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Firm Specialisation in Clean Energy Technologies: the Influence of Path Dependence and Technological Diversification

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Firm specialisation in clean energy technologies: the influence of path dependence and technological diversification

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Abstrac
We introduce two changes with respect to the substantial literature dealing with the determinants of firms' clean energy innovations. First, we consider, not the firms' performance in clean innovations, but the firms' specialisation in these new technologies, through the index of revealed technological advantages. Secondly, we test the effects of variable path dependence (the past level of specialisation) and technological diversification. Our empirical analysis is based on a sample of 946 large global firms, which have a very high level of R&D expenditure. The results of the different estimations show that: 1) there is a path dependence effect, i.e. the past specialisation in clean energy technologies explains the current specialisation, 2) the path dependence effect is stronger in the frame of recency: the recent specialisation better explains the current specialisation than does the former specialisation, 3) the past technological diversification explains (but only weakly) the current specialisation in clean energy innovation. Otherwise, some determinants highlighted for firms' innovation performance also play a role, in particular the firms' knowledge capital in clean technology.

Key words: patent, Firm's specialisation, clean technology, path dependence, technological diversification, knowledge

Introduction: research question and contribution

The transition towards a clean technologies economy, allowing fossil fuel emissions to be reduced, is acknowledged to be a very important challenge for limiting the effects of global warming. Numerous studies have noted that *a real commitment by the private sector* to producing new clean energy

technology is needed (see among others Veugelers, 2012). This paper adopts this view by considering and explaining the level of large worldwide firms specialisation in the production of clean technologies aiming at triggering a drastic reduction in greenhouse gas emissions. Among the more relevant studies, there appears to be a consensus to consider that a high oil price tends to drive energy saving innovations (Popp, 2002; Hassler et al., 2012). In a very different vein, Aghion et al. (2016) show how carbon taxes could trigger clean innovations (meaning technology improvements that have a positive impact in terms of the decarbonated world) in the automobile sector. Acemoglu et al. (2012) suggest a slightly different insight; they support the idea of a combination of research subsidies and carbon taxes in order to *redirect technological change* towards much cleaner technologies. All these studies propose a mix of regulation and incentives to channel the technological change in order to trigger a transition towards a cleaner economy. These types of analysis drive us to consider that firms in the private sector have to modify their technological specialisation in favor of clean technologies. In this context specialisation is the phenomenon that is of crucial importance here.
With respect to the technological specialisation, the literature underlines that it is highly stable over time and highly differentiated according to the main products (Patel and Pavitt, 1995). Regarding the scale of firms' technological specialisation, two opposing trends appear in the literature (Breschi et al., 2003). One suggests that the firms *focus* their research on a small number of technologies, and tend to be rather specialised. On the other hand, authors claim that large firms are constantly engaged in opening up windows on new technologies (Granstrand et al.,1997), or investing in technologies that are complementary in terms of their knowledge base (Breschi et al., 2003). In other words, diversification is not marginal.

In this paper we do not discuss the underlying economic mechanisms behind the direction of technological change, but we rather want to highlight their implications in terms of the firms' knowledge base and specialisation drivers. We are particularly interested in one specific class of green innovations: those in the energy field dedicated to mitigating global warming and reducing GHG emissions (Veefkind et al., 2012). Consequently, along the lines of previous works (Laurens et al., 2016a; Laurens et al., 2016b) we define *clean* inventions or clean technologies (or clean tech) as coming under the umbrella of greentech inventions, and specifically those which contribute to the mitigation of global warming and reductions in GHG. In this paper we basically address clean inventions[1]. We have built a specific sample of large, global, mainly industrial firms, for which we

[1] Clean energy technologies could be considered as a particular set of technologies matching a technological paradigm. On this notion we draw on Dosi and Nelson (2010). A paradigm embodies a definition of the relevant problems to be addressed and the patterns of enquiry in order to find out solutions. Encompassing scientific and technological principles relevant to meeting those tasks, and the specific technologies employed it entails *specific patterns of solution to selected techno-economic problems.* Here in the case of clean technologies the search aims to mitigate global warming by decreasing the volume of GHG put in the air. De Stefano et al. (2016) provide rich empirical insights on the management of clean technology in the car industry.

follow the patenting activity as a measure of their inventive performance in the field of clean energy technologies[2].

The question of firm specialisation has gained the attention of scholars for a long time. But surprisingly we know little about the causes or the drivers of this process, however crucial in order to explain the firm technological and economic performance. There are two notable exceptions. For example, Malerba and Montobbio (2003) define international technological specialisation as the technological performance of a country in a specific technology relative to its overall international technological performance. In fact, they use RTA (Revealed Technological Advantages) as a measure of country specialisation for three industrial sectors (Chemicals, Electronics and Machinery). Two results merit particular attention. Specialisation is a persistent process, in other words, it is a path-dependent trend. Moreover, as a performant process it is affected by the direction of cross-sectoral knowledge spillovers within countries. On the other hand, Nesta and Dibiaggio (2002) argued that technological specialisation is a twofold process of knowledge accumulation and articulation of given scientific and technological disciplines. They conclude that the nature of technological specialisation in a specific industry changes over time. At the beginning of an industry, when a new technological paradigm emerges, firms tend to have narrow technological portfolios, while in the phase of maturity firms' technological portfolios become larger. It must be noted that, if many empirical studies deal with the determinants of firm innovative performance in clean technologies (for example among those that are more documented: Aghion et al., 2016; Laurens et al., 2016b; Stucki and Woerter, 2012), to the best of our knowledge we have no previous work on the drivers of firm specialisation in clean technologies.

We address this issue through the behavior of large global firms with regard to their innovative activity in clean technologies, measured by their patent applications.

The aim of the paper is twofold. First we extend the current literature by emphasizing new technological specialisation drivers and how they can work. Second we contribute to the literature on clean technologies in several ways. We suggest measuring the extent to which firms are involved in the production of clean technology through an index of *relative technological advantages* which we use for the first time in the context of firms. This approach can be considered as a specialisation approach, as opposed to an innovative performance approach, recently developed by the literature (see for example Aghion et al., 2016; Laurens et al., 2016b; Stucki and Woerter, 2012). We give more

According to Dosi and Nelson (2010) the main features of technological paradigms both provide a focus for efforts to advance a technology and channel them along distinct *technological trajectories* in the space of techno-economic characteristics of artifacts and production processes. Trajectories may be understood in terms of the progressive improvements in the supply responses to such potential demand requirements. Because the paradigm channels the progress and the search tend to improve the existing technological knowledge we stay in the frame of path-dependent adaptation

[2] Here we deal with *technological* innovation and do not address others kinds of innovation that could be important for firm environmental performance (Gilli et al., 2014, Mazzanti and Rizzo, 2017).

details on the indexes we use in this research in section 3 and appendix 1. We identify the main determinants of clean technology specialisation at the large firm level. In particular, we show the pivotal role of the path dependence process, mitigated by the level of firm technological diversification. Lastly, we contribute to organizational and strategy research by considering how stable the process of path dependence is, related to a particular set of technologies (clean, in fact) when technological diversification is dealt with as an independent variable.

