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Going Green: The dynamics of green technological alliances

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Abstract

The literature on the determinants of green technologies (GTs) has already identified regulation as a key driver of environmental innovations. However, relatively little is known on how the regulatory framework affects the knowledge generation process. This paper contributes this literature by investigating the impact of collaboration networks and environmental regulation, and of their interaction, on the generation of green technologies. The empirical analysis is carried out on a newly constructed dataset of European firms over the period 2005-2011 and it is articulated in two steps. Firstly, we test the existence of a relationship between the environmental regulation, as measured by the OECD Environmental Policy Stringency index, and GTs, proxied by patent applications. We then employ a dynamic network analysis model to explore the dual role of GTs both as the determinant of the collaboration network and as the outcome of firms' collaboration strategies. We find that, even though there exists a strong and positive relationship, the regulatory framework has not

a direct effect on GTs but rather it stimulates firms to search for new qualified collaboration. Then, it is the nature and the structure of these collaborations that encourages firms to generate new green technological knowledge.

Keywords: Green technologies, environmental regulation, firms' strategies, innovation networks, proximity, Dynamic Network Analysis

JEL Classification codes: O33

1 Introduction

In the last decades, there has been increasing concern about the short and long-run effects of climate change and the exhaustion of natural resources. The latest report by the European Environment Agency (2020) stress that many economic actions involving production and consumption are important sources of environmental degradation and resources exploitation, calling for urgent actions to achieve a sustainable and low-carbon society. Green technologies have been indicated by a large body of literature as crucial to achieve the decoupling of economic growth from environmental degradation (Porter and van der Linde, 1995).

For this reason, the academic literature has largely focused on the understanding of the determinants of eco-innovation across firms and countries (Barbieri et al., 2016). Given the externalities associated to the effects of green technologies, public policies and environmental regulation have been indicated as the main levers to stimulate the diffusion of green technologies in the economy (Rennings, 2000; Requate, 2005). In particular, the increase in the stock of green technological knowledge is triggered by the market-creation effect of environmental regulation (Hoppmann et al., 2013; Nemet, 2009). Howeveer, most of the extant studies, while focusing on the determinants of eco-innovation, has failed to elaborate a framework encompassing the antecedents of green invention, i.e. the mechanisms underlying the generation of this specific subset of technologies (del Río González, 2009). This paper aims at filling this gap by looking at how strategic technological alliances can represent a response of innovating firms to the increased prospects for prospects in markets for green technologies, engendered by the increasingly stringent environmental framework.

Based on the recombinant knowledge approach, we stress how the production of green technologies always involves some degree of technological diversification, both for incumbents and new entrants in the markets for these technologies. This is due to their intrinsic complexity, for which they are often the outcome of combinations of very heterogeneous knowledge sources. In this context, firms

prefer to resort to strategic technological alliances to get access to complementary knowledge assets, likely distant from their core competences. This allows them to keep the pace with green knowledge production and provide markets with new technological solutions. Accordingly, strategic technological alliances are expected to drive green invention in response to stringent environmental regulation.

Our empirical analysis is carried out on a newly constructed dataset of European firms, over the period 2005-2011. The dataset consists of technological alliance data from the SDC platinum database, patents and environmental regulation data from OECD and OECD Regpat database, and firm-level balance sheet data from AMADEUS database. The empirical analysis is articulated in two steps. First, we explore the relationship between environmental regulation and the generation of GTs by means of standard regression analysis. We then employ a dynamic network analysis model to investigate the dual role of GTs both as the determinant of inter-firm network formation and as the outcome of firm collaboration strategies. Our results suggest that when firms operating in highly stringent regulatory frameworks do not possess the required competencies to manage internally complex and diversified technologies such as GTs, they may turn to external knowledge sources through technological alliances. Then, it is the nature of these qualified collaborations and the structure of the local interactions that encourage firms to generate new green technological knowledge.

The rest of the paper is organized as follows. Section 2 elaborates the theoretical framework and spells our the main working hypotheses. Section 3 provides the description of data and measures. In Section 4 we explain our empirical strategy. Section 5 presents the results of the empirical analyses, while in Section 6 we discuss our results and provide concluding remarks.

2 Theory and hypotheses development

2.1 Regulation and eco-innovation

An increasing body of literature has emerged in the last decades, investigating the determinants and effects of green technological change and eco-innovation (see Barbieri et al. (2016) for an extensive survey). The motivation for such interest lies in the expected role of green technologies in the route to the decoupling of economic growth from environmental degradation.

The economic literature considers green technologies and environmental regulation as strictly intertwined, due to two distinct and yet related arguments. On the one hand, green technologies are featured by the so-called 'double externality' problem (Rennings, 2000). As for any kind of innovation, one source of externality is due to the public good nature of technological knowledge, and the consequent appropriability problems that keep private investments in innovation activities below the social optimum. The positive environmental impact driven by these technologies represents a further source of externality, because of the social benefits for which firms are not rewarded. In this context, the 'regulatory push-pull' effect suggests that policy intervention seems unavoidable to keep investments in green technologies at appropriate levels (Frondel et al., 2008; Horbach et al., 2012; Renning and Rammer, 2011; del Río González, 2009; Lanjouw and Mody, 1996; Brunnermeier and Cohen, 2003; Jaffe and Palmer, 1997; Popp, 2006).

On the other hand, regulation is deemed crucial due to the well-known Porter hypothesis, according to which stringent environmental regulation yields the twofold impact of triggering eco-innovation and improving firms' environmental and economic performances (Porter and van der Linde, 1995). A *weak* and a *strong* version of this hypothesis can be identified in the literature, the former being related only to the incentive to eco-innovate, while the latter also to the joint effect on economic performance (Jaffe and Palmer, 1997; Van Leeuwen and Mohnen, 2017). The basic mechanism behind these dynamics is grounded on the

inducement effect engendered by stringent environmental regulation. Similarly to the framework set forth by (Hicks, 1932), stringent environmental regulation leads to an increase in the production costs of polluting firms. These latter can save polluting costs engendered by regulation, by introducing innovations that allow for the improvement of the environmental impact of production processes (Johnstone et al., 2012; Ghisetti and Quatraro, 2013)

The empirical testing of this hypothesis led to mixed results (Costantini and Mazzanti, 2012; Rubashkina et al., 2015; Franco and Marin, 2017; Rexhäuser and Rammer, 2014) finding evidence of positive effects, but also of nil effects or negative ones. This can be also dependent by the endogeneity of the regulation itself, which is correlated with the unobserved determinants of the outcome e.g. competitiveness (Dechezleprêtre and Sato, 2017).

Overall, although mixed evidence is depicted in the literature, it can be summarized that on the one side high support is found that environmental regulation exerts a stimulus on innovation, while relatively less clear-cut support is found for the competitiveness returns of such regulation.

The inducement effect also yields an important effect related to the increase or creation of demand-driven incentives for the generation of green technologies (Ghisetti and Quatraro, 2013). An indisputable effect of demand-pull deployment policies actually consists of the creation of new markets for green technologies. The size of these markets is also affected by policy-driven demand, so that prospects for growth of inventing firms are boosted by policy-induced market growth (Nemet, 2009; Hoppmann et al., 2013; Colombelli et al., 2014).

2.2 Firms' capabilities, absorptive capacity, and green innovation strategies

According to the previous discussion, environmental regulation is expected to open up new economic opportunities in markets for green technologies. As a consequence, it is reasonable to expect a surge in the efforts to generate this kind of innovations. It becomes therefore crucial to focus on the antecedents of eco-

innovation, i.e. on the dynamics underlying the generation of green technologies (del Río González, 2009). Theories of innovation suggest that the generation of new knowledge is the outcome of the combination of different knowledge inputs. Novelty emerges out of a search process across the technology landscape, by means of which innovating agents identify knowledge and ideas that can be combined to one another (Fleming, 2001; Weitzman, 1998; Kaufmann, 1993; Saviotti, 2004, 2007).

However, such dynamics require the development of specific capabilities enabling the implementation of successful combinatorial search. The concept of recombinant capabilities extends the seminal dynamic capabilities approach, to stress that the generation of innovation at the firm level stems from recombination and that such an activity is characterized by important dynamic scale economies engendered by learning dynamics (Teece and Pisano, 1994; Carnabuci and Operti, 2013).

Learning to recombine involves several dimensions. First, it is related to the capacity to move across the technology landscape and spot pieces of knowledge that can be fruitfully combined together. Second, it concerns the mastering of the knowledge and competences that are necessary to access, decode and understand external knowledge in order to assess the complementarity amongst different knowledge inputs. In other words, recombinant innovation requires absorptive capacity (Cohen and Levinthal, 1990). Firms willing to engage in knowledge generation activities must have developed sound technological and scientific competencies allowing for effective processing of external knowledge sources (Rosell et al., 2017; Takeishi, 2001).

