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GOING GREEN: ENVIRONMENTAL REGULATION, ECO-INNOVATION AND TECHNOLOGICAL ALLIANCES

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Going Green: Environmental Regulation, eco-innovation and 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 affect 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 2005-2012 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 determinant of the collaboration network and as outcome of firm 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. Main responsible of these phenomena are considered firms' production activities and polluting plants. Green technologies have been indicated by large body of literature as crucial to achieve the decoupling of firms' 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 main lever to stimulated 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).

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 Rio Gonzalez, 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 increasingly stringent environmental framework.

Based on the recombinant knowledge approach, we stress how the production of green technologies always involve 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 allow 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 2005-2012. 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 the 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 determinant of inter-firm network formation and as outcome of firm collaboration strategies. Our results suggest that when firms operating in highly stringent regulatory frameworks do not possess the required competences 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 this qualified collaborations and the structure of the local interactions that encourages firms to generate new green technological knowledge.

The rest of the paper is organized as follows. Section 2 elaborates the theoretical framework and spells out the main working hypotheses. Section 3 provides the description of data and measures. In Section 4 we explain our empirical strategy. Section 5 present 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 Rio Gonzalez, 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).

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 rms. 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 lead to mixed results (Costantini and Mazzanti, 2012; Rubashkina et al., 2015; Franco and Marin, 2017; Rexhauser 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 (Dechezlepretre 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 e orts 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 Rio Gonzalez, 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 competences allowing for effective processing of external knowledge sources.

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 e orts 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 e orts 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 e orts is likely to be mitigated by decreasing returns, above all when search is conducted in the neighbourhood of a firm's established technological competences. On the other hand, technological diversification is shaped by the cognitive proximity between firms' core competences 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; Dechezlepretre et al., 2014; Colombelli and Quatraro, 2017).

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. 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 o 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).

Yet, there is insufficient knowledge about how technological diversification for the generation of green technologies relies on forms of technological collaboration. Recent literature has 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., 2017). Other studies have instead focused on collaboration with the context of collaborative research promoted by public funding (Fabrizi et al., 2018).

Technological alliances represent an interesting case of technological collaboration that allow firms to access competences 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).

Based on the discussion carried in the Section, we are able now to spell our working hypothesis. 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.

One of the main channels through which environmental regulation achieve its objective is represented by the inducement mechanism. Regulation makes environmental degradation an important cost for polluting rms. These latter resort 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 mechanisms 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 e orts if they are already active.

Given the inherent complexity of green technologies, their generation is very often the outcome of 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 rm.

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 new entrant. Strategic technological alliances are therefore expected to drive the generation of green technological knowledge. Innovating firms are expected to prefer to establish link 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 and measures

3.1 Data and measures

Technological alliances. To study the evolution of the network of collaborations we constructed a new large dataset of European firms, over the period 2005-2011. The panel includes all the publicly reported alliances between firms located in France, Germany, Italy, Spain and United Kingdom in the period considered. Alliance data have been collected via SDC Platinum database,[1]including both joint ventures and strategic alliances agreements. The choice of studying the network structure represented by publicly reported partnership is guided by the importance of strategic alliances and joint ventures as a mechanism for sharing knowledge among a wide range of firms and industries, as confirmed by previous research (Powell et al., 1996; Gulati, 1998).

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 assumed that alliance relationships last for three years (Schilling and Phelps, 2007; Phelps, 2003), other instead used a ranging window up to five years (Gulati and Gargiulo, 1999; Stuart, 2000).

However, our six-years time window makes it reasonable to assume that alliances signed at the beginning of our sample last until the end, so we decided to adopt a conservative approach and not to set any termination date, to avoid bias due to arbitrary choices on alliances duration.

Firm-level data. The alliance database contains few information on individual firms engaged in alliances so it has been integrated with additional firm level data. Balance sheet information were gathered from the Bureau Van Dijk (BVD) AMADEUS database. In this phase, great efforts have been spent in matching firms involved in alliances, as reported by SDC Platinum, with its corresponding record in Amadeus. This procedure is a bit complex as names of firms may vary according to the dataset used, but, in this case, the SDC database had little information on

[1] 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.

firms other than their name and address. In other words, no unique identification code is available to directly match alliances data with external sources of information on those rms.

