Department of Economics and Statistics "Cognetti de Martiis"
Campus Luigi Einaudi, Lungo Dora Siena 100/A, 10153 Torino (Italy)
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WHERE DO GREEN TECHNOLOGIES COME FROM? INVENTOR TEAMS' RECOMBINANT CAPABILITIES AND THE CREATION OF NEW KNOWLEDGE

GIANLUCA ORSATTI, MICHELE PEZZONI and FRANCESCO QUATRARO

Bureau of Research on Innovation, Complexity and Knowledge

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Where do green technologies come from? Inventor teams' recombinant capabilities and the creation of new knowledge

Gianluca Orsatti[a,b] – Michele Pezzoni[b,c] – Francesco Quatraro[a,b,c]

a) Department of Economics and Statistics Cognetti de Martiis, University of Torino
b) BRICK, Collegio Carlo Alberto
c) GREDEG-CNRS and University of Nice Sophia Antipolis

ABSTRACT

By exploiting the EPO universe of patent data, we investigate how inventors' teams recombinant capabilities drive the creation of Green Technologies (GTs). Results suggest the importance of recombinant creation patterns in fostering the generation of GTs. We also find diverse moderating effects of technological green experience and environmental regulation stringency on exploration behaviors. Precisely, the positive effect of team's explorative behaviors is magnified for teams lacking technological green experience, even more in regimes of weak environmental regulation. Conversely, the effect of explorative behaviors is reduced for green experienced teams, especially in regimes of weak environmental regulation. Finally, we find positive effects of both team's previous technological green experience and environmental regulation stringency.

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JEL Classification Codes: O31 – O32

Keywords: Recombinant capabilities; Inventors' teams; Exploration; Exploitation; Green Technologies.

1 Introduction

A wide body of literature has elaborated upon Schumpeter's seminal intuition that new inventions can be the outcome of the recombination of existing knowledge (Schumpeter, 1939). Accordingly, research in strategy and management has stressed the importance of 'recombinant capabilities' in shaping firms' innovation performances (Carnabuci and Operti, 2013; Galunic and Rodan, 1998; Hargadon and Sutton, 1997; Henderson and Clark, 1990; Yayavaram and Ahuja, 2008). In a recent study, Carnabuci and Operti (2013) have further documented the relevance of 'recombinant capabilities'. They proposed a refinement of the conceptualization by introducing the distinction between 'recombinant creation' and 'recombinant reuse', which points to the ability to create combinations using technologies that have never been combined before or using technologies that have already proven to work well together. They show that the configuration of firms' intra-organizational network and firms' knowledge diversity can explain the prevalence of recombinant creation rather than reuse.

While many efforts have been devoted to the understanding of the emergence of the different types of recombinant capabilities, few attempts can be found in the literature to investigate how these can affect the creation of knowledge in specific technological domains. Consistently, this study attempts to fully deploy the explanatory power of the 'recombinant capabilities' approach to understand the mechanisms behind the generation of new knowledge in the field of green technologies (GTs). The present study represents therefore one of the few attempts to understand the antecedents of invention of GTs (Del Rio, 2009; Taylor et al., 2005).

We investigate how recombinant capabilities drive the generation of GTs, as well as the potential moderating effect of environmental policies. More precisely, we investigate whether the generation of green patents is driven by explorative ("recombinant creation") or exploitative ("recombinant reuse") patterns of knowledge recombination, or a mix of both. Our focus is on inventor teams' recombinant capabilities. In line with earlier work (Fleming, 2001), we develop indicators of recombinant creation and reuse by exploiting the information concerning the technological components combined within an inventor team's patented innovations.

The results reveal an overall prevalence of recombinant creation patterns in the generation process of GTs. However, a finer grained analysis suggests that the dynamics at stake are somewhat more articulated, due to the relevance of path-dependence dynamics.

Furthermore, results also confirm the critical role played by environmental policies in boosting the generation of GTs and, interestingly, in moderating the effects of different recombinant capabilities. Indeed, our results seem to suggest that the more stringent is the environmental regulation the more effective is the role of recombinant creation in triggering the generation of GTs for teams lacking previous technological experience in the green domain. Conversely, for experienced team, the premium of recombinant creation is almost absent in regimes of high levels of environmental policy stringency.