The notion of proximity becomes relevant in this contest. Proximity is a multidimensional concept, and it can be applied to different notions of space (Perroux, 1950; Boschma, 2005). The large body of literature on innovation and knowledge flows has put systematic evidence about the constraining role of geographical proximity in knowledge exchange dynamics, above all when these involve knowledge that is scarcely codified (Quatraro and Usai, 2017). Moreover, the literature investigating the determinants of knowledge generation through

recombination has stressed the importance of cognitive proximity, i.e. the degree of technological relatedness between a firm's technological competences and the technological domain in which they want to be active (Nesta, 2008; Quatraro, 2010; Antonelli and Colombelli, 2017). According to Nooteboom et al. (2007), cognitive distance affects a firm's capacity to absorb external knowledge, as well as the efforts to process and reuse it in a creative way. While some degree of heterogeneity is crucial to novelty creation, and especially to creation high-value innovations, excess heterogeneity is found to harm the knowledge generation process. Technological experience augments absorptive capacity but reduces the scope for high-value innovation because of the constraints to the exploration of the technology space.

From the microeconomic viewpoint, the market-creation (or expansion) effect engendered by stringent environmental regulation produces a rightward shift of the demand schedule for green technologies. Other things being equal, the higher opportunities to capture rents would stimulate technology suppliers to enter the markets for green technologies. Inducement mechanisms would ultimately result in the intensification of technological efforts of suppliers that are already specialized in the generation of green technologies, as well as the technological diversification of suppliers that are active in other technological domains.

However, our understanding of knowledge generation dynamics and the appreciation of the resource constraints suggest that the dynamics are more complicated. On the one hand, the intensification of R&D efforts is likely to be mitigated by decreasing returns, above all when search is conducted in the neighborhood of a firm's established technological competences. On the other hand, technological diversification is shaped by the cognitive proximity between firms' core competencies and the features of new markets.

These problems are exacerbated by the specific features of green technologies, as far as the recombinant dynamics underlying their generation are concerned. An increasing body of literature indeed elaborates upon the intrinsic complexity of green technologies. Theoretical and empirical evidence suggests that they are

more likely to emerge out of the hybridization of technologies that do not share important commonalities. In a large number of cases, green technologies are the outcome of new and unprecedented ways to combine green and dirty technologies (Zeppini and van den Bergh, 2011; Dechezleprêtre et al., 2014; Colombelli and Quatraro, 2017; Barbieri et al., 2020; Orsatti et al., 2020).

2.3 Green innovation networks, partners and proximity

From the previous discussion, it follows that even for firms that are already active in the green technological domain, it is important to search and explore areas of the technological space that are far away from their core specializations (Corrocher and Ozman, 2019). In other words, green invention always involves some degree of technological diversification. Collective invention dynamics and technological collaboration emerges as an optimal solution to this issue.

The strategic management literature indeed suggests that when technological diversification is at stake, firms are basically confronted with the trade-off between the leveraging of internal competences or resorting to external knowledge sourcing. When knowledge generation involves the combination of heterogeneous knowledge sources, the establishment of technological collaborations, or inter-firm networks, becomes the best available option to warrant successful innovation performances (Nooteboom et al., 2007; Nooteboom, 2008; Hagedoorn, 1993; Uzzi, 1997; Prahalad and Hamel, 2006).

In this direction, recent literature has provided evidence of the importance of collaborations for the generation of green innovation (De Marchi, 2012; Cainelli et al., 2012; Wagner and Llerena, 2011; Melander, 2017). The main rationale lies in the high degree of complexity and recombinant novelty typical of green technologies, as discussed in the previous Section. Ghisetti et al. (2015) introduces the concept of 'open eco-innovation mode' to highlight the importance of the concept of open innovation also in the green domain (Chesbrough, 2003). Accordingly, openness to external sources of knowledge might be crucial for compensating the lack or insufficient development of the necessary capabilities

to deal with the combination of knowledge components that are dispersed in the knowledge space (Grant and Baden-Fuller, 2004).

For the same reasons, other studies based on patent data have stressed the importance of teamwork organization in inventive activities to ensure the command of loosely related areas of the technological space that is required by green invention (Quatraro and Scandura, 2019; Orsatti et al., 2020).

Yet, there is insufficient knowledge about how networking affect the process of generation of green technologies. A recent exception in this respect is the contribution by Fabrizi et al. (2018), wherein green research networks are investigated to assess the impact of their size and composition on green innovation, as well as their interplay with the effect of public policies.

The investigation of network structural properties is important to detect how the generation of GTs can represent an objective that shape firms' networking strategies. In this respect, technological alliances represent an interesting case of technological collaboration that allows firms to access competencies that they lack internally and that are far away from their specializations (Hagedoorn and Duysters, 1999). Technological alliances are considered as a means not only to share the risks and uncertainties that are intrinsic to the innovation process but also (and mainly) to get access to new and complementary technologies, to access new markets and to monitor the evolution of non-core technologies (Hagedoorn, 1993; Teece, 1986; Giuri et al., 2004; Vonortas and Zirulia, 2015).

Based on the discussion carried in the Section, we are able now to spell our main arguments. In view of the increasing concerns about the dramatic effects of climate change and the exhaustion of natural resources, environmental regulation is becoming more and more stringent to force economic agents to improve the environmental impact of their activities [1].

[1] See Crespi et al. (2015) for a taxonomy of environmental policies. Typical examples are market-based instruments lie the Emission Trading System implemented by the European Union, or command and control instruments, like the regulation concerning the use of chemical compounds (REACh). These kinds of instruments constrain the actions of economic agents, to make them less harmful for the environment. In doing, they create an incentive for the adoption and, consequently, the generation of green technologies.

One of the main channels through which environmental regulation achieves its objective is represented by the inducement mechanism. Regulation makes environmental degradation an important cost for polluting firms. These latter resorts to the adoption of green technologies in order to improve the environmental performances of their activities and save the costs that would have been engendered by the missing compliance with the environmental regulation.

An important effect of this mechanism is the creation of new market niches for green technologies, or the expansion of existing ones. In this context, firms willing to reap the benefits stemming from increasing for green technologies will enter this market or will intensify their efforts if they are already active.

Given the inherent complexity of green technologies, their generation is very often the outcome of the combination of rather heterogeneous knowledge sources, involving search dynamics across very wide areas of the technological space. As a consequence, both for incumbents and new entrants, the generation of green technologies requires some degree of technological diversification, mostly in domains that are distant from the core of the firm.

In these situations, external knowledge sourcing is preferred to internal diversification. Technological alliances become the best available option for firms willing to keep the pace with rapid technological change in the green domain, no matter whether incumbent or a new entrant. Strategic technological alliances are therefore expected to drive the generation of green technological knowledge. Innovating firms are expected to prefer to establish links with partners that possess complementary competences, so as to ensure the adequate level of heterogeneity that is necessary for the success of their strategies.

3 Data

3.1 Dataset construction

To investigate the evolution of the collaboration network we construct a new large dataset of European firms, observed over the period 2005-2011. The panel

includes all the publicly reported alliances involving firms located in France, Germany, Italy, Spain and United Kingdom. Alliances data are collected through the SDC Platinum database,[2] which includes joint ventures, strategic alliances, and R&D agreements. Following existing literature, the choice of exploiting publicly reported partnerships to characterize the inter-firms network structure is guided by the well-documented importance of strategic alliances, joint ventures and other formal agreements as a mechanism for sharing knowledge among a wide range of firms and industries (Powell et al., 1996; Gulati, 1998; Schilling and Phelps, 2007).