To minimize mistakes in the matching procedure, which has been built on the name of the firms and on their geographical location (disaggregated at their NUTS 3 level), first all the names were cleaned following the harmonization routines proposed by NBER Patent Data Project. The actual name's parsing has been performed using the utility *stnd_compname* of the Stata's package on record linkage (reclink). Given its flexibility, the utility allows to account for the specificity of different countries' name registration procedures and rules. This allowed us to standardize and clean firms names both in AMADEUS and in the alliances database. Secondly, we matched the two datasets by using, in Stata, a combination of the matching algorithm "matchit" as described in Raffo and Lhuillery (2009) and "reclink" package. Precisely, we employed a 2-gram matching algorithm, which represents an acceptable trade o between the desired precision rate and recall rate. For high score matches a visual screening of each link has been performed to check that no wrong matches were performed. Regarding low score matches, instead, records have been checked using OpenRefine.[2] Its intuitive matching visualization allowed us to reduce the false positives and increase the overall recall rate. In this way we have been able to assign as much BDV identification codes (*bvd_id*) as possible to firms in SDC Platinum. The resulting dataset includes 4408 firms (of which 3312 successfully matched with Amadeus) involved in 3561 alliances.

Green technologies and Environmental regulation. Patent data for each matched firm have been extracted from the OECD, REGPAT Database, March 2018, which collects all the patent applications led to the EPO and under the PCT (Patent Co-operation Treaty) from the 1977. Each patent is associated with at least one (or usually more) technological class indicating the subject to which the invention relates (IPC or CPC codes). Thus, patents are assigned to the environmental-related field by using the OECD ENV-TECH (Hascic and Migotto, 2015) classification which is based on the International Patent Classification (IPC) and Collaborative Patent Classification (CPC).

Finally, to investigate role and effect of the environmental policies we use the OECD Environmental Policy Stringency Index (EPS),[3] which measures yearly the stringency of the environmental policy for each country.

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[2] OpenRefine is a Google's powerful tool for working with messy data. See http://openrefine.org.

[3] 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 behavior. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). The index covers 28 OECD and 6 BRIICS countries for the period 1990-2012. It is based on the degree of stringency of 14 environmental policy instruments" (Botta and Kozluk, 2014).

Table 1 Collaboration patterns

		2005	2006	2007	2008	2009	2010	2011	2012
New participants		228	243	316	285	95	53	141	163
New alliances		148	170	216	191	79	39	97	119
Participants per alliance:									
	2	140	162	205	174	76	34	89	108
	3	7	2	9	14	2	5	7	8
	4	0	5	1	1	0	0	1	0
	5	0	1	0	2	1	0	0	3
	6	0	0	1	0	0	0	0	0
	7	1	0	0	0	0	0	0	0

3.2 Technological Alliances and Network Structural Properties

Table 1 provides an overview of the collaboration pattern in our sample. As it is evident the largest part of formal collaboration agreements from 2005 onward involve two members at most. The number of new alliances signed per year as well as the number of new members seems to drop substantially in the years immediately after the financial crises, recovering partially during the last years of our sample. Interestingly, this decreasing trend coincides with an increase in the use of Joint Ventures compared to Strategic Alliances, as can be seen in Figure 1. A possible explanation is that the negative shock led firms to prefer Joint Ventures as a form of collaboration because of the major protection to risks that such type of agreements provide.

An important advantage of our newly constructed database is that, considering the full range of economic activities, it allows us to specifically explore the patterns of collaboration within and between economic sectors. SDC data about industrial sector classification are available at the four-digit SIC level for each alliance. Figure 2 shows the yearly share of new alliances in each registered industrial sectors, aggregated in 10 macro categories according to the SIC division structure. Until 2009, the most prominent sector is Services accounting for about 40% of the new alliances, followed by Finance, Insurance and Real Estate, Manufacturing and Transportation, Communication and Energy related services, each accounting for about 20% of the total. This

