KNOWLEDGE RELATEDNESS AND PATHS OF INDUSTRIAL DIVERSIFICATION IN ENVIRONMENTAL TECHNOLOGIES

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Introduction

Ecoinnovation or Environmental *innovations* are defined by "the production, assimilation or exploitation of a product, production process, service, management, or business methods that are novel to the firm [or organization] and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use)" (Kemp and Pearson, 2007). One important issue about innovation in environmental technologies (ET) is what determines their rhythms of creation and adoption. As any other innovation, the creation or adoption of EI depend mostly on the firm's and markets' behaviour. More specifically, environmental awareness; cost-saving strategies to reduce the consumption of inputs, as raw materials, energy, and water; costumer demands for green products and pressure from costumers and stakeholders for good practices can contribute for investments in ET. It also depends on the governments and institutions (rules) as promoters of this kind of innovation to achieve specific environmental goals. Environmental regulations, pollution taxes and requirements for public procurement are pointed out as important ecoinnovation drivers. (Horbach, Rammer and Rennings, 2012; Hojnik, Ruzzier, 2016).

Unlike other recent technologies, ET have a strong transversal character at least in three dimensions. First, at the technological level, ET refers to product, processes, and organizational innovation [even simultaneously]. Second, at the firm level, ET entails the whole of firms' competences, those are, productive, technological, and managerial. Third, at the industrial level, ET are referred to environmental issues that usually affect a quite large number of production processes and products across the industry.

From an evolutionary perspective, firm's growth is basically a phenomenon of transformation and adaption by diversification. As technologies evolve, firms must adapt to the new competitive environments following non-random paths of diversification. That means that firms develop paths of diversification from their own knowledge base, that is, diversification is coherent with their own core-technological, productive, and managerial competences. The path of technological diversification at the firm level determines the path of evolution of the industrial knowledge base which becomes more variated, related, and complex. The extent to which new technical fields are incorporated into an industrial knowledge base depends on how they are related to the old ones, that is, on how old and new knowledge complement each other to create new or improved technologies.

As ET are transversal at the industrial level, they potentially can establish connections with a wide range of technologies in different industries representing paths of industrial knowledge base evolution. In this sense, the aim of this paper is to identify at sectoral level in what extend ET are related to the industrial knowledge bases and represent a potential natural path of technological evolution, and in which industries they are not. In the former case, public policy plays an important role in guiding the connections between technologies, for example, supporting environmental solutions for specific environmental problems in specific industries. In the last case, when ET are low related to the industrial knowledge base and, public policies must establish incentives to stimulate ET creation or adoption more compulsory.

To pursue our objective, we develop three exercises: (i) we identify the ET positioning as technological competences in the knowledge bases at sectoral level; (ii) we calculate the relatedness between the ET and the central technological domains at sectoral level; and (iii) we associate the path of technological diversification towards ET with the relatedness between ET and the central technologies at industrial level.

The paper contributes with the evolutionary literature associating the process of technological diversification at the firm level with the evolution of the industrial knowledge bases at the sectoral level. Also, the methodology proposed in the paper allows to identify *gaps* of technological coherence in the evolution of sectoral knowledge bases, which should assist the formulation of public policies and incentives to foster specific environmental innovations by industry.

1. Competences, coherence, firm's diversification and the evolution of sectoral knowledge bases.

The theory of corporative coherence points out that the growth of the firm is not random but determined by the paths of technological accumulation on a set of old and new competences that, above all, are coherent (Teece et al., 1994). As competences of the firm are productive, technological, and managerial, the set of technological competences developed by firms must exhibit at least two kinds of coherence: (1) coherence with the productive activities the firms are involved in; and (2), coherence between them due to the 'knowledge relatedness'. The knowledge relatedness emerges from knowledge proximity, that is, when knowledge learnt from one technology spill over another due to their similarity or complementarity (local learning); knowledge commonalities, when the same knowledge has applications to more than one technology; knowledge complementarities, when more than one type of knowledge is needed to be used together to develop one technology; and generic technologies, when knowledge complementarities are applied to a wide range of products and technologies (Breschi et al 2003)

Considering the nature of productive coherence and the bounded rationality and uncertainty associated to innovation processes, innovations are not only the result of pursuing the most profitable technologies, but the result of searching in specific knowledge domains that are complementary and interrelated. In this sense, innovation happens pushed by complementary knowledge [internal, external (subcontracting) or cooperation] (Bonte and Dienes, 2013). From this perspective, innovation in firms depends strongly on the technological coherence of the firms' technological domains related to their core activities and complementary assets (Chiu et al, 2008).