Alliance termination dates are rarely reported, so in principle, an explicit assumption about the duration of the alliances would be required. Previous research adopted different approaches. Some studies assumed that alliance relationships last for three years (Schilling and Phelps, 2007; Phelps, 2003), while, other studies consider a ranging window up to five years (Gulati and Gargiulo, 1999; Stuart, 2000). In this paper, we adopt a more conservative approach and opt for not setting any termination date. We are aware that such an assumption may lead to possible bias in our empirical analysis. On the other hand, biases could also be introduced by arbitrary choices on alliance duration. We believe that the potential drawbacks of not assuming any alliance-specific duration may only marginally affect our estimates, for two main reasons. First, given our relatively short time-period of observation (i.e. from 2005 to 2011), it seems reasonable to assume that the formal partnerships in our sample, which require long-lasting and effective efforts to be set-up, last until the end the period considered (2011), thus implicitly assuming a maximum duration for each alliance of 6 years. Secondly, the dynamic network analysis model employed in the empirical analysis is able to explicitly taking into account the "only grow-

[2]SDC is a division of Thomson Financial and provides information on a wide range of financial transactions, including global new issues, securities trading, and mergers and acquisition. SDC tracks a very wide range of agreement types, including joint ventures, strategic alliances, research and development (R&D) agreements, sales and marketing agreements, manufacturing agreements, supply agreements, and licensing and distribution pacts.

ing" nature of our network, thus giving higher relevance to the dynamics of alliances formation and their effect on the structure of the network.[3]

The alliances' database contains very limited information on the individual firms involved in the agreements. Therefore, it needs to be integrated with additional data at the firm level. First, we collect balance sheet information, with respect to firms' assets and profitability, from the Bureau Van Dijk (BVD) AMADEUS database. Unfortunately, no unique identification code is available to directly match alliances data with external sources of information on the corresponding firms. Further, the SDC database collects very few and incomplete information on firms other than their names and addresses. Therefore, a great effort is posed on matching firms involved in alliances, as reported by SDC Platinum database, with their corresponding record in BVD AMADEUS. The performed matching strategy involves several steps. First, in order to minimize false positives, firms names are cleaned following the harmonization routines proposed by NBER Patent Data Project[4] and Thoma et al. (2010).[5] Secondly, we match the two datasets relying on the harmonized firms names and their geographical location aggregated at the province level (NUTS 3 level of the 2016 NUTS classification).[6] For each potential match, a reliability score ranging from 0 (completely dissimilar records) to 1 (perfect 1-to-1 match) is produced. To ensure matching precision, for high – but smaller than 1 – scores a visual screening of each link is performed. Low score matches are checked using the Google's tool *OpenRefine*.[7] The intuitive matching visualization of such tool allow us to

[3] An "only growing" network can be defined as a network in which links can only be created but they are not dissolved.

[4] Available at `https://www.sites.google.com/site/patentdataproject`

[5] The actual names parsing is performed using the utility *stnd_compname* of the Stata package *reclink*. Given its flexibility, the utility allows to account for the specificity of different countries' name registration procedures and rules. This allows to obtain cleaned and standardized firms names in both AMADEUS and SDC database

[6] The matching is performed by combining the matching routine "matchit", described in Raffo and Lhuillery (2009), and the reclink Stata package. We employ a 2-grams matching algorithm, as it is considered an acceptable trade-off between the desired precision and recall rate.

[7] Available at `https://www.openrefine.org`.

reduce the false positives and increase the overall recall rate. In this way, we are able to assign as many BVD identification codes (coded as bvd_id) as possible to firms present in the SDC Platinum database. Eventually, the matching procedure allows us to successfully match 3312 firms, out of a full sample of 4408 firms, involved in 3561 alliances. To validate the matching procedure and check the reliability of the matched sample we provide statistics on the resulting dataset based on the pre-existing information contained in the SDC Platinum database. In particular, we compared the distribution of firms and alliances by reported economic sector and by their country location in the original sample and the matched one. The corresponding figures, reported in the Appendix (figures A1, A2, and A3), show that the two distributions present very similar characteristics, thus ruling out the hidden assumption of potential self-selection of firms in our matched sample.

In our analysis, the focus is on firms' innovative capabilities and efforts in the domain of green technologies. Hence, we collect information on patent applications for each firm from the *OECD, REGPAT Database, March 2018*, which provides all the patent applications filed to the EPO and under the PCT (Patent Co-operation Treaty) from 1977. To identify patents related to environmental technologies we exploit the Cooperative Patent Classification (CPC) scheme that provides, for each patent application, the technological classes indicating the subject to which the invention relates. To properly select domains related to green technologies we follow the OECD ENV-TECH (Haščič and Migotto, 2015) classification, which is based on both the International Patent Classification (IPC) and Collaborative Patent Classification (CPC).[8] Notwithstanding the well-known drawbacks in the use of patent data for empirical studies, the information contained in patent documents represent a major source of data, though imperfect, for studying the development and evolution of technological knowledge (Griliches, 1990; Pavitt, 1985; Jaffe et al., 2002; Strumsky et al.,

[8]For each IPC listed in Haščič and Migotto (2015) we identify the corresponding CPCs using the concordance table available at `https://www.cooperativepatentclassification.org/cpcConcordances.html`.

2012).

Lastly, to explore the role of environmental policies we rely on the OECD Environmental Policy Stringency (henceforth EPS) index (Botta and Kozluk, 2014). The EPS index is a "country-specific and internationally-comparable measure of the stringency of environmental policy". Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour, and it is based on the degree of stringency of 14 environmental policy instruments (Botta and Kozluk, 2014). The index ranges from 0 (not stringent) to 6 (highest degree of stringency). It covers the 28 OECD countries and 6 BRIICS countries over the period 1990-2012.[9]

3.2 Descriptive evidence

Table 1 provides an overview of the collaboration patterns in our sample. The number of new signed alliances, as well as the number of new firms setting up partnerships, steadily increases until 2008. After a drop in the years immediately following the financial crises, the patterns partially recover their increasing trend during the last year of our sample. Interestingly, the table also shows that most of the formal collaboration agreements involve two members at most.

An advantage of our newly constructed database is that, considering the whole range of economic activities, it allows to dig into the patterns of collaboration within and between different economic sectors. SDC Platinum data about industrial sector classification are available at the four-digit SIC level for both individual alliances and firms. Figure 1 plots the proportion of alliances by their assigned primary SIC code, aggregated at the 1 digit level. Until 2009, Services represents the most prominent sector, accounting for 35%, on average, of technology alliances, followed Manufacturing, and Transportation, Communication and Energy-related services, each accounting for around 20%. Figure

[9]It is worth stressing that the EPS index is measured at the country level, therefore, firms located in the same country are exposed to the same levels of Environmental Policy Stringency

Table 1: Collaboration patterns

	2005	2006	2007	2008	2009	2010	2011
New participants	228	243	316	285	95	53	141
New alliances	148	170	216	191	79	39	97
Participants per alliance:							
2	140	162	205	174	76	34	89
3	7	2	9	14	2	5	7
4	0	5	1	1	0	0	1
5	0	1	0	2	1	0	0
6	0	0	1	0	0	0	0
7	1	0	0	0	0	0	0

2 plots, instead, the relative proportion of firms according to their primary sector of activity. As expected, from 2005 to 2011, Manufacturing firms represent about one-third of the firms in our sample, followed by the firms operating in the Services, Transportation, Communication and Energy-related Services, and Finance sectors. At a first sight, the highest share of technology alliances registered in the Services sector (figure 1), together with the prevalence of Manufacturing firms (figure 2) might seem unexpected. According to the SIC classification, both Manufacturing and Services includes a wide range of technology-intensive economic activities (such as Biotechnology, Semiconductor, and Pharmaceutical in the Manufacturing sector and ICT related activities among Services), which make large use of partnerships to manage the increasing complexity in technology in their markets. Further, the vast majority of Services technology alliances in our sample are coded under the SIC sub-sector (group) "Research, Development, And Testing Services", thus explicitly referring to the coordination of joint development activities between the alliances' members. As an illustrative example, we report the case of a joint collaboration agreement signed in 2008 between the UK based company CMR Fuel Cells plc and the Acta SpA, based in Italy. CMR core business consists of developing high-performance compact fuel cell stacks for the portable consumer electronics industry. Acta SpA develops

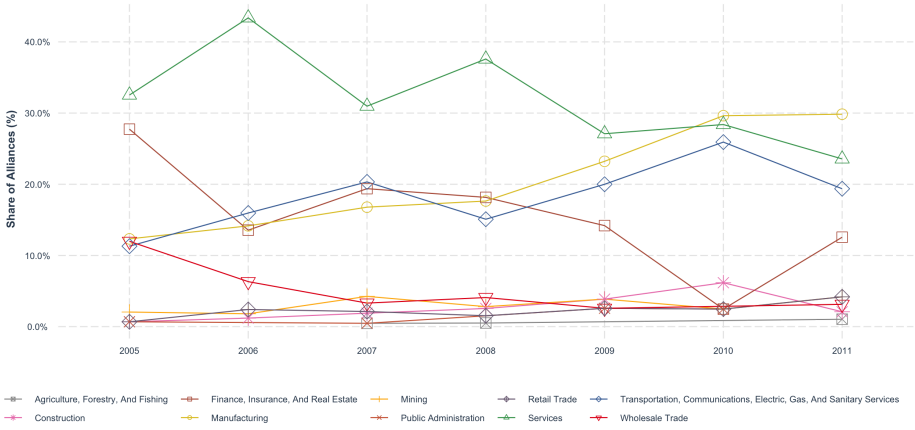

Figure 1: Yearly share of alliances by primary economic sectors (1 digit SIC code) from 2005 to 2011

and manufactures unique patented catalysts, initially launched to the renewable energy, automotive and portable battery market. Both companies operate within the Manufacturing sector. However, the alliance primary SIC group code is "Research, Development, And Testing Services", within the Services sector. Indeed, as reported in the alliance announcements: "the Agreement is expected to lead to joint development activities... in which CMR brings outstanding stack and system engineering expertise... and Acta brings high-performance low-cost catalysts as well as extensive expertise in the specific technology of alkaline membrane fuel cells.". Interestingly, this technological alliance provides a concrete example on the use of collaborations for knowledge exchange purpose, and on the role of partnerships as a vehicle for firms (the CMR Fuel Cells company) to accesses specific knowledge in the green technologies domain from experienced partners (the Acta Spa).