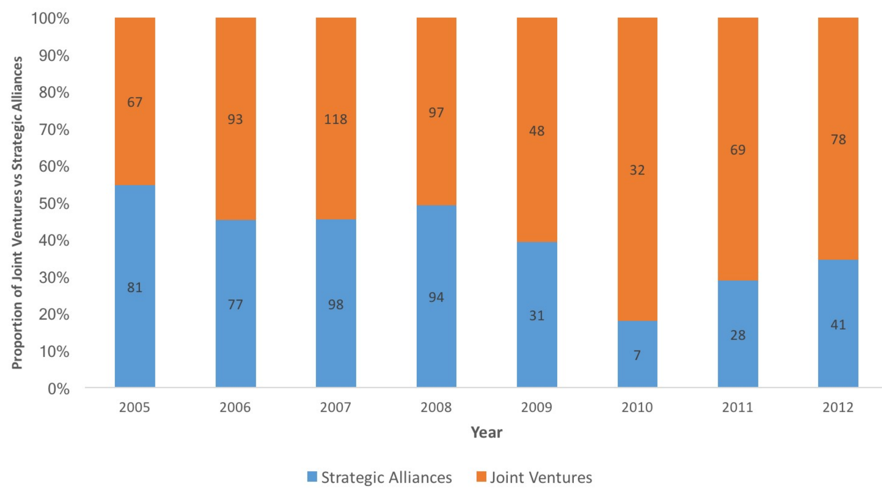


Figure 1 Share of Joint Ventures versus Strategic Alliances in new agreements

evidence is not surprising since sectors as Services or Manufacturing include technology intensive areas which make great use of partnerships to manage the increasing complexity in technology in their markets.[4] After the 2009 we observe a fall in share of Finance and Real Estate together with a substantial increase in the Manufacturing sector, becoming the predominant sector.

In Figure 3 we plot the alliances sectoral decomposition trying to disentangle the patterns of collaboration within and between economic sectors. The coloured strings departing from each subsection of the circles represent the partnerships among sectors in terms of new entrants. The width of the strings in proportional to the number of actors setting up alliances. The figure shows that the share of Manufacturing (D) is very similar to that of Services (H). However, although alliances tend to be greatly intra-sectoral, the majority of inter-sectoral partnerships involves the Services sectors. These alliances are then registered as belonging to Services, thus giving an explanation of the disparity seen in Figure 2, until the overtake of Manufacturing registered alliances in 2010.

Concerning the structure of the alliances network, Figure 4 illustrates the cumulative degree distribution of alliances in the years 2005, 2008, 2010 and 2012 on a logarithmic scale. The degree distributions are highly skewed. It represents a typical configuration of collaboration networks, i.e. the most of the actors in the network tend to have a very small number of connections, while very few organizations are the most active players, being involved in many alliances. In addition, when

[4] According to the SIC Information Technology activities are included in Services and Biotech and Pharmaceutical activities are part of the Manufacturing sector