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

2 Theory and hypotheses

2.1 Recombinant capabilities and innovation

Schumpeter (1934) proposes that novelty is brought about in the economy by means of combinatorial activity: “To produce means to combine materials and forces within our reach [...]. To produce other things [...] means to combine these materials and forces differently” (Schumpeter, 1934: 65). Following this seminal intuition, scholars in both economics and management of innovation have elaborated upon the concept of knowledge recombination. The recombinant growth hypothesis (Weitzman, 1996 and 1998) draws on analytical models showing that new ideas are generated through the recombination of existing ideas, under the constraint of diminishing returns to scale in the performance of the research and development (R&D) activities necessary to apply new ideas to economic activities (Caminati, 2006). The economic bearings of this framework have been further articulated by Olsson (2000) who introduced a preliminary metrics to account for recombination costs. Olsson and Frey (2002) propose the notion of technological space, suggesting that the costs of knowledge recombination are a function of knowledge distance.

Kauffman (1993) elaborates the so called N-K model of recombinant knowledge generation, according to which the success of a search process depends on the topography of a given knowledge landscape shaped by the complementary relations (K) among the different elements (N) of a given unit of knowledge. Fleming and Sorenson (2001) tested the implication of this approach, by proposing the existence of a nonlinear relationship between the interdependence of the components of the technological landscape and the search.

Strategy researchers have developed the implications of the recombinant approach for the management of innovation activities within firms and across their boundaries. The creation of new knowledge – hence, any kind of novelty – can be represented as a search process across a set of multiple existent components (Gavetti and Levinthal, 2000; Katila and Ahuja, 2002). Large emphasis has been given in this context to the investigation of the impact of recombinant capabilities on firms’ performances (Henderson and Clark, 1990; Galunic and Rodan, 1998; Kogut and Zander, 1992).

The identification of two different and yet complementary dimensions of recombinant capabilities, *i.e.* recombinant creation and reuse, marks an important step forward in the understanding of the very dynamics of knowledge creation (Carnabuci and Operti, 2013).

This advance sheds light on the antecedents of recombinant capabilities, and helps the understanding of the tension between exploration and exploitation in organizations (March, 1991; Katila and Ahuja, 2002). Exploration requires the development of new knowledge, or moving away from the existing technological competences (Benner and Tushman, 2002; Levinthal and March, 1993), while exploitation builds upon existing knowledge and competences and strengthens existing skills, processes, and structures (Abernathy and Clark, 1985; Benner and Tushman, 2002; Levinthal and March, 1993).

The organization science literature stresses the importance of inventors' collaboration networks in shaping the propensity to recombinant creation and recombinant reuse (Nerkar and Paruchuri, 2005; Paruchuri, 2010). For this reason, our unit of analysis in this study is not the individual inventor, but inventors' teams. Specific recombination patterns indeed emerge out of knowledge exchanges amongst inventors working together to develop new technological solutions (Hagardon and Sutton, 1997; Obstfeld, 2005). The present analysis is thus focused on two aspects characterizing the creation of knowledge in the field of GTs. In line with preliminary evidence in previous literature (Dechezlepetre et al., 2014), we firstly look at the extent to which inventors' teams rely on recombinant creation or reuse in the generation of GTs. Second, we investigate the role of different policy regulatory frameworks in shaping the balance between recombinant reuse and creation, for different levels of accumulated knowledge experience.

2.2 Recombinant creation and reuse for the creation of GTs

The analysis of GTs has gained momentum in the last two decades, following the well-known argument set forth by Porter and van der Linde (1995), according to which green technical change is likely to enhance both firms' environmental performances and their production efficiency (Ambec et al., 2013).

As noticed by Del Rio (2009), most studies investigating the determinants of GTs have focused on the understanding of the innovation and the diffusion stages, while the early phase of invention has not received so far comparable attention. As for the diffusion stage, Ghisetti et al. (2015) find that the mastering of diverse knowledge sources enables the adoption of eco-innovative behaviors. Dechezlepetre et al. (2014) compare knowledge spillovers from dirty and clean technologies, finding that clean technologies are largely more cited than the dirty ones. They suggest that this evidence could be partially explained by the fact that GTs have more general applications, and they are radically new as compared to more incremental dirty innovation.

The extant literature, although still scarce, provides evidence supporting the idea that GTs draw upon increased knowledge diversity, as they span across many different technological fields and are mostly radical. These characteristics are prevalently associated to novelties emerging out of recombinant creation. These arguments lead to the following hypothesis:

H1: The more the inventor team will innovate by creating new technological combinations, the higher the probability that they will create new knowledge in the field of GTs.

2.3 Knowledge accumulation

Individuals are essentially cognitively bounded (Grant, 1996). As an implication, they can master only a limited portion of knowledge. From a synchronic viewpoint, this implies that knowledge creation is more likely to occur when individuals exchange their bits of knowledge. From a dynamic viewpoint it implies a gradual process of specialization, through the consolidation of successful innovation routines (Cohen and Levinthal, 1990; Nelson and Winter, 1982; Stuart and Podolny, 1996).