In Figure 3 we try to disentangle the collaboration patterns of firms within and between the different sectors of activity. The strings departing from each block on the left side of figure 3 represent the number of technological alliances signed between firms operating in the left-block economic sector and firms in the right-block corresponding sector. The width of the string is proportional

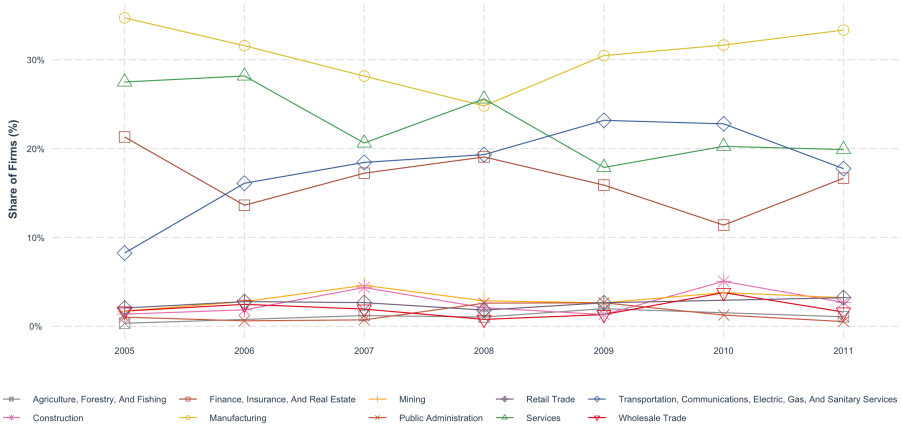

Figure 2: Yearly share of firms by primary economic sectors (1 digit SIC code) from 2005 to 2011

to the number of alliances between the two groups (the number of collaboration links). To illustrate, Manufacturing firms collaborate to a larger extent with firms operating in the same sector, as indicated by the large strip going from the Manufacturing block on the left to the Manufacturing block on the right. Further, Manufacturing firms importantly collaborate with Services, Finance, and Transportation, Communication, Electric, and Energy-related Services firms. Services firms follow collaboration patterns very similar to those of Manufacturing. Indeed, while the bulk of alliances occurs within the Services sector, we can also observe a non-negligible amount of collaborations between Services and other sectors. Overall, figure 3 shows that technology alliances tend to be highly concentrated within economic sectors, though with significant signals of cross-collaborations between them.

3.3 Network structure

The aim of the paper is to investigate the interplay between collaboration, green technologies, and environmental regulation, adopting a network perspective. By looking at firms as nodes and the technological alliances between them as links

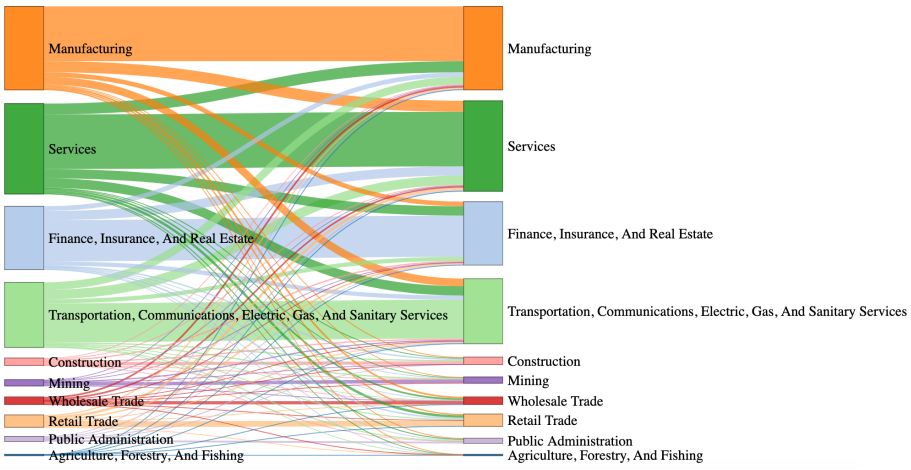

Figure 3: Overall patterns of collaboration within and between firms primary economic sectors (1 digit SIC code)

we are able to build the network of inter-firms collaboration. Previous research has extensively examined the key role of alliance network structure on firm performances and innovation, highlighting the importance of the patterns that exist between the network actors and their distinctive features. Thus, a description of the network structure may provide important preliminary insights when building network analyses. To this end, table 2 provides descriptive statistics of the alliance network structure. In our collaboration network density is very low (sparse network), indicating that of all possible linkages among nodes less than 1% of them are actually present. Because establishing a connection comes at a cost (particularly in the presence of formal partnerships, given the amount of formal requirements needed) and only valuable links tend to be created and maintained, sparsity is a common characteristic in collaboration networks. When looking at the triadic level connections, it can be noted the general tendency of firms to link with the "friends of a friend", i.e. inter-organizational alliances tend to occur, ceteris paribus, between organizations that already have an alliance partner in common, closing triangles of relationships. This feature is reflected by the level of the average clustering coefficient, which is higher than

Table 2: Network Structural Descriptive Statistics

Year	N. nodes	N. ties	Av. degree	Clustering coeff.	Av. path length	Density
2005	3122	2710	1.7361	0.2617	8.3103	0.0006
2006	3361	2918	1.7364	0.2537	8.2333	0.0005
2007	3675	3171	1.7257	0.2444	7.8401	0.0005
2008	3958	3413	1.7246	0.2401	7.7701	0.0004
2009	4052	3505	1.7301	0.2336	7.7154	0.0004
2010	4106	3554	1.7311	0.2312	7.7051	0.0004
2011	4246	3670	1.7287	0.2254	7.5022	0.0004

the expected clustering coefficient of a random network with similar characteristics. To be more precise, the 25%, on average, of all connected triplets of vertices are closed triplets. Together with relatively low geodesic distances (the average path length between any two nodes in the network is approximately 8 steps), these statistics indicate high overall connectivity in the network. Even though organizations are located in different geographic areas, they are still closely localized to each other in network terms.

4 Empirical strategy

The empirical analysis is articulated in two steps. First, we empirically test the existence of a relationship between the stringency of environmental regulation and the generation of Green Technologies by using standard regression techniques. In the second step, building on the importance of the network structural properties described in Section 3.3, we employ a dynamic network analysis model to explore the dual role of GTs both as a determinant of the collaboration network and as the outcome of the collaboration strategies of firms, providing new evidence on the role that the regulatory framework plays on the generation of new GTs.

4.1 Count-data model

4.1.1 Dependent variable

Following established literature on innovative performances at the firm level, we adopt a Knowledge Production Function (KFP) approach to estimate the relationship between policy stringency and the generation of GTs. In particular, we employ a reduced form of KFP, where the dependent variable is represented by the stock of green patents ($GTStock_{i,t}$) of firm i at time t. The use of a patent stock, instead of its flow, allows us to account for both the accumulated amount of knowledge and the net yearly knowledge generation, avoiding the volatility of yearly patents counts. In line with prior literature, we calculate the stock measure following the permanent inventory method (Bloom and Van Reenen, 2002; Peri, 2005; Dechezleprêtre et al., 2015): starting from 1977, the green patent stock for each firm i at time t is given by the net amount of patent applications in green technologies in t plus the depreciated green patent stock at time $t-1$.[10]

4.1.2 Independent variables

Our main explanatory variable is the environmental policy stringency index ($EPS_{i,t}$), described in Section 3.1. To account for different firm-level characteristics the estimation includes several controls. First, we control for firms established innovative capabilities by including the yearly stock of patents of each firm, calculated excluding green patent applications ($KStock_{i,t}$). Secondly, to control for firms' heterogeneity in their propensity to patent we control for firms size, calculated as the (log) value of their assets ($Size_{i,t}$). Third, the network of alliance relationships constitutes a direct channel for firms to share and gain access to information and knowledge. Hence, firms embeddedness in

[10] In the literature, there have been several attempts to estimate the most appropriate patent depreciation rate (Schankerman, 1998; Pakes and Schankerman, 1979). In this paper, we adopt an obsolescence rate at 15%, as it is the most commonly used value in the literature (see among others Hall et al. (2005); Keller (2002); McGahan and Silverman (2006); Nesta (2008).

alliance networks plays a key role in enhancing their innovative performances. Therefore, we control for the possibility that firms occupying more central positions in technology alliance networks may generate more innovations in the green domain. We operationalize firm centrality by using the degree centrality ($Degree_{i,t}$), which counts, for each firm, the number of active technology alliances. To capture the tendency of firms to cluster in alliance networks, we use a measure of local network transitivity ($Transitivity_{i,t}$). It is measured as the proportion of actual links between a firm's alliance partners over the total number of possible links between them.