We present our ideas as follows. In section 1 we identify our theoretical framework. Section 2 is dedicated to the formulation of our main hypotheses. Section 3 considers the dataset we have built, the main variables we have defined and the econometric strategy we have followed. Finally, in section 4, we present and comment the results.

Section 1. Theoretical framework

Our analytical approach has its origin at the crossroads of two important economic theoretical paradigms: the knowledge-based approach of the firm, and the Smithian tradition emphasising the importance of specialisation.

The starting point of the knowledge-based approach of the firm is the rich idea that the essence of the firm lies in its ability to create, transfer, assemble, integrate and exploit knowledge assets (Teece, 2000). This idea is shared by the evolutionary tradition through the notion of routines (Nelson and Winter, 1982) and the model of firm dynamic capabilities (Teece and Pisano, 1994). In this framework, innovation must be thought of as a process of knowledge creation with economic benefits. In that model, knowledge is a key resource for driving superior firm performance, as taught by the resource-based view of Barney (1991). Innovation is the result of a variety of activities, even if Research and Development and Design are often important determinants. On the other hand, learning is a generic term for delineating how individual agents and organisations accumulate bits of knowledge over time and behaviour. But the important point is that learning processes of different kinds play a major role in accumulating the competence that is necessary to generate new technological knowledge and to introduce innovations (Antonelli, 2011). Such a process is a path-dependent phenomenon. In the knowledge-based view of the firm, the tangible and intangible resources managed by organisations are mainly irreversible. Because the firms are localised in a limited section of the technological knowledge and competence space, they cannot innovate in many directions. In other words, their competences and their capacity for learning are technologically localised. This limits the global search of firms and constrains their search for new technologies in the proximity of techniques already in use (Antonelli, 2011). It explains the important property of technological path dependence, marked by strong irreversibilities and lock-ins. But the firms are not totally stuck in their context. Firms can change their trajectories as a result of their intentional actions.

The management of such a bifurcation is complex by nature and depends on several idiosyncratic elements captured in the economic context and geographical locations. In this respect, the vision of the firm matters (Swann and Gill, 1993).

The idea that specialisation produces an engine of firm performance goes back to the seminal analysis by Adam Smith on the division of labor: an increased specialisation in knowledge production leads to higher levels of performance in the production processes of goods and services (see among others Swann, 2009). The traditional competence-based approach took over this idea to a certain extent. It crucially underlines the fact that firms tend to build their competitive advantage by specializing their assets around core competencies (Prahalad and Hamel, 1990). Focusing their investment on a limited number of expertise fields reduces the range of the firms' technological knowledge. Specialisation has several advantages. Among these, and perhaps the more important, are the economies of scale associated with the learning process. Moreover, this facilitates the transfer of knowledge between the core technologies of the firm (Garcia-Vega, 2006). At last companies that focus their R&D in a small number of technological fields can profit from the specialisation of their research activities. It may be relevant to also consider the property of *local search* (Rosenkopf and Nerkar, 2001), meaning that firms focus their research projects close to their operative technologies (Nelson and Winter, 1982) as a particular attribute of specialisation.

On the basis of these principles, we assume that knowledge creation is considered to be a path-dependent evolutionary process in which learning and creative voluntary strategies are strongly involved (Nelson and Winter, 1982). There is path dependence because the acquisition of a certain type of knowledge facilitates the acquisition of further knowledge of the same type (Loasby, 1999). Much of the bulk of inventions produced in a particular time period involves the recombination of past bits of knowledge spread over time. Path dependence means that the current situation or the current equilibrium towards a process converging is due to a historical path followed by the economic system (David, 1997)[3]. Following the analysis by Arthur (1989), path dependence sets up a way of capturing an increasing return of adoption. Lock-in effects and self-reinforcing mechanisms set up important attributes of path dependence dynamics (Vergne and Durand, 2010; Cecere et al., 2014). As far as technology is concerned there exists in the literature a large range of explanations for this process. One of them, popularized by Dosi (1988), is related to technological channeling: the choice for solving technical problems is defined by the prevailing knowledge that restricts the possible technological

[3] As stated by Antonelli (2011): "Path dependence is the specific aspect of complex dynamics most apt to understand the process and the outcomes of the interactions among myopic agents embedded in their own context and constrained by their past decisions, yet endowed with creativity and able to generate new knowledge by means of both learning and intentional innovative strategies, as well as through structural changes". An important point deserving of attention is that a path-dependent process is not a pure picture of a past-dependent evolution.

combinations. But this lock-in effect (Arthur, 1989) may lead to an evolutionary process that converges towards inferior technological solutions.

In general empirical studies consider a simple model of path dependence in which the pivotal variable Y(t) is explained by Y(t-n) and other regressors (see for example Malerba and Montobbio, 2003). New insights related to *Path dependence* as an approach characterising organisational evolution have been recently suggested (see Cecere et al., 2014). For example, Vergne and Durand (2010) have noted that the impact of initial conditions is weak. Sydow et al., (2009) have conceptualised the emergent process of path dependence according to three distinct stages. Some authors, more critical towards the main properties of path dependence, have built new alternative approaches. For example, Garud et al. (2010) mentions the path creation in order to show that 'lock in" is a temporary stabilisation of the paths in the making. Analyses do not exclude the fact that the organisation breaks the path and fights the self-reinforcing mechanisms. For example, Sydow et al. (2009) have pointed out that the likely breaking of the path can vary in intensity and complexity. Without excluding complex cases, they promote the idea that the effective restoration of a situation of choice between diverse alternatives is possible. But breaking organisational paths seems to be easier than escaping a technological lock-in Sydow et al. (2009).

The necessary specialisation of the firm knowledge base does not exclude a certain level of technological diversification[4]. A firm is diversified in terms of technological activity when it masters several technological fields of knowledge more and less interdependently (Granstrand et al., 1997) as a prerequisite for production (Breschi et al., 2003). For Quintana-Garcia and Benavides-Velasco (2008), it can be defined as diversity in the knowledge system and principles underlying the nature of products and processes. The first advantage of technological diversification (often termed technological diversity) is related to cross-fertilization between different technologies mastered by firms (Granstrand, 1998). A large strand of the literature highlights that firms that are more technologically diversified can create (and maintain) competitive advantages. Specialisation and diversification must be seen as "the 2 faces of the same coin"[5]. Consequently, the technological diversification and the technological specialisation can evolve together[6]. According to Nelson (1959), firms diversifying their

[4] Regarding the technological diversification, it has been found that the larger corporations have the greater technological diversification (Chandler, 1990) and that firms tend to become more diversified over time (Granstrand et al., 1997).