According to the evolutionary approach to knowledge and innovation, the process by which inventors accumulate competences over time is such that they become increasingly specialized and familiar with a specific set of innovating routines (Nelson and Winter, 1982). While this generally positively affects the effectiveness of the invention process, it prevents inventors from the exploration of unfamiliar areas of the technology landscape. The invention process is *path-dependent* in that it is constrained by the dynamics of knowledge accumulation at the inventor and the team level (Leonard-Barton, 1992).

The development of core competences in the generation of GTs can therefore make exploitation more likely to occur in the creation of new GTs (Prahlad and Amel, 1990). Learning dynamics influences the balance between recombinant creation and recombinant reuse. The cumulativeness of technological competences enables inventors to successfully rely on recombinant reuse, but this can substantially constrain the effectiveness of more exploratory strategies embedded in recombinant creation (Ahuja and Lampert, 2001). In other words, inventors with sound competence in a specific technology area tend to highly value knowledge that is close to their cumulated knowledge, and to devalue more distant knowledge (Kim et al., 2012). These arguments lead us to specify the following hypotheses:

H2: Previous experience in the creation of GTs positively affects the probability to generate new GTs.

H3: The positive association between recombinant creation and the generation of GTs is mitigated by inventors' teams' previous experience in the creation of new GTs.

2.4 Regulatory frameworks

In view of the so-called 'double externality problem' (Jaffe et al., 2005; Rennings, 2000), the extant literature analyzing the determinants of GTs has intensively the inducement mechanisms set forth by the implementation of stringent environmental regulatory frameworks (Porter, 1991; Frondel et al., 2008; Del Rio, 2004; 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; Acemoglu et al., 2012; Ghisetti and Quatraro, 2013). The 'double externality' problem provides policymakers with a key role in the stimulation of research efforts towards the generation of new GTs. The so-called inducement hypothesis maintains that when environmental degradation becomes costly for firms due to the design of stringent regulatory frameworks, firms prefer to invest resources to improve the environmental performance of their production process, rather than to pay to pollute. While the empirical evidence regarding the effects of different policy tools amongst sectors and countries is mixed (Horbach et al., 2012; Peters et al., 2012), the extant literature almost unanimously agrees on the key role of regulatory frameworks in triggering the generation of new GTs. This effect passes mainly through the creation of new markets for green technology producers and through the advancement of knowledge in the green domain. Moreover, as a general result for specific policy tools, demand-pull policies seem to benefit more mature green technologies, while technology-push policies seem to affect both more and less mature technologies .

Few studies have recently explored the link between modes of innovation and demand-side policies, with particular attention to deployment policies. Since the year 2000 on, deployment policies have become central in the design of policy architecture aiming at boosting the diffusion of GTs. Indeed, in a rising number of countries, resources dedicated to deployment policies by far exceed the incentives for R&D activities (references). Following the inducement hypothesis, most of the aforementioned studies are based on the assumption 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 (e.g. Nemet, 2009). Few studies stress that, by enhancing exploitative search strategies, deployment policies could reduce technological diversity in an industry – rather than stimulating the search for radically new technological solutions – even contributing to the emergence of lock-ins into more mature, non-necessarily superior, technological trajectories (with respect to the PV industry, see: Menanteau, 2000; Sandén, 2005; Sartorious, 2005; van den Heuvel and van den Bergh, 2009).

Hoppmann et al. (2013) provide theoretical and empirical grounds to the link between deployment policies and the tension between exploration and exploitation. Based on comparative evidence from 9 leading firms in the photovoltaic module industry, they argue that deployment policies are likely to yield differential effects in terms of firms' exploration vs. exploitation strategies, according to both the rate of policy-induced market growth and the maturity of firms' technological competences. More precisely, market growth constitutes an incentive to invest in exploration for both firms pursuing more mature and firms pursuing less mature technologies. However, in the balance between exploitation and exploration, the latter by far dominates the former, when firms face high rates of market growth. Thus we hypothesize that:

H4: Stringent regulatory frameworks positively affect the probability to generate new GTs.

H5: The positive association between recombinant creation and the generation of GTs is enhanced by the availability of stringent regulatory frameworks, especially for teams with no previous green competences.

3 Data, variables and methodology

3.1 Data

Our study sample includes all the patents filed in at the European Patent Office (EPO), from 1995 to 2009.[1] The main dataset we exploit comes from PatStat and is maintained by the CRIOS Center for Research on Innovation, Organization and Strategy[2]. It provides the

[1] We are aware about traditional pros and cons of using patent data (to be extended).