4.1.3 Model specification

The dependent variable in this paper, $GTStock$, is assimilated to a count variable and takes on only positive or zero values. In the case of count data, the nonnormal distribution of residuals violates one of the main assumptions of linear regression models. Therefore, to deal with count data the most reliable models are Poisson regressions or their variants. However, our dependent variable, the stock of green patents, exhibits significant overdispersion and excess zeros. In such cases, a commonly used alternative is the zero-inflated negative binomial model (ZINB). The ZINB is often indicated as the most appropriate model in the presence of count data with a high number of zeros. ZINB allows to account for two different processes that may generate a zero in the outcome variables. The model estimates simultaneously two equations, a binary logistic, called the inflation part, and a negative binomial. To give an example, in our sample there may be firms that are actively patenting but none of these patents is assigned to green technologies (the sampling zeros), while some other firms may show no patenting activity at all (the structural zeros). To distinguish between the two processes we estimate the inflation part via a probit equation based on firms stock of total patents ($KStock_{i,t}$) and firms size ($Sizei,t$). We hypothesize that, other things being equal, large firms and firms with higher internal knowledge stock are more likely to develop new green technologies.

Hence, firms size and patent stock are expected to negatively correlate with the probability of observing a structural zero.

The panel implementation of a ZINB model allows also to control for possible sources of unobserved, or unobservable, heterogeneity. In this study, unobserved heterogeneity may mainly stem from systematic period effects, such as differences in macroeconomic conditions, and industry effects, that may affect the patenting rates in GTs of all the firms in our sample. To control for these two sources of unobserved heterogeneity we include in the estimation both year fixed effects and economic sectors fixed effects (measured at the 1 digit SIC level). Formally, the estimated full model takes the following form:

$$\begin{aligned} GTStock_{i,t+1} =& \beta_0 + \beta_1 EPS_{i,t} + \beta_2 KStock_{i,t} + \beta_3 Size_{i,t} + \\ &+ \beta_4 Degree_{i,t} + \beta_5 Transitivity_{i,t-1} + \theta_t + \phi_j + \epsilon_{i,t} \end{aligned} \tag{1}$$

where θ_t are time fixed effects, ϕ_j are industry fixed effect, and $\epsilon_{i,t}$ is the error term. In the baseline specification, we assume a lag structure of one year. Existing literature does not provide an unambiguous consensus about the appropriate lag structure. Hence, to explore the robustness of our results across alternatives, we also estimate models using a two-year lag between the dependent and the independent variables.

4.2 Modeling network dynamics: the SIENA model

The empirical investigation of network dynamics is concerned with complex relational structures that require specific statistical models (Snijders, 2001). An intrinsic property of the network structure is the presence of conditional dependencies between observations, which of course violate the assumption of independence of standard statistical procedures, leading to unreliable estimates. Therefore, from a methodological point of view, we need a network analysis instrument able to empirically capture the dynamic nature of economic and social relationships between actors. Recently, several statistical network models

have been developed in order to cope with network dependencies. Among these, the Stochastic Actor Oriented Model (SAOM), implemented in the R package SIENA (Simulation Investigation for Empirical Network Analysis), is a statistical tool developed to evaluate network dynamics, based on observed longitudinal network data, through classical statistical inference (Snijders et al., 2010). SIENA models are able to statistically estimate the effect on the dynamics of network structure (macro-structure) of a large variety of micro-mechanisms (at the actor level), which may operate simultaneously. Indeed, such models allow the inclusion of numerous and different sets of network dynamics called "tendencies", such as structural endogenous network effects, individual characteristics, the behaviour of actors and other relevant variables. SIENA models, then, give a good representation of the stochastic dependence between the creation of different network ties and provide the means to estimate the extent and the strength with which the micro-mechanisms are associated with network evolution between.

Social network studies have also underlined the importance of getting a deeper understanding of relational structures and specific behaviours, studying the dynamics of network structures, individual outcomes, and how these two mechanisms co-evolve. As the network configuration may change as a function of actors behaviour and endogenous network mechanisms, so the behaviour of actors may change as a function of itself and the network structure. The former mechanism is often referred to in the literature as the selection process, while the latter is called influence process. In other words, the similarity (or dissimilarity) between network actors it is in part due to a selection process, in which actors select themselves because of their similarity (or dissimilarity), and in part, because they tend to influence each other once they are connected (influence process). Thus, in a network analysis framework, separating selection from influence mechanisms is determinant in explaining the endogenous change of behaviours. Methodologically, this implies that both the network structure and the actor variables must be treated as joint dependent variables in a longitudinal framework to estimate the extent to which they co-evolve. SAOM models

allow to develop a "selection and influence stochastic model" in which the dependent variables consist of both network links and actors behaviour. Hence, the two processes are estimated simultaneously, controlling one effect for the other. In order to investigate the co-evolution of collaboration networks and green technologies in this paper, we employ a selection and influence SAOM model, in which the network dynamics are represented by the firms' technological alliances and the behaviour variable is represented by their innovative efforts in the generation of green technologies.

4.2.1 Model functioning

SAOM models are, technically, continuous-time Markov chain models, in which changes in the network are modeled as a Markov process. The time is assumed to runs continuously between observations so that the change process is decomposed into its smallest time steps, called micro-steps. The estimation procedure assumes that the network is observed at discrete points in time (as determined by the observed data) but these observed changes are the results of a sequence of unobserved changes. Therefore, the probabilities of changes in the network and in the behaviour at time $t+1$ depend on the combination of both at time t. At each micro-step, one actor gets the opportunity to make a network change or the opportunity to change his or her behaviour. Two independent rate functions – one for network and one for behaviour – rule the frequency with which the actors get a change opportunity. The waiting time between change opportunities is modeled according to two exponentially distributed variables, with parameter $\lambda_i^{network}$ and $\lambda_i^{behaviour}$. In this way, the probability that the next micro-step of actor i is a network one is given by $\lambda_i^{network}/\lambda_{total}$, likewise, in the case of a behaviour micro-step, is given by $\lambda_i^{behaviour}/\lambda_{tot}$. λ_{total} is simply the sum of the two independent parameters over all the actors.

Once an actor gets the opportunity for changing his/her own status, the probabilities with which changes actually occur are modeled by two separate objective functions, one for the network and one for the behaviour. While the

formal structure and the interpretation of the two functions are equivalent, in practice, the behaviour objective function may, and should, differ from the network objective function, in terms of parameters. This is because the behaviour objective function expresses how actors choose their behaviour, and it may depend on a different set of micro-mechanisms with respect to networking behaviour. As for the network dependent variable, the model implies that changes in the dependent behaviour variable are a function of the endogenous evolution of the behaviour itself (both of the focal actor and it network partners), on network structural effects, and a set of individual (or dyadic) attributes. The mutual dependence between network dynamics and behaviour dynamics is generated by their own changes which, controlled for each other, both influence the dynamics of the structure and the behaviour.

4.2.2 Model Specification

Technological alliances networks are usually treated as undirected networks, given the complexity of assessing link directionality. Among the different model types provided by the SIENA tool for non-directed networks, we model the creation of new links by using the "unilateral initiative and reciprocal confirmation model". The model works as follows: "one actor takes the initiative and proposes a new tie or dissolves an existing tie; if the actor proposes a new tie the other has to confirm, otherwise the tie is not created; for dissolution, confirmation is not required" (Ripley et al., 2011).

As described in Section 4.2.1, the model requires the specification of two distinct objective functions. For both, we consider two main sets of drivers: i) endogenous structural variables or effects; ii) individual and dyadic non-structural control variables.

