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THREE ESSAYS ON THE DETERMINANTS OF GREEN INNOVATION

Gianluca Orsatti

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Thesis supervisor: Francesco Quatraro

Thesis co-supervisor: Francesco Lissoni

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Introduction

Fostering green technical change is at the top of the global policy agenda. No long-run economic growth is indeed possible without timely addressing climate change issues.

A theoretical cornerstone for understanding green innovation dynamics is represented by the so-called "double externality" issue affecting the incentives to invest in green R&D projects. On the one hand, non-appropriability and non-exclusivity of technological knowledge give way to the kind of externalities that are common to any innovation, and that lead to under-investment in the private sector. On the other hand, because of their potentially pervasive influence, GTs that effectively contribute to containing or preventing the negative effects of climate change bring about global benefits in the form of environmental protection that represent a positive externality for society, therein including non-innovating firms. This double externality exacerbates the traditional uncertainty that surrounds the development of new technologies and provides a rationale for public policy interventions that create positive preconditions for investments in GTs.

With this clear-cut issue at stake, the literature on the economics of green innovation flourished during the last two or more decades. First, given its uniqueness, scholars widely investigated the peculiarities of the green innovation process. Second, due to the essential need of publicly intervening, scholars deeply entered into the analysis of the heterogeneous effect on green innovation dynamics of diverse policy tools from micro, meso and macro level perspectives.

Mainly exploiting information contained in patent data, the present thesis aims at contributing the empirical literature on the determinants of green innovation processes under several original perspectives. It indeed provides evidence, on the one hand, about the very antecedents of green inventions by looking at the way how inventor teams recombine extant technological knowledge and, on the other hand, on how two diverse and under-explored policy tools, namely government-funded R&D and public procurement, affect green innovation dynamics. The thesis is thus a collection of three research articles. I briefly provide here a description and the main findings of those studies.

The first chapter is coauthored with Michele Pezzoni and Francesco Quatraro and focuses on the antecedents of green innovation processes from a micro viewpoint. By exploiting the European Patent Office universe of patent data, it investigates how inventor teams' recombinant capabilities and green-tech experience drive the creation of green inventions. Furthermore, the chapter also explores differential effects of both combinatorial abilities and experience according to heterogeneous levels of environmental policy stringency.

The team dimension of green innovation processes has been almost neglected by the extant studies. The main argument of the chapter is instead that it is of crucial importance since GTs are likely to emerge out of hybridization of existent technological processes, thus requiring continuous collaboration and exchanges.

Results suggest that green technological change is positively associated with recombinant creation, previous experience in the green-tech domain, and high stringency of regulatory frameworks. Interestingly, teams lacking experience in green technological processes benefit more from the recombinant creation, especially in regimes characterized by weak environmental regulation. To the bunch of GT drivers, the chapter originally adds evidence of the importance of the team's ability in creatively recombining extant technological knowledge.

Passing from the team perspective to a more general one, the second part of the thesis focuses on the investigation of the inducement effect of two precise policy tools, named public R&D and public procurement. Even if responsible for a large part of the governments' intervention, the influence of those policy tools on green innovation has been surprisingly under-investigated by the extant literature.

The second chapter investigates the effect of changes in the level of government-funded R&D on both the rate of green-tech knowledge accumulation and the direction it takes, exploiting information contained in patent citation data. The study sample includes green patents applied at the European Patent Office from 1980 to 1984. Citations are observed from 1981 to 1988, together with their qualitative characteristics. To find a causal effect of a change in the level of public R&D expenditures on citations received by green patents, the analysis has been framed in a quasi-experimental environment, exploiting the Chernobyl nuclear disaster occurred in 1986 as an exogenous shock affecting the public intervention in the energy sector.

Results reveal that a 1% increase in Government R&D budget increases by 0.14% the yearly average number of citations a green patent receives. Similar evidence emerges for the number of citations coming from highly original and radical patents, and from non-green patents. Government-funded R&D is thus an important lever for both consolidating the established green technological trajectory and accelerating the process of changing technological paradigm. However, the magnitude of the estimated effects suggests that an unprecedented effort in public R&D investments is required to timely shift from dirty to clean production systems.

While the second chapter provides evidence of a specific kind of supply-side public intervention, the third chapter mainly focuses on the effect of a demand-oriented kind of public intervention, named green public procurement. It is coauthored with Davide Consoli, François Perruchas and Francesco Quatraro and it investigates whether and through which channels green public procurement (GPP) stimulates local environmental innovation capacity. To this end, detailed data sources on green patents and procurement expenditures at the level of US Commuting Zones (CZs) for the period 2000-2011 have been exploited. The chapter also checks for the moderating effects of the local labor market composition in the relation between green public procurement and green innovation capacity. Lastly, by exploiting the richness of information contained in patent documents, the chapter tests for differential effects of green public procurement on different classes of green technologies.

The main finding is that GPP is an important driver in explaining the growth of local green-tech stocks. The positive effect of GPP is mainly driven by expenditures for procured green services and is magnified by the local presence of high shares of abstract-intensive occupations. When separately considering diverse kinds of green technologies, the evidence of a more pronounced effect of GPP on the growth of local knowledge stocks of mitigation technologies emerges.

1 Antecedents of Green Technologies: The Role of recombinant capabilities and team knowledge production[1]

Abstract

Understanding the antecedents of green technologies (GTs) is of crucial importance for firms' green innovation strategies. The chapter investigates how inventor teams' recombinant capabilities, green experience, and environmental regulation stringency drive the creation of green inventions. Our results show that green technological change is positively associated with recombinant creation, previous experience in the green-tech domain, and high stringency of regulatory frameworks. Moreover, we find that teams lacking experience in green technological processes benefit more from the recombinant creation, especially in regimes of weak environmental regulation. These results have implications for the strategic management of inventor teams within firms willing to grasp the opportunities set forth by the emergence of new markets for green technologies.

[1]This chapter is coauthored with Michele Pezzoni and Francesco Quatraro. We acknowldge participants in: the *DRUID Academy 2016* conference, University of Bordeaux, Bordeaux, France; the *GCW 2016 – Innovation, Employment and Environment* conference, INGENIO [CSIC-UPV], Valencia, Spain; and the *What's new in the economics of innovation? Theory, empirics and public policy* conference, December 2016, Grenoble, France.

1.1 Introduction

Green technologies (GTs) are deemed crucial assets to decouple firms' growth from environmental degradation. Their implementation is expected to lead to improvements in both firms' productivity levels and environmental performances (Porter and van der Linde, 1995). For this reason, GTs have been the object of the increasing research on environmental and innovation dynamics. Many studies have enquired so far into the determinants of the generation and the adoption of these technologies, as well as into their actual effects on economic and environmental outcomes (Barbieri et al., 2016).

Empirical applications investigating the determinants of green knowledge production have mainly focused on the role of environmental and innovation policies. The rationale behind the prominent role of public interventions as a lever for the generation and diffusion of GTs resides in the so-called "double externality problem" (Rennings, 2000). On the one hand, like any other kind of technologies, GTs are intrinsically featured by appropriability problems. On the other hand, their diffusion in the economy yields positive impacts on the environment, generating benefits to those who do not bear the costs. Accordingly, the allocation of resources to the production of GTs is expected to be sub-optimal. Environmental regulation and innovation policies gain therefore a crucial role in this framework.

In light of the regulatory push/pull effect (Rennings, 2000), both supply and demand oriented policies have proved to be effective in stimulating the production and adoption of GTs (Requate, 2005). Demand side policies are based on the induced innovation effect, according to which stringent regulatory frameworks push firms to adopt GTs to save production costs. As an effect, these measures lead either to the modification of existent markets or to the emergence of new niches that make it profitable for firms to enter the GTs business and allocate resources to their production (Nemet, 2009; Johnstone et al., 2012; Hoppmann et al., 2013). Supply-side policies, conversely, represent a direct support for technological change. They include subsidies, loans, tax credits, grants, pricing schemes, R&D funding for risky innovative processes, and so on.

The choice to engage in green knowledge production may be deemed as a strategic decision for a firm willing to reap the profit prospects opened by policy interventions. For this reason, this chapter aims at shedding light on the very antecedents of GTs (Taylor et al., 2005; del Río González, 2009) by analyzing the collective invention dynamics behind their production. Specifically, we investigate the factors affecting the probability that an inventor team produces a green invention.

A large number of studies stresses the importance of the team dimension of knowledge production (Singh and Fleming, 2010; Bercovitz and Feldman, 2011; Dornbusch and Neuhäusler, 2015; Teodoridis, 2017). As invention dynamics based on team collaborations benefit from leveraging heterogeneous competences for recombinant innovation (Weitzman, 1998; Fleming, 2001), specific attention has been devoted to investigating how the team composition influences its innovation outcomes. Accordingly, this study seeks to provide an answer to the research question as to how inventor teams recombine knowledge to produce GTs.

In doing so, we elaborate on the concept of recombinant capabilities (Henderson and Clark, 1990; Hargadon and Sutton, 1997; Galunic and Rodan, 1998; Yayavaram and Ahuja, 2008). We primarily focus on the distinction between 'recombinant creation' and 'recombinant reuse', framing such dichotomy in the inventor teams' context (Carnabuci and Operti, 2013). In the team context, 'recombinant creation' points to the team's ability to adopt an explorative behavior combining knowledge that has never been combined before. On the contrary, 'recombinant reuse' points to the adoption of an exploitative behavior. In line with earlier works (e.g. Fleming, 2001), we develop indicators of innovation by 'recombinant creation' vis-à-vis 'reuse' in inventor teams, and study which typology of recombinant capability drives the generation of green inventions. The potential moderating effects of environmental policies and of teams' previous experience in the green domain is also investigated.

Results reveal an overall dominance of the impact of recombinant creation capabilities. However, a finer grained analysis suggests that the dynamics at stake are somewhat more articulated, due to learning dynamics and knowledge accumulation within inventor teams. 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 suggest that, for teams lacking previous technological experience in the green domain, the more stringent is the environmental regulation the more effective is the impact of recombinant creation in triggering the generation of green inventions. Conversely, for teams with green experience, the impact of recombinant creation turns out to be negative especially in regimes characterized by low levels of environmental policy stringency.

The rest of the chapter 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.

1.2 Theory and hypotheses

1.2.1 Green knowledge production and inventor teams

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). Green technological change is indeed likely to enhance both firms' environmental performances and their production efficiency (Ambec et al., 2013). As noticed by del Río González (2009), most studies investigating the determinants of GTs have focused on the understanding of the innovation and the diffusion stages, while the antecedents of green invention have been somewhat neglected.

Invention involves collective dynamics (Allen, 1983). A wide body of literature has stressed how the tale of lone inventors and individual genius is a myth with scant empirical support. In the last century there has been indeed a marked shift towards teamwork knowledge production (de Solla Price, 1963; Adams et al., 2005; Wuchty et al., 2007). Several factors have been proposed as possible explanations of this trend. On the one hand, according to the 'knowledge burden' hypothesis (Jones, 2009), emerging teamwork organization is deemed a consequence of the increasing individual specialization and narrowing of expertise engendered by the advancing knowledge frontier (Jones, 2009; Agrawal et al., 2016). On the other hand, it is enabled by advances in theoretical understanding of problems, instrumentation, and computational capability, and the parallel increasing relevance of general and abstract knowledge (Arora and Gambardella, 1994). These forces have indeed stimulated an increasing division of labor in inventive processes, as well as the fragmentation and dispersion of knowledge, paving the way to the rise of collective invention dynamics based on the collaboration amongst numerous individuals, often organized in teams (Teodoridis, 2017).

Recent studies have shown that teams of inventors are more productive and better able to produce impactful inventions than lone inventors. In line with the recombinant knowledge approach (Kauffman, 1993; Weitzman, 1996, 1998; Olsson, 2000; Fleming, 2001; Olsson and Frey, 2002; Caminati, 2006), the key source of such comparative advantage lies in the augmented potential combinatorial opportunities made possible by the diversity of competences and experiences of individual inventors belonging to the team. Such knowledge variety influences teams' search patterns, increasing the number of possible new combinations (Singh and Fleming, 2010).

However, diversity of competences cannot be considered a sufficient condition to ensure teams' good performances. Indeed, the composition of the group represents a crucial aspect. In this framework, some studies have stressed the importance of including academic staff in the team, while others have focused on the difference between scientists and engineers (Bercovitz and Feldman, 2011; Gruber et al., 2013; Dornbusch and Neuhäusler, 2015; Teodoridis, 2017). An often-neglected issue concerns the impact of the recombination patterns pursued by inventor teams.

The notion of recombinant capabilities, developed by strategy researchers, can be fruitfully extended from the firm to the team domain (Henderson and Clark, 1990; Kogut and Zander, 1992; Galunic and Rodan, 1998). Team's recombinant capabilities can be defined as the ability of its members to combine knowledge to produce technological innovations. Moreover, recombination patterns are not all alike, and the distinction between recombinant 'creation' and recombinant 'reuse' seems particularly useful in this context. The former involves experimentation with unexplored interdependencies, while the latter concerns the refinement and improvement of known technological combinations (Carnabuci and Operti, 2013).[2] Inventor teams may therefore differ with respect to the capacity of their members to generate inventions drawing on recombinant creation vis-à-vis reuse capabilities.

Recent empirical evidence suggests that green inventions are more likely to emerge out of the hybridization of technologies that do not share important commonalities. GTs are often the result of the combination of green and dirty technologies in new and unprecedented ways (Zeppini and van den Bergh, 2011; Dechezleprêtre et al., 2014; Colombelli and Quatraro, 2017). In this direction, the composition of inventor teams is particularly relevant when green inventions are at stake, as the combination of knowledge inputs that are loosely related requires the capacity to manage exploration-oriented

[2]By shedding light on the antecedents of recombinant capabilities, this distinction helps understanding 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 (Levinthal and March, 1993; Benner and Tushman, 2002), while exploitation builds upon existing knowledge and competences and strengthens existing skills, processes, and structures (Abernathy and Clark, 1985; Levinthal and March, 1993; Benner and Tushman, 2002)

search processes to move beyond the fences of established technological domains and envisage new recombination opportunities (Nightingale, 1998; Bercovitz and Feldman, 2011). These arguments lead to the following hypothesis:

H1: *Inventor teams leveraging recombinant creation dynamics are more likely to generate green inventions.*

1.2.2 Regulatory frameworks, green inventions and the impact of recombinant capabilities

An established tenet in the literature on the determinants of GTs production concerns the key role of environmental regulatory frameworks. This is due to the so-called 'double externality problem' characterizing the generation and the diffusion of GTs (Jaffe et al., 2005; Rennings, 2000). Inducement mechanisms, set forth through the implementation of stringent environmental regulatory frameworks, stimulate research efforts aimed at generating new GTs, by means of demand pull and technology push dynamics (Porter, 1991; Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; del Río González, 2004; Frondel et al., 2008; Nemet, 2009; Johnstone et al., 2010; Popp et al., 2010; Renning and Rammer, 2011; Acemoglu et al., 2012; Costantini and Mazzanti, 2012; Horbach et al., 2012; Ghisetti and Quatraro, 2013; Hoppmann et al., 2013). These arguments lead us to spell the following hypothesis:

H2: *Stringent regulatory frameworks are positively associated to the probability of generating green inventions.*

The way how heterogeneous regulatory frameworks affect GT dynamics by modifying innovation strategies has received scant attention by the extant literature. Only few studies have recently explored the link between modes of innovation and deployment policies. 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 this specific policy tool by far exceed the incentives for R&D activities (Hoppman et al., 2013). Most of the evidence assumes that deployment policies, 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). Some studies highlight 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. In the balance between exploitation and exploration, the latter by far dominates the former when firms face high rates of market growth.

However, the extant literature does not provide exhaustive evidence about the role of the whole policy architecture for addressing environmental issues on the adoption of diverse innovation modes pursued by economic actors. We argue that a stringent policy strategy leads to raise the demand for GTs by means of both modifying existent markets and creating new niches. At the same time, it provides incentives to explore previously untried combinations, which are more likely to result in breakthrough green inventions. In view of this discussion, we thus propose the following hypothesis:

H3: *The positive association between the team's leveraging of recombinant creation and green inventions is magnified in contexts of stringent regulatory frameworks.*

1.2.3 Learning dynamics

Innovation processes involve the combination of both tacit and codified knowledge (Rosenberg, 1976; Nelson and Winter, 1982; von Hippel, 1994). Different and yet complementary learning processes have been identified by the extant literature. Learning-by-doing increases the effectiveness of production processes, engendering dynamic scale economies (Arrow, 1962; Hatch and Mowery, 1998). Learning-by-using concerns advantages accruing to the end users of a product as their understanding of it increases as a function of usage. This makes user-producer relationships an important source of innovation (Rosenberg, 1982; von Hippel, 1988).

Cohen and Levinthal (1989, 1990) stress how learning dynamics influence the effectiveness of innovation production, in that they affect the ability of innovating agent to either successfully combine different inputs in new and unprecedented ways or find out new applications of known combinations. These mechanisms are better managed by agents that have previously committed resources to the accumulation of both tacit and codified knowledge. Knowledge accumulation increases agents' absorptive capacity, i.e. the ability to understand, process, and recombine external knowledge inputs (Pavitt, 1984). This is due to the inherent stickiness of knowledge, which in turn is determined by learning dynamics themselves and the associated emerging tacit knowledge (von Hipple, 1994). In other words, the evolutionary process by which absorptive capacity is developed leads to the emergence of innovation routines, i.e. *"routines for the support and direction of innovative efforts"* (Nelson and Winter, 1982: 134). Innovation routines involve the generation of new combinations and the selection of most promising research avenues (Tidd et al., 1997).

In this framework, the team's accumulation of competences in the domain of GTs is expected to enhance the absorptive capacity of inventors and to improve their recombinant capabilities, leading to the generation of further green inventions. In view of these arguments, we spell out the following hypothesis:

H4: *Teams' previous experience in GTs positively affects the probability of generating green inventions.*

Learning dynamics are not only cumulative, but also local (Dosi and Grazzi, 2006, 2010). This means that search processes and the development of new technologies is likely to take place in the neighborhood of the technological competences already developed by innovating agents (David, 1975; Antonelli, 1995). Therefore, while improving the general effectiveness of the innovation process, both learning dynamics and the development of innovation routines are likely to constrain the direction of technological change. All other things being equal, path-dependence is likely to limit the scope for the experimentation of new combinations, pushing inventors to deal with familiar areas of the technology landscape.

The two features of learning, i.e. locality and cumulativeness, make recombinant reuse preferable to recombinant creation, as inventors with sound competence in a specific technology area will attribute a high value to knowledge that is close to their cumulated knowledge, and will value distant knowledge inputs less (Ahuja and Morris Lampert, 2001; Kim et al., 2006). Accordingly, inventors already experienced in the green-tech domain will likely exploit their specific cumulated knowledge to further produce other green inventions. These arguments lead us to specify the following hypothesis:

H5: *The impact of inventor teams' recombinant creation on the generation of green* *inventions is mitigated by inventor teams' previous experience in GTs.*

As a corollary, it is reasonable to expect that stringent regulatory frameworks enhance recombinant creation for the generation of GTs mostly for teams in which no members have previous experience in the green domain. Conversely, such augmenting impact is less pronounced as far as inventors' teams composed by experienced green inventors are concerned.

1.3 Data, variables and methodology

1.3.1 Data

Our study sample includes 706,943 patents filed at the European Patent Office (EPO), from 1995 to 2009. The main dataset we exploit is PatStat, released by the EPO and maintained by the CRIOS Center for Research on Innovation, Organization and Strategy.[3] The correct attribution of the patents included in our sample to their inventors might be affected by homonymy problems. We rely on the Massacrator© Algorithm to disambiguate the inventors' identity and to correctly attribute patents to inventors (Lissoni et al., 2006; Pezzoni et al., 2012).

1.3.2 Variables

Dependent variable

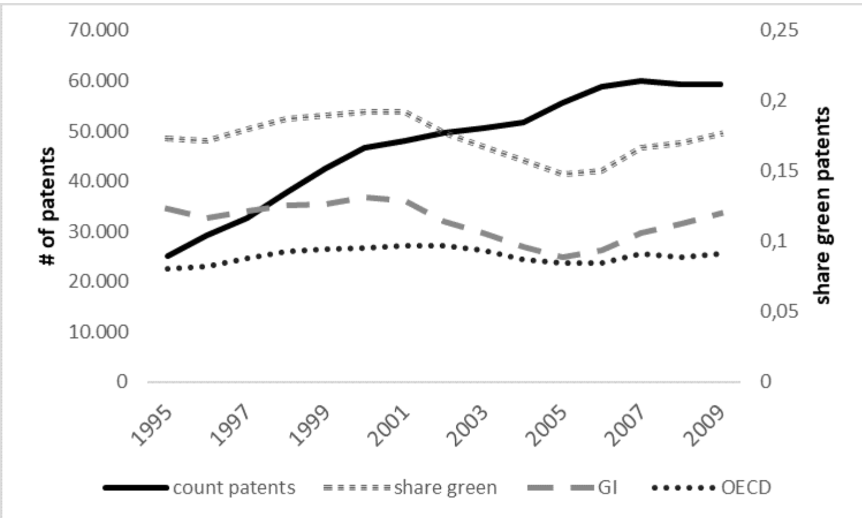
Patents are classified as green on the basis of the two main worldwide existent classifications: 1) The World Intellectual Property Organization (WIPO) "IPC green inventory", an International Patent Classification that identifies patents related to the so-called "Environmentally Sound Technologies" and scatters them into their technology fields; 2) The

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

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 to define our dependent variable (*Green*). The variable *Green* is a dummy that equals one if the focal patent is classified as green either in the WIPO or in the OECD classification, zero otherwise. Figure 1 shows the yearly count of patents, the count of green patents according to the two classifications, and the share of patents identified as green according to our variable *Green*.

Figure 1.1: Total number of patents and shares of green patents by year



Patent-based knowledge-search indicators

In order to construct a measure proxying inventor teams' recombinant creation capabilities, we proceed in three steps.

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

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 define: $IE_{(i,t-1)} = \left(\frac{\sum_p IE_p}{N}\right)$; $COH_{(i,t-1)} = \left(\frac{\sum_p COH_p}{N}\right)$; $CD_{(i,t-1)} = \left(\frac{\sum_p CD_p}{N}\right)$. The numerators are the sums of the observed values of IE, COH and CD for each patent p in the inventor i stock; N is the total number of patents in the inventor's i stock, namely the patents filed by inventor i up to time $(t-1)$.

Finally, we assign the average values of IE, COH, and CD of each inventors to the inventor team of the focal patent.

By focusing the analysis at the inventor 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. Precisely, an explorative behavior is positively correlated with IE and CD, and negatively correlated with COH (Krafft et al., 2014). Coherently, to provide a synthetic indicator of knowledge search behaviors characterizing the technological portfolio of the inventor team, we perform a principal component analysis on IE, COH, and CD, measured at the team level. Table 1 reports the results. 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. Thus, we consider high values of the dominant component as representative for recombinant creation dynamics.

We use the dominant component to calculate the dummy *RecCreation* that equals one

Table 1.1: 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
Cum. % of tot variation	0.43	0.74	1

if the score of the component is above its average value and zero if it is below its average value. In the former case the team is leveraging recombinant creation capabilities, while in the latter case the team is adopting a 'recombinant reuse' behavior.

Team green experience and environmental policy stringency

As for the team's green experience, we define a dummy *GreenExp* 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 architectures. 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 (stringent). It covers 28 OECD and 6 BRIICS countries for the period 1990-2012 (Botta and Koźluk, 2014). The value of the index is assigned to each observed patent on the basis of the applicant country of residence. The dummy *Stringency* equals 1 if the index is above its average value, zero otherwise. Table 2 shows the descriptive statistics of our dependent and independent variables. Table 3 shows the conditional average of the dependent variable *Green*, according to high (above the average) and low values (below the average) of

RecCreation, *GreenExp*, and *Stringency*.

Table 1.2: Descriptive statistics

	obs.	mean	sd	min	max
Dependent variable					
Green dummy	706943	0.172	0.377	0.00	1.00
Variables of interest					
RecCreation (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
Stringency (Dummy)	706943	0.554	0.497	0.00	1.00
GreenExp (Dummy)	706943	0.355	0.478	0.00	1.00
Team controls					
N. of inventors	706943	3.253	2.209	1.00	60.00
Team experience (Stock)	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					
Applicant patenting experience (Stock)	706943	1193	3444	0.00	34855
Applicant green experience (Dummy)	706943	0.706	0.456	0.00	1.00

Table 1.3: Percentage of green patents. Conditional mean for each variable of interest

variables	High	Low	diff	Pvalue
RecCreation (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
Stringency (Dummy)	0.187	0.154	-0.033	0.00
GreenExp (Dummy)	0.389	0.053	-0.34	0.00

Obs: 706,943

1.3.3 Methodology

We test the hypotheses proposed in Section 2 with a series of nested regression models.

First, we estimate the effect of the inventor teams' recombinant creation capabilities (*RecCreation*), the presence in the country where the applicant resides of stringent environmental policies (*Stringency*), and team green experience (*GreenExp*) on the probability to observe a patent with green technological content (Equation 1).

$$\begin{aligned} Pr(GREEN = 1)_p &= \beta_0 + \beta_1 RecCreation + \beta_2 Stringency + \\ &\quad + \beta_3 GreenExp + \boldsymbol{X'}\beta_4 + \epsilon_p. \end{aligned} \tag{1.1}$$

Second, to investigate whether environmental policy stringency (*Stringency*) and team green experience (*GreenExp*) moderate the effect of recombinant creation (*RecCreation*) on the generation of GTs, we extend the model described in Equation 1 by testing for all the possible interactions (Equation 2).

$$\begin{aligned} Pr(GREEN = 1)_p &= \beta_0 + \beta_1 RecCreation + \beta_2 Stringency + \\ &\quad \beta_3 GreenExp + \beta_4 RecCreation \times Stringency + \\ &\quad \beta_5 RecCreation \times GreenExp + \\ &\quad \beta_6 Stringency \times GreenExp + \\ &\quad \beta_7 RecCreation \times Stringency \times GreenExp + \\ &\quad \boldsymbol{X'}\beta_8 + \epsilon_p. \end{aligned} \tag{1.2}$$

In both models, represented by Equation 1 and 2, we include a comprehensive set of controls at the level of the inventor team and the applicant. At the level of the team, we control for several characteristics: *i)* the number of inventors (*N. of inventors*); *ii)* the number of previous patents as proxy of the team experience (*Team experience*); *iii)* the share of the team members' granted patents (*Share of granted patents*); *iv)* the share of the team members' triadic patents (*Share of triadic patents*); and *v)* the number of backward citations of the focal patent (*Number of backward citations*).