[2] For a complete description of the data supplied by the CRIOS Center for Research on Innovation, Organization and Strategy, see Coffano and Tarasconi (2014).

inventors' identity information disambiguated with the Massacrator© Algorithm (Lissoni et al., 2006; Pezzoni et al., 2012).

3.2 Variables

3.2.1 Dependent variable

Patents are classified as green 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. We combine both classifications in order to define the dependent variable (*Green*).

[FIGURE 1 ABOUT HERE]

3.2.2 Patent-based knowledge-search indicators

We calculate the team recombinant creation variable (*Exploration*) in three steps.

First, for each patent, we calculate three technological knowledge indicators relying on the IPCs contained in their backward citations: *technological-knowledge variety (IE), knowledge coherence (COH),* and *cognitive distance (CD)* (see BOX1 in the Appendix for a complete description of the mechanics behind the calculation of the indicator).

Second, we assign to each inventor listed in the focal patent document the average value of IE, COH, and CD she accumulated in her previous patenting activity, up to time $(t-1)$. For each inventor i we thus define: $IE_{i,t-1} = \frac{\sum_p IE_p}{N}$; $COH_{i,t-1} = \frac{\sum_p COH_p}{N}$; $CD_{i,t-1} = \frac{\sum_p CD_p}{N}$. The numerators are the sums of the observed values of IE, COH and CD; N is the total number of patents filed by inventor i up to time $(t-1)$. Then, we assign the average values of IE, COH, and CD of each inventors to the inventors' team of the focal patent.

By focusing the analysis at the inventors' team level, the combination of these indicators allows us to capture the complexity of the knowledge search behavior behind the generation of an invention. However, only precise combination of the values of the three indicators can be interpreted as the evidence of an explorative behavior (recombinant creation). Precisely, an explorative behavior is positively correlated with IE and CD, and negatively correlated with COH (Krafft et al ., 2014). Thus, we perform principal component analysis using IE, COH, and CD at the team level, in order to provide a synthetic indicator of knowledge search behaviors characterizing the technological portfolio of the inventors' team.

[TABLE 1 ABOUT HERE]

The analysis identifies only one dominant component with eigenvalue above one. It captures the 43% of the total variance. It is positively correlated with IE and CD, and negatively correlated with COH (Table 1). Thus, we consider the dominant component as representative for explorative behaviors (recombinant creation). The dummy *Exploration* equals one if the score of the component for the focal patent is above the component average value, zero otherwise.

3.2.3 Team green experience and environmental policy stringency

As for the team green experience, we define a dummy *team green experience* that equals one if the team has at least one patent in green technologies in its patent stock, up to t-1, zero otherwise.

As for the policy stringency variable, we include in the analysis the OECD Environmental Policy Stringency Index (EPS), which is a country-specific and internationally-comparable measure of the stringency of environmental policy. OECD defines "stringency" as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The composite index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution and it ranges from 0 (not stringent) to 6 (highest degree of stringency). It covers 28 OECD and 6 BRIICS countries for the period 1990-2012 (Botta and Kozluk, 2014). The level of the index is assigned to each observed patent on the basis of the applicant's country of residence. The dummy *Stringent policy* equals 1 if the index is above its average value, zero otherwise.

3.2.4 Control variables

As for the controls, we account for a comprehensive set of variables at the level of the inventors' team and the applicant. At the level of the team, we control for several characteristics: *i)* the number of inventors; *ii)* the number of previous patents (stock); *iii)* share of granted patents; *iv)* share of triadic patents; *v)* number of backward citations. At the level of the patent applicant we control for i) the number of previous patents; and ii) previous green experience (dummy). Finally, we control also for patent priority-year dummies, country dummies (based on the applicant's residence address), OST7 technology dummies (assigned on the basis of the team's previous patenting activity). Tables 2 and 3 show the descriptive statistics.

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

3.3 Methodology

We test the theoretical arguments and the research questions proposed in Section 2 with a series of nested regression models. First, we estimate the effect of team recombinant creation (*Exploration*)[3], environmental policy stringency (*Stringent policy*), and team green experience (*Team green experience*) on the probability to observe a patent *p* with green technological content. We control for an extensive set of variables characterizing the inventors' team, the patent applicant, and the calendar year (Equation 1).

$$\Pr(GREEN = 1)_p = \alpha + \beta_1 Exploration + \beta_2 Stringent\ policy + \beta_3 Team\ green\ experience + \gamma CONTROLS + \varepsilon_p \quad \text{[Equation 1]}$$

Second, in order to investigate the potential moderating effects of environmental policy stringency and team green experience on team recombinant creation, we extend the model in equation 1 by testing for all the possible interactions (Equation 2).

$$\Pr(GREEN = 1)_p = \alpha + \beta_1 Exploration + \beta_2 Stringent\ policy + \beta_3 Team\ green\ experience + \beta_4 Exploration * Stringent\ policy + \beta_5 Exploration * Team\ green\ experience + \beta_6 Exploration * Stringent\ policy * Team\ green\ experience + +\beta_7 Stringent\ policy * Team\ green\ experience + \gamma CONTROLS + \varepsilon_p \quad \text{[Equation 2]}$$

We apply OLS estimations, although the results are robust to Logit estimations.