Because of the coherence among technological domains, innovation and diversification are closely related. On one hand, from innovative activities firms learn, extend, and diversify their own base of technological competences. On the other hand, technological diversification stimulates innovation because allows the firm to exploit the spillovers from one technology to another (crossfertilization among related knowledge and technologies), to obtain gains from non-related technologies, to explore opportunities, to reduce the risks of searching, to capture more social benefits of their own innovations, and to prevent negative lock-in of narrow specialization in one technology (Vega, 2006). In addition, Patel and Pavitt (1997) identify two reasons why firms spread their technological competences over a wider set of technologies than their products. First, by technological interdependence given the complexity and complementarity between products and production processes (suppliers, materials, components, machinery, and equipment, etc.). Interdependence demands backward competences to identify, integrate and adapt technological changes in the production system. Second, by emerging technological opportunities that potentially means business opportunities. Emerging technologies can be marginal at the initial stages (like alternative energy production), but they can become more central as the firm identify and explore their potential in relation to the firm core business.

However, there is a certain trade-off between technology specialization and diversification. As much the firm diversify technologically, it loses economies of scale in learning processes and competitive advantages, as well as reduce capacity to transfer knowledge between its core competences and increase coordination costs (Yi-Chia Chiu, Hsien-Che Lai, Yi-Ching Liaw, Tai-Yu Lee, 2010). The trade-off between specialization -usually associated to path dependency- is associated with the technology diffusion cycle and the emergence of new paradigms (Lavarello, 2016). At the initial stages, the search for new solutions and applications pushes the firms to diversification. Along this process, firms develop a set of 'secondary' technological competences that complement 'core competences' that allows them to expand their technology portfolios and their knowledge base in a coherent way. Afterwards, they stabilize focusing their R&D and learning efforts on the existing knowledge.

At the sectoral level, technological coherence refers to the knowledge base hosted in the firms' productive, technological, and managerial competences that belong to the same industry. The sectoral knowledge base express, in aggregated terms, not only the technological core-competences of the firms that compose the industry, but also their complementary assets, their patterns of search and their paths of technological diversification. The aggregation of competences at the sectoral level expresses a set of problems, methods, and solutions to specific problems and, therefore, potential micro-trajectories of technical progress by industry. Usually, technological competences are industry-specific, that is, industries are characterized by a set of common and dominant technologies labelled as 'core' highly persistent and path-dependent (Patel and Pavit, 1997). However, when new technological paradigms emerge, the cycle of technological diversification at the firm level cannot converge with the sectoral knowledge bases, which means a process of non-related diversification that progressively became related when came from internal learning (Lavarello, 2016; Krafft et al, 2011). If diversification came from external efforts by fusions and acquisitions to control complementary assets or to create barriers to entry, the result is 'conglomerate diversification' and coherence could have no place. The 'long wave' view supposes that eventually new technological paradigms will affect all the industries (Fai and Von Tunzelmann, 2001). In addition, as much the technologies are pervasive -like environmental technologies-, innovation not only could take place in one specific industry, but also along the path of the diversification of the set of industries whose bases of knowledge the innovation are related to (for example, innovation in medical equipment by pharma industry). As a result, a process of technological convergence between industries takes place.