At the level of the patent applicant, we control for *i)* the applicant experience, proxied by the number of previous patents (*Applicant patenting experience*) and *ii)* the applicant previous green experience, proxied by the dummy *Applicant green experience* that equals one if the applicant has in its stock of patents at least one green patent, zero otherwise.

Finally, as further controls, we include a set of dummies, one for each patent *Priority-year*, and a set of *country dummies*, one for each country reported in the applicant's residence address. We control also for the team's previous patenting activity in specific technology classes, as defined by the OST7 classification (Schmoch et al., 2003). Precisely, we consider seven *OST7 technology dummies*, each dummy assuming value one if at least one of the team members has patented in that class, zero otherwise. Table 2 shows the descriptive statistics of the control variables.

In the next Section we present results from OLS estimations.[4] All regression exercises are conducted at the patent level.

1.4 Results

In Table 4 we estimate six nested models. In columns 1, 2, 3, and 4 we estimate the effect of *RecCreation*, *GreenExp*, and *Stringency*, on the dependent variable *Green*. In column 5 we add the team characteristics. In column 6 we also add the applicant characteristics. In all the six specifications we include as controls *country*, *OST7 technology*, and *Priority-year* dummies.

Results reveal that recombinant creation capabilities shows a premium on the probability of observing a patent with green technological content, confirming hypothesis 1 stated in Section 2. Precisely, the capacity to combine knowledge inputs in previously untried ways increases the probability of observing a green patent by 1.32% (column 6). This evidence confirms that inventor teams leveraging recombinant creation capabilities

[4]Results are consistent also applying Logit estimations.

Table 1.4: Probability of observing a green patent. OLS estimation

	(I) Pr(green)	(II) Pr(green)	(III) Pr(green)	(IV) Pr(green)	(V) Pr(green)	(VI) Pr(green)
Variables of interest (lagged t-1)						
RecCreation t-1 (Dummy)	0.0131***			0.0205***	0.0134***	0.0132***
Stringency t-1 (Dummy)		0.0168***		0.0144***	0.0135***	0.0149***
GreenExp 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

are more likely to introduce green technologies into the market. Moreover, environmental policy stringency has a positive effect (+1.49%), as well as the team green experience (+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 generating green inventions, revealing a strong path-dependence. Building teams that persistently perform green R&D is thus the best strategy that firms should pursue for introducing GTs.

As for the controls, the number of inventors positively impacts the probability of generating green inventions, as well as the number of 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.

In Table 5 we estimate 6 regression models adding sequentially a set of interactions that allow us to test both hypothesis 3 and hypothesis 5, namely whether team's green experience and stringent environmental policy frameworks moderate the effect of team's recombinant creation capabilities on the generation of green inventions. 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 between *RecCreation*, *Stringency*, and *GreenExp*. Finally, in column 6 we add the triple interaction between the three variables.

In order to simplify the interpretation of the interaction terms reported in the complete specification of column 6 (Table 5), we show in Table 6 the marginal effects of *RecCreation* in different conditions of policy stringency and team green experience. Precisely, we consider the effect of recombinant creation capabilities in four scenarios: (i) the team has experience in GTs (*GreenExp* equals 1) and the green policies are stringent (*Stringency* equals 1), (ii) the team has no green experience and the policies are

Table 1.5: Probability of observing a green patent, interactions. OLS estimation

	(I)	(II)	(III)	(IV)	(V)	(VI)
	Pr(green)	Pr(green)	Pr(green)	Pr(green)	Pr(green)	Pr(green)
Variables of interest (lagged t-1)						
RecCreation (Dummy)	0.0132***	0.0280***	0.0115***	0.0132***	0.0242***	0.0310***
RecCreation * GreenExp		-0.0413***			-0.0430***	-0.0665***
RecCreation * Stringency			0.00310*		0.00772***	-0.00534***
RecCreation * Stringency * GreenExp						0.0391***
Stringency * GreenExp				-0.00310*	-0.00812***	-0.0306***
Stringency (Dummy)	0.0149***	0.0150***	0.0132***	0.0158***	0.0133***	0.0203***
GreenExp (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

stringent, (iii) the team has green experience and the policies are not stringent, and (iv) the team has no green experience and the policies are not stringent.

Table 1.6: Marginal effect of *RecCreation*, summary

		Stringency	
		high	low
GreenExp	high	-0.17%	-3.55%
	low	2.56%	3.10%

Note: results based on estimations in Tab. 5, Col. 6.

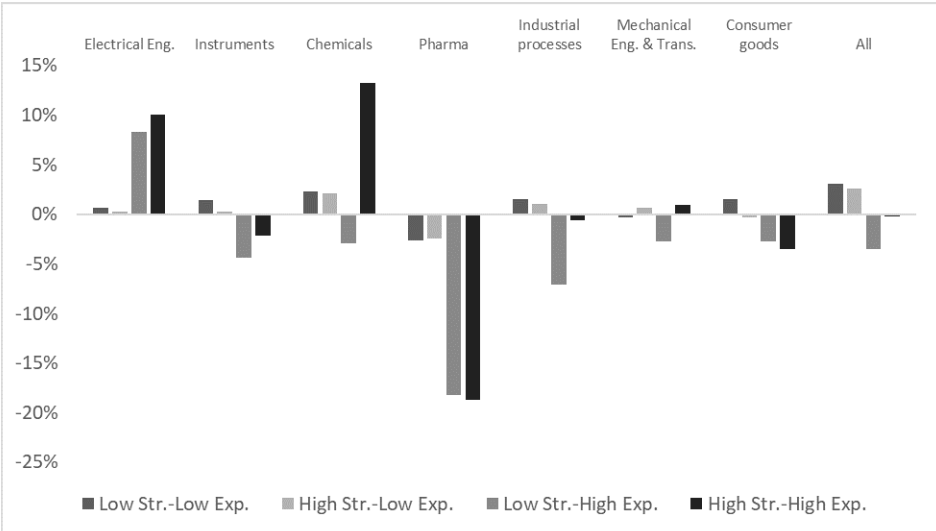
We find that recombinant creation fosters the probability of observing a green invention in contexts of low team's green experience. Interestingly, the marginal effect is higher when the stringency level of environmental policy is weak (+3.1%). Conversely, for teams showing higher levels of green experience, the marginal effect of recombinant creation is negative, namely recombinant reuse is more effective in generating green inventions. Moreover, this effect is magnified when the environmental policy stringency is weak (-3.55%).

Summing up, firms aiming at generating green inventions face a trade-off between pursuing exploitative strategies relying on experienced teams and pursuing explorative strategies performed by non-experienced inventors. Reasonably, if a firm already employs experienced teams, exploitative research strategies guarantee a premium in terms of green-tech production. Conversely, the choice of a firm lacking previous green experience and aiming at entering the green technological realm should be between assembling teams whose inventors reveal higher abilities in recombining technological knowledge and hiring green-experienced inventors. Furthermore, the policy context matters in this decision process. Indeed, the more stringent the policy regime in which the team operates the lower the relative incentive to pursue exploitative strategies for experienced teams. This suggests that a proper combination of both exploitative and explorative strategies is likely to ensure successful R&D performances in the green domain.

1.4.1 Sensitivity analysis

By exploiting the OST7 classification (Schmoch et al., 2003), we perform the same estimations as in column 6 of Table 5 for each technological macro-sector. Table 7 reports the sector-specific marginal effects of recombinant creation capabilities on the probability of observing a green invention. Precisely, columns 1-4 report the results for the four different scenarios mixing diverse combinations of team's technological experience in GTs and environmental policy stringency. Figure 2 plots the marginal effects reported in Table 7 for each technological macro-sector.

Figure 1.2: *RecCreation* marginal effects by OST technogical areas



A heterogeneous picture emerges, confirming the relevance of sector specificities when investigating patterns of green technological emergence. Indeed, if the overall effect of recombinant creation capabilities is significantly positive only in scenarios characterized by low previous green experience, when empirical estimations are conducted separately by technological domain, conclusions change notably.

For interpreting those results, at least two aspects must be simultaneously considered. First, each technological domain cultivates its own specificity in the ways innovative activities are structured and organized. Second, the green dimension of the innovative

Table 1.7: Marginal effects of *RecCreation* by OST7 technological areas. OLS estimations

OST7 Tech. area	Obs. (%Green)	$\downarrow Str. \downarrow Exp.$	$\uparrow Str. \downarrow Exp.$	$\downarrow Str. \uparrow Exp.$	$\uparrow Str. \uparrow Exp.$
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%
Mech. 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%

processes within a specific sector differs from technology to technology, due to complementarities and vertical linkages across sectors.

We expect to observe domains characterized by high stability, concentration in innovation activities, and with low levels of entry, to introduce – ceteris paribus – green technologies more incrementally, by exploiting previous knowledge and without attempting to disrupt consolidated technological patterns. Conversely, domains characterized by lower concentration of innovative activities, lower stability in the hierarchy of innovators, and higher relevance of new innovators are supposed to introduce – ceteris paribus – green technologies more dynamically, through recombinant creation dynamics. At the same time, the more a technological area is vertically related in terms of green knowledge to the rest of the technological space, the higher the importance of recombinant creation in explaining the introduction of innovative (green) technologies. Conversely, the less is its relatedness to the rest of the space, the more likely the process through which technical change emerge is based on exploitation strategies.

Four technological macro-sectors are of particular interest as representative of different conditions of concentration, stability in hierarchy of innovators, and levels of entry. We focus our comments on electrical engineering, chemicals, pharma, and mechanical engineering.

When the analysis is restricted to patents related to the macro technological area of electrical engineering, the premium of pursuing explorative patterns is always positive. This is of particular evidence in cases of high previous team's experience (independently from the level of the policy stringency in place). This technological domain is characterized by low levels of concentration of innovative activities, low stability in the hierarchy of innovators and high relevance of new innovators. Furthermore, it is highly vertically related to other technological areas, facing a heterogeneous demand for technology. Given these characteristics, recombinant creation dominates in explaining the emergence of green technologies in this domain.

We observe a similar effect for innovation processes related to the macro technological field of chemicals. However, this domain shares with the electrical engineering one just the level of vertical relatedness with the rest of the technology space. The chemicals rely mostly on demand coming from external domains. A particularly strong positive premium for recombinant creation capabilities emerges indeed in cases of high previous team's innovative experience, combined with high levels of policy stringency. The higher the overall environmental stringency, the higher the potential demand the chemical domain faces. To attack this heterogeneous demand, recombinant creation is preferred to recombinant reuse strategies.

A completely reverse scenario emerges in the case of the pharma sector, which reveals a complete dominance of exploitation strategies in explaining the emergence of green-related inventions, also in cases of low previous green experience. Green technologies in the pharma domain seem to emerge exclusively within the domain itself, without spreading across technological boundaries. They respond to internal demand and serve mainly the goal of abating costs. Exploitation of existent techniques is thus the predominant strategy pursued in the pharma domain for innovating green.

The mechanical engineering and transportation macro area deserves a final comment. Contrary to the overall evidence, for this technological macro-domain the level of overall policy stringency, and not the level of accumulated experience, seems to matter the most for recombinant creation to induce green inventions. Given the relevance of the domain in terms of emissions, to promptly respond to regulation, this domain relies on explorative strategies.

For the rest of the analyzed macro-sectors, results are in line with our expectations.

1.5 Conclusions

By exploiting the EPO universe of patent data, the present study aims at capturing the effect of diverse knowledge recombination patterns, mastered by inventor teams, as important drivers for the generation of GTs. Empirical evidence shows a positive premium of recombinant creation capabilities in the generation of GTs, confirming our first hypothesis that recombinant creation increases the probability that a team produces a green invention. Moreover, we find positive effects of both team's previous technological green experience and environmental regulation stringency, confirming, respectively, our second and forth hypotheses. We also find diverse moderating effects of technological green experience and environmental regulation stringency on recombinant creation. Precisely, the positive effect of team's recombinant creation capabilities is magnified for teams lacking technological green experience, even more in regimes of weak environmental regulation. Both third and fifth hypotheses are thus confirmed, showing a complex architecture behind the generation process of green inventions.

Our results bring interesting implications for firms aiming at performing green R&D activities. GTs are indeed likely to positively respond to explorative strategies: assembling teams of inventors able to creatively recombine extant technological knowledge increases the firm's probability of introducing new GTs. However, path dependence plays a fundamental role also in the green technological realm, suggesting that experienced teams are those that show highest rates of success in introducing green inventions. Finally, the level of local policy stringency is relevant in virtue of the innovation mode a firm pursues. Indeed, explorative strategies seem to enhance their positive effect when the level of stringency is sufficiently high, and, at the same time, teams lack previous green experience. Therefore, firms aiming to generate green inventions and operating in technological domains where both regulation schemes and previous green experience are weak should assemble teams formed by inventors able to creatively recombine sparse and heterogeneous technological knowledge.

From a policy perspective, our results lead to two main policy implications.

First, building proper levels of green technological knowledge within a sector, as represented by the presence of teams with experience in GTs, is by far the most important driver for boosting GTs. However, teams with green experience that adopt explorative behaviors, especially in regimes of weak environmental regulation, are less likely to generate green inventions. This combination of presence of experienced teams and absence of incentives to adopt explorative behaviors could be harmful in terms of possible emergence of technological lock-ins. Proper innovation policies aiming at guaranteeing systemic variety and exploration strategies are thus suggested in contexts of high green-technological specialization.

Second, in contexts where the level of advance of green technological knowledge is scarce, recombinant creation dynamics reveal their relevance in fostering GTs. Interestingly, when these exploration-oriented behaviors are combined with elevated levels of stringency, their effect is magnified. Thus, the importance for policy makers of combining environmental stringency with innovation policies oriented towards the exploration of technological niches. This combination is the most effective channel boosting green technical change for countries/sectors where the green technological infrastructure is weak.

Appendix - Technological Knowledge Indicators

Technological variety 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.[5] 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, 1986; 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):

$$H(X,Y) = \sum_{j=1}^{q} \sum_{m=1}^{w} p_{jm} log_2 \left(\frac{1}{p_{jm}} \right) \tag{1.3}$$

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

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

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:

$$H\left(X, Y\right) = H_Q + \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} H_{gz} \tag{1.4}$$

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,

$$H_Q = \sum_{g=1}^{G} \sum_{z=1} Z P_{gz} log_2 \left(\frac{1}{P_{gz}} \right) \tag{1.5}$$

$$P_{gz} = \sum_{j \in S_j} \sum_{m \in S_z} P_{jm} \tag{1.6}$$

$$H_{gz} = \sum_{j \in S_j} \sum_{m \in S_z} \frac{P_{jm}}{P_{gz}} \left(\frac{1}{\frac{p_{jm}}{P_{gz}}} \right) \tag{1.7}$$

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).

Technological coherence 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). 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}:

$$WAR_{lt} = \frac{\sum_{j \neq l} \tau_{lj} P_{jt}}{\sum_{j \neq l} P_{jt}} \tag{1.8}$$

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

$$R = \sum_{j \neq l} WAR_{lt} \times \frac{P_{lt}}{\sum_l P_{lt}} \tag{1.9}$$

It is worth stressing that this index 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.

Cognitive distance 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, 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:

$$S_{lj} = \frac{\sum_{k=1}^{n} V_{lk} V jk}{\sqrt{\sum_{k=1}^{n} V_{lk}^2} \sqrt{\sum_{k=1}^{n} V_{jk}^2}} \tag{1.10}$$

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:

$$d_{lj} = 1 - S_{lj} \tag{1.11}$$

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:

$$WAD_{lt} = \frac{\sum_{j \neq l} d_{lj} P_{jit}}{\sum_{j \neq l} P_{jit}} \tag{1.12}$$

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:

$$CD_{lt} = \sum_{l} WAD_{lit} \times \frac{P_{lit}}{\sum_{l} P_{lit}} \tag{1.13}$$

2 Government-funded R&D and the accumulation of green knowledge. Evidence from EPO patent-citation data[1]

Abstract

The present study investigates the effect of changes in the level of government-funded R&D on the process of green knowledge accumulation, measured through patent citations. The sample includes green patents applied at the European Patent Office from 1980 to 1984. Patent citation data are collected from 1981 to 1988, together with their qualitative characteristics in terms of technological originality and radicalness. The level of government-funded R&D is instrumented through the policy reaction to the 1986 Chernobyl-accident, affecting the energy-generation domain. Results reveal that a 1% increase in government-funded R&D increases by 0.14% the yearly average number of citations a green patent receives. Similar evidence emerges for the number of citations coming from highly original and radical patents, and from non-green patents. Policy implications are manifold.

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2.1 Introduction

The design of public policies for pursuing environmentally sustainable growth is at the top of the global policy agenda. To necessarily and timely abate CO_2 emissions and concentration in the atmosphere, only two interrelated options seem to be viable: one is to develop feasible and cost-effective technologies for capturing carbon from the air and storing it safely; the other is to drastically reduce the future consumption of fossil fuels. Both are a matter of systematic policy interventions, requiring long-term systemic vision and strong coordination between institutions (Covert et al., 2016).

Innovation plays a crucial role. Scholars substantially agree in stating that public interventions, both market and R&D oriented, will be required at least until green technologies (hereafter GTs) will overcome the sunk-cost advantage of incumbent technologies (Acemoglu et al., 2012).

Importantly, technological change is a process of knowledge cumulativeness, gradual specialization and consolidation of successful routines (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Stuart and Podolny, 1996), inexorably path dependent (David, 1985).

Furthermore, the intrinsic limits to the appropriability of knowledge reduce the incentives to generate it, leading to constant under-supply. This calls for systematic public interventions to restore efficiency by means of either subsidies or direct generation through large public research systems (David, 1993; Antonelli, 2009).

Popp (2006b) stresses the importance of considering that social returns to research are high. Precisely, the author states that "[T]*he welfare gains from ITC* [induced technological change] *nearly double when market failures for knowledge are corrected, increasing from 9.4% to 16.7%. For policymakers, these findings suggest that government-funded R&D can play an important role in climate change policy*" [pag. 599].

Therefore, a better understanding of the way how the accumulation process of green-technological knowledge responds to changes in government-funded R&D[2] is required to optimally design the policy architecture targeting green technical change.

Surprisingly, the extant literature provides little evidence about this relationship. This is the reason why the present chapter aims at investigating the causal effect of changes in public R&D on green knowledge accumulation dynamics, under several perspectives.

The first question I aim to answer is: does an increase in government-funded R&D expenditures foster the broad accumulation process of green technological knowledge?

As a second step of the analysis, I enter more deeply into the technological content of inventions making use of the established green knowledge. In other words, I investigate the direction that the accumulation process of green knowledge takes.

Two aspects characterizing the technologies making use of green knowledge are of primary interest in this sense: their qualitative technological content and whether they pertain to dirty trajectories. Indeed, if green knowledge enters trajectories with higher-than-the-average technological quality, it is reasonable to expect both high rates of its diffusion and an increase in the likelihood of the emergence of breakthrough technical advances.[3] Furthermore, if it also enters dirty trajectories, it is reasonable to expect a positive, faster substitution effect of dirty with clean technologies.

Accordingly, I firstly test for the effect of changes in government-funded R&D on the rate of accumulation of green knowledge in highly original, radically new and potentially breakthrough invention processes.

Second, I investigate whether changes in public R&D efforts lead to the modification of non-green trajectories: do changes in government R&D expenditures facilitate the

[2]Throughout the chapter the terms "government-funded R&D", "government R&D", "publicly-funded" R&D and "public R&D" are used as synonyms.

[3]By investigating the relationship between innovation complementarity and environmental productivity at the EU level, Gilli et al. (2014) conclude that incremental strategies dominated radical strategies so far, leading to insufficient results when looking at long-run economic and environmental goals. Fostering radical attempts seems thus a real priority.

entry of green knowledge in non-green invention processes?

To answer this set of questions, I analyze the early stage phase of development of GTs. Precisely, I exploit patent information data, considering all green patents filed at the European Patent Office (EPO) from 1980 to 1984, together with their citation patterns, to measure the level of knowledge accumulation in response to changes in government R&D investments.

To overcome endogeneity issues characterizing the relationship between technical advance and public intervention, I rely on the occurrence of the Chernobyl nuclear accident (April 1986) as an exogenous shock for the design of policies targeting the energy generation domain. According to the arguments proposed in Section 3, the policy reaction to the Chernobyl nuclear accident allows me to instrument the level of government R&D expenditures. Once instrumented, I estimate its effect on several characteristics of the green knowledge accumulation process.

Results reveal that increasing the level of government-funded R&D fosters the broad accumulation process of green technological knowledge. Furthermore, public R&D leads to the use and reuse of established green technological knowledge both in technologies revealing higher breakthrough potential and in trajectories not classified as environmentally friendly. This evidence demonstrates that increasing the level of public funding for R&D activities would be an important lever for both consolidating the established green technological trajectory and accelerating the process of changing technological paradigm. However, the magnitude of the estimated effects suggests that an unprecedented effort in public R&D investments is required to timely shift from dirty to clean production systems.

The rest of the chapter is structured as follows. Section 2 reviews the extant literature and proposes three main hypotheses. Section 3 describes the research design, the identification strategy, the data collection, the variables construction and the empirical models applied. Section 4 presents the results. The last section concludes.

2.2 Theoretical background and hypotheses

The uniqueness of the green technological realm traditionally resides in two well documented theoretical arguments, resumed in the so-called ‘double-externality’ concept (Rennings, 2000): first, GTs are affected by environmental externalities; second, common to any innovation process, firms are systematically not able to entirely capture the social value of performed R&D, due to the intrinsic characteristics of (partial) non-rivalry and non-excludability of technological knowledge. This double issue leads to a constant sub-optimal level of investments in green innovation processes. Public intervention for restoring systemic efficiency and guaranteeing long-term growth is thus indispensable (Jaffe et al., 2002*a*). Starting from this consciousness, since the mid-1990s the literature investigating the mechanisms through which green innovation processes respond to policy interventions has experienced a tremendous upsurge.

Public R&D and green knowledge accumulation

During the last decades a variety of policy schemes and tools has been implemented to foster both the demand- and the supply-side of the green innovation process.

Demand oriented policies act in modifying consumer preferences, changing long-term consumption patterns. Examples of demand interventions include greenhouse gas emission targets, environmental standards, or carbon taxes. These tools represent an indirect stimulus to develop green technologies. Supply-side policies, conversely, represent a direct support for technological change. They include subsidies, loans, tax credits, grants, pricing schemes, R&D funding for risky innovative processes, and so on.

While indirect stimuli would be suitable to foster the introduction and the spreading of existent, mature green technologies, direct stimuli would instead be more likely able to create the ground for the generation of technological novelties (less mature technologies) with breakthrough potential (Nemet, 2009; Hoppmann et al., 2013; Costantini et al., 2015).

Browsing the extensive extant literature investigating the role of different types of instruments in shaping eco-innovation activities, we can conclude that the evidence of a strong policy effect on the generation and diffusion of GTs is crystalline.[4]

However, only few studies specifically focus their attention on the role of government-funded R&D in fostering GTs, all of them related to the energy sector.

Klaassen et al. (2005) examine the impact of (subsidy-induced) capacity expansion and public R&D expenditures on cost reducing innovation for wind turbine farms in Denmark, Germany and the UK during the 1990s by both reviewing the extant literature and proposing a finer empirical analysis. The proposed survey of the literature suggests that R&D policy in Denmark was most successful in supporting innovation, and capacity promoting subsidies were most effective in Denmark and Germany in stimulating innovation. From their empirical analysis they conclude that results support the validity of the two-factor learning curve formulation, in which the cost reductions are explained by cumulative capacity and the R&D-based knowledge stock.

Sagar and van der Zwaan (2006) discuss aspects of public R&D and 'learning by doing' again in the energy realm. They conclude that "[s]*till, however uncertain the precise payoff of spending in research and development may be, there is little doubt that public ER&D budgets ought to be maintained, and probably increased, if we are to seriously address global problems such as climate change. The prime reason is that R&D efforts have been the basis for historical changes in energy production and conversion, and will*

[4]Among all, see: Green et al. (1994); Jaffe and Stavins (1995); Porter and van der Linde (1995); Lanjouw and Mody (1996); Jaffe and Palmer (1997); Kemp (1997); Rennings (2000); Jaffe et al. (2002*a*); Popp (2002); Brunnermeier and Cohen (2003); Popp (2003); Beise and Rennings (2005); Jaffe et al. (2005); Popp (2006*b*); Frondel et al. (2007, 2008); Crabb and Johnson (2010); Johnstone et al. (2010); Popp et al. (2010); Renning and Rammer (2011); Costantini and Mazzanti (2012); Horbach et al. (2012); Costantini and Crespi (2013); Ghisetti and Quatraro (2013).

underlie the technological changes that need to occur for transitioning to a sustainable energy system. Given the public-goods aspects of such a transition, the government's role will remain crucial" (pag. 2607).

Bointner (2014) estimates the level of the cumulative energy knowledge stock induced by public R&D expenditures in 14 IEA-countries from 1974 to 2013, with specific emphasis devoted to renewable knowledge. The author concludes that "[o]*n total, public energy R&D expenditures were increasing over the last five to ten years and, thus the cumulative knowledge stock is currently also increasing*" [pag. 745]. As for the renewable energy knowledge stock, the analysis shows that heterogeneous patterns emerge according to the technology type and between countries.

The 'double-externality issue' characterizing GTs and the evidence provided by the extant literature about the positive effect of supply-side policy tools on green innovation outcomes lead to the following hypothesis:

H1: *Increasing government-funded R&D augments the broad accumulation of green technological knowledge.*

Public R&D and the direction of the green knowledge accumulation

To understand the possible direction that green knowledge may take in response to changes in government-funded R&D, the analysis of the intrinsic characteristics of the knowledge involved in green innovation processes is required. As well relevant and complementary is the uniqueness of government-funded R&D activities. The combination of these two aspects as a lever for green technical change has been almost neglected by the extant literature.

As highlighted by Ghisetti et al. (2015), environmental innovation processes are characterized by intrinsic systemic nature and general purpose content – requiring, on average, the combination of more heterogeneous and distant knowledge than other innovations to be performed (Renning and Rammer, 2009; Horbach et al., 2013).