[3] From here on we alternatively define the variable "exploration" as either team explorative strategy or team recombinant creation.

4 Results

As a starting point of the analysis, we estimate six nested models (Table 4). In columns 1, 2, 3, and 4 we estimate the effect of, respectively, *exploration* (recombinant creation), *team green experience*, and *stringent environmental policy*, including country, technological area and calendar year dummies. In column 5 we add team characteristics as further controls. Finally, in column 6 we also account for applicant characteristics.

[INSERT TABLE 4 ABOUT HERE]

Results reveal that adopting an explorative behavior shows a premium on the probability of observing a patent with green technological content, confirming hypothesis 1 stated in Section 2. Precisely, adopting an exploration behavior increases such probability of observing a green patent by 1.32% (column 6). Moreover, environmental policy stringency has a positive effect (+1.49%), as well as the team green experience dummy variable (+33.6%). Hypothesis 2 and 4 are thus confirmed. Interestingly, what emerges is the prominent role of the team green experience in driving the probability of observing a GT.

As for the controls, the number of inventors positively impacts the probability of observing a GT, as well as the number of team's backward citations, and the applicant's green previous experience. On the contrary, the team's stock of patents, the team's share of granted and triadic patents, and the applicant's stock of patents, show a negative effect.

[INSERT TABLE 5 ABOUT HERE]

In Table 5 we estimate 6 regression models adding sequantially a set of interactions that allow us to test for moderating effects of both team green experience and stringent environmental policy on team's explorative behavior. The same model estimated in Table 4, column 6, represents our baseline model in Table 5, column 1. In columns 2,3,4, and 5 we sequentially add to the baseline model all the possible double interactions. Finally, in column 6 we add the triple interaction between team exploration behavior, stringent environmental policy, and team green experience variables. The marginal effects of the team exploration behavior, taking into account the moderating effects of green experience and policy stringency, are presented in Table 6.

[INSERT TABLE 6 ABOUT HERE]

We find that adopting an explorative behavior fosters the probability of observing a green patent in contexts of low team green experience. Interestingly, the marginal effect is higher when the stringency level of environmental policy is weak (+3.1%). Conversely, for teams showing higher levels of green experience, the marginal effect of adopting an exploration behavior is negative, namely exploitative behaviors are more effective in generating a GT. Moreover, this effect is magnified when the environmental policy stringency is weak (-3.55%). As for the controls, the effects are consistent with the ones estimated in Table 4.

5 Conclusions

The present study aims at capturing the effect of diverse knowledge recombination patterns, mastered by inventors' teams, as important drivers for the generation of green technologies (GTs). Evidence shows a positive premium of adopting explorative patterns in the generation of GTs, confirming the hypothesis 1 we propose in section 2. Moreover, we find positive effects of both team's previous technological green experience and environmental regulation stringency, confirming, respectively, hypotheses 2 and 4. We also find diverse moderating effects of technological green experience and environmental regulation stringency on exploration behaviors. Precisely, the positive effect of team's explorative behaviors is magnified for teams lacking technological green experience, even more in regimes of weak environmental regulation. Conversely, the effect of explorative behaviors is reduced for experienced teams, especially in regimes of weak environmental regulation. Both hypotheses 3 and 5 are thus confirmed, showing a complex architecture behind the generation process of GTs.

Policy implications are multiple. Firstly, in contexts where the level of advance of green technological knowledge is scarce, exploration modes reveal their relevance in boosting GTs. Building proper levels of green technological infrastructures is by far the most important driver for boosting GTs. However, this is a long term, not easy to achieve, goal. Thus, by incentivizing explorative behaviors, policy makers could boost GTs more rapidly in contexts of weak green-technological infrastructures. Interestingly, in cases of no previous team green experience, when explorative behaviors are combined with high levels of stringency, the total effect is magnified. Thus, the importance of combining environmental stringency with innovation policies (oriented towards new niches and explorative technologies) is the most effective strategy for countries/sectors where the green technological infrastructure is weak.