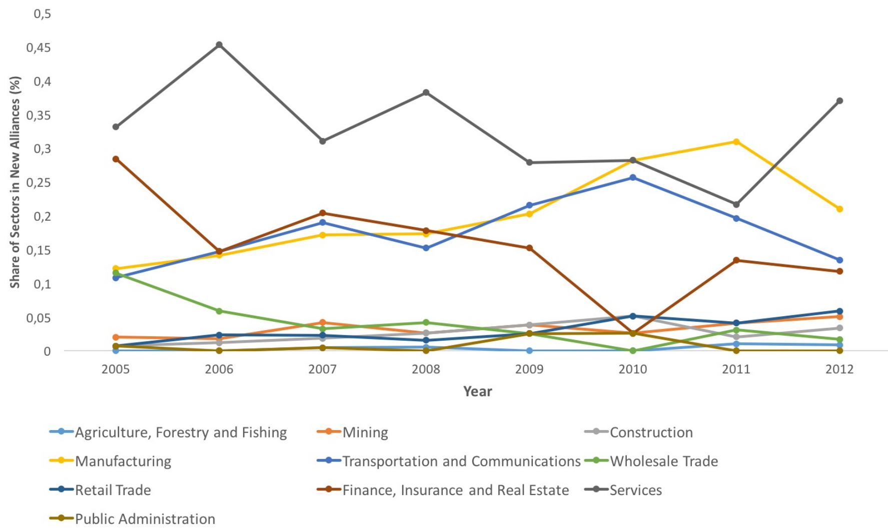
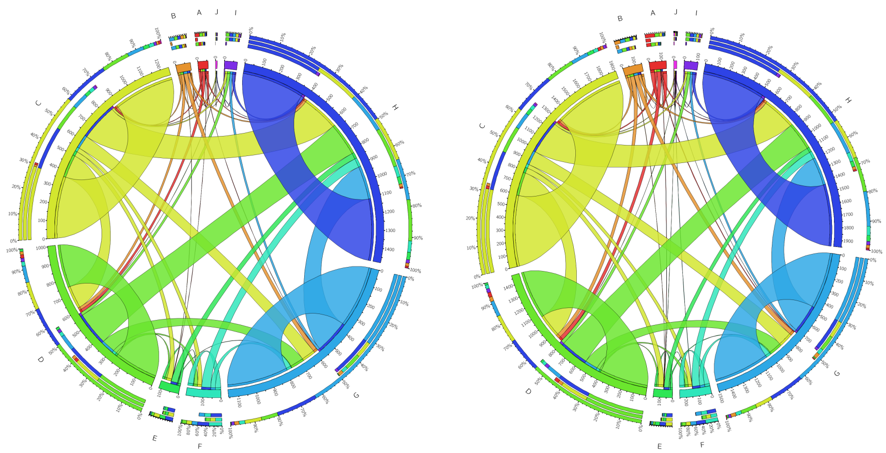


Figure 2 Registered Industrial Sector of New Signed Alliances

the degree distribution follows (asymptotically) a power law distribution, these structural characteristics is known as scale-free property (Barabasi and Albert, 1999). Scale free networks indicate a strong hierarchical nature in the relational structure and in fact many real-world networks are thought to be scale-free, including in particular: social network, collaboration networks, citation networks, knowledge networks etc. The most significant properties of scale-free network are: i) the presence of high-degree node called hubs and their correlation with the network robustness to failure; ii) a clustering coefficient which decreases as the node degree increases: iii) an average distance between nodes which is relatively small compared to highly ordered networks (as lattice graph). To claim that our inter-organizational alliance network is scale-free we tested the power law hypotheses on the degree distributions. The results of the test indicate that at 1% significance level we cannot reject the null hypotheses, stating that the degree distributions follow a power law distribution with an average exponent of 2,71. In fact, the red lines in the Figure 4 represents the t of the power law, con firming the power law hypotheses.

Table 2 further analyze the structure of alliances network. The density is very low, indicating that of all possible linkages among nodes less than 1% of them are actually present. "Sparsity" is a very common characteristic in collaboration networks, as usually establishing a connection comes at a cost and only valuable links are created and maintained this can be particularly true for strategic alliances and joint ventures given the amount of formal requirements needed. Interestingly, looking at the triadic level, we observe a general tendency of actors to link with the "friends of friend", i.e. inter-organizational alliances tend to occur, on average, between organizations that already have a



(a) 2005 (b) 2012

Figure 3 Patterns of collaboration within and between economic sectors on two temporal snapshots

alliance's partner in common, creating triangles of relationship. This feature is reflected by the level of the average clustering coefficient, which is higher than what we can expect from a random network structure with the same characteristics. On average the 25% 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), the descriptives indicates an high overall connectivity of the network so that, even if they organization are located in different geographic areas, they are still very close and strongly localized in few parts of the global structure.

Altogether, the structural description of the inter-organizational network shows that the structure itself contains a lot of information in terms of actors networking behaviour. Therefore, structural aspect should be taken into account in modelling the determinants of inter-organizational partnerships, as they may engender relevant feedback mechanism not clearly identifiable in static or nonnetwork approaches.