[5] In this paper specialisation is the related opposition clean/not clean, by contrast diversification is defined by taking a large spectrum of technologies.

[6]One interesting idea would be that specialisation and diversification could be linked to the exploitation/exploration trade-off. Academics in Strategy and Organization Theory observed that dynamic capabilities are anchored in a firm's ability to both exploit and explore (March, 1991; Weick, 1969). This well-known trade-off, *exploitation and exploration*, sets up a general theoretical frame through which specialisation and diversification can, to some extent, be compatible (Benner and Tuschman, 2003). The basic assumption here is that when a firm specialises its technological activity it mainly follows an innovation trajectory that aims to exploit its accumulated knowledge. In contrast, if it diversifies its technological base it can perform exploratory innovations on a larger scale. As a consequence, specialisation and diversification, far from being opposed, are

technological competence are likely to benefit from greater new technological opportunities. Firms obtain a more diversified profit from spillovers generated by their R-D activities because they can capture the spillovers across technologies. They internalize the social benefits of their technological improvements. Finally, according to Garcia-Vega (2006), technologically diversified firms may invest more in R&D (also supported by Granstrand et al., 1997), because the diversification in their research portfolio tends to reduce the risks inherent in R&D projects. It is a well-known argument put forward in favor of diversified portfolios (Tirole, 1988). Having many advantages, technological diversification is often considered as a determinant of firm innovative performance and a driver firm growth (Granstrand et al., 1997; Cantwell et Piscitello, 2000).

In accordance with this later view, we consider that managing technological diversification establishes a *capacity to achieve technological bifurcations*. This means that the firm can follow (exploit) a new technological path because it has explored it before. In other words, technological diversification can prevent from a lock-in effect in a poor technological option, and can also create the conditions for "curbing" the specialisation path inherited from past decisions,

Path dependence and technological diversification have been two consistent themes across several approaches to research in technological performance. They are at the core of the framework we mobilize in this paper for explaining technological specialisation.

Section 2. Research Hypotheses

Path dependence is at the core of this paper. As a consequence we have to put forward hypotheses related to its effects. Following the empirical evidence gathered by Malherba and Montobbio (2003), the process of specialisation on a particular set of technological knowledge is path dependent. As a consequence, the first hypothesis related to clean technologies that we want to test is:

Hypothesis 1

The more a firm was specialised in clean technologies in the past, the higher its present level of specialization is.

The hypothesis is coherent with the idea that an economic agent is locked in a certain path (here of specialisation) created by the choices made in the past. In such a context a bifurcation is risky and costly (due the presence of switching costs). Consequently, the decision to stay on the same path is fully rational.

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two different ways to create new technologies. The two ways necessarily coexist, in particular within ambidextrous organizations. It remains exploitation may be related to functional inertia within a given technological trajectory, while exploration increases the firm's technological scope and responsiveness to new customer needs (Henderson et al, 1998).

Another aspect deserves special attention. The idea of path dependence means history matters. But nothing tells us if we have to go a long way back in the past, or only to very recent periods of time. Evidence from studies dealing with knowledge recombination may help us. The findings of the paper by Nerkar (2003) suggest that there is a balance in combining current knowledge with the knowledge available across large time spans to explain the impact of new knowledge. But recency is never the unique law of making new knowledge. Academics have contested the economic importance of *recent knowledge* for recombination and have proposed the idea that old (or less recent) pieces of knowledge matter as well (Adner and Snow, 2010; Capaldo et al., 2015)[7]. As a consequence, maturity may be important in many cases. For our study on path dependence we adopt the view the path followed in recent past time periods is important and could have more impact. As far as the issue of the time effect is concerned we assume that, to explain the current scale of technological specialisation, it is not the long period of specialisation that matters. In short, the current scale of technological specialisation is better explained by the level of firm specialisation expressed over a recent time period (to put it simply: recency matters). Because clean technologies are new at the very beginning of their development, it seems to us that the mechanisms envisaged by Nerkar (2003) play here in favor of recency. Evidence gathered at the nation level goes in the same direction (see for instance the work by Malerba and Montobbio, 2003). It follows:

Hypothesis 2

The recent level of firm past technological specialisation explains the present level better than that of a long period.

In the theoretical framework pictured in section 1, learning is a crucial phenomenon for firm technological performance. It pushes the firm's capacity for creating and maintaining sustainable advantages. Moreover, in the literature path dependence is mainly related to learning. Empirical insights on the path dependence of environmental innovation are now available at the national level (Popp, 2002; Popp et al., 2011), at the industry level (Stucki and Woerter 2012; Crespi et al., 2016), about a single industry (Aghion et al., 2016), or for a large set of MNCs (Laurens et al., 2016b). These studies indicate that there is a robust positive association between the (past) knowledge-accumulated capital related to clean technologies and the number of inventions produced in that field, even after controlling for industry and national fixed effects and other factors. The magnitudes of the coefficients are very similar, while the data and the scale of the investigation are different. Path dependence is a little complex because firms accumulating large technological experience in other technologies (not clean) perform better in the production of clean inventions (see in particular: Aghion et al. 2016; Laurens et al., 2016b). This cross-technology learning effect, that is internal to the firm is, however,

[7] We can assume here that the type of technology matters for defining the relevant timing.

small in comparison to those related to learning effects within the same technology. To put it simply, intra-technology learning is found to be strong over time (evidenced in Laurens et al., 2016b).

In the framework of our research the phenomenon we want to explain is firm specialisation in clean technologies. Drawing on the quoted empirical studies we expect a positive association between the capital of knowledge accumulated in clean technologies and the current level of firm specialisation:

Hypothesis 3

The higher the past capacity of learning in clean technologies of the firm was, the greater its level of present clean technological specialisation is

The issue of diversification is crucial for our study because we want to track firms' capacity to switch their dominant technological knowledge base towards cleaner environmental trajectories. Recent empirical studies tend to support the idea that a diversified technology base positively affects firm innovative competence (Quintana-Garcia and Benavides-Velasco, 2008). In the same vein, on a panel of European R&D active companies, Garcia-Vega (2006) finds that both R&D intensity and patents increase with the degree of technological diversification of the firm. Interestingly, one advantage of technological diversity proposed by Granstrand et al. (1997) is that it increases the opportunities to engage in technology-related new business. From this finding we can hypothesize that a firm more diversified in terms of technological competence will be more prone to seize the opportunity to engage economic and competence resources in clean technologies. A strong specialisation in a particular technology does not exclude a more local diversification within this field or an "exotic" diversification far from the dominant technology (Suzuki and Kodama, 2004).

