(\frac{1}{P_{gz}}\right)$$

$$P_{gz} = \sum_{j \in S_j}\sum_{m \in S_z} p_{jm}$$

$$H_{gz} = \sum_{j \in S_j}\sum_{m \in S_z} \frac{p_{ij}}{P_{gz}} log_2 \frac{1}{p_{jm}/P_{gz}}$$

Following Frenken et al. (2007), we can refer to between-group and within-group entropy, respectively, as *unrelated technological variety* (UTV) and *related technological variety* (RTV), while total information entropy is referred to as *general technological variety* (TV) . The distinction between related and unrelated variety is based on the assumption that any pair of entities included in the former generally are more closely related or more similar to any pair of entities included in the latter. This assumption is reasonable given that a type of entity (patent, industrial sector, trade categories, etc.) is organized according to a hierarchical classification. In this case, each class at a given level of aggregation contains “smaller” classes, which, in turn, contain yet “smaller” classes. Here, small refers to a low level of aggregation. We can reasonably expect then that the average pair of entities at a given level of aggregation will be more similar than the average pair of entities at a higher level of aggregation. Thus, what we call related variety is measured at a lower level of aggregation (three-digit class within a one-digit macro-class) than unrelated variety (across one-digit macro-classes).

Second, we define the *knowledge coherence* measure as the average relatedness of any technology randomly chosen within the patent’s portfolio of backward citations with respect to any other technology present in the technological space (Nesta and Saviotti, 2005, 2006; Nesta, 2008). To yield the knowledge coherence index, several steps are required. First of all, we calculate the weighted average relatedness WAR_l of technology l with respect to all other technologies present within the technological space. Such a measure builds upon the measure of technological relatedness τ_{lj} (see Nesta and Saviotti, 2005). Following Teece et al. (1994), WAR_l is defined as the degree to which technology l is related to all other technologies $j \in l$ in the technological space, weighted by patent count P_{jt}:

$$WAR_{lt} = \frac{\sum_{j \neq l} \tau_{lj} P_{jt}}{\sum_{j \neq l} P_{jt}}$$

Finally the coherence (or relatedness) of the patent’s knowledge base is defined as the weighted average of the WAR_l measure:

$$R = \sum_{l \neq j} WAR_{lt} \times \frac{P_{lt}}{\sum_l P_{lt}}$$

It is worth stressing that such index implemented by analysing co-occurrences of technological classes within patent applications, measures the degree to which the services rendered by the co-occurring technologies are complementary one another. The relatedness measure τ_{lj} indicates indeed that the utilization of technology l implies that of technology j in order to perform specific functions that are not reducible to their independent use.

Lastly, the similarity amongst different types of knowledge can be captured by a measure of *cognitive distance*. A useful index of distance can be derived from the measure of *technological proximity* originally proposed by Jaffe (1986 and 1989), who investigated the proximity of firms' technological portfolios. Subsequently Breschi et al. (2003) adapted the index in order to measure the proximity, or relatedness, between two technologies. We follow the same approach, but adapting the analysis at the patent level. The idea is that each patent is characterized by a vector V of the k IPC classes (technologies) that occur in its backward citations. Knowledge similarity can first be calculated for a pair of technologies l and j as the angular separation or un-centred correlation of the vectors V_{lk} and V_{jk}. The similarity of technologies l and j can then be defined as follows:

$$S_{lj} = \frac{\sum_{k=1}^{n} V_{lk} V_{jk}}{\sqrt{\sum_{k=1}^{n} V_{lk}^2} \sqrt{\sum_{k=1}^{n} V_{jk}^2}}$$

The idea underlying the calculation of this index is that two technologies j and l are similar to the extent that they co-occur with a third technology k. The cognitive distance between j and l is the complement of their index of similarity:

$$d_{lj} = 1 - S_{lj}$$

Once the index is calculated for all possible pairs, it needs to be aggregated at the patent level to obtain a synthetic index of technological distance. This can be done in two steps. First of all one can compute the weighted average distance of technology l, i.e. the average distance of l from all other technologies.

$$WAD_{lt} = \frac{\sum_{j \neq l} d_{lj} P_{jit}}{\sum_{j \neq l} P_{jit}}$$

Where P_j is the number of patents in which the technology j is observed. Now the average cognitive distance for a patent is obtained as follows:

$$CD = \sum_{l} WAD_{lit} \times \frac{P_{lit}}{\sum_{l} P_{lit}}$$

3.3.2 Previous green patenting experience

In order to test whether having previous green patenting experience – both at the level of the applicant and at the level of the inventors' team – affects the probability to observe a patent with green content, we include a dummy variable which signals us for the presence of previous patents filed in by, respectively, the same applicant and the same inventor listed in the focal patent.