4. Empirical strategy

The empirical analysis is articulated in two steps. As a first step, we empirically test the existence of a relationship between the stringency of environmental regulation, and the generation of Green Technologies. In the second step, building on the importance of the network structural properties highlighted above, we employ a dynamic network analysis model to explore the dual

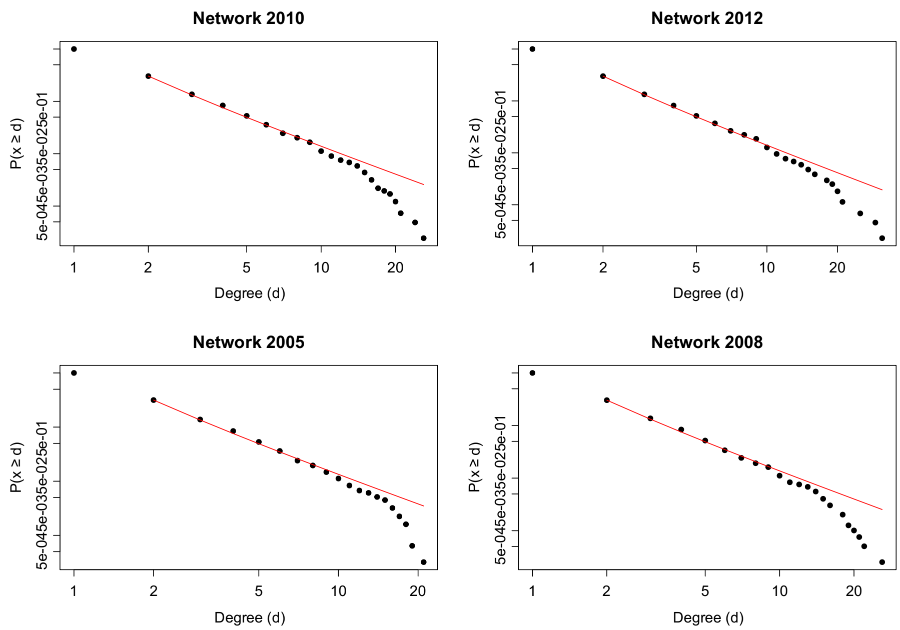


Figure 4 Log-log degree distribution of four temporal snapshots

role of GTs both as determinant of the collaboration network and as 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 Standard count-data model

Following existing 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 the stock of green patents ($GTStock_{i,t}$) of firm *i* at time *t*. The use of a patent stock, instead of its ow, allow 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; Dechezlepretre et al., 2015): starting from 1977, the green

Table 2 Network Structural Descriptive Statistics

Year	N. of nodes	N. of 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
2012	4408	3832	1.7387	0.2202	7.3628	0.0004

patent stock at time t is given by the net amount of patents in t plus the depreciated green patent stock at time $t-1$.[5]

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 we include in the estimation a number of controls. First, we control for firms-specific innovative capabilities by including the stock of patents calculated over the total number of patents, both green and non-green ($KStock_{i,t}$). Secondly, we control for firm profitability measures ($Pr_{i,t}$), as they may affect firm propensity to introduce new GTs. In particular, we include: the profits/losses before interest and taxes (*PLBT*), which measures the level of earnings after paying operating expenses, but before paying income taxes and interest on debt; the return on equity (*ROE*), which calculates the financial performance of a company by dividing net income by shareholders' equity; the value of assets (*Asset*). We also control for firms networking behaviour ($Net_{i,t}$) by including the network degree (*Degree*) of each firm (i.e. number of active technology alliances), and a measure local network centrality which we proxy with the 'network local efficiency' index (*Efficiency*).[6] Lastly, to account for the general patenting propensity of specific sectors we include a dummy ($HT_{i,t}$) taking value 1 if the firm operates in Manufacturing or Services sector, 0 otherwise.

[5] We choose to depreciate the patent stock by applying an obsolescence rate of 15% (Keller, 2002)

[6] The Local efficiency of a node i characterizes how well information is exchanged by its neighbors when the node itself is removed. Saying it differently, it measures to what extent the network positions of a firm is crucial to the connectivity of its partners. The average efficiency of a network G is given by: $E(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d(i,j)}$, where $d(i,j)$ defines the length of the shortest path between node i and node j. Then local efficiency is defined as: $E_{loc}(G) = \frac{1}{n} \sum_{i \in G} E(G_i)$ where G_i is the local subgraph consisting only of a node i's immediate neighbors, but not the node i itself.