How to explain that technological diversification could have an impact on clean technologies specialisation? The firm's entire technological experience included in not clean technologies is not lost for clean energy technologies (evidence provided by Aghion et al., 2016; Laurens et al., 2016b). As a consequence, we test the hypothesis that past technological diversification enables firms to enhance their specialisation in clean technologies in the current time period. Here it is important to underline that a very high level of technological diversification can damage the balanced state between diversity and specialisation. In other words, after a certain threshold, more diversification does not entail more specialisation. In this context an inverted U-shape relationship should be expected (raised for example by Quintana-Garcia and Velasco (2008)). Due to the small number of studies dealing with the specialisation determinants it appears difficult to develop a definitive precise hypothesis on the *form* of the relationship between these parameters. As a consequence, we think that the best option is to test a realistic hypothesis:

Hypothesis 4

The higher the past firm technological diversification was, the greater its level of clean technological specialisation is

In the following sections, we test the different hypotheses implementing a cross section econometric model.

Section 3. Methods

In this section, we present the dataset, the variables, the econometric specification and estimator in turn.

3.1. Dataset

As in many previous studies, we use patent data as a proxy to follow inventive activities in the energy clean tech field (see Brunnermeir and Cohen, 2003; Nameroff et al.; 2004; Wagner; 2007, Albino et al., 2014; Popp, 2006). In order to have a complete overview of the R&D activities, to avoid geographical bias and to be as close as possible to the date and location of the inventions, as proposed for example by de Rassenfosse (2013), we follow inventive activities using the global priority patent applications filed worldwide, i.e. the very first patent applied for to protect a new invention, wherever it was filed.

We have first collected the priority patent applications filed between 1986 and 2005 by more than 2 000 worldwide firms with intensive R&D activities considering a consolidated perimeter of the firms. Then we have tagged among the overall patent portfolios, the patents related to energy clean tech using a classification available in the patent database (Patstat) .

The list of large industrial R&D performers was established by complementing the list of 2000 firms identified in the 2009 edition of the IPTS "Industrial R&D Investment Scoreboard", by top patent applicants from the WIPO, EPO and USPTO rankings. This produced a final list of 2300 firms. Then, relying on the Orbis database edited by Bureau van Dijk Electronic Publishing, we identified the subsidiaries included in the consolidated perimeter of these industrial groups (considering only subsidiaries in which one of the Global Ultimate Owners had more than 50.01% of the share). Corporations' boundaries are based on a single outline of subsidiaries established in 2008. We end with a list of more than 316,000 names (global firms' ultimate owners and subsidiaries).

After preliminary steps of name cleaning and name harmonizing the firm database and the patent database are matched together by looking for the names of the firms and their subsidiaries as potential applicant names in the Patstat database (containing more than 22 million applicants' names). After further final checking and manual cleaning of the results of of the database matching, we have ended up with a patent database of more than 8 million patents filled between 1986 and 2009 by 2,058 firms.

This includes approximately 9.5 million applicants and 19 million inventors. In order to focus on the largest and most R&D-intensive firms, we have then restricted our set of firms to 946 firms that have a sustained inventive activity and which filed at least five patents in the mid-1990s (between 1994 and 1996) and in the mid-2000s (between 2003 and 2005). These 946 firms are our set of top global R&D investors. They have set up our population of firms on which we have built our empirical analysis.

At last, we identify the priority patents related to energy cleantech inventions as the patents belonging to the Y02E class in the Patstat database. This classification is now widely adopted by researchers using cleantech patents (Bointner, 2014; Frankhauser 2013, Laurens et al., 2016a) and covers a broad range of clean energy technologies. It gathers inventive technologies in the field of energy that control, reduce or prevent greenhouse gas emissions of anthropogenic origin, as set out in the Kyoto Protocol[8]. In our final energy cleantech patent dataset, 68.2% of the patents are in the field of *"Technologies with a contribution to GHG emissions mitigation"* (this covers energy storage (batteries) (44.8%), fuel cells (17.1%), hydrogen technology (2.2%)), 18.4% relates to "*Renewable energy sources"* (including photovoltaic (13.3%), wind (1.8%), thermal solar (1%), hydro (2.1%), oceanic (0.7%) and geothermal (0.1%) energies), 3.4% are in "*Nuclear Energy"*, 2.6% in "*Technologies for the production of fuel of non-fossil origin"* (biofuel (0.7%), from waste (1.9%)), 2.6% in "*Combustion technologies with mitigation potential"* (Combined Heat and Power, …) and 2.6% in "*Technologies for efficient electrical power generation, transmission or distribution"*.

From 1986 to 2005, our set of firms applied for 99,773 Y02E priority patents. During the period 1994-1996, 1.62% (11 445 patents) of all our firms' patents belonged to the Y02E classification. This share grew to 2.30% (20 273 patents) in 2003-2005.[9]

3.2. Variables

Explained variable

We compute the index of relative specialisation of firms in clean energy tech as the ratio of their specialisation relative to the average specialisation of firms in clean energy tech (C for Clean energy) (see appendix 1 for details). In order to avoid the noise induced by instable patent filing, we decided to compute the index over a three years period, the 2003-2005 period. The specialisation of firm i in clean energy is then the share of clean energy tech C in the firm patent portfolio $S_{it} = {P_{it}^{C}}/{P_{it}}$ where P is the number of patents (clean or total) and t=2003-2005. In the same way, the average clean energy

[8] This classification was built using EPO experts, who first select technologies or applications that have the potential for the mitigation of, or adaptation to, climate change. They then define procedures to retrieve the relevant patents, relying both on existing classifications (ICP, ECLA) and a lexical analysis of abstracts or claims (EPO, 2010; Veefkind et al., 2012).

[9] Appendix 2 provides information on the sample composition.

specialisation C over the period is in our sample $\overline{S_t} = \sum_i P_{it}^C \Big/ \sum_i P_{it}$. The relative specialisation of firm i in clean energy is thus defined by $RS_{it} = S_{it} \big/ \overline{S_t}$ where RS_{it} is between 0 and ∞. We thus use the same transformation as in Laursen (1998), and we obtain a symmetric relative specialisation index: $SRS_{it} = (RS_{it} - 1) \big/ (RS_{it} + 1)$ that can vary between -1 and +1 and is computed over the 2003-2005 period.

Explanatory variables

The present technological specialisation (t=2003-2005) of the firms is explained by the firm past technological specialisation, the level of knowledge capital (the capacity of learning) and the knowledge diversification.

We use two complementary dimensions to understand how past technological specialisation impacts the present specialisation in clean energy technology inventive activities. We first consider the past specialisation of firms in clean energy technology fields. After SRS_{it}, we thus compute SRS_{it-1} where t-1 is the value of the variable related to the past time period. Two definitions will be however provided for this lagged variable. The index can be computed over the overall 1986-2002 period but also on sub-periods such as the recent 1994-2002 period.