Secondly, as well as for other kinds of innovations, path dependence plays a crucial role also for GTs. Moreover, especially in regimes of weak environmental regulation, there seems to be a premium for recombinant reuse behaviors (exploitation) for teams showing previous green experience. This combination of effects could be harmful in terms of possible emergence of technological lock-ins. Proper innovation policies aiming at boosting systemic variety and exploration strategies are thus suggested in contexts of high green-technological specialization.

Further extensions

First, we split the sample according to the specific technological macro areas characterizing the observed patent (OST7) and we estimate separated regressions for each sub-sample. The estimated marginal effects of the team exploration behavior for each one of the sub-samples are reported in Table A1 and graphically represented in figure A1 (see Appendix). We find interesting sector specificities that we are trying to properly interpret.

Second, we split environmental policies between demand-pull and supply-push, and we are testing for differential effects of different levels of stringency for both policy tools. What we expect to observe is that i) when demand tools are stringent, there is an exploration premium for teams without previous green technological experience; ii) when supply tools are stringent, there is an exploration premium for both teams.

Third, we split our sample between radical and incremental focal patents and we estimate our model for the two groups. What we expect to observe is that there is an exploration premium in the generation process of GTs for both groups, larger for teams pursuing radical technologies, showing low previous green experience, and facing stringent supply-oriented regulatory frameworks.

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7 Figures and Tables

Figure 1: Total number of patents and shares of green patents by year

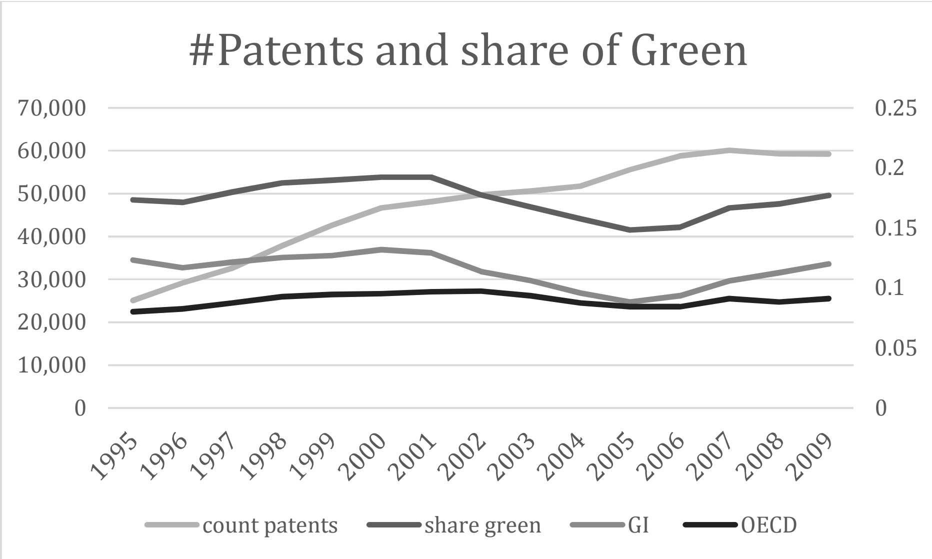


Table 1: Principal Component Analysis

Component number	1	2	3
Coherence	-0.67	0.02	0.74
Variety	0.54	-0.67	0.51
Cognitive Distance	0.51	0.74	0.44
Eigenvalues	1.28	0.95	0.77
Cumulative Perc. of total variation	0.43	0.74	1

Table 2: Descriptive statistics

	obs.	mean	sd	min	max
Dependent variable					
Green dummy	706943	0.172	0.377	0.00	1.00
Variables of interest (lagged t-1)					
Exploration (Dummy)	706943	0.547	0.498	0.00	1.00
High Variety (Dummy)	706943	0.471	0.499	0.00	1.00
High Coherence (Dummy)	706943	0.424	0.494	0.00	1.00
High Cognitive Distance (Dummy)	706943	0.499	0.500	0.00	1.00
Policy stringency (Dummy)	706943	0.554	0.497	0.00	1.00
Team green experience (Dummy)	706943	0.355	0.478	0.00	1.00
Team controls (lagged t-1)					
n. of inventors	706943	3.253	2.209	1.00	60.00
Team experience (Stock of patents)	706943	20.841	143.995	1.00	4259
Share of granted patents	706943	0.514	0.379	0.00	1.00
Share of triadic patents	706943	0.531	0.386	0.00	1.00
Number of backward citations	706943	90.719	380.153	1.00	19043
Applicant controls (lagged t-1)					
Applicant patenting experience (Stock of patents)	706943	1193	3444	0.00	34855
Applicant green experience (Dummy)	706943	0.706	0.456	0.00	1.00