Therefore, we estimate the following equation:

$$GTStock_{i,t} = \beta_0 + \beta_1 KStock_{i,t-1} + \beta_2 EPS_{i,t-1} + \beta_3 HT_{i,t-1} + \\ + \gamma Pr_{i,t-1} + \delta Net_{i,t-1} + \theta_t + \epsilon_{i,t} \qquad (1)$$

where all independent variables have been lagged by one year (we also present results with a two-year lag). The model includes year effects, and standard errors are clustered at the firm level to account for firm-specific effects. The estimation is performed through a zero-inflated negative binomial regression (ZINB). The ZINB model is the most appropriate when dealing with a dependent variable in which there is a high number of zeros as it is the case when using green patents. ZINB models allow to account for two different processes that may generate a zero in the dependent variables by estimating simultaneously two equations, a binary logistic (inflation part) and negative binomial. In our case, there may be firms which are actively patenting but not in GTs (referred as true zeros) while some others may have not been patenting at all (referred as certain zeros). Therefore, to distinguish between these two processes the inflation part is estimated via a probit equation based on firms stock of total patents ($KStock_{i,t}$) and firms level of assets ($Asset_{i,t}$).

4.2 Modelling network dynamics: SIENA model

From a methodological point of view, we need a network analysis instrument that can empirically capture the dynamic nature of economic and social relationships between actors. 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. However, recently have been developed statistical network models 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. In fact, it is possible to include numerous different sets of network dynamics "tendencies", such as structural endogenous network effects, individual characteristics, behaviour of actors and other relevant variables. The model, then, should give a good representation of the stochastic dependence between creating or maintaining different network ties. It also provides a means to test hypotheses about effects and it estimates the parameters expressing the ways, the extent and the strength with which these factors are associated with network evolution between observations.

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

A very strength point of SAOM is represented by its flexibility and extension possibilities. SAOM allows to develop a "selection and influence stochastic model" where the dependent variables consist in both the network i.e. the tie variable and the relevant actor's behaviour variable. Hence, the two processes are estimated simultaneously, controlling one effect for the other. In this paper we employ a SAOM model in the selection and influence version, where the network dynamics are represented by the technological alliances between firms and the behaviour is represented by the generation of new green technologies.

Model functioning. SAOM models are, technically, continuous-time Markov chain models, in which changes in the network are modelled 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 assume that the network is observed at discrete point in time (as determined by the observed data) but these observed changes are the results of a sequence of unobserved changes. Here "changes" refer to network as well as behaviour evolution, in such a way that at time $t+1$ the probabilities of change in both depend on the combination of network structure and behaviour variables in t.

At each micro-step one actor get the opportunity to change one tie variable or alternatively the opportunity to change his behaviour. The frequency of opportunity to change is determined by two independent rate functions one for network and one for behaviour with the same functional form. Waiting time is modelled according to two exponentially distributed variables, with parameter λ_i^{net} and λ_i^{beh}. In this way, the probability that the next micro-step of actor i is a network one is given by $\lambda_i^{net}/\lambda_{tot}$, likewise, in the case of a behaviour micro-step is given by $\lambda^{beh}{}_i/\lambda_{tot}$; where λ_{tot} is the sum of the two independent parameters over all the actors.

In the co-evolution model, the probabilities of changes are modelled by two separate objective functions, one for the network and one for the behaviour. Although the structure and the interpretation of the functions is equivalent, the behaviour objective function will differ from that of the network in term of parameters. This because the behaviour objective function may depend on a different set of micro-mechanisms (incentives and restrictions), as it needs to express actor's behaviour and not networking actions. Like for network dependent variables, the model implies that changes in the dependent behaviour variable depend on the endogenous evolution of the behaviour itself (to capture the influence process) both for the focal actor and its network neighbours, on network structural effects and on a set of individual (or dyadic) attributes. The mutual dependence between network dynamics and behaviour dynamics is generated by the changes in the network and in the behaviour which, controlled for each other, both influence the dynamics of the structure and of the behaviour.