Using the patent portfolio, we compute the 2002 stocks of inventions made over the 1986-2002 period in order to approximate the 2002 firm's capital of knowledge in the field of clean energy technology (C) or in all other technological fields except clean energy technologies (-C for technologies other than clean energy). The perpetual inventory is completed according to: $K^k_{it} = P^k_{it} + (1-\delta) K^k_{i,t-1}$ with k=C, -C. K is the stock of knowledge accumulated for year t that is approximated by the inventions filed in year t plus the depreciated stock of inventions filed before this. We use a standard knowledge depreciation rate, δ, which is 15%. K^k_{it} variable is taken in logarithm.

We define the variable related to diversification of technologies controlled by firm i over the 1986-2002 period as DIV_{it-1}, that is calculated as the inverse of the Herfindhal Index computed on the IPC shares of patents at the two-digit level (35 technology classes). DIV is the equivalent number: it is the number of technology fields, therefore including technologies other than cleantech, where a firm i is skilled if the importance of the different skills was equivalent[10]. Diversification can be squared to test if a concave relationship exists between specialisation and diversification. Too much variety can

[10] Diversification is linked but not collinear to specialisation: one firm can be highly or not specialised in green tech with a very low or very high number of invention fields.

indeed be a problem to master and be able to derive from it green tech inventions. In other words, as often considered in the literature the relation can be considered as concave.

At the firm level, we defined additional variables to control for sectoral fixed effects. Using the OECD classification of industries and services, we defined six different dummies based on industry R&D intensity: Low Tech, Medium Low Tech, Medium High Tech, High Tech, Knowledge intensive services (KIS) and Low Knowledge Intensive service (LKBIS=1) sectors (Eurostat). We further defined a set of industries in which energy is core and thus innovation around clean energy technologies is critical. The definitions of these variables are detailed in table 1.

Insert here table 1

To consider the differences among countries, we controlled for national heterogeneity, introducing national dummies or national variables. Differences in national market size and wealth are likely to influence the ability of firms to develop new technologies, particularly in the fields of clean energy technologies. The first dimension is proxied by GDP and the second by GDP per capita. In accordance with the large number of countries we have in our dataset, we cannot approximate the role of the various national policies in clean energy to the different affiliates over the period. We also introduced additional country variables dealing with environmental issues (See Laurens et al., 2016b). To control for this possible transnational policy effect, we defined a EU dummy that is set to 1 for countries belonging to the EU, and set to 0 otherwise, in order to assess the influence of home country policies on our multinationals.

3.3. Econometric strategy

Our cross-sectional model explains firms' relative specialisation in energy cleantech:

$$\mathrm{SRS}_{it}^{C} = \alpha_1\ \mathrm{SRS}_{it-1}^{C} + \alpha_2\ \mathrm{DIV}_{it-1} + \alpha_3\ K_{it-1}^{C} + \alpha_4\ K_{it-1}^{-C} + \sum \gamma Controls_t + \varepsilon_i$$

where the specialisation over the 2003-2005 period (t) is explained by the past specialisation in energy cleantech, the level of technological diversification and the stock of knowledge accumulated over the 1986-2002 period.

On our core variable, which is the impact of past specialisation, the first hypothesis H1 tells us that we expect $\alpha_1 > 0$. More precisely, when we differentiate the pace of specialisation, separating specialisation over the 1986-2002 period from the more recent specialisation index for 1994-2002, we expect that the impact of specialisation on present specialisation is higher for recent specialisation. In other words, that α_1 is significantly higher when SRS_{it-1}^{G} is defined over the 1994-2002 period than when it is defined over the 1986-2002 period. Finally, the scope (diversification) of technology is expected to be positively related to the subsequent specialisation (α_2 >0).

Firms are more likely to be able to specialise in clean energy technologies when their technological level (measured by their capital of knowledge a measure of the learning capacity) in that field is high (α_3 >0). The accumulated experience in other technologies (the capital of knowledge accumulated in those technologies) is however expected to hamper specialisation in new clean energy technologies (α_4 <0).

The explained variable, SRS is continuous and a standard OLS estimator is implemented in order to identify the parameters of interest (Model 1). Standard errors are robust standard errors. However, more than half of the firms in our sample have no patent in clean technology over the 2003-2005 period. Therefore, more than half of our sample has a 0 value for RS and thus a -1 SRS value observed. However, we can consider invention as a latent variable: many firms produce inventions in many fields and do not file them for different reasons. It means that the observed values for RS and SRS are not the true values for this category of firms that are actually specialised. In order to deal with the potential bias in the identification of the coefficients due to the censored data, we introduced a Tobit estimator. The results obtained with the OLS estimator are also provided.

The estimations in Model 2 and 3 aim to test H1 and H4. In Model 3 we used a variable for the square of DIV in order to check the existence of a U-shaped relationship related to this factor. The Model 4 aims testing H2 related to the larger impact of recency. Finally, with Model 5, we include a variable of interaction between green specialisation and technological diversification (DIV). Because we always put in the equations the variable related to the firm knowledge capital in clean technologies we consequently test H3. Our results are robust to many different specifications (available upon request). Further robustness checks were performed in line with Laurens et al. (2016b).Descriptive statistics are reported in Table 2. It shows that firms in our sample are on average have a relative specialisation of 1.35 (or SRC of -0.54) over the 1986-2002 period. Firms on average master about 6 different technological fields and are producing much more inventions in non-clean technologies than in clean technologies (what was expected). The stocks of patents are on average obviously lower than 1 patent when Clean Energy is considered. 39% of firms did not file any patent over the 1986-2002 period. The sample is dominated by multinationals doing business in high tech and KIBS where energy is at stake in 15% of cases. Many firms’ headquarters belong to EU. An appendix 3 displays the matrix of correlation.

Insert here table 2

Section 4. Results

The results are given in Table 3. We begin by commenting on the impacts of our two main independent variables, specialisation and diversification (DIV).

The results for model 1 show there is a positive and significant association between past firm specialisation (over 1986-2002) and the current level of the firm specialisation index (2003-2005). There is a process of path dependence: past specialisation in clean energy technologies explains current specialisation. The results thus support our first hypothesis (H1). When we compute the specialisation variable to a more recent time period, the effect of the recent specialisation is found to be significantly higher than for the impact of a specialisation carried out on a longer period: the coefficient is indeed of 5% for 1986-2002 to be compared to 8% for 1994-2002 ($t=40.7$, $p<0.01$). This suggests that the path dependence effect is stronger in the frame of recency: the recent specialisation explains the current specialisation more and better, supporting our second hypothesis (H2).