Table 3: Percentage of green patents. Conditional mean for each of variables of interest.

variables	High	Low	diff	Pvalue
Exploration (Dummy)	0.167	0.178	0.011	0.00
High Variety (Dummy)	0.164	0.18	0.015	0.00
High Coherence (Dummy)	0.166	0.18	-0.014	0.00
High Cognitive Distance (Dummy)	0.17	0.174	0.004	0.00
Policy stringency (Dummy)	0.187	0.154	-0.033	0.00
Team green experience (Dummy)	0.389	0.053	-0.34	0.00
obs: 706943				

Table 4: Probability of observing a green patent. OLS estimation.

variables	(1) Pr(green)	(2) Pr(green)	(3) Pr(green)	(4) Pr(green)	(5) Pr(green)	(6) Pr(green)
Variables of interest (lagged t-1)						
Exploration t-1 (Dummy)	0.0131***			0.0205***	0.0134***	0.0132***
Stringent policy t-1 (Dummy)		0.0168***		0.0144***	0.0135***	0.0149***
Team green experience t-1 (Dummy)			0.345***	0.345***	0.353***	0.336***
Team controls (lagged t-1)						
n. of inventors					0.00509***	0.00480***
log(Stock of patents)					-0.0272***	-0.0258***
Share of granted patents					-0.00506***	-0.00546***
Share of triadic patents					-0.00739***	-0.00758***
log(Number of backward citations)					0.00397***	0.00458***
Applicant controls (lagged t-1)						
log(1+Stock of patents)						-0.00876***
Applicant green experience (Dummy)						0.0773***
Other controls						
Country dummies (Applicant)	yes	yes	yes	yes	yes	yes
OST7 dummies (Team)	yes	yes	yes	yes	yes	yes
Calendar year dummies	yes	yes	yes	yes	yes	yes
Constant	0.128***	0.128***	0.130***	0.117***	0.120***	0.107***
Observations	706,943	706,943	706,943	706,943	706,943	706,943
R-squared	0.064	0.063	0.219	0.220	0.224	0.228

Table 5: Probability of observing a green patent. OLS estimation. Interactions.

variables	(1) Pr(green)	(2) Pr(green)	(3) Pr(green)	(4) Pr(green)	(5) Pr(green)	(6) Pr(green)
Variables of interest (lagged t-1)						
Exploration (Dummy)	0.0132***	0.0280***	0.0115***	0.0132***	0.0242***	0.0310***
Exploration * Team green experience		-0.0413***			-0.0430***	-0.0665***
Exploration * Stringent policy			0.00310*		0.00772***	-0.00534***
Exploration * Stringent policy * Team green experience						0.0391***
Stringent policy * Team green experience				-0.00310*	-0.00812***	-0.0306***
Stringent policy (Dummy)	0.0149***	0.0150***	0.0132***	0.0158***	0.0133***	0.0203***
Team green experience (Dummy)	0.336***	0.359***	0.336***	0.337***	0.365***	0.379***
Team controls (lagged t-1)						
n. of inventors	0.00480***	0.00484***	0.00479***	0.00480***	0.00484***	0.00483***
log(Stock of patents)	-0.0258***	-0.0254***	-0.0259***	-0.0258***	-0.0254***	-0.0256***
Share of granted patents	-0.00546***	-0.00567***	-0.00546***	-0.00549***	-0.00575***	-0.00569***
Share of triadic patents	-0.00758***	-0.00773***	-0.00760***	-0.00753***	-0.00765***	-0.00752***
log(Number of backward citations)	0.00458***	0.00442***	0.00461***	0.00455***	0.00442***	0.00451***
Applicant controls (lagged t-1)						
log(1+Stock of patents)	-0.00876***	-0.00870***	-0.00876***	-0.00875***	-0.00865***	-0.00868***
Applicant green experience (Dummy)	0.0773***	0.0769***	0.0773***	0.0773***	0.0769***	0.0769***
Other controls						
Country dummies (Applicant)	yes	yes	yes	yes	yes	yes
OST7 dummies (Team)	yes	yes	yes	yes	yes	yes
Calendar year dummies	yes	yes	yes	yes	yes	yes
Constant	0.107***	0.0987***	0.108***	0.106***	0.0993***	0.0952***
Observations	706,943	706,943	706,943	706,943	706,943	706,943
R-squared	0.228	0.229	0.228	0.228	0.229	0.229

Table 6: Exploration marginal effect summary (based on the estimations in Table 5, Column 6)