Moreover, in order to test HP.2, we interact the dummy variable 'previous green experience' with the knowledge indicators described above. In doing so, we test for different search strategies of exploration vs. exploitation characterizing applicants and inventors' team which were already involved in green inventive activities.

3.4 Control variables

As for the controls, we account for a comprehensive set of variables at the level of, respectively, the applicant, the inventor and the patent. At the level of both the applicant and the inventor, we control for *i)* having or not previous patenting experience (dummy 'experience'); *ii)* the number of previous patents; and *iii)* the share of green previous patents over the total number of previous patents. This list of controls depicts the level of technological knowledge already possessed and applied by both the patent's applicant and the patent's inventor (in this way we control for technology-push factors which could affect new innovative activities). Moreover, we control for the number of applicants and the number of inventors listed in the patent document, accounting for the dimension in terms of actors involved in the inventive process. Specifically for the inventor dimension, we furthermore control also for observing at least one inventor which experienced previous inventive activities with different applicants (dummy 'mobility'), and for the number of previous patents filed in, during its patenting history, by the inventor with the maximum number of patents in the team (inventor 'star'). As for the controls at the patent-level, we account for *i)* its level of internationalization, by adding a dummy variable signaling for the presence of at least two applicants with different country of residence; ii) its wideness in terms of both the number of sectors (dummy 'multi-sector') and the number of technological areas (dummy 'multi-technological-field') in which it is classified; iii) a set of qualitative characteristics such as being granted (dummy 'granted'), being a triadic patent (dummy 'triadic'), experiencing a change in ownership (dummy 'change ownership'), the dimension of the patent's family, and the number of patent's claims; and iv) the number of backward citations, and the share of non-patent citations over the total number of backward citations. Finally, we control also for priority-year dummies, residence-country of the applicant dummies, NACE sector dummies, OST7 technology dummies and for the patent office which firstly assigned to the focal patent its IPC classes.

4 Results

Results seem to confirm HP.1 stated in Section 2. Indeed, while the effect of knowledge coherence is significant and positive, the reverse is true for the cognitive distance indicators. Moreover, experiencing previous green inventive activities positively affect the generation of GTs. This pattern works for both the applicant and the inventors' team, signaling for important exploitative search strategies characterizing GTs.

At the same time, GTs require the mastering of knowledge inputs stemming from heterogeneous sources, they are characterized by intrinsic systemic nature and, possibly, they are multi-purpose. Results in Table 1 go in this direction for what concerns the positive effect the total variety shows, especially with respect to the role the inventors' team plays. Interestingly, when we split the variety indicator in its within and between parts (Table 2), results show a more complex picture. While for the applicant the unrelated variety indicator has a negative effect, the reverse effect if found with respect to the inventors' team. Conversely, the related variety indicator shows an opposite pattern. The interpretation of these results is not straightforward and requires a more in depth investigation, suggesting for the presence of a complex dynamic at work according to the maturity of the firm's technological competences (Hopmann et al., 2013).

As for HP.2, results seem to confirm that important exploitative patterns are at work in the generation process of GTs. Indeed, the effects of both the cognitive distance and the coherence indicators are magnified by their interaction with the presence of previous green patenting experience. Again, the interpretation of the interaction between the knowledge variety indicators and the green previous inventive experience leads to the necessity to more in depth investigate the existence of different and possibly complementary search strategies of exploitation and exploration, according to the technological capabilities possessed by both applicants and inventors.

Lastly, a brief look at the controls seem to suggest a substantiation of the systemic and multi-purpose nature of GTs (indeed, both the 'multi-technology' and 'multi-sector' dummies show important positive effects). Moreover, for both the applicant and the inventors' team, the share of previous green patenting activities over the total previous patenting experience has a positive effect on the generation of GTs, suggesting the importance of specialization in green technological fields.