According to the recent strand of literature investigating the labor market implications associated with the transition towards green production systems (Consoli et al., 2016; Vona et al., 2017, 2018), green occupations exhibit a stronger intensity of high-level cognitive skills compared to non-green jobs. Furthermore, the extant empirical evidence suggests that occupations that are changing qualitatively (*i.e.* in terms of their skill content) have on average more formal education, more work experience and more on-the-job training relative to non-green jobs (Consoli et al., 2016).

The complexity associated with environmental innovation processes is likely to generate technological knowledge with broad potential in terms of applicability. Using patent citation data in four technological fields (energy production, automobiles, fuel and lighting), Dechezleprêtre et al. (2014) find that clean patents receive on average 43% more citations than dirty patents. Furthermore, the authors find that clean technologies receive on average more citations by highly-cited patents. They individuate two factors able to explain the clean superiority: clean technologies have more general applications, and they are radically new compared to more incremental dirty innovation. These findings represent an important message in terms of potential positive effect of green technical change on growth. At the same time, they raise an issue with respect to the system of incentives for their generation: high spillover effects are indeed possibly associated with harmful appropriability disadvantages. Direct innovation-oriented public interventions seem thus to be required for guaranteeing the optimal level of green knowledge generation (either R&D subsidies or direct, public R&D investments).

A second argument refers to the nature and the purposes of government-funded R&D activities. The prior that public R&D points to more basic research is common in the literature. Indeed, in a competitive market setting, the amount of basic research generated is likely to be sub-optimal (Nelson, 1959). This is due to the intrinsic features of basic research: the quantification of its economic value and the large number of externalities it generates.

The former feature is due to the fundamental Knightian uncertainty characterizing the outcomes of basic research (there is no known probability distribution over their attainment). Furthermore, even when scientific discoveries occur, the timing in the realization of economic payoffs is uncertain.

Second, the discoveries that stem from basic research tend to produce large externalities: results and applications may be performed that are distant from those that were expected ex ante ("serendipity") and hence they may benefit several economic agents that are unconnected to those that provided the primary investments. As a consequence, social returns to basic research are typically larger than private returns.

These features cause a systematic market failure, calling for necessary public investments in basic research.

Relevant for our analysis is that the nature of GT processes and the features characterizing basic research show high degree of potential common reinforcement. Indeed, green knowledge shares with basic research the strong uncertainty related to both the rate of attainment and the time required for the realization of the relative economic payoffs. Furthermore, the concept of "serendipity" seems to perfectly fit the outcomes of green R&D, due to the global nature of the phenomenon. Publicly-funded R&D projects are thus natural candidates for carrying out a more than compensatory role in the environmental realm. In other words, they may more than correct for the typical market failures attached to green-tech investments, playing an active role. These arguments lead to the following hypothesis:

H2: *Increasing government-funded R&D fosters the entry of green knowledge into more radical, original and potentially breakthrough innovations.*

Technologies emerge out of combinatorial attempts (Weitzman, 1996, 1998). The amount and heterogeneity of available knowledge affect the probability that combinations take place. The cost opportunity of applying specific knowledge inputs in innovation processes is an important factor explaining which combinations will be performed, selected within the overall bunch of disposable knowledge pieces from which inventors can draw.

In the knowledge landscape, green knowledge represents a portion. To switch from dirty to clean methods of production it is crucial that this portion mixes with traditional knowledge. Hybridization processes have been indeed individuated as fundamental engines for green technical change to take place (Zeppini and van den Bergh, 2011).

Several contrasting mechanisms should be considered when investigating whether and how the knowledge content of green innovation processes spills over, combines with diverse non-green pieces of knowledge and, eventually, contributes to the modification of traditional, non-green technical processes.

To start, due to its systemic and partially general purpose nature, knowledge embodied in green innovation processes is expected to be exploited and to spread more broadly than general knowledge. In other words, its large technical applicability may make its cost of usage relatively more competitive than the cost of using traditional knowledge. However, if it is true that the systemic characteristic of GTs increases their applicability, it is also true that the required skills for adopting and exploiting the incorporated knowledge of green technical processes are likely to be higher than the average. This may negatively impact on the cost opportunity of its usage. Furthermore, the presence of environmental externalities exacerbates the common appropriability issue affecting innovation, again with a negative impact on the cost of usage of green knowledge as an input in the knowledge production mechanism.

The coexistence of these forces is likely to translate into sub-optimal rates of green knowledge adoption by traditional technological trajectories. In other words, these forces are likely to slower the process of transformation of traditional trajectories.

Following the arguments set forth in drawing the second hypothesis, public R&D is intended to target research areas with possibly more relevant and larger impact in terms of knowledge generality and applicability (basic research). Importantly, when targeting green projects, it should also absorb (at least indirectly and partially) the negative effect of environmental externalities.[5] Furthermore, public R&d to be performed is attached to universities and contexts of high education and skills. As a result, the cost of using green knowledge is likely to decrease if public R&D for green projects increases, enhancing the probability of its combination with other components. Thus,

H3: *Increasing government-funded R&D enhances the use of green knowledge by traditional, incumbent technological processes.*

The next section will punctually describe the methodology adopted for testing these three hypotheses.

2.3 Methods

2.3.1 Research design and identification strategy

To test for the effect of government R&D expenditures on green knowledge accumulation dynamics, I exploit information contained in patent documents. Precisely, I estimate the effect of government expenditure in R&D on: *a)* the number of yearly citations received by green patents applied at the European Patent Office (EPO) from 1980 to 1984; *b)* the yearly number of citations coming from the highest original and radical patents; *c)* the yearly number of citations coming from non-green patents.[6]

[5]International public investments in green R&D would probably better contrast the negative effect of environmental externalities, due to the global nature of climate change.

[6]Patent citations are observed from 1981 to 1988.

In estimating the effect of government R&D expenditures on green knowledge accumulation, several endogeneity problems emerge, both related to unobservables and reverse causality.

For what concerns potential omitted variables, both policy decisions and innovation dynamics are affected by the quality of the local institutional context, which is pretentious to properly proxy. Second, human capital features – again, almost unobservable – affect both policy decisions and innovation.

For what concerns reverse causality in explaining the relationship between public policies and innovation outcomes, the established level of deployed technologies should be relevant in designing an innovation-oriented policy measure. This is particularly true for key, strategic industries, such as the energy one. Moreover, the higher the level of development of an industry, the higher its impact in terms of employment and value added generated, with reverse effects on policy decision-making processes. Thus, technology pulls policy intervention through several channels.

To overcome endogeneity issues, I rely on the Chernobyl nuclear accident occurred in 1986 as an exogenous shock impacting the policy architecture of the energy industry.

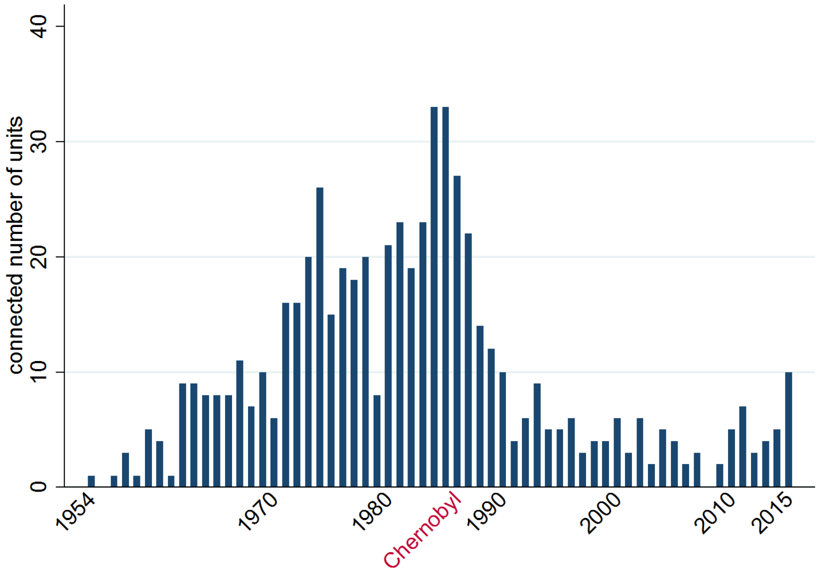
The energy sector in the 1970s and 1980s

The energy sector experienced a durable reconfiguration in the decades of the 70s and the 80s of the last century, mainly due to the energy crises (1973 and 1979). With the aim of guaranteeing economic sustainability and self-sufficiency of the energy production system, an important wave of investments in alternative energy generation technologies took place worldwide, starting from the 1970s. This process was driven by vast investments in nuclear technologies (see Figure 1).

As an example, the share of electricity[7] produced from nuclear sources in Europe

[7]Fossil fuel combustion is responsible for approximately 65 percent of global greenhouse gas emissions (US Environmental Protection Agency). Of these emissions, coal contributes for 45%, oil for 35%

Figure 2.1: Number of new reactors connected to the grid (1954- 2015)



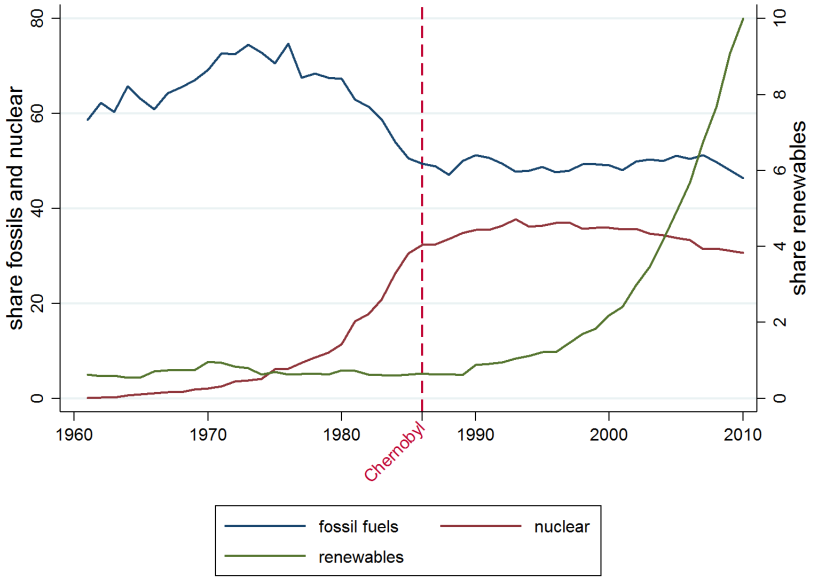
Source: IAEA 2016.

increased from about 2 percent in the early 1970s to about 35 percent in 1990, stabilizing at that level afterward. Conversely, the share of electricity production from fossil fuels (oil, gas and coal) fell from about 70% to about 50% in the same period for European countries. The US experienced very similar patterns. As for renewable sources (*i.e.* solar and wind), a public push for their development started in the late 1970s. The world first on-shore wind farm (0.6 MW) was installed in southern New Hampshire (US) in December 1980 and, similarly, the first photovoltaic park was launched in the US at the end of 1982. However, looking again at the electricity generation sector, the share of its production from renewable sources was almost irrelevant up to the end of the last millennium (abundantly below 2% worldwide), revealing a pattern of stagnation (see Figure 2). Several reasons stay behind this sort of almost two decades' congestion, since their launch, in the adoption of renewables for substituting fossil fuels in the energy

and natural gas for 20% (Carbon Dioxide Information Analysis Center). The major sectors demanding fossil fuels are the electricity and the transportation sectors. Having a descriptive look at the electricity sector is thus very informative.

generation process.

Figure 2.2: Electricity production by source, shares (EU, 1960-2010)

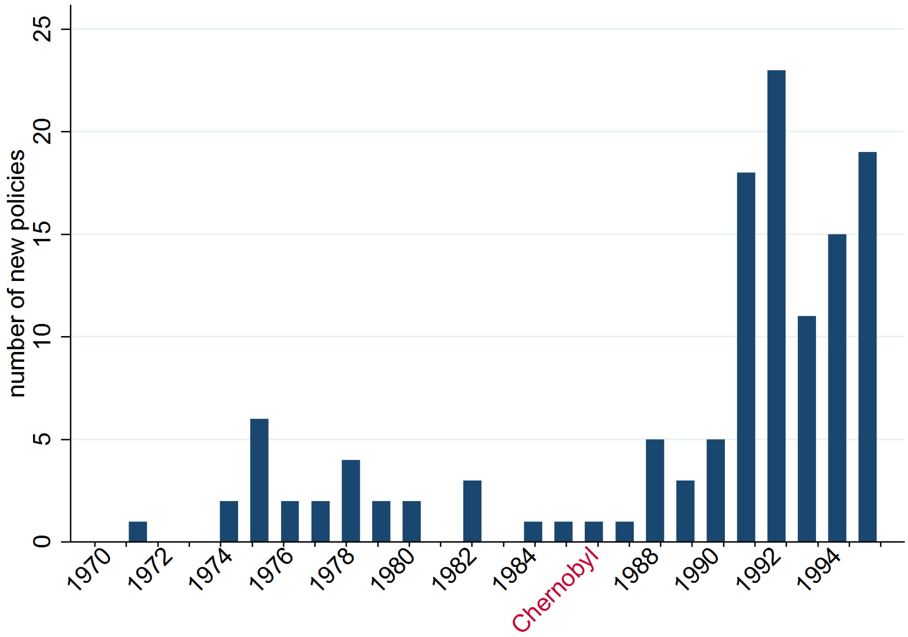


Notes: Electricity production from hydroelectric sources excluded. *Source*: The World Bank, 2017.

In the 1970s and the early 1980s, renewables were embryonic technologies, not able to immediately guarantee a large-scale, cost-effective production of energy. Therefore, investments in R&D for renewable sources were riskier and more subject to uncertainty than investments in R&D for more mature energy generation technologies. Their development and deployment required public support in terms of supply push. Furthermore, there was scarce international policy pressure with respect to environmental issues at that time, unable to compensate for market distortions related to environmental externalities, and thus to direct demand towards more green sources (see Figure 3).

Given the energy crises that have been characterizing the 1970s, the urgency of guaranteeing long-run economic sustainability of the energy generation industry led governments to start supply-oriented public investments in alternative-to-fossil-fuels technologies. Within alternative energy generation technologies, nuclear power technologies were by far the leading technologies. Their tremendous development, by indirectly weaken-

Figure 2.3: Number of new introduced environmental policies (IEA countries, 1970-1995)

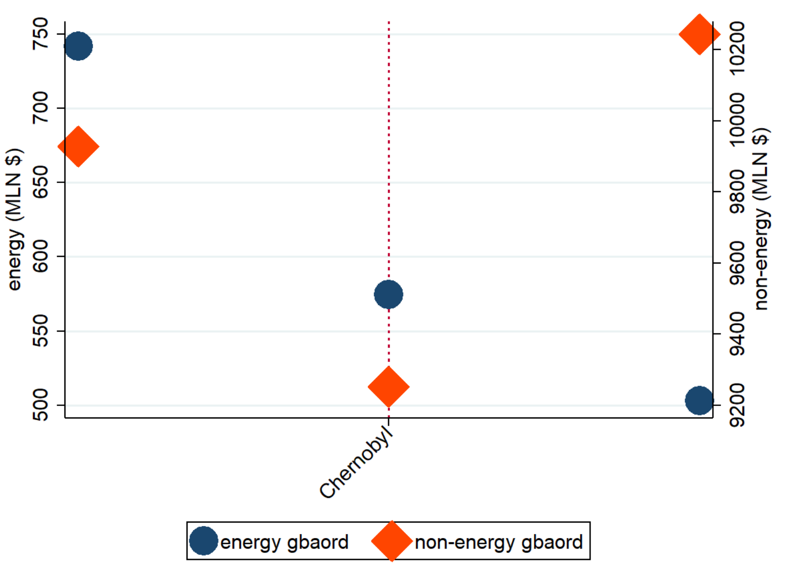


Notes: All IEA Member Countries considered. *Source*: IEA, 2017.

ing the oil and gas industry, opened the way for investments also in other alternative technologies, *i.e.* solar and wind. In the early 1980s, renewables represented thus a peripheral part of the overall policy architecture for reducing the dependence from fossil sources. Consequently, their development was strongly attached to the nuclear advance.

The 1986 Chernobyl disaster is classified as "Level 7: Major accidents" by the International Nuclear and Radiological Event Scale (INES), and is considered – together with the 2011 Fukushima Daiichi disaster – as the most relevant nuclear accident ever occurred. The effects of the Chernobyl accident prompted strong international debates about the sustainability and the security of the entire energy generation system, calling for immediate policy responses worldwide. As a matter of fact, several European countries adopted rigid policy interventions against nuclear power investments, immediately after the Chernobyl event. Finland shelved the application on its fifth nuclear power station and decided not to expand its nuclear program. Similarly, the Netherlands congested its nuclear power program and Austria decided not to start any investment in nuclear power generation, even if the construction of its first reactor was already completed at that time. Italy was one of the countries that more strongly replied to the accident. After the 1987 referendum, the Italian government decided indeed to phase-out its nuclear power activity, definitively shutting down all the active reactors.

Figure 2.4: GBAORD average level (Energy vs. Non-Energy, 1985-1987)



Notes: OECD average level of expenditures in 2010 mln USD, PPP. *Source*: OECD, 2017.

Summing up, the main hypothesis I draw is that the entire policy architecture for boosting alternative-to-fossil-fuel technologies has been exogenously affected by the Chernobyl accident, negatively. Figure 4 plots the pattern of the average government spending for R&D in energy vs. non-energy fields (OECD Countries) between 1985 and 1987. The descriptive evidence shows a similar declining trend in both kinds of expenditure from 1985 to 1986. However, while non-energy-related public R&D expenditures increased on average by around 10.7% between 1986 and 1987, public energy R&D continued decreasing (-12.4% from 1986 to 1987).[8]

[8]The decreasing trend of public energy R&D started in the early 1980s (the average level decreases by around 12% from 1981 to 1985). Dooley (1998) found that most IEA member states reduced public

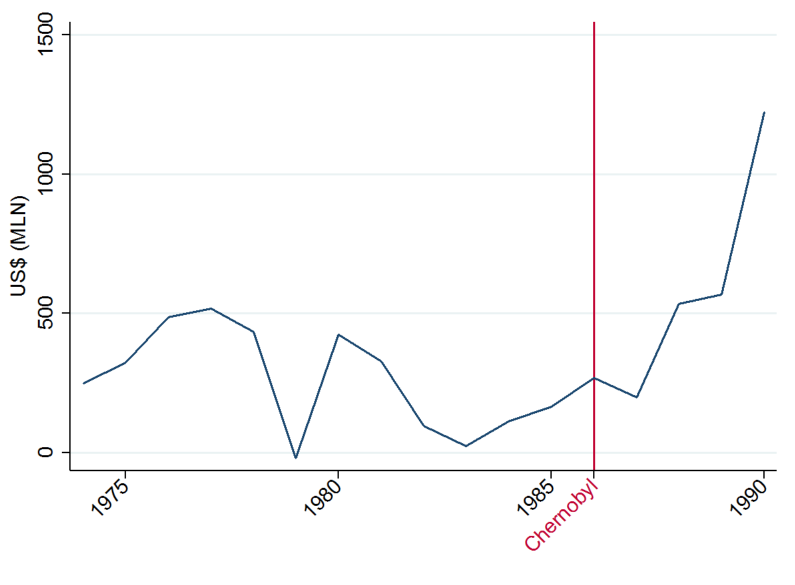
Unfortunately, the disposable data on aggregate government R&D expenditures from 1980 to 1990 allow for disentangling between green and non-green targets only in the energy field, making impossible to compare this pattern with the ones experienced by other domains. Exploiting this data as a further descriptive support of the arguments proposed above, Figure 5 draws the difference in the level of the US government R&D expenditures between fossil-fuels and renewables. After a minimum experienced in 1979 as a response to the second oil crisis, the divergence between fossil-fuel and renewables has returned to the early-1970s levels in 1986. Afterwards, a tremendous increase is evident, confirming a restored relative public interest in supporting R&D for fossil-fuels technologies. According to Bointner (2014), public renewable energy R&D expenditures indeed peaked in Carter's last year of presidency in 1980, leading to a first knowledge maximum in 1985 and decreasing afterwards. A similar pattern emerged also for other OECD countries. This evidence allows me to assume that, in relative terms, the fall in public R&D expenditures due to the Chernobyl accident was mainly driven by reducing public resources to alternative to fossil fuel technologies.

Identification strategy

The arguments proposed above allow me to investigate the causal effect of innovation policies on the cumulativeness of green technological knowledge. The time at which a patent receives citations (pre- or post-Chernobyl) as well as its technological domain (energy versus other technological domains) determine the likelihood of being affected by a change in policy intervention. The identification strategy relies on the fact that only the technological knowledge cumulativeness of energy patents was affected by the

energy R&D expenditures from the mid-1980s to the 1990s. He argues that this decrease is mainly due to deregulation of the energy markets, and that the remaining R&D money was shifted towards short-term, less risky research projects. According to Wiesenthal et al. (2012), this decrease is partly influenced by liberalisation and privatisation of the energy sector. However, a tremendous drop is evident in the second half of the 1980s (on average, -38% from 1985 to 1988) due to, I argue, the consequences of the Chernobyl accident. Conversely, non-energy domains maintain a stable pattern of growth in government R&D funding during the 1980s.

Figure 2.5: US-Gov energy-R&D expenditure: difference between fossil-fuels and renewables (1974-1990)



Notes: difference expressed in 2010 mln USD. *Source*: OECD/IEA 2017.

exogenous change in innovation policies after the Chernobyl disaster. The knowledge cumulativeness of green energy patents before Chernobyl and the knowledge cumulativeness of green non-energy patents before and after Chernobyl were not affected by the change in the innovation policy design. Therefore, I can combine differences in innovation policy design within different technological domains (energy vs. non-energy) with differences across cohorts induced by the shock (pre-Chernobyl vs. post-Chernobyl). After controlling for the energy field and the cohort effect (post-Chernobyl), the interaction between the two can be used as an exogenous variable capturing the causal effect of the shock, which can be used as an instrument for the level of policy intervention. Finally, I can estimate the relationship between the level of innovation policy intervention and the level of technological knowledge cumulativeness in the green field.

If the Chernobyl accident exogenously decreased the policy effort towards alternative to fossil fuel technologies, the interaction between the dummy signaling for an energy-related patent and the post-Chernobyl dummy should have a negative and significant effect on the level of innovation policy effort, while controlling for energy field and cohort effects. This difference-in-differences (DD) specification controls for overall time trends in policy pressure (across all green technologies) and for time invariant unobserved differences between technological fields (Angrist and Pischke, 2008). Moreover, DD regression allows me to include further control variables affecting the level of policy pressure, such as country, year and technology characteristics.

The DD can be interpreted as the causal effect of the Chernobyl accident under the assumption that, in the absence of the Chernobyl shock, the pattern of policy intervention for technological advance would not have been systematically different between energy and non-energy green domains. To further strengthen this assumption, I apply the Coarsened Exact Matching (CEM) technique (Iacus et al., 2009, 2011) to match green energy patents with green non-energy patents on several pre-Chernobyl characteristics (see the Appendix).

2.3.2 Data and sample

I study the effect of the innovation policy effort on the level and the qualitative characteristics of the green technological cumulativeness exploiting information contained in EPO patent citation data. Precisely, I select green patents applied at the EPO from 1980 to 1984, and I estimate the effect of the innovation policy effort in R&D on both the number of yearly citations they receive (overall accumulation process) and the qualitative characteristics of these citation patterns (the yearly number of citations coming from, respectively, highly original and highly radical patents; the yearly number of citations coming from non-green patents).

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[9], 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. I combine both classifications to define a patent as green, excluding from the analysis nuclear power-related patents.

The resulting dataset consists of 27515 unique green patents. Patent citations they received have been observed from 1980 to 1988. The sample reduces to 7431 unique green patents when applying the CEM technique.

2.3.3 Variables

Dependent variables

The level of the overall knowledge cumulativeness is measured through the number of yearly citations a patent receives. The number of citations a patent receives reveals that the knowledge incorporated in the protected technology is somehow subsequently used by innovating and producing companies (Trajtenberg, 1990). Indeed, since citations show the degree of novelty and inventive steps of the patent claims, they identify the antecedents upon which the invention stands. In this respect, a citation from patent A to patent B indicates that part of the knowledge protected by patent B is also used in generating the technology protected by the patent A. Citations thus capture the

[9] `http://www.oecd.org/env/indicators-modelling-outlooks/greengrowthindicators.htm`

technological impact of an invention: the more a patent is cited the more the protected technological knowledge is used by further innovation processes (impacting on their evolution).[10] The number of yearly forward citations to green patents is corrected for DOCDB patent families to account for the entire flow of citations a specific technology receives.[11]

As for the second and third step of the analysis, I estimate the effect of a change in the level of government R&D expenditures on: *a)* the number of citations coming from, respectively, the 5% more original and the 5% more radical patents;[12] *b)* the number of citations coming from non-green patents.

As stressed by Trajtenberg et al. (1997), important patents are those that get higher number of citations, and are cited by patents that are themselves relatively highly cited. For what matters for the present study, testing for the quality of the patents citing green patents would be thus very informative to assess the effect of public R&D expenditures on the implementation of green knowledge in the evolution of technological trajectories. For this reason I look at the number of citations coming from patents pertaining to the 95th percentile of, alternatively, the number of forward citations and the level of originality in a given year.

Patents in the top of the citations distribution are indeed considered as radical inventions (Ahuja and Lampert, 2001).[13] Similarly, more original patents should protect

[10] As stressed by Jaffe & de Rassenfosse (2016, pag. 12), "(c)*itations are, first and foremost, an indicator of technological impact*". Due to the richness of information contained in patent documents, citations are also used in the literature to track knowledge flows (Jaffe et al. 1993; Jaffe and Trajtenberg 1999; Maurseth and Verspagen 2002; Bottazzi and Peri 2003; Bacchiocchi and Montobbio 2010). Griliches (1990) and Breschi et al. (2005) provide a path-breaking and renowned survey. For a recent survey about the use of patent citation data in social science research, see Jaffe & de Rassenfosse (2016).