To move from the competences of the firm to the industrial knowledge base is an aggregation matter. One way to do that is to deal with the technological competences at the firm level as pieces of knowledge. Nevertheless, if those pieces are combined in specific ways to resolve specific patterns of problems, heuristics and procedures, aggregation cannot be only by addition, but also by their interconnections like in a network. Therefore, the hierarchical categorization of different types of knowledge at the sectoral level must consider at least two criteria: *centrality* and *relatedness*. The frequency and linkages of every single piece of knowledge used in an industry determine its *centrality*. On one side, frequency measures the relative importance of a piece of knowledge among the set of pieces of knowledge that compose the range of technological competences of the firm. On the other side, linkages measure how any piece of knowledge is related to the central technological domains. In this sense, one piece of knowledge can be central not only by its frequency, but also by its relatedness to the central technological domains at sectoral level. Therefore, the centrality of one piece of knowledge in a sectoral knowledge base reveal the aggregated core-competences (core-technologies) at the firm level. The more frequent the links among technologies are (set of technological competences), the more *related* that piece of knowledge will be at the sectoral level. Then, at the sectoral level, relatedness indicates the specific way through which an industry combines knowledge to solve problems, extending and thickening its own knowledge base. In this way, centrality and relatedness of the technological domains in an industry reveal the technological coherence of the firms that contains. Using both, one can observe how the structure of the sectoral knowledge base evolved as new pieces of knowledge, connections or both are introduced within. Consequently, the evolution of the sectoral knowledge base reflects the path of diversification followed by the firms from their own technology base composed by their core competences and the related knowledge to them and to the complementary assets that the firm develops in products and services.

Hypothesis

Environmental technologies usually refer to a set of technologies that resolve traditional environmental issues recently focused on the main environmental challenges in the millennium goals of climate change: reducing carbon emissions, treating waste in soil and water, and exploring alternative and low-impact energy sources. Carbon emissions and waste management represents social costs and, economically, they present externality problems with elevated social costs. Alternative and low-impact energy sources have also positive externalities, but they represent directly private returns and cost reductions as they became cheaper.

In general terms, the environmental problems are transversal to all industries. Following the corporative coherence of the firm, specific environmental technologies should be developed in industries where environmental issues are directly related to the productive core-competences in products and production processes, but also, to their complementary assets. Therefore, the centrality of environmental technologies in each industry depends on how environmental issues are representative in their products and productive processes. To get a better approach on the specificities of environmental issues by industry, we elaborated table 1 distinguishing the three millennium goals of climate change affecting products and process as well as the environmental technology associated.

Table 1 allow us to cluster industries in five categories. 1) Pollutant industries by GHG gases and Wastes in process; 2) Pollutant industries by GHG gases by their products; 3) Pollutant industries by Wastes in products; (4) High intensity energy consumers; and (5) Low contaminant industries. This taxonomy differentiates between high polluting industries (wastes and GHG gases) and high energy consumers. Both environmental micro-paradigms have different implications in terms of social and private returns.

Table 1 – Most important environmental issues by industry.

	Polluting (gases)	Wastes	High intensity consumption of energy
Processes	· Textiles · Paper and paper products · Coke and refined petroleum products · Fabricated metal products, exc. m. & eq.	· Textiles · Tobacco products · Leather and related products · Paper and paper products · Fabricated metal products, exc. m. & eq. · Basic pharmaceutical products and pharmaceutical preparations	· Other non-metallic mineral products* · Basic metals** · Paper and paper products · Chemicals and chemical products · Food products · Beverages · Coke and refined petroleum products
Products	· Motor vehicles, trailers and semi-trailers · Other transport equipment	· Computer, electronic and optical products · Basic pharmaceutical products and pharmaceutical preparations · Chemicals and chemical products · Rubber and plastic products · Electrical equipment · Wearing apparel · Food products · Beverages	
Low Pollutant	· Wood and of products of wood and cork, except furniture; Articles of straw and plaiting materials · Printing and reproduction of recorded media · Furniture · Other manufacturing · Repair and installation of machinery and equipment		
Associated technology	Transportation	Waste Management	Alternative Energy Production Energy conservation

Darkest	Pollutant industries by GHG emissions in products
Dark	Pollutant industries by GHG emissions and waste in process
Light	Pollutant industries by waste in products
Lightest	High intensity energy consumers
None	Low pollutant industries

Source: Own elaboration

Using the taxonomy of industries proposed in table 1 and the previsitions on competence distribution and technological diversification, we formulate the following hypothesis;

Proposition 1: *ET acquire a higher centrality according to the way environmental issues affect the core-business of industries. So, Transportation, Agriculture/Forestry and Waste Management will be more central in Pollutant industries and Alternative Energy production and Energy conservation will be more central in High energy consumer industries.*

Proposition 2: *Alternative Energy production and Energy conservation constitute a cost-reduction focus of technological trajectory in firms, its centrality will be more transversal and pervasive among industries than ecoinnovations focused in reducing externalities and social costs.*