The (past) capital of knowledge accumulated in relation to clean technologies is found with a positive and significant influence on current SRC. Thus, when the stock of patents in clean technologies increases it is likely to increase the current (2003-2005) level of firm specialisation in this set of technologies. In contrast, the coefficient related to the (past) capital of knowledge in non-clean technologies is found without significant influence on the relative specialisation of firms in clean technologies. That supports our hypothesis H3.

Whenever firms having a strong, consistent history in non clean technologies can also innovate in clean technologies (see Aghion et al., 2016; Laurens et al., 2016b; Stucki and Woerter, 2012), they cannot build the base required to achieve a relative technological specialisation in clean energy technologies. Of course, this result is conditional on the definition of our specialisation indicator. Moreover, it is robust enough to consider our findings with a certain generality. Firms accumulating large technological experience in clean technologies are thus better placed to obtain a higher level of specialisation in clean technologies. Thus, the technology learning effect that is internal to the firm exists. In contrast, there is no positive effect of cross technology learning. Because the value of the coefficient for past specialisation is larger than for learning effects (for all models), past investment in clean knowledge activity “pays” less than an ancient specialisation in clean technologies.

Regarding the effects of our third independent variable of interest, firm technological diversification (over 1986-2002), it has a positive and significant effect ($p<0.05$) on firm specialisation. The result provides support for our H4 hypothesis that cannot be rejected. In accordance with our theoretical base on recombination theory the explanation may be the following: for producing clean minor inventions the firms need bits of knowledge coming from different technological fields, including in fields outside clean energy related fields.

The introduction of a second order term shows that there is no inverted U-shaped relationship for technological diversification as we have previously suggested. The introduction of a cross effect between past specialisation and past diversification does not bring much power to our model. The cross-effect is however found negative and significantly different from 0. The coefficient is different from 0 at 10% and multicollinearity problems hamper the proper identification of diversification parameters. A negative sign suggests that whereas the past diversification impacts positively the present relative specialisation in clean technologies, such variety may have a negative effect if the firm was already relatively specialised into clean energy fields.

With respect to the control variables, many results are consistent with what we expected on the basis of our previous work (Laurens et al., 2016b). The size of the country (GDP) does not play a significant role. National market size does not appear to be a lever for firms to produce new clean energy inventions[11]. As stated by Laurens et al. (2016b), large firms from small countries are likely to be more active than others. The variable related to the level of technological development[12] (GDP per capita) is negative and significant except for Model 1. As a consequence, it is difficult to claim that the technological level of the country would have a positive impact on a firm's clean invention specialisation. The opposite seems more relevant: firms from less technologically developed countries tend to specialise their knowledge base in clean energy fields. This last finding was also supported by Laurens et al. (2016b), when dealing with large firm innovative *performance* in clean inventions (versus specialisation here).

An EU dummy was not found to be influential on clean energy technologies. This result might suggest that EU policies and regulations do not help firms to develop specialised clean technologies.[13]. Other dummy variables aimed to assess the role of technological opportunities approximated by industry fixed effects. Two important features deserve attention here. Industry fixed effects are not found to be significant and are thus not introduced in our basic models. As expected, the energy sector dummy has a significant positive effect on specialisation in clean technologies, compared to others. It is within this sector that the firms are more specialised.

Insert here table 3

[11] This result is opposed to the idea supported by Acemoglu (2002) according to which the size of the market is important for directing technical change.
[12] Or economic development, in short.
[13] At this stage it is important to recall that we address clean energy technologies specialisation just after the Kyoto Protocol, over the time period 2003-2005.

Conclusion

We work on a sample of 946 large global firms having a very high level of R&D expenditures. We can summarise our main findings as follows as far as firm specialisation in clean technologies is concerned:

- There is a process of path dependence: past greentech specialisation in clean energy technologies explains current greentech specialisation (Hypothesis 1)
- The path dependence effect is stronger in the frame of recency: recent greentech specialisation explains the current greentech specialisation more and better (Hypothesis 2)
- The firm capital of knowledge in clean technologies is a determinant of the firm specialisation in that area. (Hypothesis 3).
- The past technological diversification significantly explains current the greentech specialisation (Hypothesis 4).

Our model presents two significant improvements with respect to the literature that aims to better understand firm behaviour in clean energy inventions. First, we take firm level *specialisation* as a main phenomenon to be explained, and not firm *performance*, as is usually the case[14]. Second, as far as determinants are concerned, in our empirical models we consider both path dependence[15] *and* firm technological diversification. Often only the first is envisaged as a powerful driver of firm innovation performance in a particular field (see Aghion et al., 2016). To the best of our knowledge, technological diversification (an index of technological variety) is never considered as a relevant driver. Our findings highlight the fact that large firms' technological accumulation in clean energy (through their knowledge capital in clean technologies) sets up another channel for path dependence. This effect is correlated to internal learning. It means it is easier (and without doubt less costly) for a firm to develop innovations through its knowledge base in clean energy technologies. In contrast, the knowledge base accumulated in other technologies has a negative impact on firm clean energy inventions specialisation.

Thereby we show that there is a path dependence effect in innovation production. A weak specialisation in clean energy technologies in the past entails a weak current specialisation. In other words, there is considerable inertia in innovation production that hampers the quick shift towards a cleaner system of energy. But our study underlines another point that is not seen in previous research on this topic: the path dependence effect is stronger in the frame of recency. This last point has obvious implications in terms of public environmental policy. If public policy tools succeed in

[14] It remains true to some extent that specialisation is also an index of relative performance.
[15] It must be noted that path dependence is a very general phenomenon that we can apply to a large number of variables.

orientating current research towards clean energy innovation, this will able to mitigate the lock-in effect due to path dependence more quickly. And in any event, more rapidly than in a context marked by a long time period path dependence effect[16]. This is good news because it offers more effective effects on public policy. Our research enables a not so obvious finding to emerge: the more diversified a firm is in terms of a technological base in the past, the higher its level of specialisation in clean technology in the current period of time. As a consequence, technological diversification may constitute another potential lever for a public policy strategy aimed at a reorientation in favour of clean energy.

In this paper we addressed the behaviour of *large firms* in terms of clean energy. On the other hand, as a likely extension, we can calculate our main dependent variable that is related to specialisation for *each country*. This presents two main interests. First, we will able to update the work by Malerba and Montobbio (2003) that has already shown a trend of path dependence for technological specialisation[17], then, we could also examine the two-way relationships between national (country) specialisation and large firm specialisation. Our empirical findings provide a basis for further research into the design of new types of management related to clean energy innovation performance and specialisation. In this perspective, a focus on empirical work on firms from energy sectors could be a serious line of enquiry for improvements.

[16] We note that is not true for new small firms that have no past in technology.

[17] They find that the concentration of innovative activities, the emergence of new innovators and technological cooperation positively affect international technological specialisation.