[11] Patent families essentially originate from a company or an inventor applying for the protection of the same invention at different patent offices. This results in a series of equivalent filings that patent examiners and attorneys can cite indifferently. Simple patent families are quite restrictive sets of equivalents, all sharing the same priority (an original filing at one or another patent once, before extension elsewhere). DOCDB are an alternative of simple families. For a complete discussion about the opportunity of correcting citations for patent families, see Martinez (2010).

[12] The implemented measures of originality and radicalness come from Squicciarini et al. (2013).

[13] It must be stressed that other measures of radicality have been implemented. For example, Dahlin

more basic inventions (Trajtenberg et al., 1997).[14]

Finally, for the green knowledge trajectory to impose, an important feature would be the one of entering the more traditional, dirty trajectories. If this is the case, it would be likely to observe a faster and decisive switch in production processes from dirty to clean methods. Thus, I measure the effect of increasing government R&D expenditures on the number of citations coming from dirty patents.

Independent variable and controls

The main independent variable is the yearly level of *Government appropriation or outlays budget for R&D* (GBAORD) by socio economic objective (SEO).

GBAORD is a budget-based data, which allows government support for R&D to be measured. It is the result of a joint OECD-Eurostat international data collection on resources devoted to R&D. Essentially, this involves identifying all the budget items with an R&D component and measuring or estimating their R&D content in terms of funding. These estimates are less accurate than performance-based data but as they are derived from the budget, they can be linked to policy through classification by "objectives" or "goals".

GBAORD series cover R&D in exploration and exploitation of the earth, environment, exploration and exploitation of space, transport, telecommunication and other infrastructures, energy, industrial production and technology, health, agriculture, education,

and Behrens (2005) define a 'radical' invention within a given technology domain (tennis rackets, in their application) as the one that recombines previous technology elements in a new and different way, but which is then imitated and so spawns subsequent patents that combine technology elements in a manner substantially similar to the radical invention.

[14]The originality measure is retrieved from Squicciarini et al. (2013). It is based on a modification of the Hirschman-Herfindahl Index (HHI) and relies on information concerning the number and distribution of citations made (backward citations) and the technology classes (IPC) of the patents these citations come from. In calculating the index, they consider 4-digits IPC classes contained in the cited patent documents. Building on Hall at al. (2001), they define the originality indicator as: $Originality_p = 1 - \sum_j^{np} s_{pj}^2$ where sp_j is the percentage of citations made by patent p to patent class j out of the np IPC 4-digit patent codes contained in the patents cited by patent p. Citation measures are built on EPO patents and account for patent equivalents.

culture, recreation, religion and mass media, political and social systems, structures and processes, general advancement of knowledge, defense. They include R&D performed on the national territory as well as payments to foreign performers, including international organizations. GBAORD, however, covers only R&D financed by central government; local government and sometimes also provincial government are excluded.[15]

Following Stančík (2012), I assign SEOs to economic sectors (NACE rev. 2 sectors). Then, following Van Looy et al. (2014), I assign NACE codes to IPC classes. This allows me to measure the level of Government budget for R&D related to each technology classifying a patent, separating the energy domain from the others.[16,17]

Control variables include a binary variable for energy patents, and a post-Chernobyl-accident time variable. The interaction between the two will be used as the instrumental variable for the level of Government budget for R&D.

Several variables could affect the likelihood that a patent will receive forward citations. Therefore, additional controls are included: the total intramural business R&D expenditure (BERD), as a control for the overall private innovation effort at the country level; the level of country emission intensity, as a control for the overall country environmental policy effort;[18] the yearly number of patents by IPC 4digits contained in the focal

[15]A complete description of socioeconomic objectives (SEO) is provided by the Frascati Manual 2015 (OECD), chapter 12.4.

[16]Unfortunately, I am not able to measure the exact level of government R&D funding assigned to the green sub-category for each observed field. I thus proxy this level with the aggregate level of expenditures in the field, assuming implicitly that the composition of the funding (green vs. non-green) does not endogenously differ between technological domains. This assumption should not be far from the reality if there is not an evident policy line recognizing relatively diverse levels of environmental externalities affecting the funded sectors. Given the arguments proposed above, the period of analysis is not a period characterized by strong environmental pressure. I am thus confident that this variable, even if imprecise, is unbiased.

[17]Patents are assigned to countries according to the inventor's country of residence.

[18]This measure comes from The World Bank (2017) and is expressed as kg per 2010 US$ of GDP. Alternatively I include the Government budget for R&D directly related to the environment. Following the Frascati Manual 2015 (OECD), the SEO "Environment" covers R&D aimed at improving the control of pollution, including the identification and analysis of the sources of pollution and their causes, and all pollutants, including their dispersal in the environment and the effects on humans, species (fauna, flora, micro-organisms) and the biosphere. This kind of R&D seems not to be directly related to specific green technologies. It instead more generally targets basic research for environmental issues, possibly

patent (averaged over the number of IPCs), as a proxy for the level of advance of the basket of IPCs classifying the focal technology;[19] several patent quality measures such as being granted, the number of claims, and the size of the patent family; the number of patent backward citations, as a proxy for the already cumulated knowledge behind the focal technology; the number of inventors, proxying for the team effect; patent priority year, controlling for the time distance from the shock; Year and Country dummies. Furthermore, I also add the yearly level of oil prices, adjusted for inflation, as a control for potential shocks in the oil and gas industry with consequences both on the innovative efforts in the renewable energy domain and on the volatility of public energy R&D expenditures.[20,21]

2.3.4 Models

To measure the effect of a change in the government budget for R&D on the level of green technological knowledge cumulativeness and its qualitative characteristics, I estimate three specifications of the following model:

$$Y_{i,t} = \delta_c + \delta_t + \beta_1 GBAORD_{i,t} + \boldsymbol{\Omega'_{i,t}}\beta_2 + \boldsymbol{\Lambda'_i}\beta_3 + \epsilon_{c,t},$$

spreading on the overall environmental research spectrum. I thus use this kind of expenditure as a further control for the overall public policy pressure (supply-side). However, since I can not rule out the possibility that this kind of R&D precisely targets specific green technologies, I use this measure only in robustness analyses. Results do not change when included.

[19]This measure proxies the level of technological advance of the fields in which the focal patent belongs. The more a field develops the more likely a patent will receive citations. Formally, let $i = 1, \ldots, N$ the IPCs 4-digits classifying the patent document p, for each year t the measure takes the following form: $field_{p,t} = \frac{1}{N}\sum_i patent_{i,t}$.

[20]Baccini and Urpelainen (2012) found a significant and positive impact of oil prices on the volatility of public energy R&D expenditures. A period of low oil price in the 1980s may have lowered the governmental incentives to invest in energy R&D, leading to a decline of knowledge in the 1990s.

[21]Patent data information have been extracted from the CRIOS database (Coffano and Tarasconi, 2014). Data about GBAORD, BERD and GDP have been extracted from the OECD.Stat database (2010 million US Dollars, PPP). Data about emission intensity come from World Bank. Oil prices have been extracted from the IEA energy statistics database (2010 US Dollars, adjusted for inflation). Table 1 provides variables description and summary statistics.

where $Y_{i,t}$ is, alternatively, *i)* the total number of yearly forward citations received, *ii)* the number of citations coming from the more original and more radical patents, or *iii)* the number of citations coming from non-green patents; δ_c is a vector of country fixed effects; δ_t is a vector of year fixed effects; $GBAORD_{i,t}$ is the level of GBAORD affecting patent i at time t, according to the inventors' country of residence; the vector $\boldsymbol{\Omega'_{i,t}}$ contains a set of time varying controls, as described above; the vector $\boldsymbol{\Lambda'_i}$ is a vector of further controls for fixed patent characteristics, such as being granted, the number of claims, the size of the patent family, the number of patent backward citations, the number of inventors, the patent priority year, and the inventor's country of residence.

All the specifications are estimated with a two-stage least square model (2SLS). In the first stage, I estimate the level of R&D budget with an OLS in a difference-in-differences configuration. Precisely, I include the interaction between the energy domain and the cohort effect (post-Chernobyl) as an exogenous variable capturing the causal effect of the shock, energy domain, post-Chernobyl and all other further control variables. After instrumented, I estimate the effect of changes in the level of government budget for R&D on the three outcomes of interest. All 2SLS models use a single instrument resulting in a just identified estimate.

2.4 Results

The purpose of the empirical analysis is to test for the effect of publicly-conducted R&D on both the rate and the direction of the green knowledge accumulation process.

To find causality going from public R&D decisions to green innovation outcomes, I frame the empirical analysis in an instrumental variable setting. Coherently, I first estimate the first stage of the 2SLS models, predicting the level of government budget for R&D as a function of the Chernobyl shock in the energy domain and control variables. Table 2 displays the results of the first stage estimation for both the CEM subsample and

Table 2.1: Summary Statistics

CEM Sample

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
tot cit	Number of forward citations	28,134	.235	.610	0	14
tot original cit	Number of forward citations from patents in the 95th percentile of originality	28,134	.012	.120	0	6
tot radical cit	Number of forward citations from patents in the 95th percentile of radicalness	28,134	.015	.135	0	5
GBAORD	Level of government R&D budget by SEO (2010 million $, PPP)	28,134	50877.06	36136.22	16.221	93053.25
energy	Binary: energy patent	28,134	.124	.329	0	1
post-Chernobyl	Binary: citations received after 1986	28,134	.330	.470	0	1
*energy*post Chernobyl*	Binary: Energy patent and citations received after 1986	28,134	.040	.196	0	1
field tot patents	Number of patents by IPCs listed in the patent document	28,134	6.014	1.103	.693	8.919
oil price	Oil price corrected for inflation (2010 $)	28,134	3.887	.394	3.412	4.552
emission intensity	Inventors' country average emission intensity (kg per 2010 US$ of GDP)	28,134	.475	.164	.111	.677
BERD	total intramural business R&D expenditure (US Dollar, Millions, 2010)	28,134	11.050	1.098	4.161	11.951
claims	Number of claims	28,134	7.481	7.576	0	116
triadic	Binary: triadic patent	28,134	.620	.485	0	1
DOCDB family size	Number of patents constituting the DOCDB family	28,134	1.002	.048	1	2
bwd cit	Number of backward citations	28,134	.701	1.261	0	21
granted	Binary: granted patent	28,134	.671	.470	0	1
N. of inventors	Number of patent inventors	28,134	1.766	1.041	1	11

Full Sample

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
tot cit	Number of forward citations	103,482	.326	.843	0	24
tot original cit	Number of forward citations from patents in the 95th percentile of originality	103,482	.035	.236	0	9
tot radical cit	Number of forward citations from patents in the 95th percentile of radicalness	103,482	.023	.166	0	5
GBAORD	Level of government R&D budget by SEO (2010 million $, PPP)	103,482	41725.66	37107.38	.541	93053.25
energy	Binary: energy patent	103,482	.103	.303	0	1
post-Chernobyl	Binary: citations received after 1986	103,482	.328	.470	0	1
*energy * post Chernobyl*	Binary: Energy patent and citations received after 1986	103,482	.032	.175	0	1
field tot patents	Number of patents by IPCs listed in the patent document	103,482	6.648	1.464	0	9.720045
oil price	Oil price corrected for inflation (2010 $)	103,482	3.881	.392	3.412	4.552
emission intensity	Inventors' country average emission intensity (kg per 2010 US$ of GDP)	103,482	.445	.162	.111	.677
BERD	total intramural business R&D expenditure (US Dollar, Millions, 2010)	103,482	10.533	1.453	4.161	11.951
claims	Number of claims	103,482	8.269	8.648	0	157
triadic	Binary: triadic patent	103,482	.594	.491	0	1
DOCDB family size	Number of patents constituting the DOCDB family	103,482	1.088	.479	1	9
bwd cit	Number of backward citations	103,482	1.108	2.439	0	54
granted	Binary: granted patent	103,482	.663	.473	0	1
N. of inventors	Number of patent inventors	103,482	1.878	1.180	1	19

the full sample. The interaction between energy domain and post-Chernobyl, capturing the causal effect of the Chernobyl accident, has a significant negative effect on the level of government budget for R&D. Marginal effects (CEM sample results) indicate that the Chernobyl shock decreased the log level of government budget for R&D by 0.34 in absolute terms (around -26% of a pre-Chernobyl standard deviation). Overall, the results from the first stage indicate that the natural experiment had a relevant negative effect on the level of government budget for R&D: the policy reaction to the unexpected nuclear accident resulted in a reduction on the public R&D effort for 'alternative to fossil fuel' technologies.

I then estimate the effect of government-funded R&D on the broad accumulation of green technological knowledge, proxied by the number of citations a focal green technology receives. Table 3 reports the results of the second stage of the 2SLS model, estimating the effect of the government budget for R&D on the yearly number of forward citations a green patent receives. The government budget for R&D has a significant positive effect on the overall level of green knowledge cumulativeness. Precisely, results suggest that a 1% increase in government R&D budget increases the average yearly number of citations by 0.14% (CEM sample results). This result confirms the first hypothesis proposed in Section 2, according to which government-funded R&D represents an effective tool for restoring (at least partially) efficiency in the generation and diffusion of green knowledge into the system. Public R&D is indeed likely to relax both kinds of externality affecting GT processes, and, due to its nature, to guarantee their cumulativeness.

We then enter more in depth into the understanding of the direction that the green knowledge accumulation process takes.

The second hypothesis of the chapter is indeed that an increase in public R&D fosters the entry of green knowledge into more radical and more original technological trajec-

Table 2.2: First stage results

	Full sample	CEM sample
energy*post-Chernobyl	-0.358***	-0.344***
	(0.010)	(0.016)
energy	-2.682***	-2.701***
	(0.004)	(0.006)
post-Chernobyl	0.008***	0.022***
	(0.002)	(0.005)
tot patents by field (log)	0.002***	-0.001
	(0.000)	(0.001)
oil price (log)	0.017***	0.029***
	(0.003)	(0.007)
emission intensity	0.221***	-0.009
	(0.059)	(0.224)
BERD (log)	0.433***	0.592***
	(0.013)	(0.076)
N. of claims	0.000***	0.000
	(0.000)	(0.000)
triadic	-0.006***	-0.001
	(0.001)	(0.002)
docdb family size	-0.002**	-0.003
	(0.001)	(0.020)
bwd cit	0.001***	0.002***
	(0.000)	(0.001)
granted	-0.001	0.000
	(0.001)	(0.002)
N. of inventors	-0.001	0.001
	(0.001)	(0.001)
time trend	yes	yes
priority year dummies	yes	yes
country dummies	yes	yes
R^2	0.991	0.990
Observations	103482	28134

Dep. Var.: Annual level of GBAORD (log.). Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 2.3: GBAORD effect on the annual number of forward citations (2SLS results)

	CEM sample	Full sample
GBAORD (log)	0.137***	0.084***
	(0.041)	(0.020)
energy	0.380***	0.220***
	(0.116)	(0.055)
post-Chernobyl	-0.031**	-0.038***
	(0.014)	(0.005)
tot patents by field (log)	0.016***	0.018***
	(0.003)	(0.001)
oil price (log)	0.010	0.021**
	(0.026)	(0.009)
emission intensity	-0.585*	-0.584***
	(0.307)	(0.093)
BERD (log)	0.041	0.036
	(0.079)	(0.023)
claims	0.000	0.002***
	(0.000)	(0.000)
triadic	0.058***	0.067***
	(0.008)	(0.003)
docdb family size	-0.117***	-0.060***
	(0.040)	(0.003)
bwd cit	0.021***	0.025***
	(0.003)	(0.001)
granted	0.050***	0.039***
	(0.007)	(0.002)
N. of inventors	0.005	0.009***
	(0.003)	(0.001)
time trend	yes	yes
priority year dummies	yes	yes
country dummies	yes	yes
R^2	0.046	0.075
Observations	28134	103482

Dep. Var.: Annual number of forward citations (log). Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

tories: public R&D plays an active role for green technical change. Results confirm this hypothesis, revealing a positive and significant impact of an increase in government-funded R&D on the yearly number of citations received by highly original and highly radical patents (Table 4). Precisely, a 1% increase in government R&D budget increases the average yearly number of citations from highly original and radical patents by, respectively, 0.012% and 0.025% (CEM sample results). The nature of GT knowledge and the uniqueness of publicly-performed R&D are likely to mutually operate in rendering green trajectories technologically superior.

The last aim of the analysis is the one of investigating whether green knowledge is also likely to pervade traditional trajectories. The third hypothesis proposed by the present chapter is that government-funded R&D makes the usage of green knowledge more competitive compared to traditional, dirty knowledge, thus enhancing the probability of hybridization of non-green trajectories.

Table 5 displays the effect of GBAORD on the number of yearly citations received from non-green patents. Results reveal a positive and significant effect of government investments in R&D on the level of green knowledge accumulation in traditional, non-green domains, confirming such hypothesis. Precisely, a 1% increase in government R&D budget increases the average yearly number of citations from non-green patents by 0.059% (CEM sample results). This evidence demonstrates that green knowledge is more likely to enter traditional technological trajectories if governments increase their effort in public R&D. By making green knowledge more competitive in its usage, public R&D may foster hybridization attempts, accelerating the transition towards sustainable production methods.

The overall evidence demonstrates that the public effort in R&D is likely to importantly foster the green technological advance. However, the magnitude of the estimated effects reveals that, probably, both an unprecedented effort in public R&D investments

Table 2.4: GBAORD effect on the annual number of citations from the more original and more radical patents (2SLS estimates, CEM sample)

	(I) Original	(II) Radical
GBAORD (log)	0.012*	0.025***
	(0.007)	(0.010)
energy tot	0.030	0.065**
	(0.020)	(0.027)
post-Chernobyl	-0.002	0.002
	(0.003)	(0.004)
tot patents by field (log)	0.003***	0.004***
	(0.001)	(0.001)
oil price log	0.001	0.003
	(0.006)	(0.006)
emission intensity	-0.017	-0.107
	(0.098)	(0.101)
BERD (log)	-0.010	-0.011
	(0.025)	(0.026)
claims	-0.000	0.000
	(0.000)	(0.000)
triadic	0.000	0.003
	(0.002)	(0.002)
docdb family size	0.002	-0.006
	(0.007)	(0.005)
bwd cit	0.001**	0.000
	(0.001)	(0.001)
granted	0.001	0.001
	(0.002)	(0.002)
N. of inventors	-0.000	0.000
	(0.001)	(0.001)
time trend	yes	yes
priority year dummies	yes	yes
country dummies	yes	yes
R^2	0.004	0.005
Observations	28134	28134

Dep. Var.: Annual number of forward citations (log) from more original (Col. I) and more radical (Col. II) patents. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 2.5: GBAORD effect on the number of citations from non-green patents (2SLS estimates, CEM sample)

	Non-green
GBAORD (log)	0.059**
	(0.024)
energy	0.105
	(0.069)
post-Chernobyl	-0.018
	(0.012)
tot patents by field (log)	0.010***
	(0.002)
oil price (log)	0.015
	(0.021)
emission intensity	-0.374*
	(0.219)
BERD (log)	0.020
	(0.057)
claims	0.000
	(0.000)
triadic	0.038***
	(0.007)
docdb family size	-0.019
	(0.037)
bwd cit	0.010***
	(0.002)
granted	0.023***
	(0.006)
N. of inventors	-0.003
	(0.002)
time trend	yes
priority year dummies	yes
country dummies	yes
R^2	0.032
Observations	28134

Dep. Var.: Annual number of forward citations (log) from non-green patents. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

and a more systematic intervention for decisively attracting private green investments are required to timely shift from dirty to clean production systems.[22]

2.5 Conclusions

Simultaneously fostering the emergence of breakthrough green technologies and substituting traditional-emitting technologies with new, clean ones are crucial policy targets for guaranteeing long-run growth. Given the level of advance of dirty technologies and the cumulative nature of innovation processes, supply side oriented (public) interventions are indispensable for filling the technological gap between environmentally friendly and traditional technologies. The present chapter aims at contributing the literature on policy-driven green technical change dynamics by providing evidence of the causal effect of changes in public R&D on both the rate and the direction of green technological cumulativeness. This would represent a key step forward in the design of the entire policy architecture targeting green growth.

Results reveal a significant positive effect of increasing government budget for R&D on the overall process of green technological knowledge accumulation. Indeed, a 1% increase in R&D budget increases by around 0.14% the yearly average number of citations a green patent receives. Even if positive, this effect seems discouraging, partially revealing how difficult would be fostering the entire green domain in the short-medium run.

As for the effect of government R&D expenditures on the number of citations coming from highly original and radical patents, the emerging picture follows the general one. This demonstrates that public R&D is likely to positively impact on the process of green knowledge spilling over into the system. In turn, this may also be beneficial for economic growth.

[22] For robustness I replicate the same kind of analysis estimating models presented in Tables from 2 to 5 in patent fixed effects and applying the Negative Binomial estimator. Results are consistent with the ones presented in this section (see Appendix B).

Similarly, public R&D significantly fosters the use of green knowledge by non-green innovation processes, even if at low rates. This last result sheds light on the role of public R&D for enhancing combinatorial technological attempts and hybridization, with beneficial consequences on both the substitution of dirty with clean methods and the maintenance of systemic variety (e.g. reducing the risks associated with possible technological lock-ins).

Policy implications are manifold. First, shifting all the public R&D resources from dirty to green targets is likely to significantly reduce the time required by green technologies to overcome the technological advantage of incumbent, dirty technologies.

Second, this mechanism is likely to indirectly increase (decrease) the relative cost of dirty (clean) technologies, presumably letting the market prices adjusting consequently and reducing the future consumption of fossil fuels, creating also incentives for urgently-needed private green-investments.

Finally, the overall evidence proposed shows that a finer systematic investigation is needed for individuating technological R&D niches with the highest potential in terms of green radicalness and breakthrough to be systematically publicly funded. Heterogeneity in designing direct public R&D investments is indeed likely to be required to more efficiently foster green technical processes. In other words, the management of green public R&D is a topic that requires further systematic investigation.

Appendix A - Coarsened Exact Matching

In an experiment, one ideally observes two identical groups over time whereby one group is affected by an exogenous treatment at a particular point in time. To decrease the chance that pre-treatment differences between treated and control groups confound the results, I construct a matched subsample of patents using Coarsened Exact Matching (CEM).

CEM is a nonparametric multivariate matching method that reduces the covariate imbalance between treated and control groups (Iacus et al. 2009, 2011). The objective of CEM is to improve the estimation of causal effects by reducing imbalance, model dependence and statistical bias.

To improve the pre-treatment similarity between treated and control groups, I match green energy patents to green non-energy patents on the following pre-Chernobyl characteristics:

- average yearly rate of change of Government R&D budget in the patent-related SEOs;
- patent characteristics such as being granted, being triadic, patent DOCDB family size, number of backward citations and number of claims;
- average yearly number of pre-shock citations received;
- number of inventors and their patent stock;
- geographical location of the inventors listed in the patent (country of residence);
- patent priority year (as a proxy for patent age);
- technological field (IPC 4-digits) age, proxied by the minimum priority year of the first patent classified in the IPC 4-digits codes listed in the patent document;

- the level of technological advance of the field the patent belongs to, proxied by the number of patents assigned to the IPC 4-digits classifying the focal patent.

I rely on CEM coarsening algorithm to develop coarsened strata. Jointly applying these criteria, I obtain 7,666 strata. For each stratum I retain only energy and non-energy matched patents. The resulting sample consists of 7,431 patents (27% of the original sample of green patents). The large majority of dropped patents (99.2%) belong to the control group of green non-energy patents that do not provide a proper control for the green energy patents. In the analysis, the matched green energy patents get a weight of 1 and the matched control patents get a weight equal to $\left[\frac{\#MCP_i}{\#MTP_i}\right] \times \left[\frac{\#TP_i}{\#CP_i}\right]$, where, for each stratum i, $\#MCP_i$ is the number of matched control patents, $\#MTP_i$ is the number of matched treated patents, $\#TP_i$ is the number of treated patents, and $\#CP_i$ is the number of control patents.

Appendix B - Robustness

Fixed effect estimations

Table 2.6: First stage results. Fixed effect

	Full sample	CEM sample
energy*post-Chernobyl	-0.480***	-0.479***
	(0.004)	(0.006)
post-Chernobyl	0.020***	0.036***
	(0.002)	(0.006)
tot patents by field (log)	0.096***	0.051***
	(0.005)	(0.010)
oil price (log	0.016***	0.029***
	(0.002)	(0.009)
emission intensity	0.118*	-0.058
	(0.064)	(0.300)
BERD (log)	0.425***	0.582***
	(0.019)	(0.125)
trend	0.011***	0.006
	(0.002)	(0.006)
R^2	0.561	0.623
Observations	103482	28134

Dep. Var.: Annual level of GBAORD (log.). Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 2.7: GBAORD effect on the yearly number of citations (2SLS estimates). Fixed effect

	CEM sample	Full sample
GBAORD	0.078***	0.020
	(0.029)	(0.014)
post-Chernobyl	-0.027**	-0.042***
	(0.013)	(0.004)
tot patents by field (log)	0.063***	0.083***
	(0.024)	(0.008)
oil price (log)	0.008	0.021***
	(0.023)	(0.008)
emission intensity	-0.769***	-0.602***
	(0.295)	(0.089)
BERD (log)	0.096	0.062***
	(0.083)	(0.021)
trend	-0.003	0.004
	(0.009)	(0.003)
R^2	0.012	0.011
Observations	27072	99672

Dep. Var.: Annual number of forward citations (log). Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 2.8: GBAORD effect on the yearly number of citations from more original and radical patents (2SLS estimates). Fixed effect (CEM sample)

	(I) Original	(II) Radical
GBAORD	0.009*	0.020***
	(0.005)	(0.007)
post-Chernobyl	-0.002	0.001
	(0.003)	(0.004)
tot patents by field (log)	0.007*	0.001
	(0.004)	(0.006)
oil price (log)	0.001	0.004
	(0.006)	(0.006)
emission intensity	-0.022	-0.083
	(0.088)	(0.094)
BERD (log)	-0.008	-0.011
	(0.024)	(0.027)
trend	0.001	0.001
	(0.002)	(0.002)
R^2	0.001	0.002
Observations	27072	27072

Dep. Var.: Annual number of forward citations (log) from more original (Col. I) and more radical (Col. II) patents. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 2.9: GBAORD effect on the yearly number of citations from non-green patents (2SLS estimates). Fixed effect (CEM sample)

	Non-green
GBAORD	0.038**
	(0.017)
post-Chernobyl	-0.022**
	(0.011)
tot patents by field (log)	0.056***
	(0.018)
oil price (log)	0.017
	(0.018)
emission intensity	-0.373*
	(0.217)
BERD (log)	0.005
	(0.062)
trend	0.006
	(0.007)
R^2	0.010
Observations	27072

Dep. Var.: Annual number of forward citations (log) from non-green patents. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Negative binomial estimations

Table 2.10: Negative binomial results

	N. fwd cit	N. original cit	N. radical cit	N. non-green cit
GBAORD	0.113***	0.059	0.063	0.332***
	(0.018)	(0.062)	(0.057)	(0.029)
tot patents by field (log)	0.132***	0.667***	0.277***	0.067***
	(0.006)	(0.020)	(0.020)	(0.008)
oil price (log)	0.076	-0.199	-0.146	0.184**
	(0.051)	(0.136)	(0.154)	(0.072)
emission intensity	-4.808***	-6.136***	-5.818***	-3.605***
	(0.631)	(1.668)	(1.913)	(0.919)
BERD (log)	0.981***	0.917**	1.688***	0.788***
	(0.165)	(0.386)	(0.518)	(0.237)
claims	0.007***	0.016***	0.004*	0.004***
	(0.001)	(0.002)	(0.002)	(0.001)
triadic	0.503***	0.552***	0.603***	0.616***
	(0.018)	(0.053)	(0.059)	(0.026)
docdb family size	-0.331***	-0.272***	-0.222***	-0.251***
	(0.020)	(0.048)	(0.054)	(0.028)
bwd cit	0.108***	0.076***	0.056***	0.087***
	(0.003)	(0.007)	(0.007)	(0.004)
granted	0.289***	0.071	0.159***	0.226***
	(0.018)	(0.048)	(0.054)	(0.025)
N. of inventors	0.064***	0.056***	0.064***	0.034***
	(0.006)	(0.015)	(0.017)	(0.009)
time trend	yes	yes	yes	yes
priority year dummies	yes	yes	yes	yes
country dummies	yes	yes	yes	yes
Observations	103482	103482	103482	103482

* $p < .1$, ** $p < .05$, *** $p < .01$.