Proposition 3: *the higher the relatedness between ET and the central technologies of the industry, the higher the technology diversification towards ET.*

2. Database.

To measure competences and build industrial knowledge bases, we use a patent database (OECD, 2009; Patel and Pavitt, 1997; Krafft et al, 2011). Patents represent results of formal or informal innovation efforts and provide detailed data in a regular and long time series grouped by firm, country, geographic location, and technical field, which makes them appropriate to analyze technological competences at the firm level and at industrial level (Patel and Pavitt 1991). Nonetheless, there are some limitations of patents as an indicator of competences. In the first place, measuring technological specialization to develop specific products and industries can involve a classification of technological fields that do not respond to the usual ones in patent classifications. Therefore, additional criteria for product aggregation could be necessary. Second, some technological competences can be underestimated when they are built on non-patentable technologies or on technologies that are not protected by patents. Furthermore, the option of patenting a particular object depends, among others, on firms' strategies, the features of the object, and the intellectual property system of the country. Not every effort involved in processes of technological change will necessarily result in patenting, and the propensity to patent varies according to the country, sector, and size of the firms (Cohen et al., 2002; Arundel, 2001; Levin et al., 1987; Nagaoka, Motohashi and Goto, 2010; Hall 2009). Third, patents do not capture some categories of ET (Oltra, Kemp, & De Vries, 2010). These are relative to methods linked to marketing strategies, organizational and management changes, and institutional arrangements to promote ET. Patents applications statistics do not evaluate the environmental impact of any adopted technology.

Four significant methodological aspects are worth to be noted concerning the treatment given to the information contained in the patent database. First, patents are the only source of information that synthesize national R&D efforts with the potential for innovation by technical field. Second, the database for industry knowledge base includes patents filed only by companies and excludes patents filed by other applicants, such as government agencies, universities, and individuals[1] or that have an unknown NACE code. Third, one patent represents a technology that combines different pieces of knowledge. For this reason, a patent can correspond to more than one technical field.

The analysis uses patents applications filed at the EPO between 1969 and 2016. Data were extracted using the EPO PATSTAT Global - 2020 Spring Edition (EPO, 2020). EPO database in EPO

[1] As a reference for the nature of the applicant, it was used the classification available on ORBIS - Bvd for stakeholder and affiliate types, and the following applicant categories were disregarded: Foundation/Research Institute, Employees/Managers/Officers, Individuals/Families, Public Authorities/State/Government, or Not Identified. As for the industry sectors in which each firm acts, it was used the classification created by ORBIS - Bvd based on the revised Statistical Classification of Economic Activities in the European Community (NACE Rev.2), and were included only the companies listed in sections A to L.

PATSTAT represents the best source of information for international comparisons for several reasons. Firstly, because a simple patent is extensible to all Munich Convention member countries, which reduces country bias of the domestic effect. Secondly, fee applications are relatively higher, which excludes from the database patents of low industrial value. Thirdly, EPO publishes grants and deposits of patents eighteen months after the application (by mean), while other bases are more delayed [for example, UPSTO only publishes after two years (by mean)] (Grupp and Schmoch, 1999; Le Bas and Sierra, 2002; van Zeebroeck et al., 2006).

The classification of patents applications by technical fields was based on Schmoch (2008) . For the ET, we use the following five categories based on the "IPC Green Inventory" developed by the WIPO according to environmental technologies listed by United Nations Framework Convention on Climate Change (UNFCCC): Alternative Energy Production, Transportation, Energy Conservation, Waste Management and Agriculture / Forestry (table 2).

Table 2 - Environmental technical fields

Technical fields	Description
ALTERNATIVE ENERGY PRODUCTION	Bio-fuels, Integrated gasification combined cycle (IGCC), Fuel cells, Pyrolysis or gasification of biomass, Harnessing energy from manmade waste, Hydro energy, Ocean thermal energy conversion (OTEC), Wind energy, Solar energy, Geothermal energy, Other production or use of heat, not derived from combustion, e.g., natural heat, Using waste heat, Devices for producing mechanical power from muscle energy
TRANSPORTATION	Vehicles in general, Vehicles other than rail vehicles, Rail vehicles, Marine vessel propulsion, Cosmonautic vehicles using solar energy
ENERGY CONSERVATION	Storage of electrical energy, Power supply circuitry, Measurement of electricity consumption, Storage of thermal energy, Low energy lighting, Thermal building insulation, in general, Recovering mechanical energy
WASTE MANAGEMENT	Waste disposal, Treatment of waste, Consuming waste by combustion, Reuse of waste materials, Pollution control
AGRICULTURE / FORESTRY	Forestry techniques, Alternative irrigation techniques, Pesticide alternatives, Soil improvement