INSERT TABLE 1 ABOUT HERE

INSERT TABLE 2 ABOUT HERE

5 Conclusions

The paper investigates the extent to which the generation of GTs is driven by exploitative or explorative search behaviors. Drawing upon the recombinant approach to knowledge generation (Weitzman, 1998; Fleming, 2001), we focus the analysis on the characteristics of the knowledge base of the focal actors involved in the inventive process, *i.e.* patents' inventors and applicants, as fundamental drivers for the generation of GTs. More precisely, we investigate whether the generation of a green patent is driven by more explorative ("search scope") or by more exploitative ("search depth") patterns of knowledge recombination, or a mix of both.

Results suggest that the generation process of GTs is driven by important exploitative strategies. Empirical evidence also confirms that GTs are characterized by systemic and potentially multi-purpose nature, and the involved knowledge required for their generation is intrinsically heterogeneous, coming from multiple sources. The ability of mastering technological differentiation among the required knowledge base is thus focal for generating GTs. It derives that explorative patterns are inevitably at work, according to the different level of knowledge possessed by the actors involved in green inventive activities.

This last preliminary conclusion constitutes the starting point for our work in progress.

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Table 1 – Probit estimation (marginal effects)

	VARIABLES	(1) Model 1	(2) Model 2
APPLICANT	COH_4dg	0.00235***	0.00150***
		(0.000156)	(0.000266)
	IE_4dg	-0.00346***	0.000865*
		(0.000372)	(0.000471)
	CD_4dg	-0.00606***	-0.00422**
		(0.00140)	(0.00174)
	dummy green previous experience (GI)	0.00973***	0.0140***
		(0.000538)	(0.00264)
	COH_X_green_exp(GI)		0.00162***
			(0.000299)
	IE_X_green_exp(GI)		-0.00819***
			(0.000642)
	CD_X_green_exp(GI)		-0.00335
			(0.00240)
	dummy previous patenting experience	-0.0464***	-0.0523***
		(0.00159)	(0.00279)
	tot n patents (t-1)	9.37e-07***	8.50e-07***
		(6.91e-08)	(5.77e-08)
	share green patents (GI) (t-1)	0.141***	0.142***
		(0.00103)	(0.00109)
TEAM	COH_4dg	0.00191***	0.000996***
		(0.000181)	(0.000152)
	IE_4dg	-0.00112***	0.00120***
		(0.000279)	(0.000409)
	CD_4dg	0.00146	0.000981
		(0.00129)	(0.00136)
	dummy green previous experience (GI)	0.0218***	0.0205***
		(0.000697)	(0.00236)
	COH_X_green_exp(GI)		0.00203***
			(0.000259)
	IE_X_green_exp(GI)		-0.00573***
			(0.000613)
	CD_X_green_exp(GI)		0.000871
			(0.00219)
	dummy previous patenting experience	-0.0559***	-0.0549***
		(0.00177)	(0.00173)
	tot n patents (t-1)	-0.000265***	-0.000258***
		(1.51e-05)	(1.48e-05)
	share green patents(GI) (t-1)	0.144***	0.143***

		(0.00127)	(0.00124)
CONTROLS	Inventor star's tot n of pat (t-1)	0.000220***	0.000211***
		(1.21e-05)	(1.16e-05)
	n of inventors	-5.78e-06	3.14e-06
		(9.49e-05)	(0.000101)
	Inventor star's tot n of green pat (t-1) (GI)	0.000553***	0.000574***
		(5.17e-05)	(4.74e-05)
	dummy n of applicants' country > 1	0.00967***	0.00977***
		(0.00198)	(0.00252)
	dummy n of applicant > 1	0.00312***	0.00309***
		(0.000568)	(0.000514)
	dummy multi tech field	0.0238***	0.0239***
		(0.00101)	(0.000893)
	dummy multi sector	0.0162***	0.0163***
		(0.000603)	(0.000605)
	dummy triadic	-0.00565***	-0.00560***
		(0.000438)	(0.000326)
	dummy granted	0.00165**	0.00165**
		(0.000664)	(0.000736)
	docdb_family_size	0.000686***	0.000707***
		(0.000132)	(0.000133)
	n of patent's claims	0.000312***	0.000311***
		(1.64e-05)	(1.92e-05)
	tot n of cits (patent + npl)	0.000223***	0.000232***
		(1.18e-05)	(1.18e-05)
	share npl	0.0154***	0.0155***
		(0.000720)	(0.000722)
	dummy CHG_OWN	-0.00837***	-0.00836***
		(0.000547)	(0.000661)
Observations		2,112,530	2,112,530
Dummy Country		YES	YES
Dummy Year		YES	YES
Dummy Technology		YES	YES
Dummy Sector		YES	YES
Dummy Patent Authorithy		YES	YES