3 Public procurement, local labor markets and green technological change: Evidence from US Commuting Zones[1]

Abstract

The present chapter investigates whether and through which channels green public procurement (GPP) stimulates local environmental innovation capacity. To this end, we use detailed data sources on green patents and procurement expenditure at the level of US Commuting Zones for the period 2000-2011. We also check for the moderating effects of local labor market composition in the relation between green public procurement and green innovation capacity. Lastly, we exploit the richness of patent information to test for differential effects of green public procurement on different classes of green technologies. The main finding is that GPP is an important driver in explaining the growth of local green-tech stock. The positive effect of GPP is mainly driven by expenditures for procured green services and is magnified by the local presence of high shares of abstract-intensive occupations. When separately considering diverse kinds of green technologies, we do find evidence of a more pronounced effect of GPP on the growth of local knowledge stocks of mitigation technologies.

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[1]This chapter is coauthored with Davide Consoli, François Perruchas and Francesco Quatraro. We acknowledge participants in the GEOINNO18 Conference, January 2018, University of Barcelona, Barcelona, Spain.

3.1 Introduction

While all the avenues of the debate about climate change seemingly lead to innovation, the nature of the problem, of the possible solutions and the roadmap towards implementation remain highly contested. The academic and policy circles place great expectations in the prospect that technology, both old and new, can assist in striking that balance between running business operations within the limits of environmental sustainability while staying in the game for innovation and high competitiveness (Porter and van der Linde, 1995).[2] There exists wide consensus on the importance of other forces that, alongside technology, can accelerate the transition to sustainable growth. For one, policy can create propitious conditions across the board, not just for technological innovation but, also, for promoting broader social engagement on the benefits of a low-carbon economy. It goes without saying that none of the above would be feasible absent a body of know-how that enables the necessary adjustments in the attendant technological, organizational and institutional domains. Last but not least, climate change is a global phenomenon with marked local manifestations, which entails that the dynamics of both policy and of the knowledge base carry strong spatial dimensions that cannot be neglected. The present chapter enters this debate with a view to explore empirically the extent to which policy and human capital enable or thwart local green innovation capacity in the local economies of the United States (US).

The three dimensions of interest for our study are connected in complex ways. To begin with, innovation in green technologies (GTs) suffers from a double externality problem (Rennings, 2000). On the one hand, non-appropriability and non-exclusivity of technological knowledge give way to the kind of externalities that are common to any innovation, and that lead to under-investment in the private sector. On the other hand, because of their potentially pervasive influence, GTs that effectively contribute

[2]See Barbieri et al. (2016) for an extensive survey.

to containing or preventing the negative effects of climate change bring about global benefits in the form of environmental protection that represents a positive externality for society, therein including non-innovating firms (Jaffe et al., 2002*b*). This double externality exacerbates the traditional uncertainty that surrounds the development of new technologies and provides a rationale for the second dimension of interest, namely public policy interventions that create positive preconditions for investments in GTs (del Río González, 2009; Mowery et al., 2010). The portfolio of available mechanisms is wide and encompasses setting emission standards, stimulating the demand for green technologies (pull effect) or restoring incentives for private investments in innovation (push effect) (Johnstone et al., 2012). Last but not least, the scale of changes involved in these diverse but interconnected dimensions call upon specialized know-how. Human capital is a key asset to facilitate the development of new technology but the transition towards low-carbon economies requires capabilities beyond the strictly technical sphere, for example operation management skills to manage the reconfiguration of industrial processes as well as legal and administrative skills to comply with regulatory standards (Vona et al., 2018).

In the view proposed here the interplay between policy, technology and human capital offers a compelling framework to account for the space-bound co-existence of technology push and demand pull forces (Requate, 2005; Horbach, 2008; Ghisetti and Quatraro, 2013). The chapter draws on and contributes to this research by investigating whether and to what extent Green Public Procurement (GPP) of environmentally sustainable products and services enhances the introduction of new GTs in 722 US Commuting Zones (CZs) over the period 2000-2011. Our proxy for environmental innovation at local level is the stock of green patents granted to CZ residents. The main findings of our analysis are four. First, GPP exerts a positive impact on the generation of GTs in US CZs. Second, the configuration of the local bundle of skills has a significant impact on green knowledge production. In particular, the positive effect of abstract skills intensity is persistent across all estimates. Third, these two dimensions show a high degree of interdependence, as the positive and significant coefficient for the interaction between the variables suggests the existence of a mutual reinforcing effects. Fourth, we find interesting patterns when disentangling the effects of product-related vis-à-vis service related GPP, as well as when we disentangle mitigation vis-à-vis adaptation oriented GTs.

Our findings add to prior literature in several respects. To begin with, in spite of an intense debate about the importance of demand-side policy instruments, there is a gap on the role of public procurement as a driver of green innovation. While existing research has focused on the impact of public procurement on innovation in general (Nelson, 1982; Geroski, 1990; Ruttan, 2006), only a few studies concentrate on the domain of environmental sustainability and innovation (Ghisetti, 2017). Second, the inclusion of occupational structure as a proxy of the skill endowment of the local workforce brings to the fore explicitly the dynamics of know-how and learning that can both enable or thwart the development of a new technological trajectory. While recent exploratory studies propose novel approaches to account for the analysis of environmental skills and green jobs at the level of occupations (Consoli et al., 2016; Vona et al., 2018) and of US geographical areas (Vona et al., 2017), no study has so far explored the role of local human capital endowment on green technological change. Further, our focus on the determinants of eco-innovation in the US enriches existing empirical studies that is mainly centered on European countries. On the whole, our empirical analysis connects the geography of eco-innovation and the literature on the determinants of eco-innovation which remains an appealing, yet arguably underdeveloped, space of future research (Ghisetti and Quatraro, 2017; Montresor and Quatraro, 2017).

The rest of the chapter is structured as follows. Section 2 articulates the theoretical framework and develops the hypotheses. In Section 3 we outline the research design. Section 4 presents the results of the econometric analysis. In Section 5 we provide a critical discussion of our findings and derive concluding remarks.

3.2 Theory and hypotheses development

Knowledge generation and diffusion stem out of local interactions that confer innovation a space-bound nature. According to an established tenet, geographical and cognitive proximity are necessary, but not sufficient, to reduce coordination and transaction costs among otherwise dispersed individuals, and to eventually spur learning, knowledge creation and innovation (Breschi and Lissoni, 2001; Boschma, 2005; Quatraro and Usai, 2017). The spatial dimension of innovation is especially relevant to analyse cross-regional heterogeneity in the composition of economic activities and in the attendant competences and innovation capabilities (Quatraro, 2009; Storper and Scott, 2009).

Empirical studies based on the knowledge production function (KPF) approach of Griliches (1984) and Jaffe (1986) insist that the variance in the quality of regional innovation systems and of intensity of investments in R&D activities explains a substantial portion of the difference of cross-regional innovation performance (Acs et al., 2002; Fritsch, 2002; Marrocu et al., 2013; Paci et al., 2014; Miguelez and Moreno, 2017). A strand in evolutionary economic geography adds to this that regional idiosyncratic factors affect not only the rate of local innovation activities but also their direction, thus accounting for the effects of path-dependency on regional technological branching (Colombelli et al., 2014; Montresor and Quatraro, 2017).

Following on the above, we argue that the spatial features underlying the generation and diffusion of green technology have been somewhat underplayed. The only exceptions are studies based on the KPF approach that emphasize the role of R&D activities and of the regulatory framework in influencing the rate of green technological change (Ghisetti and Quatraro, 2013). Spatial patterns of GTs production have been analyzed from an evolutionary perspective only in the fuel cell industry in EU regions with a view to capture the role of technological relatedness (Tanner, 2014 and 2015). We propose to fill this gap by articulating the analysis of eco-innovation in the KPF framework with a view to gain greater understanding of the geographical characteristics of green innovation.

Eco-innovations carry a number of features that set them apart from other types of innovation (Rennings, 2000). To begin with, besides the classical sources of externalities that affect any kind of knowledge, green knowledge has positive effects on firm-level, and hence local-level, environmental performance. These effects can be internalized by private agents only after policy has restored the appropriate incentive for private investments. To be sure, there are several variants of environmental policy such as setting technological standards, regulating prices or establishing pollution thresholds that induce firms to renew their production processes. As a result of these inducement effects new market for GTs emerge due to higher R&D efforts (Johnstone et al., 2012; Nemet, 2009; Hoppmann et al., 2013). These considerations bring the institutional context to the core of the analysis of the drivers of GTs. Since institutions are place-specific, empirical studies at the micro, meso and at the macro-level consider the regional or national regulatory framework as a key discriminant to explain differences in the ability to generate eco-innovations across firms, regions and countries (Barbieri et al., 2016). Only few scholars have so far considered the role of supply side policies aimed at fostering the development of technological capabilities in green domains through R&D supporting schemes (Costantini et al., 2015). More than this, to the best of our knowledge only Ghisetti (2017) has hitherto explored the role of innovative green public procurement.

Building on the notion that public procurement is place-specific and that it exhibits variance both between and within regions over time (Heald and Short, 2002; Morgenroth, 2010), we propose that filling such a gap would create a bridge between the literature on the determinants of eco-innovation and that on the geography of eco-innovation. GPP is touted as a key lever to stimulate the development of new technology that can facilitate meeting environmental sustainability targets. This is because the pathway to successfully developing green technology entails dealing with substantial uncertainty (Mowery et al., 2010). Under this perspective, GPP is regarded as a direct form of public intervention to stimulate the demand for GTs by the government (Parikka-Alhola, 2008). These arguments lead us to propose the first hypothesis:

H1: *Territorial differences in GPP are associated with green technological change differentials across regions.*

The full appreciation of the mechanisms underlying knowledge production is crucial to gain a comprehensive view on the spatial dynamics of GTs generation. Knowledge recombination has long been understood to be a key driver of new competences that are eventually embodied in new technology (Weitzman, 1996 and 1998; Fleming and Sorenson, 2001). Proximity in the cognitive domain facilitates the recombination of know-how, and indeed highly coherent knowledge bases increase significantly the chances of successful innovation (Quatraro, 2010; Krafft et al., 2014). This is relevant to eco-innovations in that their emergence is associated with the hybridization of green and dirty technologies (Zeppini and van der Bergh, 2011; Dechezlepetre et al., 2004; Colombelli and Quatraro, 2017). According to an established tenet, skilled individuals can more quickly adapt their activities to the changing incentives that follow the emergence of new technologies (Nelson and Phelps, 1966) and, in the case at hand, the transition to low carbon economies calls upon a broad competence base that goes beyond the merely technical domain (Vona et al., 2018). However, geographical areas are likely to differ in terms of both the endowment of human capital as well as in the capacity to adapt their occupational structure to the new opportunities (Vona et al., 2017). This entails that agglomeration economies due to geographic concentration of economic activities may account for significant differences in the capacity to generate green technology across space. On these grounds, we propose the second hypothesis:

H2: *The prevalence of exploration-oriented skills in local contexts is associated with higher levels of green technological change.*

Last but not least, human capital endowment and GPP are ideal candidates to explain the green innovation capacity of local economies. This holds true also for their interaction. Due to the double externality problem of eco-innovation, the endowment of exploration-oriented skills at the local level can hardly display its full potential in terms of GTs enablers because of the reluctance of economic agents to bear the uncertainty associated with externalities and low appropriability conditions. At the same time, high levels of GPP are likely to be more effective in the stimulation of the production of environmentally sound technologies in areas that are characterized by local availability of exploration-oriented skills. Accordingly, we expect the two dimensions to show a high degree of interdependence and mutual enforcing effect on green innovation capacity. These considerations lead us to spell out our third hypothesis.

H3: *The prevalence of exploration-oriented skills and high levels of GPP in local context are mutually enforcing in affecting the rate of green technological change.*

The remainder of the chapter will elaborate an empirical analysis to test the hypotheses laid out in this section.

3.3 Research design

This section details the key data sources, the variable construction and the proposed empirical strategy. As anticipated earlier, all the key dimensions of interest for the present study, eco-innovation, public procurement and human capital, are space-bound. For the purpose of their analysis we focus on US Commuting Zones. These spatial units were first developed by Tolbert and Sizer (1996) using county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong and weak commuting.[3] Compared to other territorial units, CZs carry the advantage of covering the entirety of the US territory while at the same time being constructed in such a way that meaningful mobility patterns are accounted for.[4]

3.3.1 Data and variables

We exploit three main sources of data at the level of CZs to measure: *i)* the local green innovation capacity proxied by patenting activity; *ii)* the level of local green procurement expenditures and *iii)* the local composition of human capital proxied by the occupational structure of the attendant local labor market.

Patent data We measure green innovation capacity as propensity to introduce eco-innovations using data on US-invented patents with priority year between 1970 and 2012 (Source: PATSTAT, version 2016a).

Patents are assigned to the environment-related domain using the ENV-TECH classification (OECD, 2015) based on the International Patent Classification (IPC) and the Collaborative Patent Classification (CPC). Therein, eight environmental areas are featured: (a) environmental management, (b) water related adaptation technologies, (c) climate change mitigation technologies related to energy generation, transmission or distribution, (d) capture, storage, sequestration or disposal of greenhouse gases, (e) climate change mitigation technologies related to transportation, (f) climate change mitigation technologies related to buildings, (g) climate change mitigation technologies related to

[3]Of them, we only consider the 722 CZs that cover the entire mainland United States (both metropolitan and rural areas).

[4]See Dorn (2009) for further details on empirical analysis at US CZ level

wastewater treatment or waste management, and (h) climate change mitigation technologies in the production or processing of goods.

Since the ENV-TECH classification uses both IPC and CPC codes[5] we first convert IPC codes into CPC codes using the concordance tables of EPO and USPTO.[6] Subsequently, we use information contained in patent documents to extract CPC codes and assign patents to ENV-TECH categories. For what concerns the geographical dimension, we assign a patent to a US territory by means of information contained in inventors' addresses. This is an original methodology for geo-localizing US green patents to the level of counties. The 2016a version of PATSTAT does not provide an address for every inventor. To minimize the number of missing addresses, we follow two parallel strategies. First, we rely the IFRIS version of PATSTAT. IFRIS recovers missing addresses combining several external patent sources (REGPAT, INPI, etc). Second, we propagate the inventor's address into the relative patent family: for each patent family and missing address, we check if there is an inventor with a similar name (applying the Levenshtein distance) and with a non-missing address. If it is the case, we fill the missing address with the one found. Combining both sources, we diminish the missing rate to 10%.

The next step consists in assigning precise geographical coordinates to each address and, thus, to each patent. To do this we, first, extract the postal code included in the inventor's address, when available, to identify US cities according to the GeoNames postal code table. For each country, GeoNames indeed provides a regular expression to find postal codes according to their official format. We apply it to identify postal codes in inventor's addresses. Second, addresses that could not be assigned to a specific postal code were parsed through an iterative algorithm that would identify the name of the city within the address field. Once extracted this information was matched with names of US

[5]Almost all the IPC codes are present in the CPC classification but not the other way around.
[6]http://www.cooperativepatentclassification.org/cpcConcordances.html

city above 5000 inhabitants in GeoNames.[7] Third, we exploit the Google's Geocoding API resource to assign geographical coordinates to all the remaining addresses. This procedure allowed us to assign geographical coordinates to 90% of unique US inventors' addresses. These coordinates were subsequently matched with the 1990 US CZs map to assign each inventor to a CZ.

The local level of green innovation activity is measured through the fractionalized[8] stock of US-invented patents with at least one CPC class which relates to a green technology. The stock of green patents is corrected for INPADOC patent families[9] and weighted by forward (family) citations received[10]. Weighting by forward citations allows us to account for the intrinsic technological value of the local protected inventions.

The green patent stock per CZ j at time t is thus calculated as:

$$Stock_{j,t} = N.Pat_{j,t} + \left[(1-\delta) \times Stock_{j,t-1}\right], \tag{3.1}$$

where δ is the decay rate.[11]

Furthermore, by exploiting the ENV-TECH classification, we differentiate the GT-stock between two macro-technology groups: *i)* green adaptation technologies (ENV-TECH areas (a) and (b)); and *ii)* green mitigation technologies (ENV-TECH areas from

[7] We set a threshold on the city population to limit noise in the results. We checked manually results to remove false positives.

[8] Patent p is assigned to CZ c according to the fraction of inventors resident in CZ c over the total number of inventors filing the patent p.

[9] Patent families essentially originate from a company or an inventor applying for the protection of the same invention at different patent offices. This results in a series of equivalent filings that patent examiners and attorneys can cite indifferently. Simple patent families are quite restrictive sets of equivalents, all sharing the same priority (an original filing at one or another patent once, before extension elsewhere). For a complete discussion about the opportunity of correcting citations for patent families, see Martinez (2010).

[10] In order to make citations comparable across years and ENV-TECH technologies, we calculate a weighted number of citations, dividing the raw number of citations by the average number of citations in the same year t and the same technology j, and then by the average number of citations in the same year t, following the method proposed by Hall et al. (2001): $N.cit.weighted = \frac{\frac{N.cit}{AvgN.cit_{t,j}}}{AvgN.cit_t}$

[11] We calculate patent stocks with the permanent inventory method, applying a 15% annual rate of obsolescence.

(c) to (h)).

Procurement data Second, we collect data on environmental-related procurement expenditures by exploiting public information provided by the USAspending.gov resource.[12] Procurement information are available from 2000 onwards.

The Federal Funding Accountability and Transparency Act of 2006 (FFATA) was signed into law on September 26, 2006. The legislation required that federal contract, grant, loan, and other financial assistance awards of more than $25,000 be displayed on a searchable, publicly accessible website, USAspending.gov, to give the American public access to information on how their tax dollars are being spent. As a matter of discretion, USAspending.gov also displays certain federal contracts of more than $3,000. The initial site went live in 2007. Federal agencies are required to report the name of the entity receiving the award, the amount of the award, the recipient's location, the place of performance location, as well as other information.

In particular, using data on all registered federal contracts we extract information about the location of funding provision (5-digits Zipcode)[13] where the contract is executed and the amount of resources dedicated (in 2010 USD). The Product and Service Codes Manual (PSC, August 2015 Edition) is the guide to identify procured 'green' contracts and to distinguish between product-, and service-related.[14] Indeed, the PSC Manual provides codes to describe products, services, and R&D purchased by the federal government for each contract action reported in the Federal Procurement Data System

[12] https://www.usaspending.gov

[13] 5-digits Zipcodes allow us to assign precise levels of expenditures to counties and, consequently, to CZs.

[14] Statutory requirements and Executive Order 13514 direct the Office of Management and Budget (OMB) Office of Federal Procurement Policy (OFPP) to report on procurement of products and services with environmental attributes including recycled content, biobased, and energy efficient. Data collected in the Federal Procurement Data System include these three environmental attributes plus an 'environmentally preferable' attribute. This last attribute means products or services that have a lesser or reduced effect on human health and the environment when compared with competing products or services that serve the same purpose.

(FPDS). Since a contract may include multiple products/services, with and without environmental attributes, the PSC data element code has been selected based on the predominant product or service that is being purchased.

Occupational-task data To capture the role of human capital in local labor markets, we rely on the task-based framework originally proposed by Autor et al. (2003) and recently extended to the analysis at geographical level by Autor and Dorn (2013). This approach differs from the traditional operationalization of human capital because it focuses on the relative importance of occupations rather than on educational-based proxies such as i.e. the average number of years of education in the workforce or the share of individuals with postgraduate degrees. In this view, labor is the institutional mechanism that allows the application of individual know-how, and the changing structure of occupation reflects the growth or decline in the relative importance of the attending human capital endowment (Consoli and Rentocchini, 2015; Vona and Consoli, 2015).

In this framework work activities are grouped in three broad categories defined on the basis of the match between the main work tasks and the skills needed to perform them. First, routine tasks that entail executing codified instructions with minimal discretion on the part of the worker. Routine tasks are characteristic of middle-skilled jobs that entail repetitive cognitive (i.e. clerks) or manual (i.e. blue-collar) duties. The second main category of work task include activities that require creativity, problem-solving, intuition and social perceptiveness. These abstract tasks are characteristic of professional, managerial, technical and creative occupations that require high levels of formal education. Since analytic and interpersonal capabilities are so important, technology accrue productivity benefits to these workers by facilitating the transmission, organization, and processing of information. On the other side of the skill spectrum are manual tasks, which demand visual and language recognition, personal interaction and physical dexterity. Occupations that use intensively these tasks are typically low-skill service jobs such as food preparation, catering, driving and cleaning.

Following prior empirical studies (Autor et al., 2003, 2006; Dorn, 2009; Autor and Dorn, 2013) we merge job task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) (US Department of Labor 1977) to their corresponding Census occupation classifications to measure routine, abstract, and manual task content by occupation.[15] We combine these measures to create summary indicators of task-intensity by occupation (routine RTI, abstract ATI and manual MTI), calculated as

$$ATI_k = ln(T^A_{k,1980}) - ln(T^R_{k,1980}) - ln(T^M_{k,1980}), \tag{3.2}$$

$$RTI_k = ln(T^R_{k,1980}) - ln(T^A_{k,1980}) - ln(T^M_{k,1980}), \tag{3.3}$$

$$MTI_k = ln(T^M_{k,1980}) - ln(T^A_{k,1980}) - ln(T^R_{k,1980}), \tag{3.4}$$

where, T^R_k, T^A_k and T^M_k are, respectively, the routine, abstract, and manual task inputs in each occupation k in 1980.[16] For each kind of task, this measure rises in its importance in each occupation and declines in the importance of the other two tasks.

Next, to operationalize these measures constructs at the geographic level, we take two additional steps. We first use the task intensity index to identify the set of occupations that are in the top employment-weighted third of task-intensity in 1980. We refer to these as either abstract-, routine- or manual-intensive occupations. We next calculate for each CZ j a task employment share measure (RSH_{jt}, ASH_{jt} and MSH_{jt}) equal to:

$$ASH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot 1 \left[ATI_k > ATI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1}, \tag{3.5}$$

[15] The DOT permits an occupation to comprise multiple tasks at different levels of intensity.

[16] Tasks are measured on a zero to ten scale.

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot 1 \left[RTI_k > RTI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1}, \tag{3.6}$$

$$MSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot 1 \left[MTI_k > MTI^{P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1}, \tag{3.7}$$

where L_{jkt} is the employment in occupation k in CZ j at time t, and $1[\cdot]$ is the indicator function, which takes the value of one if the occupation is task intensive by our definition.

Finally, according to the shares calculated form (5) to (7), we assign a set of dummies equal to 1 if the CZ j is in the top third of national task share at time t:

$$AI_{jt} = 1 \left[ASH_{jt} > ASH_t^{P66} \right], \tag{3.8}$$

$$RI_{jt} = 1 \left[RSH_{jt} > RSH_t^{P66} \right], \tag{3.9}$$

$$MI_{jt} = 1 \left[MSH_{jt} > MSH_t^{P66} \right]. \tag{3.10}$$

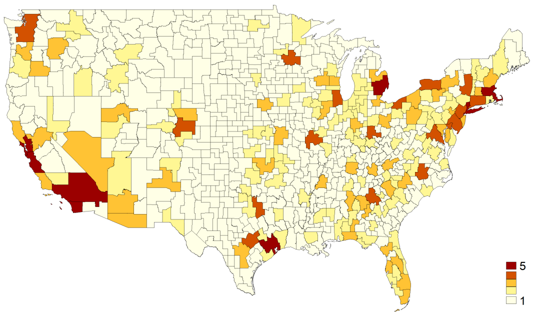
This characterization of local labor markets allows us to investigate whether diverse occupational task compositions moderate the effect of green public procurement on the generation of GTs.