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Appendix 1. Measurement issues

We measure the firm technological specialisation drawing on Laurens et al. (2016a). This analysis enables us to measure both the clean technology specialisation and the clean technology performance.

Let us use i= 1, 2, 3….n to index firms. We formally consider the firm patenting at time t as:

P_i (t) = total number of new patents of firm i at time t
$P^c{}_i$ (t) = number of new patents of firm i in energy green technologies

$P^c{}_i$ (t) is the measure of firm performance in green.
We measure the share of green patents in firm i patent portfolio as:

$$S_{ij}(t) = P^c{}_i(t) / P_i(t) \qquad (1)$$

In other terms S_i (t) is the firm i contribution to energy green technology at time period t. It is an alternative measure for firm green technologies performance.

The index of relative specialisation in energy green technologies is defined for firm and the time period t as:

$$G_i(t) = S_i(t) / (\Sigma\ \Sigma_i\ P^c{}_i(t) / \Sigma\ \Sigma_i\ P_i(t)) \qquad (2)$$

where $\Sigma\ \Sigma_i\ P^c{}_i$ (t) indicates all energy green patents in our dataset (for time t) and $\Sigma\ \Sigma_i\ P_i$ (t) the overall set of patents (whatever the technological field and for the overall number of firms) for time t.
G_i (t) is the index we use as a measure a firm specialization in energy green technologies.

Appendix 2. The sample of firms and patents

Table 4:. Distribution of firms, clean inventions and patenting, by firm country (2003-2005)

Firm country	Firm share (%)	Share of clean patents (%)	Share of all patents (%)
North America	35.2	6.0	11.8
United States	34.0	5.7	11.5
Europe	36.9	6.9	10.2
Germany	9.2	3.9	5.9
United Kingdom	6.2	0.2	0.5
France	5.3	1.8	1.6
Italy	1.2	0.1	0.1
Small countries *	7.2	0.6	1.0
Nordic countries **	6.4	0.3	1.0
Asia	27.3	87.1	77.9
Japan	23.2	83.1	62.0
Korea	1.5	3.4	13.7
World	100.0	100.0	100.0

*: Austria, Belgium, Netherlands, Switzerland

**: Denmark, Finland, Norway, Sweden

Table 5: Distribution of firms, clean inventions and patenting by industry (2003-2005)

Industrial sectors	Firm share (%)	Share of clean patents (%)	Share of all patents (%)
Industrial Goods & Services	28.4	28.7	27.3
Automobiles & Parts	9.9	26.2	14.8
Personal & Household Goods	7.0	13.2	14.5
Technology	17.8	11.1	24.0
Chemicals	9.4	9.8	10.3
Utilities	2.3	3.6	0.7
Basic Resources	2.9	2.6	2.0
Media	0.5	1.5	1.1
Construction & Materials	3.5	1.4	1.0
Oil & Gas	2.7	1.0	1.0
Telecommunications	1.3	0.6	1.8
Health Care	11.3	0.3	1.3
Banks	0.6	0.0	0.0
Retail	1.0	0.0	0.1
Financial Services	0.5	0.0	0.0
Insurance	0.1	0.0	0.0
Travel & Leisure	0.7	0.0	0.1
Total	100.0	100.0	100.0

Tables 4 and 5 show firms, total patents and clean energy patents distribution according to the location of the firm's global headquarters. In North America and Europe, the share of firms largely exceeds their share of patents, whereas the opposite is true for Asia (where one quarter of firms produces more than three quarters of the patents). This overwhelming contribution of Asian patents is largely the consequence of the institutional bias induced by counting priority patents. However, this does not prevent an unbiased comparison of the share of clean patents of a group of firms (from a given country or industry) with the share of the same group when considering all technologies. Two industries contribute to more than 50% of clean energy patenting, "Industrial goods & services" and "Automobiles & parts"[18].

[18] The strong commitment of car manufacturers to clean patenting is linked to the boom in patents in batteries and fuel cells since the late 1990s. These represent more than half the clean patents in our dataset.

Appendix 3. Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	$SRC_{1986\text{-}2002}$	1													
(2)	$SRC_{1994\text{-}2002}$	0.68*	1												
(3)	DIV	0.36*	0.39*	1											
(4)	Own Stock Clean Energy Patents	0.62*	0.77*	0.40*	1										
(5)	Own Stock Other tech Patents	0.35*	0.24*	0.22*	0.69*	1									
(6)	GDP (log)	-0.02	-0.03	0.01	0.07*	0.19*									
(7)	GDP per capita (log)	-0.07*	-0.03	-0.01	-0.03	-0.02	0.26*	1							
(8)	UE	-0.07*	-0.04	-0.01	-0.20*	-0.36*	-0.70*	0.04	1						
(9)	ML	0.06	0.04	0.08*	0.07*	0.06	-0.09*	-0.02	0.04	1					
(10)	MH	0.20*	0.15*	0.08*	0.18*	0.10*	-0.05	0.04	0.06	-0.17*	1				
(11)	HT	-0.23*	-0.20*	-0.21*	-0.14*	0.03	0.13*	-0.02	-0.19*	-0.19*	-0.45*	1			
(12)	KIS	0.06	0.05	0.12*	-0.07*	-0.10*	0.02	0.05	0.07*	-0.11*	-0.28*	-0.29*	1		
(13)	Non-KIS	-0.02	0.02	0.03	-0.01	-0.07*	-0.05	0.02	0.11*	-0.05	-0.13*	-0.14*	-0.08*	1	
(14)	Energy	0.23*	0.19*	0.05	0.17*	0.10*	-0.01	-0.10*	-0.01	0.01	0.25*	-0.29*	0.02	-0.05	1
(15)	No previous Clean Energy Patent (1986-2002)	-0.48*	-0.69*	-0.34*	-0.93*	-0.54*	-0.04	0.01	0.13*	-0.07*	-0.17*	0.13*	0.09*	-0.01	-0.13*