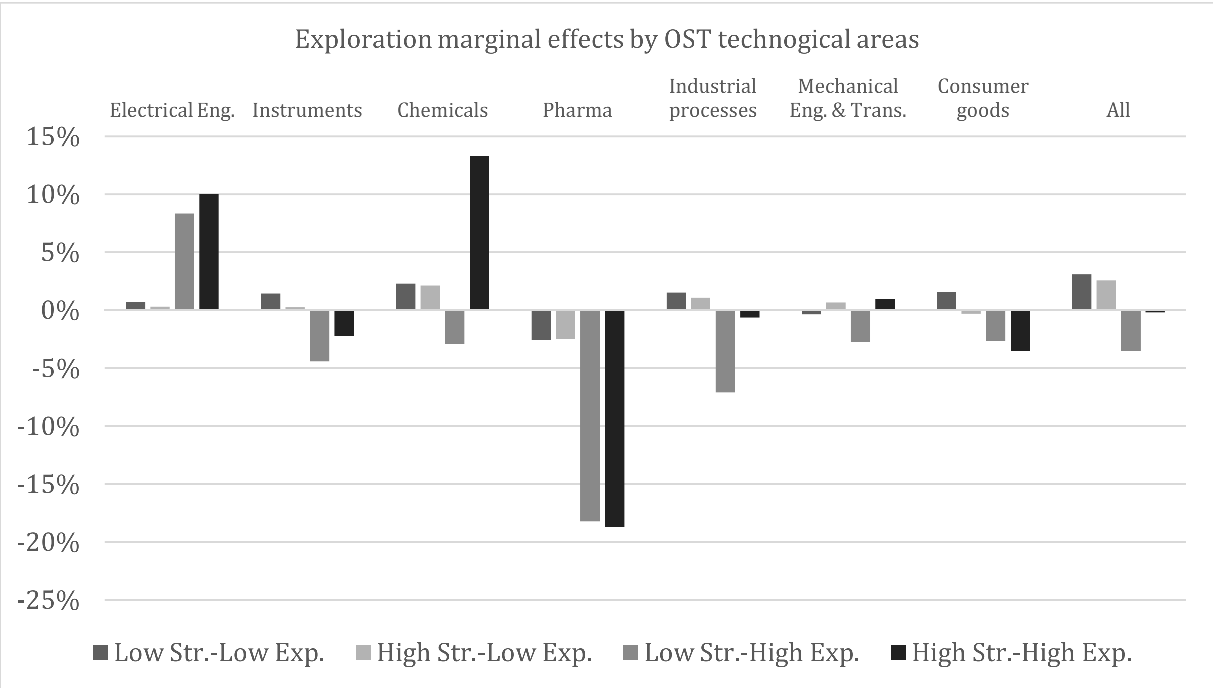
		Policy stringency	
		high	low
Team experience	high	-0.17%	-3.55%
	low	2.56%	3.10%

Appendix

Table A1: Exploration marginal effect by OST7 technological areas. OLS estimations.

OST7 Technological area	Obs. (%Green)	Low Str.-Low Exp.	High Str.-Low Exp.	Low Str.-High Exp.	High Str.-High Exp.
Electrical Eng.	206204 (15%)	0.70%	0.31%	8.34%	10.04%
Instruments	161548 (14%)	1.44%	0.24%	-4.41%	-2.20%
Chemicals	182382 (17%)	2.30%	2.14%	-2.93%	13.28%
Pharma	125810 (12%)	-2.60%	-2.46%	-18.21%	-18.72%
Industrial processes	126169 (20%)	1.51%	1.08%	-7.09%	-0.65%
Mechanical Eng. & Trans.	117698 (45%)	-0.34%	0.67%	-2.75%	0.98%
Consumer goods	44346 (12%)	1.55%	-0.29%	-2.69%	-3.48%
All	706943 (17%)	*3.10%*	*2.56%*	*-3.55%*	*-0.17%*

Figure A1: Graphical representation of the Exploration marginal effect by OST7 technological areas



Box 1 – Technological Knowledge Indicators

First, in order to measure the level of *technological-knowledge variety (IE)* 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.[4] 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 to 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 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 (IEW) measures the average degree of disorder or variety within the subsets, between-entropy (IEB) 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 $\in S_z$ $(g = 1, \ldots, G;\ z = 1, \ldots, Z)$, we can rewrite $H(X,Y)$ as follows:

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

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

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,

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

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

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

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 (COH)* 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 analyzing 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.

Third, the similarity amongst different types of knowledge can be captured by a measure of *cognitive distance (CD)*. 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-centered 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. The average cognitive distance for a patent is obtained as follows:

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