Table 1 reports the main descriptive statistics of the variables used in the analysis. Figures 1, 2 and 3 offer a visual summary of the the geographical distribution of key dimensions across CZs. Therein area boundaries are outlined in grey, the interior of each CZ is shaded according to the quintile rank in the distribution of the relevant dimension - colour coding is darker for higher quintiles and progressively lighter for lower quintiles. The distribution of GT patent stock in Figure 1 (panel a) shows that inventive activity is more concentrated along coastal areas (especially California, Florida and the north east) as well as in lakeside CZs of the north and of Texas. The figure also indicates that there is no significant difference in the distribution of patenting of the component sub-categories, namely green mitigation technologies (panel b) and green adaptation technologies (panel c). Figure 2 plots the geographic quintile distribution of the average amount of GPP expenditures (2010 USD) at the level of CZs for the period 2000-2011. Precisely, panel a) refers to the total level of expenditures, panel b) to GPP for products, panel c) to GPP for services, respectively. This pattern reveals some degree of overlap between the distribution of GPP and that of inventive activities of the previous figure. Finally, Figure 3 shows the geographic quintile distribution of task-intensive occupations at the level of CZs in 2005. Precisely, panel a) refers to abstract-intensive occupations, panel b) to routine-intensive occupations, panel c) to manual-intensive occupations, respectively. The noticeable feature is that, relative to the other categories, routine intensive occupations are more concentrated in CZs in the center and the east of the US. This resonates with the prominence of the attendant jobs in areas with high density (i.e. clerical occupations) and with higher levels of industrial activity (i.e. blue collar jobs).

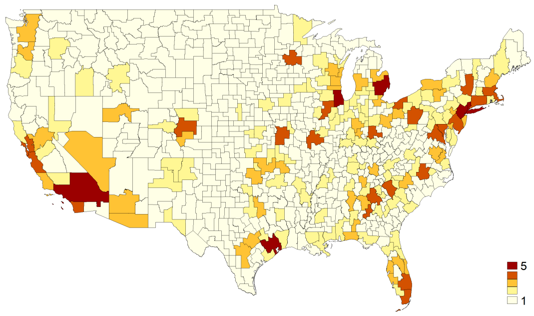
On the whole the maps show that for all the measures there is a large variance across CZs, as well as a marked evidence of spatial concentration. The maps also show interesting converging patterns in the spatial distribution of GPP, GTs and abstract-skills intensity. This evidence suggests that an economic geography approach is very suitable to analyze how policy levers and skills-intensity affect the local production of GTs over time.

3.3.2 Empirical strategy

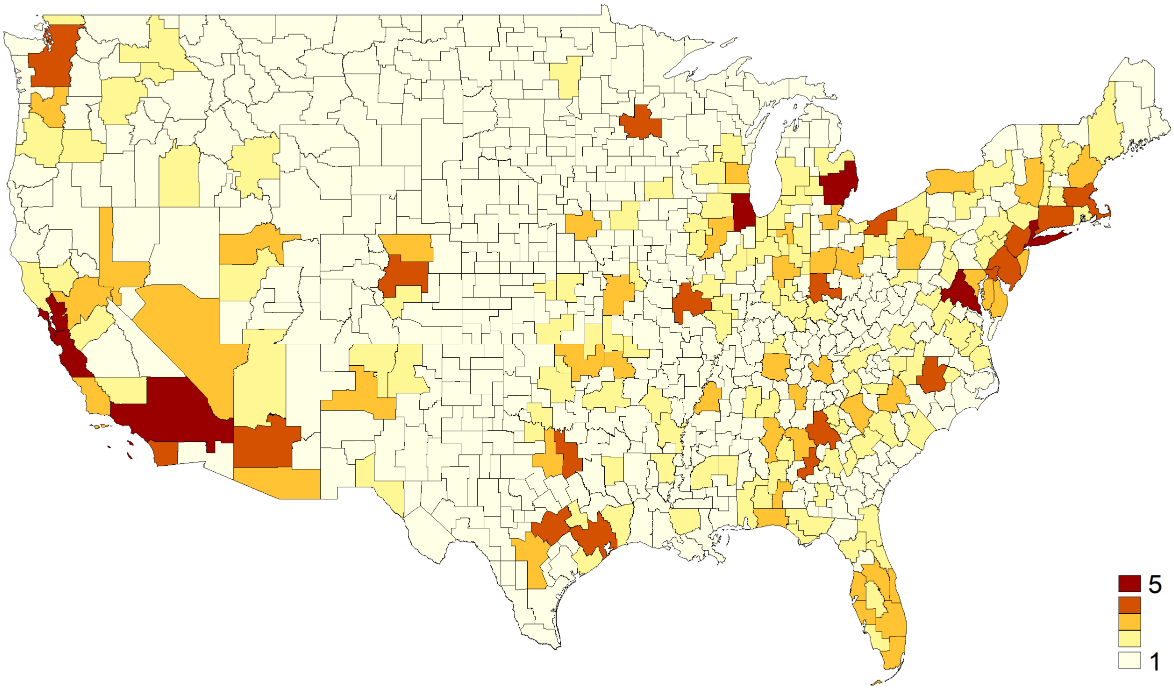
Using the full sample of 722 CZs observed from 2000 to 2011, we fit models of the following form to investigate the relationship between green public procurement and the local level of green technological activity:



(a) GT-mitigation patents

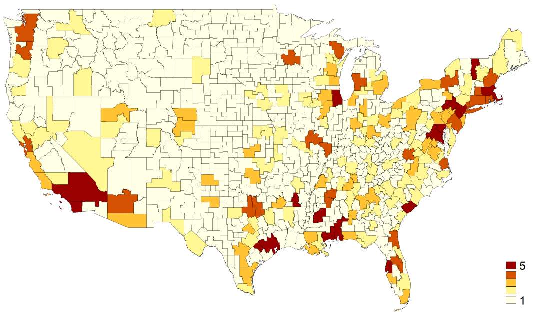


(b) GT-adaptation patents

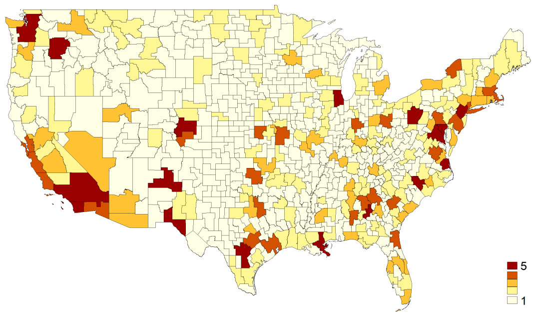


(c) Total GT patents

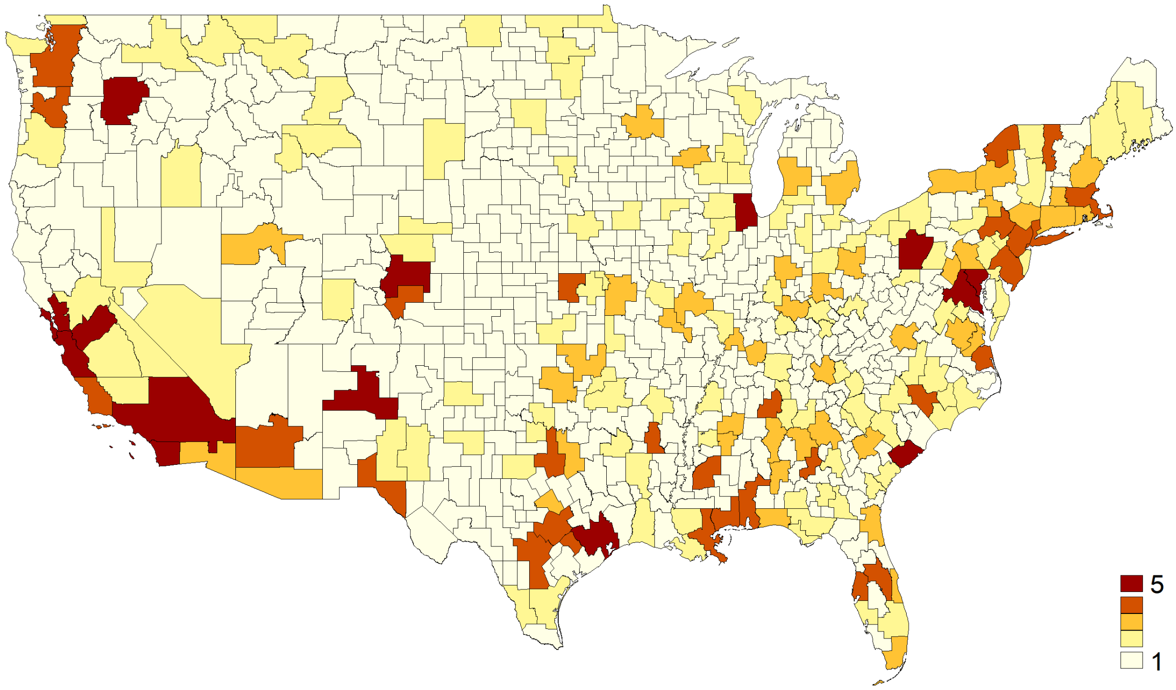
Figure 3.1: Geographic distribution of GT patent stock, 2011 (quintiles)



(a) Product GPP

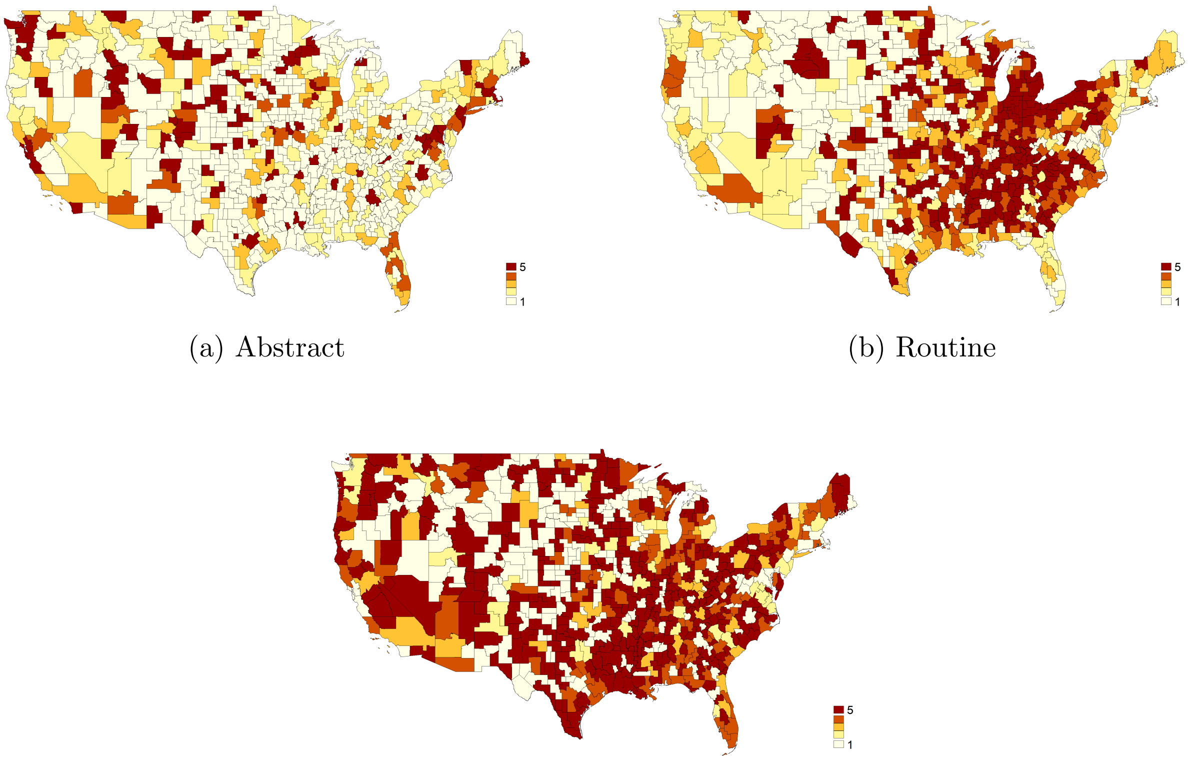


(b) Service GPP



(c) Total GPP

Figure 3.2: Geographic distribution of GPP average expenditures, 2000-2011 (quintiles)



(a) Abstract

(b) Routine

(c) Manual

Figure 3.3: Geographic distribution of task-intensive occupations, 2005 (quintiles)

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_2 + \epsilon_{j,t}, \tag{3.11}$$

where $Y_{j,t}$ is the (log transformed) fractionalized stock of green patent families (weighted by forward citations) at time t filed by inventors resident in CZ j; $GPP_{j,t-1}$ is the (log transformed) level of expenditures for green public procurement performed in CZ j at time $t-1$ (2010 USD); additionally, the vector $\boldsymbol{X'_{j,t}}$ contains (in most specifications) a rich set of controls for CZs' labor force and demographic composition that might independently affect innovation outcomes. Standard errors are clustered at the State level to account for spatial correlations across CZs.

To test for moderating effects of local heterogeneity in terms of CZ occupational task compositions on green innovation activities, we estimate three models, augmenting (11) as follows:

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 RI_{j,t-1} + \beta_3 GPP_{j,t-1} \times RI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t}. \tag{3.12}$$

$$Y_{j,t} = \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 AI_{j,t-1} + \beta_3 GPP_{j,t-1} \times AI_{j,t-1} + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t}. \tag{3.13}$$

$$\begin{aligned} Y_{j,t} \quad = \quad & \beta_0 + \beta_1 GPP_{j,t-1} + \beta_2 MI_{j,t-1} + \beta_3 GPP_{j,t-1} \times MI_{j,t-1} + \\ & + \boldsymbol{X'_{j,t}}\beta_4 + \epsilon_{j,t}. \end{aligned} \tag{3.14}$$

where dummy variables $RI_{j,t-1}$, $AI_{j,t-1}$ and $MI_{j,t-1}$ are calculated according to equations from (8) to (10).[17]

[17]Due to occupational data availability, the period considered for this second step of the analysis

Exploiting the ENV-TECH classification, we are also able to differentiate between diverse types of green technologies. In the final step of the analysis we thus change our dependent variable accordingly, re-estimating equations from (11) to (14). Precisely, we aggregate technologies in two precise groups: mitigation and adaptation GTs.[18]

3.4 Results

Section 2 puts forward the key hypotheses driving our study, according to which we expect that GPP exerts a positive impact on the local dynamics of GT generation, because of the double externality problem and the regulatory push/pull effect. Moreover, we expect that the configuration of the skill bundle in local labor markets also affect the process by which green inventions are brought about, because of the spanning of the recombinant innovation process over a large number of heterogeneous technological components.

Tables 2, 3 and 4 present the results of the baseline estimates of the relationship between expenditures in GPP and the local environmental innovation capacity. Table 2 shows the estimates for the effect of the overall levels of GPP. Tables 3 and 4 focus instead on product-related and service-related GPP, respectively. Our dependent variable is the log transformed level of fractionalized stock of local environmental patents, weighted by forward citations corrected for patent equivalents (INPADOC patent families).

Columns from I to V of Table 2 provide the results of CZ fixed-effect estimations of equation (11), by gradually saturating the empirical model with the controls described in Section 3.1. GPP in column one shows a positive and significant coefficient. Although we use CZ fixed effects, this result can hide some effects of unobserved variables that one may want to mitigate. The coefficient of GPP remains positive and significant, if slightly

reduces (2005-2011).

[18]Mitigation technologies aggregate ENV-TECH technologies from (c) to (h). Adaptation technologies are the ones related to groups (a) and (b).

lower, after controlling for the population density of the area (Column II). The estimates in Column III includes also employment share, the coefficient of which is negative and significant . The other coefficients are in line with previous estimations. In Columns IV and V we control, respectively, for the number of firms in the area and the share of R&D employment. Both coefficient are positive and significant. Still, the coefficient of GPP preserves the sign and statistical significance.

Column VI estimates equation (11) obtained by substituting fixed effects for the nine US Census macro-areas for CZ fixed-effects. The overall results suggest that the effect of GPP is robust across different model specifications. In particular, we can quantify the positive and significant impact of GPP on local green innovation activities: a 1% increase in GPP leads to some 0.077% increase in the stock of green patents in the local areas.

Tables 3 and 4 replicate the same strategy as the one proposed in Table 2 but focusing on the effects of, respectively, GPP for products and GPP for services on the total stock of green technological knowledge at the local level. We find a significant and positive effect of both types of public procurement expenditures. Importantly, we do observe that expenditures for procured green services show higher effectiveness in boosting the overall level of local green innovation activity than expenditures for procured green products. If one looks at Column VI of both tables, it comes that a 1% increase in GPP for products yields a 0.053% increase in the local stock of GTs, while the same variation in GPP for services yields a 0.087% increase in the local stock of GTs.

The overall picture emerging from this first set of estimates provides empirical support to our Hypothesis 1, according to which GPP is expected to positively affect the local accumulation of GT stock. We can now turn to investigation of the effects of the local occupational task compositions on GTs stock, drawing upon the measures proposed in Section 3.1. Our aim is to test for the direct effect of the local skills configuration on the local stock of GTs, as well as how they moderate the relationship between GPP and local green innovation capacity.

Table 5 takes as a benchmark Column VI proposed in Tables 2 to 4. As explained in Section 3.1, we built dummy variables equal to 1 if a CZ is in the top 33% of task-intensive occupations shares: abstract (ASH), routine (RSH) and manual (MSH). We include these dummy variables in the estimations, as well as their interaction with (total) GPP. Column I and II focus on RSH. Both the coefficient of the direct and moderating effects do not appear to significantly affect local GTs generation. Columns III and IV deal with AHS. The coefficient of the direct effect is positive and significant in column III, but it loses significance in column IV, when the interaction with GPP is introduced. The moderating effect shows a positive and significant coefficient. Columns V and VI report the estimations of the effect of RHS. The direct effect does not appear to be significant in any of the estimations, while the moderating effect is negative. The prevalence of routine skills appears to reduce the impact of GPP on local accumulation of GTs.

Overall, the inclusion of the local skills composition in the empirical framework seems to reduce the magnitude of the direct effect of GPP. According to the estimates in table 5, a 1% increase in GPP yields an increase in GTs ranging from 0.021% to 0.048%, which is far lower than the 0.077% increase found in Table 2. ASH is the only skill category yielding a positive impact on GTs at the local level. If one sums the coefficient of GPP and the one of the interaction of ASH with GPP, the overall effect of GPP appears to be much closer to the evidence reported in Table 2. Focusing on Column IV, in the areas in the top 33% of abstract-task intensive occupations (ASH=1), the overall impact of 1% increase in GPP consists of some 0.063% increase in local GTs stock.

Tables 6 and 7 complement the analysis proposed in Table 5 by investigating whether there are differences in the effect of GPP expenditures for, respectively, products and services on total GT stock. Results show that the direct impact found before exists for both types of expenditures. However, it is strongly driven by GPP expenditures for services, confirming the initial estimates proposed in Tables 2, 3 and 4. Moreover, the moderating effect of ASH holds for what concern GPP for services, while when one focuses on GPP for products, only the direct effect of ASH shows a positive and significant coefficient.

Figure 4 plots average marginal effects calculated on the basis of the results from Tables 5, 6 and 7. The bottom parts of the three panels plot average marginal effects of respectively, total, product- and service-related GPP when the CZ is in the top third share of task-intensive occupations (abstract, routine and manual alternatively). Top areas plot the reverse case (average marginal effects when the CZ is not in the top third share of task-intensive occupations).

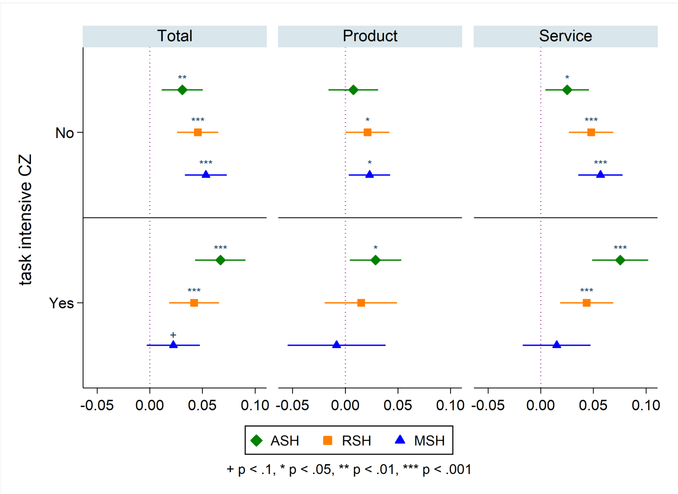


Figure 3.4: Average marginal effects of GPP on total GT stock with 95% CIs

Focusing on areas in the top third of the skill endowment, we find that the local knowledge base proxied by means of occupations brings about heterogeneity in the results. In particular, the coefficient for abstract occupations is always significant, with a stronger effect of expenditure on services as compared to product. Recall that abstract occupations are intensive in activities that require problem-solving, intuition, persuasion, and creativity. These characteristics are over-represented in professional, managerial, technical and creative occupations in areas as diverse as law, medicine, science, engineering, design, and management. Workers who are most adept in these tasks typically have high levels of education and analytic capability. This resonates with the high level of knowledge intensity of service activities that entail personal interaction, social perceptiveness and adaptability and which, in our model, augment the innovation outcome of public procurement. The coefficient for routine occupations is only significant for green-service procurement. These jobs encompass many middle-skilled cognitive (i.e., bookkeeping, clerical work) or manual activities (i.e., repetitive physical operations in production jobs). Even though the growth of routine jobs has been in decline for some time (Autor et al., 2003; Autor and Dorn, 2013), routine occupations still make up the bulk of employment in the United States. In the case under analysis, we ascribe the positive effect of routine occupations to the persistent important role of clerical and administrative workers in services. Lastly, the endowment of manual skills is only mildly significant in the general category of public procurement but not in the sub-components. This is not surprising considering that low-skill manual intensive jobs are mainly concentrated in areas such as assistance and hospitality, and thus we expect them to be only marginally related to the relation between innovation and public procurement.

3.4.1 A comparison between GTs for adaptation and mitigation

As a further step of the analysis, we exploit the OECD ENV-TECH classification to test for the differential effects of GPP on the two main groups of green technological stock: adaptation and mitigation, respectively. Columns I, II and III of Table 8 present estimates for the effect of, respectively, total, product- and service-related GPP on the stock of green mitigation technologies. Columns IV, V and VI report the similar estimates concerning the determinants of green adaptation technologies. Results demonstrate that the overall level of GPP positively affects both kinds of green technological stock (Columns I and IV). The magnitude is higher for mitigation technologies. When splitting GPP between product- and service-related, we do find a significant positive effect of both, with service-related GPP expenditures showing higher effectiveness within both groups of green technologies. The highest effect is found for service-related GPP on mitigation GT stock (results from Column III suggest that a 1% increase in service-related GPP leads to a 0.096% increase in the stock of green mitigation patents).

Next, we investigate more in depth the moderating effect of local labor market composition in the relation between green public procurement and green innovation capacity across macro-families of green technology. In particular, we analyze separately the effects on GT stock in mitigation (Tables 9, 10 and 11) and in adaptation technologies (Tables 12, 13 and 14). In short, mitigation strategies, and the attendant technologies, seek to tackle the causes of climate change such as accumulation of greenhouse gases in the atmosphere. Mitigation is understood as having a global character as opposed to adaptation strategies which, instead, aim at reducing the local impact of climate change. Mitigation is a priority in a broad range of domains such as energy, transportation, manufacturing and waste management. Conversely, adaptation strategies target primarily water and health sectors.

We find that the average marginal effects for mitigation technologies are the same as those observed in the general case above. This applies to both the significance and the magnitude of the coefficients. Once again, a high endowment of managerial, scientific and interpersonal (viz. abstract) skills yields an innovation premium (Figure 5) for public procurement in both green products and green services. Routine intensive occupations have a significant moderating effect only for green service expenditures. Conversely, among adaptation technologies, the coefficients of both routine and abstract occupations are significant only for service-related GPP (Figure 6). We ascribe this to the preponderance of intangible nature of coordinating, planning and implementing adaptation strategies at local level.

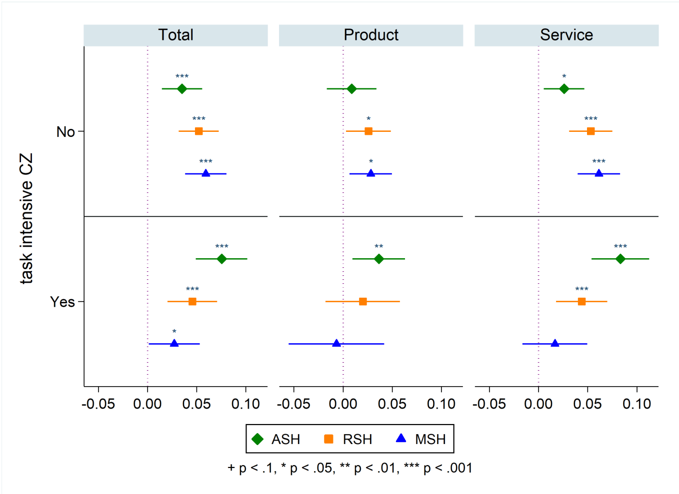


Figure 3.5: Average marginal effects of GPP on GT-mitigation stock with 95% CIs

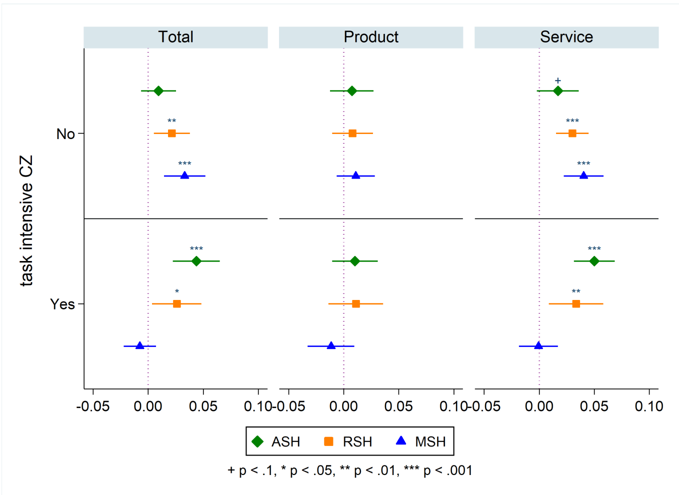


Figure 3.6: Average marginal effects of GPP on GT-adaptation stock with 95% CIs

3.5 Conclusions

Green technologies are a means to successfully decoupling economic growth and environmental degradation. Their adoption allows firms to improve both their economic and environmental performances. In view of the social desirability of the diffusion of this type of technologies, creating economic incentives for private investments in innovation remains a key issue in the policy agenda. Due to the double externality problem, sub-optimal allocation of resources in these activities is highly likely unless public intervention puts in place policies that restore incentives to invest in green technologies. In this chapter we have analyzed the impact of a somewhat neglected type of public intervention, green public procurement, on the generation of GTs. The present chapter marks an important difference with most of the extant literature in that we consider a direct demand-side policy lever (i.e. government expenditure) instead of indirect demand-pull effects engendered by the implementation of stringent environmental regulatory frameworks.