Source: WIPO – IPC Green Inventory –https://www.wipo.int/classifications/ipc/green-inventory/home

EPO database recorded 3,493,409 applications between 1969 and 2016; 1,768,628 patents were filed by industrial companies (50.6%); 455,858 patents were identified as ET, with a huge concentration in the energy technical fields (Alternative energy production and Energy conservation (Table 3). The contribution of the manufacturing industries for environmental technologies was about 45.5%, with higher participation in the Energy conservation (52.8%), Agriculture/Forestry (50.6%) and Transportation (49.7%).

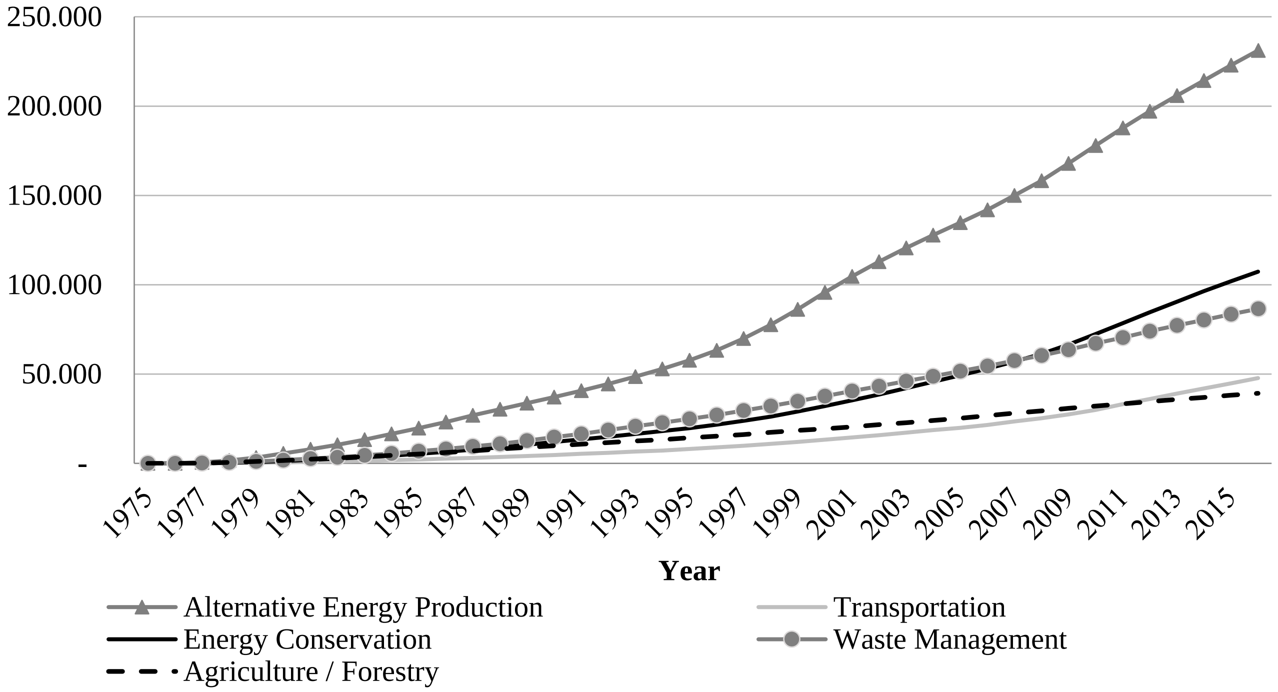
The predominance of energy technical fields in the ET's patent stock is verified along all period of analysis (Figure 1). The number of patents for Energy Alternative Production was already bigger at the beginning of 1980. Then, the stock of patents grew the most during the period 1980-2016. The moment of greatest expansion was after 1995 until the beginning of the 2000s, then it remained at a stable growth rate. That was coincident with the period of greatest expansion for Energy Conservation and Transportation. After 2005, the transportation patents had the greatest expansion cycle, intensified between 2009 and 2011. Energy conservation also had the second stronger growth after 2005. The growth rates in Agriculture/Forestry remained low in the 2000s and reduced after 2010.