*: significant at 5%

Table 1 : Variable definitions

EXPLAINED VARIABLES	
$SRS_{2003\text{-}2005}$	Symmetric Relative Specialisation index computed on the 2003-2005 period (transformed)
EXPLANATORY VARIABLES	
*Firm level variables**	
SRS	Symmetric Relative Specialisation index computed on the 1986-2002 period, in logarithm.
$SRS_{1994\text{-}2002}$	Symmetric Relative Specialisation index computed on the 1994-2002 period, in logarithm.
DIV	Inverse of the Herfindahl index computed on IPC classification (35 classes).
Own stock Clean Energy Patents (log K^{C})	Stock of clean energy patents on the 1986-2002 period
No previous Clean Energy Patent	No clean energy patents on the 1986-2002 period
Own stock other tech Patents (log K^{-C})	Stock of other tech patents on the 1986-2002 period
Low Tech	151–159, 160, 171–177, 181–183, 191–193, 200–209, 210–219, 220–229, 361–366, 371, and 372 industries in the NACE classification (rev 1.1)
Medium-Low Tech	231–233, 251, 252, 261–268, 271–275, 281–287, and 351 industries in the NACE classification (rev 1).
Medium-High Tech	241–243, 245-247, 291–297, 311–316, 341–343, 352 and 354-355 industries in the NACE classification (rev 1)
High Tech	244, 300, 321–323, 331–335 and 353 industries from the NACE classification (rev 1)
KIB Services	40, 41, 61, 62, 64-67, 70-74, 80, 85 and 92 industries in the NACE classification (rev 1).
Non KIB Services	Services that are not classified in the 40, 41, 61, 62, 64-67, 70-74, 80, 85 and 92 industries in the NACE classification (rev 1).
Energy Sectors	Automobiles & parts, Electricity, Gas, water & multi-utilities, Industrial transportation , Oil & gas producers, Oil equipment, services & distribution, Commercial vehicles & trucks
National level variables	
EU country	Dummy is 1 for EU firms
GDP (log)	GDP level in US$ (in log) 2002
GDP per capita (log)	GDP level in US$ per capital (in log) 2002

When not specified, variables are computed on the 1986-2002 period.

Table 2: Descriptive statistics

	Mean	*Std. Dev.*	*Min*	*Max*
EXPLAINED VARIABLES				
$SRC_{2003\text{-}2005}$	-0.60	0.56	-1.00	0.95
EXPLANATORY VARIABLES				
SRC	-0.54	0.54	-1.00	0.99
DIV	5.89	3.68	1.17	21.49
Own Stock Clean Energy Patents (log K^C)	-1.73	4.50	-6.91	7.91
Own Stock Other Tech. Patents (log K^D)	5.56	1.82	1.66	11.41
GDP (log)	28.63	1.37	23.23	30.03
GDP per capital (log)	10.44	0.48	5.70	11.23
UE firm	0.37	0.48	0.00	1.00
Medium-Low Tech	0.06	0.24	0.00	1.00
Medium-High Tech	0.30	0.46	0.00	1.00
High Tech	0.32	0.47	0.00	1.00
KIB Services	0.15	0.36	0.00	1.00
Non KIB Services	0.04	0.19	0.00	1.00
Energy Sectors	0.15	0.36	0.00	1.00
No previous Clean Energy Patent (1986-2002)	0.39	0.49	0.00	1.00

Table 3: Econometric results

Models / Variables	(1) OLS	(2) Tobit	(3) Tobit	(4) Tobit	(5) Tobit
$SRC_{1986\text{-}2002}$	0.376***	0.047***	0.048***		0.077***
	(0.054)	(0.017)	(0.017)		(0.024)
$SRC_{1994\text{-}2002}$				0.078***	
				(0.016)	
DIV	0.007**	0.002**	0.005	0.003**	0.001
	(0.004)	(0.001)	(0.004)	(0.001)	(0.001)
DIVsquared			-0.0001		
			(0.0002)		
Specialisation x DIV					-0.003*
					(0.002)
Own Stock Clean Energy Patents (log K^C)	0.125***	0.028***	0.027***	0.016***	0.026***
	(0.015)	(0.006)	(0.006)	(0.006)	(0.006)
Own Stock Other tech Patents (log K^D)	-0.023	-0.003	-0.003	0.005	-0.001
	(0.015)	(0.006)	(0.006)	(0.005)	(0.006)
GDP (log)	-0.008	-0.005	-0.005	-0.005	-0.005
	(0.014)	(0.004)	(0.004)	(0.004)	(0.004)
GDP per capita (log)	-0.030	-0.011*	-0.012**	-0.012**	-0.010*
	(0.028)	(0.006)	(0.006)	(0.005)	(0.006)
UE	0.005	0.002	0.002	0.001	0.003
	(0.039)	(0.011)	(0.011)	(0.011)	(0.011)
ML	0.060	0.012	0.012	0.010	0.013
	(0.059)	(0.016)	(0.016)	(0.016)	(0.016)
MH	0.089**	0.023*	0.023*	0.025*	0.023*
	(0.041)	(0.013)	(0.013)	(0.013)	(0.013)
HT	-0.028	-0.002	-0.002	0.001	-0.002
	(0.041)	(0.013)	(0.013)	(0.013)	(0.013)
KIS	0.072	0.018	0.019	0.019	0.019
	(0.047)	(0.016)	(0.016)	(0.015)	(0.016)
Non-KIS	-0.043	-0.005	-0.005	0.001	-0.004
	(0.070)	(0.020)	(0.020)	(0.021)	(0.020)
Energy	0.096***	0.024**	0.024**	0.023**	0.023**
	(0.037)	(0.009)	(0.009)	(0.009)	(0.009)
H_0 : All coeff=0	88.77***	87.92***	82.76***	95.22***	81.67***
Log Likelihood		-629.4	-629.1	-621.8	-627.7
R-Squared	0.565				

Notes: *, **, *** significant at 10%, 5% and 1% levels. The number of observations is 946. The explained variable is the relative specialisation index in clean energy technologies in the 2003-2005 period. The depreciation rate for the computation of stocks of knowledge is 15% in all columns. Country level variables: GDP, GDP per capita are 2002 variables. Industry level: 3 industry dummies according to the technological level (OECD classification extended to services), KIBS and non-KIBS dummies as well as an energy dummy. When stock values are 0, the value 0.001 is added to compute the log. A dummy is introduced when the weighted stocks of clean patents are null: The dichotomic variable No previous Clean Energy Patent is not reported in the table. For manufacturing firms: HT is set to 1 if the firm belongs to the 244, 300, 321–323, 331–335 and 353 industries in the NACE classification (rev 1). MH is set to 1 if the firm belongs to the 241–243, 245-247, 291–297, 311–316, 341–343, 352 and 354-355 industries in the NACE classification (rev 1). ML is set to 1 if the firm belongs to the 231–233, 251, 252, 261–268, 271–275, 281–287, and 351 industries in the NACE classification (rev 1). LT is set to 1 if the firm belongs to the 151–159, 160, 171–177, 181–183, 191–193, 200–209, 210–219, 220–229, 361–366, 371, and 372 industries in the NACE classification (rev 1.1). For service firms, the codification is the following: KIS is set to 1 if the firm belongs to the 40, 41, 61, 62, 64-67, 70-74, 80, 85 and 92 industries in the NACE classification (rev 1). Non-KIS is set to 1 if the firm belongs to other services. Low Tech industries are taken as a reference. Robust standard errors are in parentheses. For the Tobit models, coefficients reported are marginal effects computed at the left truncated mean, E(SRC l x, SRC > -1).