Our analysis of the link between GPP and the generation of GTs has been conducted at the territorial level of US commuting zones. We put forward the hypothesis that the local accumulation of competences represents a key enabling condition for the generation of new technologies in general. GTs show some specificity in this respect, in that they appear to emerge as an outcome of the hybridization of a variety of technologies that often are loosely related with one another. The configuration of the local bundle of skills is therefore much important in affecting local differences in the capacity to sustain green inventive activities. The prevalence of abstract skills is crucial in this respect, in that it is related to cognitive abilities to combine ideas and inputs from different fields in new and previously untried ways.

Our results provide empirical support to our hypotheses, showing that GPP exerts a positive impact on the generation of GTs. In particular, we have found that a 1% increase in GPP engenders some 0.077% increase in the local stock of GTs. The government expenditure lever can therefore prove to be efficient in the promotion of technology-driven sustainability transitions. Moreover, we have found that GPP for services yield a stronger impact than GPP for products. This suggests the existence of bandwagon effects upwards in the value chain, for which the demand for green services stimulate the generation of the technologies that make them possible.

The configuration of the local labor market plays also a role in the dynamics of GTs generation. In particular, the prevalence of abstract skills is positively associated to the generation of GTs. Moreover, this specific set of skills moderates the effect of GPP on GTs, by magnifying its coefficient. According to our estimates, the overall impact of GPP in areas in which abstract skills are prevalent is almost twice the impact of GPP in areas in which this prevalence is not observed. Finally, our analysis allowed to investigating the differential impact of GPP and local skills bundle configuration on mitigation vis-à-vis adaptation oriented green technologies.

Our results bear important implications for policy. Dealing with climate change will require timely interventions to minimize the risks of further environmental damage while at the same time making the most of the opportunities provided by the reconfiguration of intertwined legislative, production, distribution and consumption systems. Transition assistance at all levels will be important for regions that are home to high emission industries, and thus candidates for disruption, as well as for regions that can leverage natural or built assets to seize opportunities for growth. Our analysis highlights two areas of intervention.

The first concerns the role of public expenditure in boosting technology-driven sustainable development. Most of the extant literature has focused on technology push or demand pull deployment policies. We do not deny the relevance of these policy instruments. However, we show that besides these options, policymakers can affect the rate and the direction of green inventive activities by demanding for specific green services or products. While these are expected to satisfy specific needs of public administrations, the GTs that are produced are expected to be relevant for a wider set of economic activities, bearing important spillovers for prospective adopters. On the other hand, the transition to green growth entails much more than just new technologies, in that much of the innovation that is required is organizational and institutional. These innovations represent a break from established practice and entail considerable uncertainty about how to make the new practice work effectively. Therefore, supporting the creation and adaptation of human capital is the second domain of policy intervention. Active labor market policies are essential to both favor the rapid re-absorption of displaced workers and to counter, or prevent altogether, skill gaps. A smooth adaptation of the labor markets to these pressures calls upon dedicated efforts are needed to identify the direct (i.e. market demand) and indirect (i.e. through regulations) effects of dealing with climate change on existing occupational profiles and on the skills mix that is needed for new green activities. Beyond merely quantitative impact, public authorities should support business firms in facilitating the creation of decent jobs as they undergo transformations and adaptations of local labor markets to greener demands. In a dynamic perspective, nimble, adaptable and focused education and training systems are the key to prepare the ground for an egalitarian transition to a low-carbon economy. Because climate change is a global phenomenon with strong territorial specificity, local labor market institutions will be at the forefront of the dual task of accommodating national or supranational regulations while seeking to promote incentives to stimulate sustainable business activities.

Tables

Table 3.1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
total GT stock	7,937	20.325	87.865	0	2092.176
mitigation GT stock	7,937	16.932	77.027	0	1989.022
adaptation GT stock	7,937	3.393	12.845	0	318.381
total GPP	7,937	14.681	108.543	-203.139	4219.37
product GPP	7,937	4.025	55.748	-44.238	3675.805
service GPP	7,937	9.377	77.731	-158.900	2425.968
RSH	4,476	.336	.472	0	1
ASH	4,476	.333	.471	0	1
MSH	4,476	.330	.470	0	1
pop density	7,937	149.478	770.542	.255	19643.86
employment	7,937	156279.6	452789	138.5	6787960
# of establishments	7,937	10168.18	28537.29	23	434368
R&D employment share	7,937	.001	.002	0	.055

Note: The time-span of our analysis is 2000-2011. Because information on CZ occupational structures are available from 2005 onwards, the sample is reduced to 4,476 observations (from 7,937).

Table 3.2: Effect of total green procurement on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.082***	0.068***	0.067***	0.064***	0.063***	0.077***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
pop density		0.003**	0.004***	0.003***	0.003***	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
empl share			-0.000***	-0.000***	-0.000***	-0.000*
			(0.000)	(0.000)	(0.000)	(0.000)
N. of firms				0.000*	0.000*	0.000***
				(0.000)	(0.000)	(0.000)
R&D empl					6.686*	8.584**
					(3.824)	(4.260)
r2_w	0.383	0.399	0.403	0.404	0.405	0.386
r2_o	0.147	0.127	0.073	0.084	0.085	0.501
r2_b	0.551	0.125	0.071	0.082	0.082	0.508
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP lagged 1-year. Standard errors clustered at the level of State. Models I to V, estimated in fixed effect, include a constant and year dummies. Model VI includes also geographic dummies (9 Census divisions). $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Table 3.3: Effect of GPP for products on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.073***	0.050***	0.049***	0.041***	0.041***	0.053***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
pop density		0.004**	0.004***	0.004***	0.004***	-0.000
		(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
empl share			-0.000***	-0.000***	-0.000***	-0.000**
			(0.000)	(0.000)	(0.000)	(0.000)
N. of firms				0.000**	0.000**	0.000***
				(0.000)	(0.000)	(0.000)
R&D empl					6.972*	8.609**
					(3.888)	(4.378)
r2_w	0.365	0.385	0.389	0.391	0.392	0.371
r2_o	0.067	0.118	0.069	0.082	0.083	0.472
r2_b	0.432	0.118	0.068	0.080	0.081	0.478
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP lagged 1-year. Standard errors clustered at the level of State. Models I to V, estimated in fixed effect, include a constant and year dummies. Model VI includes also geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.4: Effect of GPP for services on GT stock (2001-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.093***	0.078***	0.077***	0.073***	0.073***	0.087***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
pop density		0.003**	0.004***	0.003***	0.003***	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
empl share			-0.000***	-0.000***	-0.000***	-0.000**
			(0.000)	(0.000)	(0.000)	(0.000)
N. of firms				0.000**	0.000**	0.000***
				(0.000)	(0.000)	(0.000)
R&D empl					6.716*	8.510**
					(3.772)	(4.168)
r2_w	0.384	0.400	0.404	0.406	0.406	0.388
r2_o	0.138	0.126	0.074	0.086	0.086	0.498
r2_b	0.495	0.125	0.072	0.083	0.084	0.505
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP lagged 1-year. Standard errors clustered at the level of State. Models I to V, estimated in fixed effect, include a constant and year dummies. Model VI includes also geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.5: Effect of total GPP and task composition on GT stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.039***	0.039***	0.039***	0.021**	0.040***	0.048***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
RSH	0.003	0.004				
	(0.013)	(0.012)				
GPP*RSH		-0.000				
		(0.011)				
ASH			0.041***	0.017		
			(0.014)	(0.015)		
GPP*ASH				0.042***		
				(0.010)		
MSH					-0.013	0.001
					(0.010)	(0.010)
GPP*MSH						-0.037***
						(0.012)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	6.101	6.100	6.533	6.378	6.455	6.561
	(6.303)	(6.298)	(6.272)	(6.264)	(6.348)	(6.418)
r2_w	0.328	0.328	0.328	0.331	0.327	0.329
r2_o	0.458	0.458	0.464	0.469	0.461	0.464
r2_b	0.467	0.467	0.473	0.478	0.471	0.473
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.6: Effect of GPP for products and task composition on GT stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.020*	0.021**	0.020**	0.008	0.021**	0.023**
	(0.010)	(0.011)	(0.010)	(0.012)	(0.010)	(0.010)
RSH	0.005	0.006				
	(0.013)	(0.013)				
GPP*RSH		-0.006				
		(0.018)				
ASH			0.038***	0.036**		
			(0.014)	(0.014)		
GPP*ASH				0.021		
				(0.014)		
MSH					-0.012	-0.009
					(0.010)	(0.010)
GPP*MSH						-0.031
						(0.023)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.782	5.845	6.243	6.257	6.164	6.248
	(6.243)	(6.248)	(6.220)	(6.233)	(6.302)	(6.320)
r2_w	0.327	0.327	0.327	0.327	0.326	0.326
r2_o	0.440	0.440	0.446	0.447	0.444	0.444
r2_b	0.449	0.449	0.455	0.455	0.453	0.453
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.7: Effect of GPP for services and task composition on GT stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.047***	0.048***	0.048***	0.025**	0.048***	0.057***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
RSH	0.003	0.005				
	(0.013)	(0.012)				
GPP*RSH		-0.004				
		(0.012)				
ASH			0.041***	0.018		
			(0.014)	(0.015)		
GPP*ASH				0.050***		
				(0.012)		
MSH					-0.013	0.001
					(0.010)	(0.011)
GPP*MSH						-0.042***
						(0.016)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.875	5.881	6.324	6.167	6.245	6.292
	(6.254)	(6.249)	(6.230)	(6.224)	(6.301)	(6.383)
r2_w	0.331	0.331	0.331	0.334	0.330	0.331
r2_o	0.458	0.459	0.465	0.470	0.462	0.464
r2_b	0.468	0.468	0.474	0.479	0.472	0.474
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families weighted by forward citations (log). GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.8: Effect of GPP on GT stock: mitigation and adaptation (2001-2011)

	Mitigation GT			Adaptation GT		
	(I)	(II)	(III)	(IV)	(V)	(VI)
total GPP	0.086***			0.043***		
	(0.011)			(0.008)		
prod GPP		0.061***			0.036***	
		(0.014)			(0.010)	
serv GPP			0.096***			0.049***
			(0.011)			(0.009)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000**	-0.000***	-0.000**	-0.000*	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	7.089	7.115	7.016	4.603	4.640	4.558
	(4.438)	(4.379)	(4.367)	(4.983)	(5.283)	(4.917)
r2_w	0.381	0.364	0.382	0.245	0.236	0.247
r2_o	0.510	0.479	0.507	0.558	0.539	0.556
r2_b	0.519	0.486	0.516	0.576	0.555	0.573
N	7937	7937	7937	7937	7937	7937

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP variables lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.9: Effect of total GPP and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.043***	0.044***	0.044***	0.023***	0.045***	0.053***
	(0.009)	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)
RSH	0.001	0.003				
	(0.013)	(0.013)				
GPP*RSH		-0.003				
		(0.011)				
ASH			0.044***	0.016		
			(0.016)	(0.017)		
GPP*ASH				0.049***		
				(0.011)		
MSH					-0.010	0.005
					(0.011)	(0.011)
GPP*MSH						-0.040***
						(0.013)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.863	5.870	6.360	6.177	6.206	6.320
	(6.416)	(6.413)	(6.391)	(6.384)	(6.451)	(6.528)
r2_w	0.319	0.319	0.319	0.322	0.318	0.320
r2_o	0.463	0.463	0.469	0.476	0.466	0.469
r2_b	0.473	0.473	0.479	0.485	0.476	0.479
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.10: Effect of GPP for products and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.024**	0.026**	0.025**	0.009	0.026**	0.028**
	(0.011)	(0.012)	(0.011)	(0.013)	(0.011)	(0.011)
RSH	0.003	0.004				
	(0.013)	(0.013)				
GPP*RSH		-0.006				
		(0.020)				
ASH			0.041***	0.037**		
			(0.016)	(0.016)		
GPP*ASH				0.027*		
				(0.016)		
MSH					-0.008	-0.005
					(0.011)	(0.011)
GPP*MSH						-0.035
						(0.024)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.514	5.581	6.046	6.055	5.890	5.983
	(6.337)	(6.345)	(6.320)	(6.336)	(6.388)	(6.411)
r2_w	0.318	0.318	0.317	0.318	0.317	0.317
r2_o	0.443	0.443	0.450	0.450	0.446	0.446
r2_b	0.452	0.452	0.458	0.459	0.455	0.456
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.11: Effect of GPP for services and task composition on GT-mitigation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.051***	0.053***	0.052***	0.026**	0.052***	0.061***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
RSH	0.001	0.005				
	(0.013)	(0.013)				
GPP*RSH		-0.009				
		(0.013)				
ASH			0.044***	0.018		
			(0.016)	(0.017)		
GPP*ASH				0.057***		
				(0.013)		
MSH					-0.009	0.005
					(0.011)	(0.011)
GPP*MSH						-0.045***
						(0.016)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	5.621	5.639	6.140	5.960	5.987	6.036
	(6.375)	(6.369)	(6.357)	(6.353)	(6.413)	(6.502)
r2_w	0.321	0.321	0.321	0.325	0.320	0.322
r2_o	0.463	0.463	0.470	0.476	0.466	0.469
r2_b	0.473	0.473	0.479	0.486	0.476	0.479
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.12: Effect of total GPP and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
tot GPP	0.021***	0.020***	0.022***	0.012	0.022***	0.030***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
RSH	0.003	0.002				
	(0.007)	(0.007)				
GPP*RSH		0.003				
		(0.011)				
ASH			0.020**	0.007		
			(0.009)	(0.008)		
GPP*ASH				0.023**		
				(0.010)		
MSH					-0.019***	-0.006
					(0.006)	(0.007)
GPP*MSH						-0.036***
						(0.008)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	2.601	2.590	2.815	2.737	2.902	3.013
	(4.737)	(4.732)	(4.707)	(4.720)	(4.760)	(4.856)
r2_w	0.188	0.188	0.187	0.188	0.187	0.190
r2_o	0.511	0.511	0.515	0.520	0.516	0.520
r2_b	0.525	0.525	0.530	0.535	0.530	0.535
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.13: Effect of GPP for products and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
prod GPP	0.009	0.008	0.009	0.007	0.009	0.011
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
RSH	0.004	0.004				
	(0.007)	(0.007)				
GPP*RSH		0.003				
		(0.014)				
ASH			0.018**	0.018**		
			(0.009)	(0.009)		
GPP*ASH				0.003		
				(0.012)		
MSH					-0.018***	-0.017***
					(0.006)	(0.006)
GPP*MSH						-0.022*
						(0.012)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	2.474	2.488	2.708	2.713	2.799	2.867
	(4.790)	(4.783)	(4.771)	(4.774)	(4.826)	(4.844)
r2_w	0.189	0.189	0.188	0.187	0.188	0.188
r2_o	0.497	0.498	0.502	0.502	0.502	0.503
r2_b	0.511	0.511	0.516	0.516	0.516	0.517
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3.14: Effect of GPP for services and task composition on GT-adaptation stock (2006-2011)

	(I)	(II)	(III)	(IV)	(V)	(VI)
serv GPP	0.031***	0.030***	0.032***	0.017*	0.032***	0.040***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
RSH	0.003	0.001				
	(0.007)	(0.007)				
GPP*RSH		0.003				
		(0.010)				
ASH			0.020**	0.005		
			(0.009)	(0.008)		
GPP*ASH				0.033***		
				(0.010)		
MSH					-0.018***	-0.006
					(0.006)	(0.007)
GPP*MSH						-0.041***
						(0.009)
pop density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
empl share	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of firms	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D empl	2.453	2.444	2.677	2.585	2.762	2.815
	(4.653)	(4.649)	(4.625)	(4.649)	(4.677)	(4.785)
r2_w	0.192	0.192	0.191	0.194	0.191	0.194
r2_o	0.514	0.514	0.519	0.525	0.519	0.523
r2_b	0.529	0.528	0.533	0.540	0.534	0.538
N	3851	3851	3851	3851	3851	3851

Dep. Var.: Stock of fractionalized patent families (mitigation and adaptation) weighted by fwd. cits. GPP, RSH, ASH and MSH lagged 1-year. Standard errors clustered at the level of State. All models include a constant, year and geographic dummies (9 Census divisions). * $p < .1$, ** $p < .05$, *** $p < .01$

Conclusions

The present dissertation provides original empirical evidence about three determinants of green technical change. The first part of the study focuses on micro-determinants. Precisely, it looks at inventor teams' peculiarities in mastering and recombining technological knowledge as a driver for the emergence of environmental innovations. In the second and third chapter, the study investigates the role of two specific policy tools, named government-funded R&D and public procurement, in fostering green innovation processes. Furthermore, the third chapter also provides evidence about local features of occupational task compositions as a further driver for the introduction of green technologies at the territorial level.

By exploiting the EPO universe of patent data, the first chapter aims at capturing the effect of diverse knowledge recombination patterns, mastered by inventor teams, as important drivers for the generation of GTs. Empirical evidence shows a positive premium of recombinant creation capabilities in the generation of GTs. Moreover, the empirical analysis shows positive effects of both team's previous technological green experience and environmental regulation stringency. Interestingly, diverse moderating effects of technological green experience and environmental regulation stringency on recombinant creation are at stake. Precisely, the positive effect of team's recombinant creation capabilities is magnified for teams lacking technological green experience, even more in regimes of weak environmental regulation. The overall evidence proposed by this first chapter highlights a complex architecture behind the generation process of green inventions.

Results from the first chapter bring interesting implications for firms aiming at performing green R&D activities. GTs are indeed likely to positively respond to explorative strategies: assembling teams of inventors able to creatively recombine extant technological knowledge increases the firm's probability of introducing new GTs. However, path dependence plays a fundamental role also in the green technological realm, suggesting that experienced teams are those that show highest rates of success in introducing green inventions. Finally, the level of local policy stringency is relevant in virtue of the innovation mode a firm pursues. Indeed, explorative strategies seem to enhance their positive effect when the level of stringency is sufficiently high, and, at the same time, teams lack previous green experience. Therefore, firms aiming at generating green inventions and operating in technological domains where both regulation schemes and previous green experience are weak should assemble teams formed by inventors able to creatively recombine sparse and heterogeneous technological knowledge.

From a policy perspective, results also lead to two main policy implications. First, building proper levels of green technological knowledge within a sector, as represented by the presence of teams with experience in GTs, is by far the most important driver for boosting GTs. However, teams with green experience that adopt explorative behaviors, especially in regimes of weak environmental regulation, are less likely to generate green inventions. This combination of presence of experienced teams and absence of incentives to adopt explorative behaviors could be harmful in terms of possible emergence of technological lock-ins. Proper innovation policies aiming at guaranteeing systemic variety and exploration strategies are thus suggested in contexts of high green-technological specialization. Second, in contexts where the level of advance of green technological knowledge is scarce, recombinant creation dynamics reveal their relevance in fostering

GTs. Interestingly, when these exploration-oriented behaviors are combined with elevated levels of stringency, their effect is magnified. Thus, the importance for policy makers of combining environmental stringency with innovation policies oriented towards the exploration of technological niches. This combination is the most effective channel boosting green technical change for countries/sectors where the green technological infrastructure is weak.

By exploiting an exogenous technological shock, namely the Chernobyl nuclear accident occurred in April 1986, in the second chapter the thesis aims at investigating the effect of changes in the level of government-funded R&D on both the rate of green-tech knowledge accumulation and the direction it takes. The overall evidence demonstrates that government-funded R&D is an important lever for both consolidating the established green technological trajectory and accelerating the process of changing technological paradigm. However, the magnitude of the estimated effects suggests that an unprecedented effort in public R&D investments is required to timely shift from dirty to clean production systems.

Policy implications are manifold. First, shifting all the public R&D resources from dirty to green targets is likely to significantly reduce the time required by green technologies to overcome the technological advantage of incumbent, dirty technologies.

Second, this mechanism is likely to indirectly increase (decrease) the relative cost of dirty (clean) technologies, presumably letting the market prices adjusting consequently and reducing the future consumption of fossil fuels, creating also incentives for urgently-needed private green-investments.

Finally, the overall evidence proposed shows that a finer systematic investigation is needed for individuating technological R&D niches with the highest potential in terms of green radicalness and breakthrough to be systematically publicly funded.

While the second chapter provides evidence of a specific kind of supply-side public intervention, the third chapter investigates whether and through which channels a specific type of demand-oriented intervention, namely green public procurement (GPP) stimulates local environmental innovation capacity. To this end, detailed data sources on green patents and procurement expenditures at the level of US Commuting Zones (CZs) for the period 2000-2011 have been exploited. The chapter also aims at capturing the moderating effects of local labor market composition in the relation between green public procurement and green innovation capacity. Lastly, by exploiting the richness of patent information, the study tests for differential effects of green public procurement on different classes of green technologies.

The chapter puts forward the hypothesis that the local accumulation of competences represents a key enabling condition for the generation of new technologies in general. GTs show some specificities in this respect, in that they appear to emerge as an outcome of the hybridization of a variety of technologies that often are loosely related with one another. The configuration of the local bundle of skills is therefore much important in affecting local differences in the capacity to sustain green inventive activities. The prevalence of abstract skills is crucial in this respect, in that it is related to cognitive abilities to combine ideas and inputs from different fields in new and previously untried ways.

Results show that GPP exerts a positive impact on the generation of GTs. In particular, a 1% increase in GPP engenders some 0.077% increase in the local stock of GTs. The government expenditure lever can therefore prove to be efficient in the promotion of technology-driven sustainability transitions. Moreover, GPP for services yield a stronger impact than GPP for products. This suggests the existence of bandwagon effects upwards in the value chain, for which the demand for green services stimulate the generation of the technologies that make them possible.

The configuration of the local skills bundle also proved to affect the dynamics of GTs generation. In particular, the prevalence of abstract skills is positively associated to the generation of GTs. Moreover, this specific set of skills moderates the effect of GPP on GTs, by magnifying its coefficient. According to the chapter estimates, the overall impact of GPP in areas in which abstract skills are prevalent is almost twice the impact of GPP in areas in which this prevalence is not observed.

Results bear important policy implications. The most straightforward concerns the role of public expenditure in boosting technology-driven sustainable development. Most of the extant literature has focused on technology push or demand pull deployment policies. However, the chapter shows that besides these options, policymakers can affect the rate and the direction of green inventive activities by demanding for specific green services or products. While these are expected to satisfy specific needs of public administrations, the GTs that are produced are expected to be relevant for a wider set of economic activities, bearing important spillovers for prospective adopters. On the other hand, the transition to green growth entails much more than just new technologies, in that much of the innovation that is required is organizational and institutional. These innovations represent a break from established practice and entail considerable uncertainty about how to make the new practice work effectively. Therefore, supporting the creation and adaptation of human capital is the second domain of policy intervention. Active labor market policies are essential to both favor the rapid re-absorption of displaced workers and to counter, or prevent altogether, skill gaps.

In all, the thesis puts forward that, for what concerns green technical change processes, the dynamics at stake are articulated and complex. Mastering diverse knowledge sources is indispensable for creating novelty in the green realm. Policies are a necessary but not sufficient condition for driving the transition towards less harmful production systems. Moreover, their role has been only partially explored so far. Tools such as public R&D and public procurement have indeed received scant or none attention. However, drawing from the thesis results, those tools show high potential in fostering the transition towards clean production methods. Finally, local labor market features and the geographic peculiarities of green innovation processes are crucial aspects that require systematic attention for properly designing the transition, thus guaranteeing long-run, sustainable growth.

Bibliography

Abernathy, W. J. and Clark, K. B. (1985), 'Innovation: Mapping the winds of creative destruction', *Research Policy* **14**(1), 3 – 22.

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D. (2012), 'The environment and directed technical change', *American Economic Review* **102**(1), 131–166.

Acs, Z. J., Anselin, L. and Varga, A. (2002), 'Patents and innovation counts as measures of regional production of new knowledge', *Research Policy* **31**(7), 1069 – 1085.

Adams, J. D., Black, G. C., Clemmons, J. R. and Stephan, P. E. (2005), 'Scientific teams and institutional collaborations: Evidence from u.s. universities, 19811999', *Research Policy* **34**(3), 259 – 285.

Agrawal, A., Goldfarb, A. and Teodoridis, F. (2016), 'Understanding the Changing Structure of Scientific Inquiry', *American Economic Journal: Applied Economics* **8**(1), 100–128.

Ahuja, G. and Morris Lampert, C. (2001), 'Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions', *Strategic Management Journal* **22**(6-7), 521–543.

Allen, R. (1983), 'Collective invention', *Journal of Economic Behavior Organization* **4**(1), 1–24.

Ambec, S., Cohen, M. A., Elgie, S. and Lanoie, P. (2013), 'The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness?', *Review of Environmental Economics and Policy* **7**(1), 2–22.

Angrist, J. D. and Pischke, J. S. (2008), *Mostly harmless econometrics: An empiricist's companion*, Princeton University Press.

Antonelli, C. (1995), 'Localized Technological Change in the Network of Networks: The Interaction between Regulation and the Evolution of Technology in Telecommunications', *Industrial and Corporate Change* **4**(4), 737–754.

Antonelli, C. (2009), 'The economics of innovation: from the classical legacies to the economics of complexity', *Economics of Innovation and New Technology* **18**(7), 611–646.

Arora, A. and Gambardella, A. (1994), 'The changing technology of technological change: general and abstract knowledge and the division of innovative labour', *Research Policy* **23**(5), 523–532.

Arrow, K. J. (1962), 'The Economic Implications of Learning by Doing', *Review of Economic Studies* **29**(3), 155–173.

Attaran, M. (1986), 'Industrial diversity and economic performance in u.s. areas', *The Annals of Regional Science* **20**(2), 44–54.

Autor, D. H. and Dorn, D. (2013), 'The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market', *American Economic Review* **103**(5), 1553–97.

Autor, D. H., Katz, L. F. and Kearney, M. S. (2006), 'The Polarization of the U.S. Labor Market', *American Economic Review* **96**(2), 189–194.

Autor, D. H., Levy, F. and Murnane, R. J. (2003), 'The Skill Content of Recent Technological Change: An Empirical Exploration', *The Quarterly Journal of Economics* **118**(4), 1279–1333.