Model Specification We develop a stochastic actor-oriented model in the selection and influence version, where the network dynamics are represented by the technological alliances between firms and the behaviour is represented by the generation of new green technologies. The network consists of non-directed links, so we decided to model the creation of ties by the "unilateral initiative and reciprocal confirmation model", which seem to be the most reasonable for collaboration networks among the different types provided by SIENA for nondirected network. Basically, in this type of model "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)

The model requires the specification of two distinct objective functions. For both, we consider two main sets of drivers: i) endogenous structural variables; ii) Dyadic and individual non-structural control variables.

Concerning the network objective function, the first structural effects is related to the tendency of network actors to cluster. Transitivity is included to account for the observed network triadic closure. Although there exist several ways in which transitivity can be measure, we use the most common one, simply based on counting the number of times an actor *i* has a tie with two partners which are 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 skeweness in the degree distribution, capturing the tendency of actors with a large number of partners with respect to the average to attract even more partners. We measure preferential attachment by including the sum of the degrees of the others to whom an actor *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 policy at the country level. As already mentioned, the stock of green patents (*GTStock*) is employed both in the role of explanatory variable, to investigate the role of firm knowledge competence in the green domain on the dynamics of networking activity (partner selection process), and as the dependent variable to capture the relative importance of the network and peers innovative behaviour on the propensity to develop new green technologies (influence process). We also include the stock of total patent applications (*KStock*) to evaluate how firms innovative performances affects their networking behaviour. The stock variables are calculated using the permanent inventory method, as explained in Section 4.1

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 effect on alliances formation of being co-located in the same country (*Countryproximity*), and in the same NUTS II region (*Regionproximity*). 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 (*Sectorproximity*) or sub-sector (*Subsectorproximity*) based respectively on the SIC code at 1-digit and 2-digits. Lastly, institutional proximity is included to capture the extent to which a similar institutional background, that may reduce uncertainty and transactions cost, favours the formation of new technological alliances. Thus, we generate a dummy taking value 1 when two firms have the same public institutional status and 0 otherwise.

To control for the heterogeneity of firm in their capacity to start formal partnership, we include a third set of controls based on their balance sheet information. *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.[7]. We also include two measures of firm profitability: the similarity in the Return on Equity rate (*ROEsimilarity*) and in the Profits and Losses Before Interests and Taxes (*PLBTsimilarity*).

The second objective function models the drivers of firms patenting activity in GTs as a function of endogenous network changes, firm-specific characteristics and the environmental regulation. To be consistent with the previous econometric estimation the specification of the objective function roughly follows a KPF approach as in equation 1. Similarly to the network objective function, two main sets of drivers can be identified. Our key variable of interest is the stringency of the environmental regulation (*EPS*). Among the other individual non-structural variables, we include the firm total patents stock (*KStock*) and three profitability measures as described above: firms size, pro t before taxes and the return on equity. Further, to capture the effects of endogenous network dynamics we include the number of technological alliances for each

[7] We proxy firm size by calculating the mean value of their assets over the period 2005-2012

firm (*Degree*) and the average level of GTs patents stock of firms alliances partners (*PartnersGT*). The model requires the behaviour dependent variable to be a binary 0-1 variable or must have a maximum of 10 non-negative increasing integer values (Ripley et al., 2011). Therefore, we transform the patents stock of GTs for each firm into a categorical variable based on a 1 to 10 ordinal interval scale. Thus, higher values of this variable are associated with higher levels of GTs innovative capabilities.

5. Results

In this section we present our main empirical results.

5.1 Standard count-data models

Table 3 reports the estimates of equation 1 on the effect of a stringent regulatory framework on the generation of new GTs at the firm level. Columns 1 and 2 refer to a 1-year lag structure, while in columns 3 and 4 all the explanatory variables have been lagged by two years. Models in columns 1 and 3 includes all the controls excluding the network variables. The latter are then added gradually in model 2 and 4. All models includes year dummies and are estimated with ZINB regressions. Standard errors are clustered at the firm level to control for possible spatial correlation across rms.