Bootstrapped Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2 – Probit estimates (marginal effects)

VARIABLES	(1) Model 1	(2) Model 2
Applicant_COH_4dg	0.00256***	0.00142***
	(0.000175)	(0.000244)
Applicant_IEW_4dg	-0.00481***	0.00205***
	(0.000386)	(0.000715)
Applicant_IEB_4dg	0.00122**	-0.00136*
	(0.000567)	(0.000709)
Applicant_CD_4dg	-0.00928***	-0.00283
	(0.00145)	(0.00227)
applicant dummy green previous experience (GI)	0.00987***	0.00355
	(0.000536)	(0.00222)
Applicant_COH_X_green_exp(GI)		0.00220***
		(0.000271)
Applicant_IEW_X_green_exp(GI)		-0.0122***
		(0.000873)
Applicant_IEB_X_green_exp(GI)		0.00465***
		(0.000894)
Applicant_CD_X_green_exp(GI)		-0.0123***
		(0.00298)
Team_COH_4dg	0.00211***	0.00115***
	(0.000153)	(0.000202)
Team_IEW_4dg	-0.00375***	-0.000180
	(0.000482)	(0.000479)
Team_IEB_4dg	0.00347***	0.00270***
	(0.000514)	(0.000649)
Team_CD_4dg	-0.00237*	-0.000746
	(0.00127)	(0.00135)
team dummy green previous experience (GI)	0.0219***	0.0169***
	(0.000764)	(0.00235)
Team_COH_X_green_exp(GI)		0.00210***
		(0.000258)
Team_IEW_X_green_exp(GI)		-0.00837***
		(0.000681)
Team_IEB_X_green_exp(GI)		0.00161
		(0.00102)
Team_CD_X_green_exp(GI)		-0.00438*
		(0.00253)
applicant dummy previous patenting experience	-0.0483***	-0.0519***
	(0.00189)	(0.00221)
applicant tot n patents (t-1)	9.54e-07***	8.85e-07***
	(6.39e-08)	(6.25e-08)

applicant share green patents (GI) (t-1)	0.141***	0.141***
	(0.000998)	(0.000995)
dummy n of applicants' country > 1	0.00968***	0.00980***
	(0.00250)	(0.00225)
dummy n of applicant > 1	0.00302***	0.00296***
	(0.000540)	(0.000508)
team dummy previous patenting experience	-0.0565***	-0.0558***
	(0.00164)	(0.00185)
team tot n patents (t-1)	-0.000261***	-0.000252***
	(1.30e-05)	(1.21e-05)
Inventor star's tot n of pat (t-1)	0.000217***	0.000205***
	(1.07e-05)	(1.08e-05)
n of inventors	-1.12e-05	-1.07e-06
	(9.94e-05)	(9.21e-05)
team share green patents(GI) (t-1)	0.144***	0.143***
	(0.00121)	(0.00136)
Inventor star's tot n of green pat (t-1) (GI)	0.000552***	0.000574***
	(4.81e-05)	(3.72e-05)
dummy multi tech field	0.0238***	0.0239***
	(0.000756)	(0.000890)
dummy multi sector	0.0162***	0.0163***
	(0.000651)	(0.000612)
dummy triadic	-0.00566***	-0.00564***
	(0.000386)	(0.000458)
dummy granted	0.00158**	0.00155***
	(0.000708)	(0.000564)
docdb_family_size	0.000687***	0.000711***
	(0.000117)	(0.000155)
n of patent's claims	0.000312***	0.000312***
	(1.84e-05)	(1.80e-05)
tot n of cits (patent + npl)	0.000226***	0.000236***
	(1.11e-05)	(1.41e-05)
share npl	0.0154***	0.0156***
	(0.000693)	(0.000632)
dummy CHG_OWN	-0.00831***	-0.00826***
	(0.000579)	(0.000518)
Observations	2,112,530	2,112,530
Dummy Country	YES	YES
Dummy Year	YES	YES
Dummy Technology	YES	YES
Dummy Sector	YES	YES
Dummy Patent Authorithy	YES	YES

Bootstrapped Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1