Bacchiocchi, E. and Montobbio, F. (2010), 'International knowledge diffusion and home-bias effect: Do uspto and epo patent citations tell the same story?', *The Scandinavian Journal of Economics* **112**(3), 441–470.

Barbieri, N., Ghisetti, C., Gilli, M., Marin, G. and Nicolli, F. (2016), 'A Survey Of The Literature On Environmental Innovation Based On Main Path Analysis', *Journal of Economic Surveys* **30**(3), 596–623.

Beise, M. and Rennings, K. (2005), 'Lead markets and regulation: a framework for analyzing the international diffusion of environmental innovations', *Ecological Economics* **52**(1), 5–17.

Benner, M. J. and Tushman, M. (2002), 'Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries', *Administrative Science Quarterly* **47**(4), 676–706.

Bercovitz, J. and Feldman, M. (2011), 'The mechanisms of collaboration in inventive teams: Composition, social networks, and geography', *Research Policy* **40**(1), 81–93.

Bointner, R. (2014), 'Innovation in the energy sector: Lessons learnt from R&D expenditures and patents in selected IEA countries', *Energy Policy* **73**(Supplement C), 733 – 747.

Boschma, R. (2005), 'Proximity and Innovation: A Critical Assessment', *Regional Studies* **39**(1), 61–74.

Boschma, R. and Iammarino, S. (2009), 'Related Variety, Trade Linkages, and Regional Growth in Italy', *Economic Geography* **85**(3), 289–311.

Botta, E. and Koźluk, T. (2014), Measuring Environmental Policy Stringency in OECD Countries: A Composite Index Approach, OECD Economics Department Working Papers 1177, OECD Publishing.

Bottazzi, L. and Peri, G. (2003), 'Innovation and spillovers in regions: Evidence from european patent data', *European economic review* **47**(4), 687–710.

Breschi, S. and Lissoni, F. (2001), 'Localised knowledge spillovers vs. innovative milieux: Knowledge "tacitness" reconsidered', *Papers in Regional Science* **80**(3), 255–273.

Breschi, S., Lissoni, F. and Malerba, F. (2003), 'Knowledge-relatedness in firm technological diversification', *Research Policy* **32**(1), 69–87.

Breschi, S., Lissoni, F. and Montobbio, F. (2005), 'The geography of knowledge spillovers: conceptual issues and measurement problems', *Clusters, networks and innovation* pp. 343–378.

Brunnermeier, S. B. and Cohen, M. A. (2003), 'Determinants of environmental innovation in US manufacturing industries', *Journal of Environmental Economics and Management* **45**(2), 278–293.

Caminati, M. (2006), 'Knowledge growth, complexity and the returns to R&D', *Journal of Evolutionary Economics* **16**(3), 207.

Carnabuci, G. and Operti, E. (2013), 'Where do firms' recombinant capabilities come from? intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination', *Strategic Management Journal* **34**(13), 1591–1613.

Coffano, M. and Tarasconi, G. (2014), CRIOS – Patstat Database: Sources, Contents and Access Rules, Working Paper 1, Center for Research on Innovation, Organization and Strategy, CRIOS.

Cohen, W. and Levinthal, D. (1989), 'Innovation and Learning: The Two Faces of R & D', *The Economic Journal* **99**(397), 569–596.

Cohen, W. and Levinthal, D. (1990), 'Absorptive Capacity: A New Perspective on Learning and Innovation', *Administrative Science Quarterly* **35**(1), 128–152.

Colombelli, A., Krafft, J. and Quatraro, F. (2014), 'The emergence of new technology-based sectors in European regions: A proximity-based analysis of nanotechnology', *Research Policy* **43**(10), 1681–1696.

Colombelli, A. and Quatraro, F. (2017), 'Green start-ups and local knowledge spillovers from clean and dirty technologies', *Small Bus Econ* pp. 1–20.

Consoli, D., Marin, G., Marzucchi, A. and Vona, F. (2016), 'Do green jobs differ from non-green jobs in terms of skills and human capital?', *Research Policy* **45**(5), 1046–1060.

Consoli, D. and Rentocchini, F. (2015), 'A taxonomy of multi-industry labour force skills', *Research Policy* **44**(5), 1116–1132.

Costantini, V. and Crespi, F. (2013), 'Public policies for a sustainable energy sector: Regulation, diversity and fostering of innovation', *Journal of Evolutionary Economics* **23**(2), 401–429.

Costantini, V., Crespi, F., Martini, C. and Pennacchio, L. (2015), 'Demand-pull and technology-push public support for eco-innovation: The case of the biofuels sector', *Research Policy* **44**(3), 577–595.

Costantini, V. and Mazzanti, M. (2012), 'On the green and innovative side of trade competitiveness? The impact of environmental policies and innovation on EU exports', *Research Policy* **41**(1), 132–153.

Costantini, V., Mazzanti, M. and Montini, A. (2013), 'Environmental performance, innovation and spillovers. Evidence from a regional NAMEA', *Ecological Economics* **89**, 101–114.

Covert, T., Greenstone, M. and Knittel, C. (2016), 'Will We Ever Stop Using Fossil Fuels?', *Journal of Economic Perspectives* **30**(1), 117–138.

Crabb, J. M. and Johnson, D. K. (2010), 'Fueling innovation: The impact of oil prices and cafe standards on energy-efficient automotive technology', *The Energy Journal* **31**(1), 199–216.

David, P. (1993), Knowledge, property and the system dynamics of technological change, *in* L. S. Summers and S. Shah, eds, 'Proceedings of the World Bank Annual Conference on Development Economics', International Bank for Reconstruction and Development, Washington D.C., pp. 215–248.

David, P. A. (1975), *Technical choice innovation and economic growth: essays on American and British experience in the nineteenth century.*

David, P. A. (1985), 'Clio and the Economics of QWERTY', *American Economic Review* **75**(2), 332–337.

de Solla Price, D. J. (1963), *Little science, big science*, Columbia University Press, New York.

Dechezleprêtre, A., Martin, R. and Mohnen, M. (2014), Knowledge Spillovers from Clean and Dirty Technologies, CEP Discussion Papers dp1300, Centre for Economic Performance, LSE.

del Río González, P. (2004), 'Public policy and clean technology promotion. the synergy between environmental economics and evolutionary economics of technological change', *International Journal of Sustainable Development* **7**(2), 200–216.

del Río González, P. (2009), 'The empirical analysis of the determinants for environmental technological change: A research agenda', *Ecological Economics* **68**, 861–878.

Dorn, D. (2009), Essays on Inequality, Spatial Interaction, and the Demand for Skills, PhD thesis, Dissertation University of St. Gallen no. 3613, September.

Dornbusch, F. and Neuhäusler, P. (2015), 'Composition of inventor teams and technological progress the role of collaboration between academia and industry', *Research Policy* **44**(7), 1360 – 1375.

Dosi, G. and Grazzi, M. (2006), 'Technologies as problem-solving procedures and technologies as input–output relations: some perspectives on the theory of production', *Industrial and Corporate Change* **15**(1), 173–202.

Dosi, G. and Grazzi, M. (2010), 'On the nature of technologies: knowledge, procedures, artifacts and production inputs', *Cambridge Journal of Economics* **34**(1), 173–184.

Fleming, L. (2001), 'Recombinant uncertainty in technological search', *Management Science* **47**(1), 117–132.

Frenken, K. and Nuvolari, A. (2004), *Applied Evolutionary Economics and Complex Systems*, Edward Elgar: Cheltenham, U.K. and Northampton, Mass, chapter Entropy Statistics as a Framework to Analyse Technological Evolution.

Frenken, K., von Oort, F. and Verburg, T. (2007), 'Related variety, unrelated variety and regional economic growth', *Regional Studies* **41**(5), 685–97.

Fritsch, M. (2002), 'Measuring the quality of regional innovation systems: A knowledge production function approach', *International Regional Science Review* **25**(1), 86–101.

Frondel, M., Horbach, J. and Rennings, K. (2007), 'End-of-pipe or cleaner production?

An empirical comparison of environmental innovation decisions across OECD countries', *Business Strategy and the Environment* **16**(8), 571–584.

Frondel, M., Horbach, J. and Rennings, K. (2008), 'What triggers environmental management and innovation? Empirical evidence for Germany', *Ecological Economics* **66**(1), 153–160.

Galunic, D. C. and Rodan, S. (1998), 'Resource recombinations in the firm: knowledge structures and the potential for schumpeterian innovation', *Strategic Management Journal* **19**(12), 1193–1201.

Geroski, P. A. (1990), 'Procurement policy as a tool of industrial policy', *International Review of Applied Economics* **4**(2), 182 – 198.

Ghisetti, C. (2017), 'Demand-pull and environmental innovations: Estimating the effects of innovative public procurement', *Technological Forecasting and Social Change* .

Ghisetti, C., Marzucchi, A. and Montresor, S. (2015), 'The open eco-innovation mode. An empirical investigation of eleven European countries', *Research Policy* **44**(5), 1080–1093.

Ghisetti, C. and Quatraro, F. (2013), 'Beyond inducement in climate change: Does environmental performance spur environmental technologies? A regional analysis of cross-sectoral differences', *Ecological Economics* **96**(C), 99–113.

Ghisetti, C. and Quatraro, F. (2017), 'Green Technologies and Environmental Productivity: A Cross-sectoral Analysis of Direct and Indirect Effects in Italian Regions', *Ecological Economics* **132**(C), 1–13.

Gilli, M., Mancinelli, S. and Mazzanti, M. (2014), 'Innovation complementarity and environmental productivity effects: Reality or delusion? evidence from the eu', *Ecological Economics* **103**, 56 – 67.

Green, K., McMeekin, A. and Irwin, A. (1994), 'Technological Trajectories and R&D for Environmental Innovation in UK Firms', *Futures* **26**, 1047–1059.

Griliches, Z. (1984), Market Value, R&D, and Patents, *in* 'R&D, Patents, and Productivity', NBER Chapters, National Bureau of Economic Research, Inc, pp. 249–252.

Griliches, Z. (1990), Patent statistics as economic indicators: a survey, Technical report, National Bureau of Economic Research.

Gruber, M., Harhoff, D. and Hoisl, K. (2013), 'Knowledge recombination across technological boundaries: Scientists vs. engineers', *Management Science* **59**(4), 837–851.

Hargadon, A. and Sutton, R. I. (1997), 'Technology brokering and innovation in a product development firm', *Administrative Science Quarterly* **42**(4), 716–749.

Hatch, N. W. and Mowery, D. C. (1998), 'Process Innovation and Learning by Doing in Semiconductor Manufacturing', *Management Science* **44**(11-part-1), 1461–1477.

Heald, D. and Short, J. (2002), 'The regional dimension of public expenditure in england', *Regional Studies* **36**(7), 743–755.

Henderson, R. M. and Clark, K. B. (1990), 'Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms', *Administrative Science Quarterly* **35**(1), 9–30.

Hoppmann, J., Peters, M., Schneider, M. and Hoffmann, V. H. (2013), 'The two faces of market support–How deployment policies affect technological exploration and exploitation in the solar photovoltaic industry', *Research Policy* **42**(4), 989 – 1003.

Horbach, J. (2008), 'Determinants of environmental innovationnew evidence from german panel data sources', *Research Policy* **37**(1), 163 – 173.

Horbach, J., Oltra, V. and Belin, J. (2013), 'Determinants and specificities of eco-innovations. An econometric analysis for the French and German Industry based on the Community Innovation Survey', *Industry and Innovation* **20**(6), 523–543.

Horbach, J., Rammer, C. and Rennings, K. (2012), 'Determinants of eco-innovations by type of environmental impact – The role of regulatory push/pull, technology push and market pull', *Ecological Economics* **78**(C), 112–122.

Iacus, S. M., King, G. and Porro, G. (2009), 'CEM: Software for coarsened exact matching', *Journal of Statistical Software* **30**(9).

Iacus, S. M., King, G. and Porro, G. (2011), 'Causal inference without balance checking: Coarsened exact matching', *Political Analysis* **20**(1), 1–24.

Jaffe, A. B. (1986), 'Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value', *American Economic Review* **76**(5), 984–1001.

Jaffe, A. B. (1989), 'Real Effects of Academic Research', *American Economic Review* **79**(5), 957–70.

Jaffe, A. B., Newell, R. G. and Stavins, R. N. (2002*a*), 'Environmental policy and technological change', *Environmental and Resource Economics* **22**(1-2), 41–70.

Jaffe, A. B., Newell, R. G. and Stavins, R. N. (2005), 'A tale of two market failures: Technology and environmental policy', *Ecological Economics* **54**(23), 164 – 174.

Jaffe, A. B. and Palmer, K. (1997), 'Environmental regulation and innovation: A panel data study', *Review of Economics and Statistics* **79**(4), 610–619.

Jaffe, A. B. and Stavins, R. N. (1995), 'Dynamic incentives of environmental regulations: The effects of alternative policy instruments on technology diffusion', *Journal of Environmental Economics and Management* **29**(3), 43–63.

Jaffe, A. B. and Trajtenberg, M. (1999), 'International knowledge flows: evidence from patent citations', *Economics of Innovation and New Technology* **8**(1-2), 105–136.

Jaffe, A. B., Trajtenberg, M. and Henderson, R. (1993), 'Geographic localization of knowledge spillovers as evidenced by patent citations', *the Quarterly journal of Economics* **108**(3), 577–598.

Jaffe, A., Newell, R. and Stavins, R. (2002*b*), 'Environmental policy and technological change', *Environmental & Resource Economics* **22**, 41–69.

Johnstone, N., Haščič, I., Poirier, J., Hemar, M. and Michel, C. (2012), 'Environmental policy stringency and technological innovation: evidence from survey data and patent counts', *Applied Economics* **44**(17), 2157–2170.

Johnstone, N., Haščič, I. and Popp, D. (2010), 'Renewable energy policies and technological innovation: Evidence based on patent counts', *Environmental and Resource Economics* **45**(1), 133–155.

Jones, B. F. (2009), 'The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?', *Review of Economic Studies* **76**(1), 283–317.

Katila, R. and Ahuja, G. (2002), 'Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction', *ACAD MANAGE J* **45**(6), 1183–1194.

Kauffman, S. A. (1993), *The Origins of Order: Self-organization and Selection in Evolution*, Oxford University Press, New York.

Kemp, R. (1997), *Environmental Policy and Technical Change: A Comparison of the Technological Impact of Policy Instruments*, Edward Elgar Publishing.

Kim, T.-Y., Oh, H. and Swaminathan, A. (2006), 'Framing Interorganizational Network Change: A Network Inertia Perspective', *The Academy of Management Review* **31**(3), 704–720.

Klaassen, G., Miketa, A., Larsen, K. and Sundqvist, T. (2005), 'The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom', *Ecological Economics* **54**(2), 227 – 240.

Kogut, B. and Zander, U. (1992), 'Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology', *Organization Science* **3**(3), 383–397.

Krafft, J., Quatraro, F. and Saviotti, P. P. (2014), 'The Dynamics of Knowledge-intensive Sectors' Knowledge Base: Evidence from Biotechnology and Telecommunications', *Industry and Innovation* **21**(3), 215–242.

Lanjouw, J. and Mody, A. (1996), 'Innovation and the international diffusion of environmentally responsive technology', *Research Policy* **25**, 549–571.

Levinthal, D. A. and March, J. G. (1993), 'The Myopia of Learning', *Strategic Management Journal* **14**, 95–112.

Lissoni, F., Sanditov, B. and G., T. (2006), The Keins database on academic inventors: methodology and contents, WP cespri 181.

March, J. G. (1991), 'Exploration and Exploitation in Organizational Learning', *Organization Science* **2**(1), 71–87.

Marrocu, E., Usai, S. and Paci, R. (2013), Networks, proximities and inter-firm knowledge exchanges, Working Paper CRENoS 201311, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

Martinez, C. (2010), ‘Insight into Different Types of Patent Families’, **STI Working Paper 2010/2**.

Maurseth, P. B. and Verspagen, B. (2002), ‘Knowledge spillovers in Europe: a patent citations analysis’, *The Scandinavian journal of economics* **104**(4), 531–545.

Menanteau, P. (2000), ‘Learning from Variety and Competition Between Technological Options for Generating Photovoltaic Electricity’, *Technological Forecasting and Social Change* **63**(1), 63 – 80.

Miguelez, E. and Moreno, R. (2017), ‘Relatedness, external linkages and regional innovation in europe’, *Regional Studies* **0**(0), 1–14.

Montresor, S. and Quatraro, F. (2017), ‘Regional branching and key enabling technologies: Evidence from european patent data’, *Economic Geography* **93**(4), 367–396.

Morgenroth, E. (2010), ‘Regional Dimension of Taxes and Public Expenditure in Ireland’, *Regional Studies* **44**(6), 777–789.

Mowery, D. C., Nelson, R. R. and Martin, B. R. (2010), ‘Technology policy and global warming: Why new policy models are needed (or why putting new wine in old bottles wont work)’, *Research Policy* **39**(8), 1011 – 1023.

Nelson, R. and Phelps, E. (1966), ‘Investment in humans, technological diffusion, and economic growth’, *American Economic Review: Papers and Proceedings* **61**, 69–75.

Nelson, R. R. (1959), ‘The Simple Economics of Basic Scientific Research’, *Journal of Political Economy* **67**, 297–297.

Nelson, R. R. (1982), *Government and technical progress : a cross-industry analysis*, Pergamon Press, Oxford.

Nelson, R. and Winter, S. (1982), *An Evolutionary Theory of Economic Change*, Harvard University Press, Cambridge.

Nemet, G. F. (2009), 'Demand-pull, technology-push, and government-led incentives for non-incremental technical change', *Research Policy* **38**(5), 700 – 709.

Nesta, L. and Saviotti, P. P. (2005), 'Coherence of the knowledge base and the firm's innovative performance: evidence from the U.S. pharmaceutical industry', *Journal of Industrial Economics* **53**(1), 123–142.

Nesta, L. and Saviotti, P.-P. (2006), 'Firm knowledge and market value in biotechnology', *Industrial and Corporate Change* **15**(4), 625–652.

Nightingale, P. (1998), 'A cognitive model of innovation', *Research Policy* **27**(7), 689 – 709.

Olsson, O. (2000), 'Knowledge as a Set in Idea Space: An Epistemological View on Growth', *Journal of Economic Growth* **5**(3), 253–275.

Olsson, O. and Frey, B. S. (2002), 'Entrepreneurship as Recombinant Growth', *Small Business Economics* **19**(2), 69–80.

Paci, R., Marrocu, E. and Usai, S. (2014), 'The complementary effects of proximity dimensions on knowledge spillovers', *Spatial Economic Analysis* **9**(1), 9–30.

Parikka-Alhola, K. (2008), 'Promoting environmentally sound furniture by green public procurement', *Ecological Economics* **68**(1), 472 – 485.

Pavitt, K. (1984), 'Sectoral patterns of technical change: Towards a taxonomy and a theory', *Research Policy* **13**(6), 343373.

Pezzoni, M., Lissoni, F. and Tarasconi, G. (2012), How To Kill Inventors: Testing The Massacrator©Algorithm For Inventor Disambiguation, Cahiers du GREThA 2012-29, Groupe de Recherche en Economie Thorique et Applique.

Popp, D. (2002), 'Induced Innovation and Energy Prices', *American Economic Review* **92**(1), 160–180.

Popp, D. (2003), 'Pollution control innovations and the Clean Air Act of 1990', *Journal of Policy Analysis and Management* **22**(4), 641–660.

Popp, D. (2006*a*), 'Innovation in climate policy models: Implementing lessons from the economics of R&D', *Energy Economics* **28**(5), 596 – 609.

Popp, D. (2006*b*), 'International innovation and diffusion of air pollution control technologies: the effects of NOX and SO2 regulation in the US, Japan, and Germany', *Journal of Environmental Economics and Management* **51**(1), 46 – 71.

Popp, D., Newell, R. G. and Jaffe, A. B. (2010), *Energy, the environment, and technological change*, Vol. 2, Academic Press/Elsevier, pp. 873–937.

Porter, M. (1991), 'America's Green Strategy', *Scientific American* **264**(4).

Porter, M. and van der Linde, C. (1995), 'Toward a New Conception of the Environment-Competitiveness Relationship', *Journal of Economic Perspectives* **9**(4), 97–118.

Quatraro, F. (2009), 'Diffusion of Regional Innovation Capabilities: Evidence from Italian Patent Data', *Regional Studies* **43**(10), 1333–1348.

Quatraro, F. and Usai, S. (2017), 'Are knowledge flows all alike? evidence from european regions', *Regional Studies* **51**(8), 1246–1258.

Renning, K. and Rammer, C. (2009), 'Increasing energy and resource efficiency through innovation - an explorative analysis using innovation survey data', *Czech Journal of Economics and Finance* **59**(1), 442–459.

Renning, K. and Rammer, C. (2011), 'The impact of regulation-driven environmental innovation on innovation success and firm performance', *Industry and Innovation* **18**(3), 253–283.

Rennings, K. (2000), 'Redefining innovation–eco-innovation research and the contribution from ecological economics', *Ecological Economics* **32**(2), 319–332.

Requate, T. (2005), 'Timing and Commitment of Environmental Policy, Adoption of New Technology, and Repercussions on R&D', *Environmental & Resource Economics* **31**(2), 175–199.

Rosenberg, N. (1976), *Perspectives on Technology*, Cambridge University Press, New York.

Rosenberg, N. (1982), *Inside the Black Box. Technology and Economics*, Cambridge University Press, New York.

Ruttan, V. W. (2006), *Is War Necessary for Economic Growth? Military Procurement and Technology Development*, Oxford University Press, Oxford.

Sagar, A. D. and van der Zwaan, B. (2006), 'Technological innovation in the energy sector: R&D, deployment, and learning-by-doing', *Energy Policy* **34**(17), 2601 – 2608.

Sandén, B. A. (2005), 'The economic and institutional rationale of PV subsidies', *Solar Energy* **78**(2), 137 – 146.

Sartorius, C. (2005), *Time Strategies, Innovation, and Environmental Policy*, Edward

Elgar, Cheltenham, chapter Crystalline and thin-film photovoltaic cells–competition or lock-in?, pp. 133 – 155.

Schmoch, U., Laville, F., Patel, P. and Frietsch, R. (2003), Linking technology areas to industrial sectors, Final Report to the European Commission 1, DG Research.

Singh, J. and Fleming, L. (2010), 'Lone Inventors as Sources of Breakthroughs: Myth or Reality?', *Management Science* **56**(1), 41–56.

Squicciarini, M., Dernis, H. and Criscuolo, C. (2013), 'Measuring Patent Quality: Indicators of Technological and Economic Value', *OECD Science, Technology and Industry Working Papers* **2013/03, OECD Publishing, Paris**.

Stančík, J. (2012), 'A Methodology to Estimate Public ICT R&D Expenditures in the EU Member States', **JRC Technical Note, JRC 69978**.

Storper, M. and Scott, A. (2009), 'Rethinking human capital, creativity and urban growth', *Journal of Economic Geography* **9**(1), 147–167.

Stuart, T. E. and Podolny, J. M. (1996), 'Local search and the evolution of technological capabilities', *Strategic Management Journal* **17**, 21–38.

Taylor, M. R., Rubin, E. S. and Hounshell, D. A. (2005), 'Regulation as the Mother of Innovation: The Case of SO2 Control', *Law & Policy* **27**(2), 348–378.

Teece, D. J., Rumelt, R., Dosi, G. and Winter, S. (1994), 'Understanding corporate coherence: Theory and evidence', *Journal of Economic Behavior Organization* **23**(1), 1 – 30.

Teodoridis, F. (2017), 'Understanding Team Knowledge Production: The Interrelated Roles of Technology and Expertise', *Management Science* **null**(null), null.

Theil, H. (1967), *Economics and information theory*, North-Holland Pub. Co.; Rand McNally Amsterdam, Chicago.

Tidd, J., Bessant, J. and Pavitt, K. (1997), *Managing Innovation: Integrating Technological, Market and Organizational Change*, Chichester: Wiley.

Trajtenberg, M. (1990), 'A penny for your quotes: patent citations and the value of innovations', *The Rand Journal of Economics* pp. 172–187.

Trajtenberg, M., Henderson, R. and Jaffe, A. (1997), 'University Versus Corporate Patents: A Window On The Basicness Of Invention', *Economics of Innovation and New Technology* **5**(1), 19–50.

van den Heuvel, S. T. and van den Bergh, J. C. (2009), 'Multilevel assessment of diversity, innovation and selection in the solar photovoltaic industry', *Structural Change and Economic Dynamics* **20**(1), 50 – 60.

Van Looy, B., Vereyen, C. and Schmoch, U. (2014), 'Patent statistics: Concordance IPC V8–NACE REV.2', **Eurostat, European Commission**.

von Hippel, E. (1988), *The Sources of Innovation*, Oxford University Press, New York.

von Hippel, E. (1994), '"Sticky Information" and the Locus of Problem Solving: Implications for Innovation', *Management Science* **40**(4), 429–439.

Vona, F. and Consoli, D. (2015), 'Innovation and skill dynamics: a life-cycle approach', *Industrial and Corporate Change* **24**(6), 1393–1415.

Vona, F., Marin, G. and Consoli, D. (2017), Measures, Drivers and Effects of Green Employment: Evidence from US Local Labor Markets, 2006-2014, SPRU Working Paper Series 2017-13, SPRU - Science and Technology Policy Research, University of Sussex.

Vona, F., Marin, G., Consoli, D. and Popp, D. (2018), 'Environmental Regulation and Green Skills: An Empirical Exploration', *Journal of the Association of Environmental and Resource Economists* **(Forthcoming)**.

Weitzman, M. L. (1996), 'Hybridizing Growth Theory', *American Economic Review* **86**(2), 207–212.

Weitzman, M. L. (1998), 'Recombinant Growth', *The Quarterly Journal of Economics* **113**(2), 331–360.

Wuchty, S., Jones, B. F. and Uzzi, B. (2007), 'The Increasing Dominance of Teams in Production of Knowledge', *Science* **316**, 1036–1039.

Yayavaram, S. and Ahuja, G. (2008), 'Decomposability in Knowledge Structures and Its Impact on the Usefulness of Inventions and Knowledge-base Malleability', *Administrative Science Quarterly* **53**(2), 333–362.

Zeppini, P. and van den Bergh, J. C. J. M. (2011), 'Competing Recombinant Technologies for Environmental Innovation: Extending Arthur's Model of Lock-In', *Industry and Innovation* **18**(3), 317–334.