Results show a positive and significant impact of the stringency of environmental policy on firm innovative capacity in both lag structures. The magnitude of the coefficients is slightly higher when considering a longer lag structure. This con firm our hypothesis, according to which the presence of stringent environmental regulation engenders an inducement effect that stimulates firm to introduce innovations that allow for the improvement of the environmental impact of production processes. Concerning the firm profitability controls, results show that the level of profits is positively associated with patenting in GTs, while the coefficient for the Return on Equity is negative and significant. As expected, the coefficient for the High Tech sectors is strongly positive and significant, suggesting that firm operating in these sectors show higher capability of patenting in GTs. These coefficients are stable across all models. As for the network controls in column 2 and 4, we find a positive and significant coefficient for the firm network degree, i.e. ceteris paribus, highly connected firm in terms of alliances and collaboration show better innovative performances in GTs. Instead, the firm network local efficiency does not seem to play a significant role.

5.2 Siena Model

Results of the estimated SIENA model are presented in Table 4. All parameters 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

Table 3 ZINB Regression results of environmental policy stringency on the generation of GTs

	(1)	(2)	(3)	(4)
	1-year lag		2-years lag	
EPS	0.988*	0.952*	1.099*	1.248**
	(0.547)	(0.573)	(0.583)	(0.563)
PLBT	0.370***	0.319***	0.382***	0.345***
	(0.102)	(0.091)	(0.112)	(0.098)
ROE	-0.336**	-0.401***	-0.365**	-0.441***
	(0.134)	(0.132)	(0.144)	(0.134)
HT	1.876***	1.305***	1.845***	1.121***
	(0.412)	(0.387)	(0.433)	(0.402)
Degree		0.208***		0.200***
		(0.048)		(0.044)
Efficiency		1.405		1.924
		(1.587)		(1.642)
inflate				
KStock	-1.816***	-1.911	-1.685***	-1.876*
	(0.610)	(1.187)	(0.463)	(1.108)
Asset	-0.253**	-0.330**	-0.260***	-0.359**
	(0.099)	(0.154)	(0.090)	(0.172)
Year Effects	Yes	Yes	Yes	Yes
N	15612	13276	14288	12144
Log likelihood	-3916.121	-3091.486	-3431.274	-2614.908

Dep. var.: Green Patents Stock. Robust standard errors in parentheses, clustered at firm level.
$^{*} p < .1$, $^{**} p < .05$, $^{***} p < .01$

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 coefficient 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, coefficient of the behaviour dynamics indicates 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 reports the effects of the endogenous network variables. The positive and significant coefficient for transitivity shows that there is a strong tendency of firms to form new alliances with firms who are already partner of one of their 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 framework 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 on the collaboration dynamics. We find, in fact, negative and significant coefficients for the green patent stock and total patent stock (row 4 and 5). Firms with a poor knowledge base and less experience in developing green technologies, have a higher tendency to start formal relationship with firm showing higher innovative competences and a strong GTs knowledge base.

With respect to 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 firm operating in same sector and sub-sector of activity as well as with those located in the same country, while regional proximity plays only a marginal role. Lastly, rows 11-14 refers to the coefficient 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 significant. Further, firm are more likely to search for alliance partners with high and similar level 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 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 firm 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 alliances 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 have strong competences in GTs are more likely to introduce new GTs. Therefore, firms seem to benefit from the successful innovative behaviour of their close

Table 4 Siena Model Results

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

All convergence t ratios < 0.04. Overall maximum convergence ratio 0.13.
*p<0.05; **p<0.01; ***p<0.001

connections. Rows 7-9 report the estimated coefficient for size and profitability effect. Large firms are more likely to be successful, while we find a not significant effect for the PLBT and ROE.

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 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 2005-2012. 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.

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 the environmental regulation and the generation of green technological knowledge at the firm level. Also, we found evidence that firms external knowledge sourcing, channelled 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 pre-existing 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 con firms 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 problem, 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 with another result of our empirical model. That is, firms are more likely 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 in 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 makes 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, the environmental regulation does not directly impact on the likelihood of firm 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 competences to manage internally complex and diversified technologies such as GTs, they may turn to external knowledge sources. Then, it is the nature of new qualified collaborations and the structure of the local interactions that encourages firms to generate new green technological knowledge.

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