The first structural effects in our network objective function is related to the tendency of network actors to cluster. *Transitivity* is included to account for the observed network triadic closure. Although there are several ways to operationalize transitivity, we use the most common one, based on counting the

number of times a firm i has a tie with two firms (j and h) which are alliance partners themselves. Formally:

$$T_i = \sum_{j,h} x_{ij}\ x_{ih}\ x_{jh} \tag{2}$$

The second structural variable is *preferential attachment*. It is included to account for the skewness in the degree distribution and captures the tendency of actors with a large number of partners – with respect to the average – to attract more partners. We measure preferential attachment by summing the degree of the firms to whom a firm i is linked. To be more precise we use the sum of the square root of alters to stabilize the simulation algorithm:

$$P_i = \sum_{j} x_{ij} \sqrt{\sum_{h} x_{hj}} \tag{3}$$

Among the individual and dyadic actor level characteristics we identify three sets of predictors. The first set of individual variables relates to firms' innovative capabilities and the regulatory framework. Our key variable of interest is the EPS index, which captures the stringency the environmental regulation at the country level. The stock of green patents ($GTStock$), employed both as network driver and dependent behaviour variable, captures the role of firm knowledge competences in the green domain on the dynamics of networking activity, and the relative importance of partners innovative behaviour on the propensity to develop new green technologies. We also include the stock of total patent applications ($KStock$) to estimate how firms' patenting performances affect their networking behaviour. The two stock variables, calculated using the permanent inventory method as explained in Section 4.1, are expressed in terms of similarity between firms. The second set of network drivers relates to three proximity dimensions: geographical, technological and institutional proximity. Two levels of geographical proximity are included, to capture the effect on alliances formation of being co-located in the same country ($Country_proximity$), and in the same NUTS II region ($Region_proximity$). Firms operating in related sectors of activity are more likely to collaborate, as they share similar knowledge

bases and may exchange knowledge more easily and efficiently. Therefore, technological proximity is captured by two dummies indicating whether two firms operate in the same main industrial sector ($Sector_proximity$) or industrial group/sub-sector ($Subsector_proximity$), based respectively on the SIC code at 1-digit and 2-digits. A proxy for institutional proximity is included to capture the extent to which similar institutional favours the formation of new technological alliances, by reducing uncertainty and transaction cost. We generate a dummy taking value 1 when two firms have the same public institutional status and 0 otherwise.[11]

To control for the heterogeneity of firms in their ability to manage formal partnerships, we include a third set of controls based on size and profitability indicators. $Size$ and $Size_similarity$ effects are included, respectively, to account for the ability of larger firms to manage a greater number of collaborations, and for the likelihood of firms to collaborate with others similar in size.[12]. We also include two measures of firm profitability: the similarity in the Return on Equity rate ($ROE_similarity$) and in the Profits and Losses Before Interests and Taxes ($PLBT_similarity$).

The second objective function models the drivers of firms patenting activity in GTs. The model requires the behaviour dependent variable to be either a binary 0-1 variable or a non-negative increasing categorical variable (Ripley et al., 2011). In order to restrain as much information as possible, we transform the GTs patents stock of each firm into a categorical variable based on a 1 to 10 ordinal interval scale.[13] Higher values are associated with higher levels of GTs innovative capabilities and vice-versa. Our main explanatory variable is represented by the stringency of the environmental regulation, measured with the EPS index (EPS). Among the individual non-structural variables, we include

[11]Information on public institutional status are gathered from the SDC Platinum. In particular, each firm is listed as either: Private company, Public company, Subsidiary, Joint Venture, Governmental company, Investment company.

[12]Firm size in proxied by the mean value of assets over the period 2005-2011.

[13]According to Ripley et al. (2011), the variable can have a maximum 10 non-negative integer values.

the firm total patents stock ($KStock$), firm size ($Size$), firm profit and losses before interest and taxes ($PLBT$) and, firm return on equity (ROE). Further, to capture the effects of endogenous network dynamics we include the number of active technological alliances for each firm ($Degree$) and the average level of GTs patent stock of the firms with which a given firm is collaborating via technological alliances ($Partners_GT$).

It is worth stressing that, to ensure consistency with the econometric estimation, the specification of the GTs knowledge stock objective function follows the Knowledge Production Function approach as in equation 1. However, because of the dynamic nature of the SIENA model, the two specifications are not identical. In our dynamic network analysis model, the mutual dependence between the alliance network dynamics and the dynamics in the generation of GTs are generated by their own endogenous changes and by simultaneously controlling for one dynamic on the other. Hence, GTs dynamics are modeled not only as a function of environmental stringency and firm-specific characteristics, but also depend on the firms' endogenous green innovative efforts itself and on endogenous networking strategies. These latter mechanisms are, indeed, captured by the *shape* effects, which reflect the basic tendencies that influence GTs advancements independently of the other effects, and by the $Degree$ and $Partners_GT$ variables, which incorporates the information on the dynamics of the collaboration network strategies.

5 Results

5.1 Count-data model

Table 3 reports the zero-inflated negative binomial panel regression results. Columns 1 and 2 refer to a one-year lag between the stock of green patents and the independent variables, while columns 3 and 4 report the results using a two-years lag structure. Models in columns 1 and 3 include all the controls excluding the network variables. These latter are gradually added in models 2

and 4. All models include year and industry effects. Reported standard errors are heteroskedastic-robust.

Our main expectation predicted a positive effect of the stringency of environmental policy on firm green innovative capacity. Results show a positive and significant coefficient of the EPS index across models and lag structures. The magnitude of the coefficients slightly reduces when network controls are added to the models and are systematically lower with the longer lag structure. This confirms our hypothesis, according to which the presence of stringent environmental regulation engenders an inducement effect that stimulates firms to introduce innovations that allow for the improvement of the environmental impact of production processes. Among the other variables in the models, most of them are consistent in terms of sign and significance. Both firm size and firm non-green knowledge stock are positively associated with firms green inventive efforts. The positive association between the network controls and the stock of green patents is also confirmed. Highly connected firms and firms embedded in dense clusters show better innovative performances in GTs. The estimated coefficient for network local clustering ($Transitivity$) is, indeed, positive and persistently significant in time. The number of active collaborations ($Degree$) has a positive and significant coefficient in model 2, but it fails to reach statistical significance when a two-year lag structure is considered (as in model 4). The results related to the zero-inflation part are also in line with our expectation as confirmed by the negative and significant role of both $Size$ and $KStock$ in predicting the likelihood of observing structural zeros. One concern about our results regards the possibility that we were not able to control for all firm-level time-invariant sources of heterogeneity. To check for the robustness of our results we re-estimated our models using a Poisson regression with time and firm fixed effects. The obtained results, reported in column 1 and 2 of table A1, are qualitatively very similar to those presented in table 3. A second concern is related to the fact that our index of environmental policy stringency is measured at the country level. Since nearly 48% of firms in our sample are located in the UK, we run both ZINB and Poission regression models on a reduced sample,

excluding all the UK-based firms. As shown in columns 3-6 of table A1, results are in line with our main findings.

5.2 SIENA Model

The results of the estimated SIENA model are presented in table 4. All parameter estimates are based on 3000 simulation runs and the convergence of the simulated values to the observed ones is excellent. The left part of table 4 reports the estimated effect of GTs and environmental policy on the likelihood of firms to set up new technological alliances (Network Dynamics), while the right part refers to the determinants of GTs (Behaviour Dynamics). Parameters estimates of SIENA can be interpreted as non-standardized coefficients obtained from logistic regressions. Thus, the estimates reported on the network dynamics part are simply the log-odds ratio of an alliance formation associated with one unit change in the corresponding explanatory variable. On the other hand, coefficients of the behaviour dynamics indicate how the log-odds of increasing the stock of GTs change with changes in the corresponding covariates.