Table 3 – Patent distribution by technical field and applicant (1969-2016)

Technical fields	Total (a)	Manufacturing Industries (b)	Industry contribution 100*(b)/(a)
Environmental Technologies	**455,858**	**207,570**	**45.5**
Alternative energy production	231,132	97,065	42.0
Transportation	47,744	23,707	49.7
Energy conservation	107,324	56,673	52.8
Waste management	86,483	34,613	40.0
Agriculture / forestry	39,218	19,840	50.6
Other technologies	**3,037,551**	**1,561,058**	**51.4**
Total	**3,493,409**	**1,768,628**	**50.6**

Source: Own elaboration using EPO PATSTAT / EPO (2020) and Orbis/BvD (2016).

Figure 1 - Patents stocks evolution by environmental field



3. The centrality of environmental technologies in industrial knowledge bases.

From a simple conceptualization, an industrial knowledge base is the aggregation of the firms' technological competencies. The connection between technological competences -at the firm level- and the base of knowledge -at the sectoral level- has two implications. First, the industrial knowledge base must reproduce the structure of the competences at the firm level and, therefore, the core of the firms' technological competences that belong to a specific industry must correspond to the central nodes in the industrial knowledge base. Second, the path of the technological diversification at the firm level must reveal paths of variety of the industrial knowledge base, that is, the coherence of the technology profiles at the firm level determines the evolution and the coherence of the industry knowledge base.

In relation to the competences structure at the firm level, Patel and Pavitt´s (1997) established technology profiles structure according to four categories: core, niche, background and marginal. Those categories depend on two criteria: the importance the technology has for the firm [measured as the share of patents in each technology]; and the patent share in each technology weighted by the firm's aggregate share of patents in all the fields, that is, its specialization [measured by de Revealed Technology Advantage]. When a firm dedicates a high effort to a technology in relation to its base of competences and that is also superior to the industry effort, the technology configures a core-competence. However, if the weight of this technology in the firm is below the industry effort the technology configures a background-competence. Alternatively, when a firm dedicates a low effort to a technology in relation to its base of competences but is superior to the other's firms' effort, the technology configures a niche competence. Finally, when a technology is not relatively important for the firm's base of competences and its effort is also inferior to the other's firms' effort, it is a marginal competence.

The aggregation of competences to build an industrial knowledge base also permits creating a similar taxonomy, but in a different conceptualization and with some additional methodological considerations. First, technical fields by IPC classification at any level of aggregation represent *units of technical knowledge (UTK)* that are also technologies, but refer to a more restricted space of heuristics, this is, the same pattern of problems, methods, procedures, and solutions. Therefore, IPC codes measure technological competences at the firm level, and UTKs (nodes) in the knowledge base at the sectoral level. Second, as technological efforts in ET are low in relation to other technologies, measures based on frequency -as the created by Patel and Pavitt (1997)- would underestimate the importance of ET inside the technology competences profiles. In this sense, we adapted the Patel and Pavitt's methodology using analysis of networks, which includes not only the frequency of use of each technology, but also their links and interactions. Third, the way the UTKs are connected to each other varies from one industry to another. Thus, the centrality indicator must consider not only the frequency, but also the number of relations each UTK is linked in the industry knowledge base. The more connected a UTK is to others in the base of knowledge, the higher its centrality.

The UTKs are technical fields or IPC codes assigned to each patent. As it is usual that a patent registers more than one IPC code, the co-occurrence of different UTKs in the same patent register measures the linkages between UTKs. The co-occurrence network has three components: nodes or UTKs; edges, which link nodes when these nodes co-occur on the same patent; and co-occurrence frequencies of pairs of nodes as weights for the edges. The more frequent two nodes [UTKs] are linked in, the stronger their relationship. The co-occurrence network forms an undirected and weighted graph.