Starting with the drivers of technological alliances, the first two rows of column 1 report the effects of the endogenous network variables. The positive and significant coefficient for transitivity indicates that there is a strong tendency of firms to form new alliances with firms that are collaborating with one of their existing alliance partners (transitive closure). We find instead a negative and significant coefficient for preferential attachment. The strong and positive coefficient for EPS in row 3 indicates that firms operating under stringent regulatory frameworks tend to be more active in the collaboration network, as they are more likely to set-up new technological alliances. Results show that existing innovative capabilities play an important role in the collaboration dynamics. Indeed, we find negative and significant coefficients for the green patent stock and total patent stock (row 4 and 5). This finding suggests that firms with a poor knowledge base and less experience in developing green technologies have a higher tendency to set-up technology alliances with firms possessing higher

Table 3: Panel Zero-Inflated Negative Binomial Regression results

	$GTStock_{i,t+1}$		$GTStock_{i,t+2}$	
	(1)	(2)	(3)	(4)
Count model				
EPS	0.314***	0.305***	0.145***	0.113***
	(0.037)	(0.037)	(0.039)	(0.040)
Size	0.259***	0.268***	0.249***	0.269***
	(0.005)	(0.005)	(0.005)	(0.006)
K Stock	0.747***	0.734***	0.765***	0.761***
	(0.005)	(0.005)	(0.005)	(0.005)
Degree		0.004***		−0.0003
		(0.001)		(0.001)
Transitivity		0.387***		0.415***
		(0.029)		(0.030)
Constant	−2.230***	−2.315***	−1.534***	−1.716***
	(0.188)	(0.189)	(0.204)	(0.205)
Zero-inflation model				
K Stock	−0.502***	−0.507***	−0.492***	−0.494***
	(0.020)	(0.020)	(0.022)	(0.022)
Size	−0.051***	−0.048***	−0.055***	−0.050***
	(0.013)	(0.013)	(0.014)	(0.014)
Constant	2.468***	2.452***	2.503***	2.420***
	(0.178)	(0.178)	(0.195)	(0.198)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	15,970	15,970	13,102	13,102
Log Likelihood	−15,347.61	−15,249.57	−13,580.36	−13,485.79

Notes: This table analyses the relationship between the environmental policy stringency and the green inventive performance from the 2005 to the 2011. The dependent variable is the firm' stock of green patents. Columns 1 and 2 refer to a one-year lag between the dependent and the independent variables, while column 3 and 4 consider a two-year lag structure. All models are estimated by using Zero-inflated Negative binomial regressions with industry and time fixed effects. The upper part of the table reports the negative binomial estimated coefficients (count model). The lower part reports the probit estimation of the structural zeros (Zero-inflation model). Standar errors, reported in parentheses, are heteroskedastik-robuts. *p<0.1; **p<0.05; ***p<0.01

innovative competences and a strong GTs knowledge base.

Concerning the proximity mechanisms, we find evidence of a positive and significant effect of the three dimensions considered. As reported in row 6-10, firms have a preference to collaborate with firms operating in the same sector and sub-sector of activity as well as with those located in the same country, while regional proximity plays a marginal role. Rows 11-14 refer to the coefficients for firm performance indicators. The effect of size is positive and significant, indicating that larger firms are able to manage a greater number of collaborations, while size similarity is not statistically significant. Further, firms are more likely to search for alliance partners with high and similar levels of profitability.

The right part of table 4 presents the results of the effect of endogenous network properties, regulation and individual characteristics on the generation of GTs. The linear and quadratic shape effects in rows 1-2 of column 2 reflect basic tendencies determining changes in GTs patenting independently of the other covariates. The negative sign on the linear shape, together with a positive sign on the quadratic term are signals of a U-shaped self-reinforcing mechanism in firms patenting behaviour in GTs, i.e. the gradual accumulation of knowledge and competences consolidates firms successful innovative routines, which facilitate knowledge creation processes, driving them further toward the introduction of new GTs. Interestingly, the direct effect of the environmental stringency is not significant, as reported in row 3. The coefficient for the existing knowledge stock is positive and significant (row 4). We find that the position in the alliance network (row 5) and the innovative capabilities in the green field of firms partners (row 6) play a key role in the generation of GTs. This means that highly embedded firms are more likely to generate new green technologies. At the same time, firms whose partners possess strong competences in the development of GTs are more likely to introduce new GTs. Therefore, firms seem to benefit from the successful innovative behaviour of their close connections. Rows 7-9 report the estimated coefficient for size and profitability effect. Large firms are more likely to be successful (the coefficient for Size is positive and significant), while we do not find statistically significant effects for the PLBT and ROE.

Table 4: SIENA model results

	Network Dynamics			Behaviour Dynamics	
		(1)			(2)
1)	Transitivity	2.343***	1)	Linear shape	-4.722***
		(0.090)			(0.145)
2)	Pref. attachment	-0.099***	2)	Quadratic shape	0.174***
		(0.025)			(0.022)
3)	EPS	3.471***	3)	EPS	-0.044
		(0.505)			(0.234)
4)	GT Stock similarity	-0.763**	4)	K Stock	0.361***
		(0.240)			(0.031)
5)	K Stock similarity	-0.498*	5)	Degree	0.077*
		(0.197)			(0.035)
6)	Country proximity	1.647***	6)	Partners GT	0.205**
		(0.084)			(0.064)
7)	Nuts II proximity	0.256**	7)	Size	0.297***
		(0.095)			(0.039)
8)	Sector proximity	0.765***	8)	PLBT	-0.017
		(0.025)			(0.052)
9)	Subsector pximity	1.642***	9)	ROE	-0.091
		(0.094)			(0.065)
10)	Institutional proximity	0.213***			
		(0.062)			
11)	Size	0.220***			
		(0.023)			
12)	Size similarity	0.595			
		(0.457)			
13)	PLBT similarity	0.948***			
		(0.263)			
14)	ROE similarity	-0.489*			
		(0.294)			

*N*otes: All convergence t ratios < 0.04. Overall maximum convergence ratio 0.13. The left panel (column 1) reports the estimated coefficients associated to the network dynamics (technology alliances). Coefficients on right panel (column 2) refer to the behaviour dynamics (green patents stock). Parameter estimates are based on 3000 simulation runs. *p<0.05; **p<0.01; ***p<0.001

6 Discussion and conclusions

This paper has investigated the mechanisms underlying the knowledge generation processes in green technologies. The focus is on the role of collaboration networks, environmental regulation, and their combination, as a source of advancements in the green technological field. We brought together different streams of literature to explore how the regulatory framework impact the green knowledge generation, by investigating the dynamics in the network of technological alliances. To this end, we built a novel panel dataset of European firms observed over the period 2005-2011. The dataset consists of technological alliance data from the SDC platinum database, patents and environmental regulation data from OECD and OECD Regpat database, and firm-level balance sheet data from the AMADEUS database.

Our main empirical analysis has been articulated in two steps. In the first step, we employed a standard count-data regression model. Results suggest the existence of a strong and positive relationship between the stringency of environmental regulation and the generation of green technological knowledge at the firm level. Also, we found evidence that firms external knowledge sourcing, channeled through network interactions, plays an important role on green innovative performances.

Nevertheless, a static empirical approach does not allow to grasp all the different intertwined mechanisms behind knowledge generation, regulation, and network dynamics. Therefore, in the second step of our empirical analysis, we took a dynamic perspective. We employed a stochastic actor-oriented (SIENA) model to analyze the simultaneous evolution of inter-firm network formation and firms green innovative capabilities, with a focus on the role of the environmental regulation. We have explored how the formation of technological alliances is influenced by firm preexisting innovative competences, both in green and non-green technologies, and the regulatory framework, alongside endogenous structural network effect and individual characteristics. At the same time, the model enabled us to "invert" the direction of the relationship, in order to investigate

the determinants of GTs as a function of the changing networking behaviour, innovative performances of firms, and the environmental policy framework. Our first result confirms that the structure of the network importantly affects firm networking strategy. Firm choices of alliances partners are heavily trust-based, as we find that firms are more likely to collaborate when they already share a common partner. An important finding of our analysis is the negative effect of similarity in green innovative competences. Firms with poor inventive capabilities in GTs are more likely to partner with other experienced firms in the green domain. This result is line with prior literature showing that environmental innovations are intrinsically more complex and sophisticated, as they have to comply with different technical-economic problems, and are expected to satisfy different needs (Florida, 1996; Oltra and Jean, 2005).

Therefore, creating a wide net of collaborations with external partners is increasingly becoming essential for successful innovative performances, allowing agents to access and share specialized knowledge components residing outside traditional domains (De Marchi, 2012; Petruzzelli et al., 2011). This mechanism is strongly related to another result of our empirical model. Firms are more likely to generate new GTs when they are involved in technological alliances with firms showing greater experience and competences in the development of such technologies. However, for the acquisition of external knowledge to be successfully integrated into internal processes and routines, some other conditions need to be met. Indeed, we find a positive effect of technological and geographical proximity on the likelihood to form new technological alliances. The higher complexity and systemic nature of GTs make these technologies less exposed to standardization and knowledge codification, thus knowledge exchanges may require technologically closer knowledge bases and constant interactions, which can be facilitated by relatively short geographical distances.

Last but not least, our results suggest that, when accounting for endogenous network dynamics, environmental regulation does not directly impact on the likelihood of firms to introduce new GTs. At the same time, we find a strong and positive effect of regulation on alliances formation. Our interpretation is

that the documented stimulus on innovation of environmental regulation may, in practice, operate indirectly. When firms operating in highly stringent regulatory frameworks do not possess the required competencies to manage internally complex and diversified technologies such as GTs, they may turn to external knowledge sources. Then, it is the nature of new and qualified collaborations and the structure of the local interactions that affects firms capacity to generate new green technological knowledge.

As any empirical study, also this one is not free from limitations. First, there is much debate about the use of patents as a proxy for firms' technological efforts. Patents are an imperfect output measure, as not all the research conducted by firms ends up to be patented. Moreover, from the environmental viewpoint, other kinds of innovations, like organizational changes, might be relevant. Another caveat concerns the use of technological classes to identify green technologies. Classifications based on concordance tables, even if based on rigorous statistical algorithms, risk to oversimplify complex dynamics and imply some degree of arbitrary choice. Yet, despite these caveats, patents represent so far the most reliable indicator to investigate technological dynamics at different levels (Griliches, 1984). Second, there are different datasets on firms' collaboration strategies, each one with pros and cons. However, even coverage is not complete, these data have been shown to yield reliable results in many circumstances (Schilling, 2009).

Avenues for further research emerge from this research, and provide guidance for future investigations. First, it would be interesting to carry out a finer-grained investigation of networking dynamics for the heterogenous typologies of GTs. Moreover, it would be useful to extend the coverage of networking dynamics to account for other kinds of firms' strategies beyond technological alliances. Finally, regulatory frameworks play an important role in firms decisions to adopt and generate GTs. It would be interesting to single out the differential role of different typologies of policy instruments vis-Ã -vis different strategic decisions aiming at external sourcing of technological competences.

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Appendix

A.1 Matching

Setting up a firm-level dataset linking different data sources is particularly complex, particularly in the absence of unique or harmonized firm identifiers across datasets. Following the matching procedure described in Section 3.1 we retrieve the 75% of firms of our original alliances' database, with high precision. To ensure that the resulting matched sample is not biased (i.e. no self-selection of firms is present) we check whether the distribution of firms and alliances in the matched sample does not substantially differ from the full sample. Given the lack of common data between the alliances' database (SDC Platinum) and BVD AMADEUS, we are forced to focus on characteristics provided by the former (our starting data source). Figure A1 compares the relative proportion of alliances in each registered economic sector (at the 1 digit Standard Industrial Classification (SIC) code) in the original sample with the shares in our matched sample. The figure shows that the distribution of alliances in the matched sample very closely follows the original distribution. The comparison between the distributions of firms by their main sector of activity in the two samples is presented in figure A2. The relative shares of firms after the matching are highly consistent with those calculated on the full sample. Lastly, figure A3 shows that no significant biases are introduced by the matching on the relative representation of countries, in terms of sampled firms. Overall, the three figures suggest that, notwithstanding the unavoidable loss of observations, the matched sample maintains the same distributional features of the original sample.

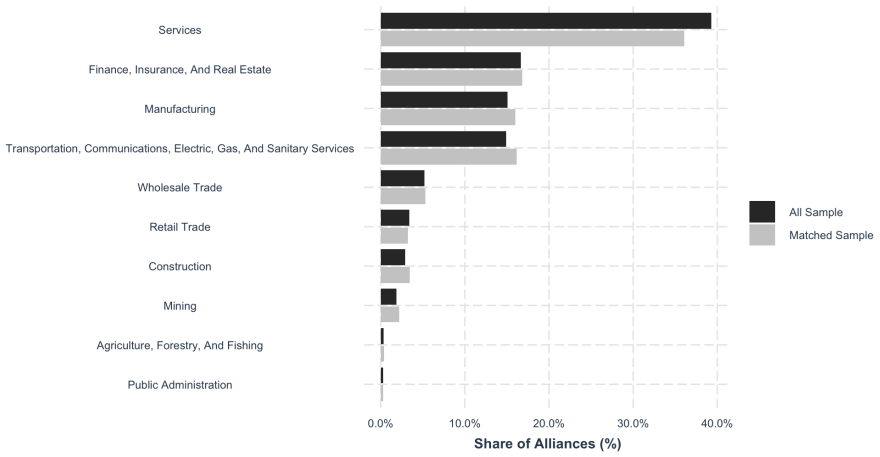

Figure A1: Share of alliances by registered economic sector (1 digit SIC) in the original sample and in the matched sample

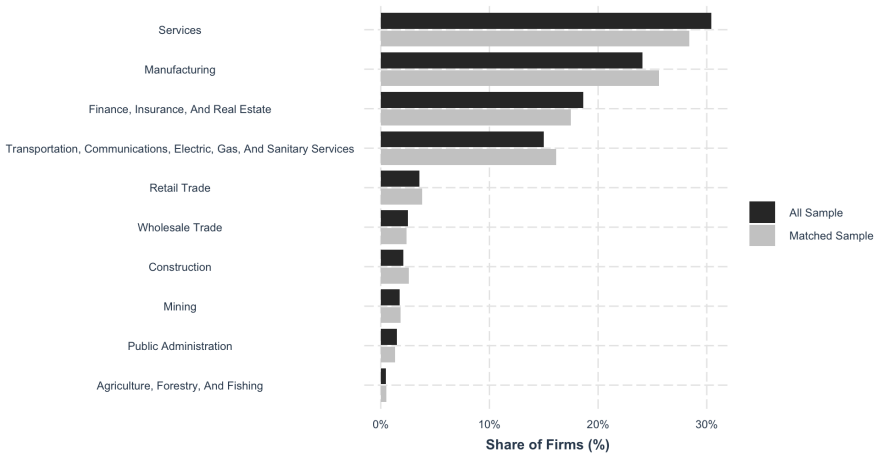

Figure A2: Share of firms by economic sector (1 digit SIC) in the original sample and in the matched sample

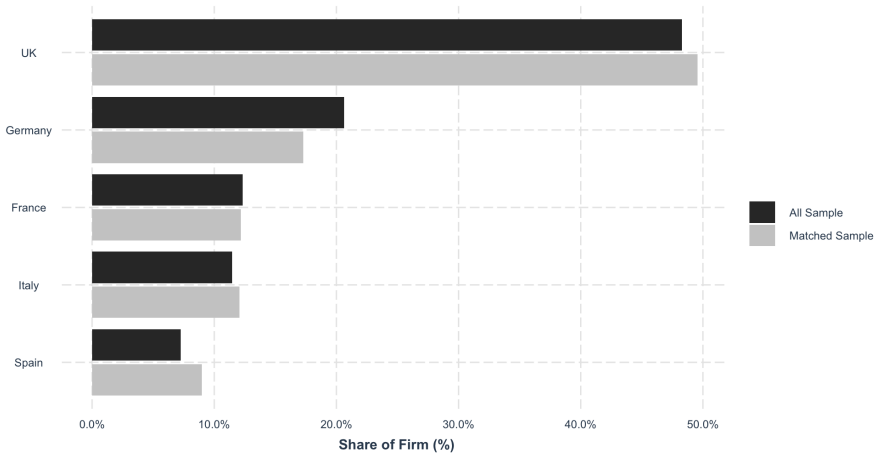

Figure A3: Share of firms by location country in the original sample and in the matched sample

A.2 Robustness check

Table A1: Panel Poisson Fixed Effect Regression models and reduced sample results

	$GTStock_{i,t+1}$					
	Poisson model				*ZINB model*	
	(1)	(2)	(3)	(4)	(5)	(6)
EPS	0.101**	0.032*	0.151***	0.053***	1.845***	1.818***
	(0.043)	(0.016)	(0.019)	(0.020)	(0.059)	(0.060)
Size	0.039	0.022	0.031*	0.016	0.333***	0.366***
	(0.053)	(0.016)	(0.017)	(0.017)	(0.005)	(0.006)
K Stock	0.975***	1.104***	1.005***	1.129***	0.750***	0.757***
	(0.089)	(0.031)	(0.031)	(0.033)	(0.005)	(0.005)
Degree		0.040***		0.040***		0.004***
		(0.003)		(0.003)		(0.001)
Transitivity		−0.093		−0.093		0.559***
		(0.089)		(0.089)		(0.028)
K Stock					−0.470***	−0.467***
					(0.024)	(0.024)
Size					−0.074***	−0.065***
					(0.018)	(0.018)
Constant					2.675***	2.521***
					(0.267)	(0.272)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	No
Sample	Full	Full	No UK	No UK	No UK	No UK
Observations	15,970	15,970	7,964	7,964	7,964	7,964
Log Likelihood	-2,430.289	-1,810.813	-1,613.785	-1,486.471	−12,667.140	−12,466.490

Notes: This table analyses the relationship between the environmental policy stringency and the green inventive performance from the 2005 to the 2011. The dependent variable is the firm' stock of green patents with a one-year lag between the dependent and the independent variables. Models in columns 1-4 are estimated by using Poisson regressions with firm and time fixed effects, while columns 5 and 6 refers to Zero-Inflated Negative Binomial estimations with industry and time fixed effects. The sample in Specification of models 3-6 exclude firms located in UK. Standard errors, reported in parentheses, are heteroskedastik-robuts. *p<0.1; **p<0.05; ***p<0.01