The UTK centrality in the co-occurrence matrix is measured by the centrality rank (CR) calculated using the PageRank algorithm. PageRank is a graph-based ranking algorithm that approximates the importance [centrality] of a UTK by considering both its inbound and outbound links (Perra & Fortunato, 2008; Ding, 2009). Nodes with more links and higher weights will get high PageRank scores. From this, UTKs that co-occur with many other UTKs [which indicates "more links"] and co-occur many times with these UTKs [which indicates "high weights"] will get higher PageRank scores. Also, nodes linked with central nodes will get higher PageRank scores.[2]

The centrality rank (CR) is calculated in each one of the 24 manufacturing industries aggregated for 39 UTKs; 5 environmental technical fields (E-UTK) and 34 other technical fields. Similarly, to Patel and Pavitt's taxonomy, we need relative values for the CR. For that, we calculate a reference value using a knowledge base where all the UTKs have the same participation resulting in equal rank values. Considering the number of UTKs and the PageRank algorithm, this reference value is a centrality rank of 0.02564. The distinguished UTKs in an industry are those whose Related Centrality Rank (RCR) is higher than 1, that is, the centrality rank in the industry is higher than the centrality rank in the whole aggregated of industries.

Considering a UTK *x*, there are four possible classifications. When $CR_x^i > 0.02564$ and $RCR_x^i > 1$ in industry *i*, it represents a 'high central' technology (Figure 2). But, if $CR_x^i > 0.02564$ and $RCR_x^i < 1$ then UTK *x* is a 'absolute central' technology in the knowledge base of industry *i*. The third possibility is $CR_x^i < 0.02564$ with $RCR_x^i > 1$, which represents a 'relative central' technology in industry *i*. In addition, if $CR_x^i < 0.02564$ and $RCR_x^i < 1$ this implies a "low central" technology.

Figure 2 - Sectorial profiles of centrality.

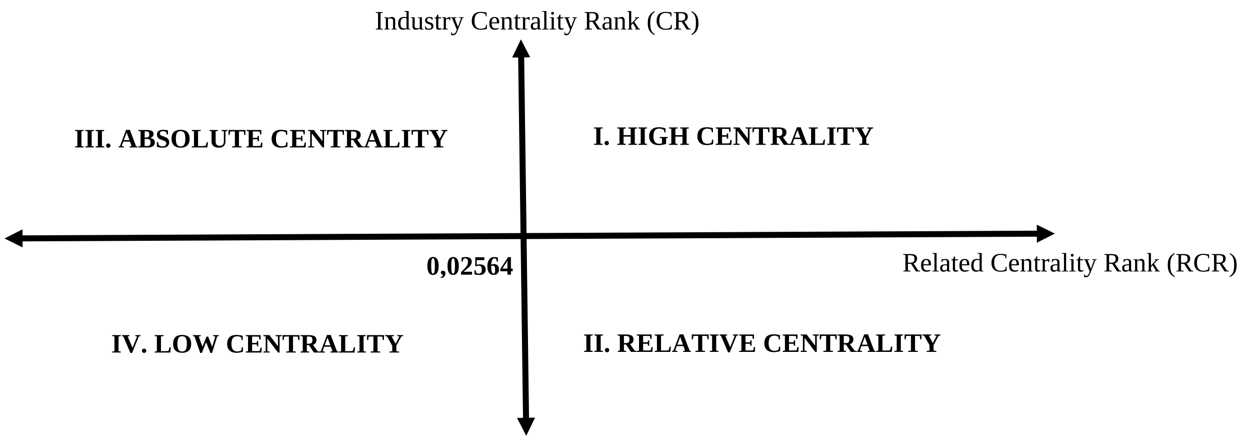


Table 4 shows the evolution of the E-UTKs centrality between 1969-1999 and 2000-2016. The total of cases is 120, that is, five E-UTKs in 24 industries. The values in the diagonal represent the stability of the centrality or the number of E-UTKs in by sector that remain in the same centrality level. In terms of centrality there is no hierarchy between relative and absolute centrality, so movements between those categories are considered also stability the rest of the cells in the matrix represent centrality gains or losses. Considering the hierarchical importance of the categories, from no competences to high centrality, the sum of the values below the diagonal represents centrality gains, while the sum of the values above the diagonal represents centrality losses.

The first observation from the table 4 is the stability of the E-UTKs centrality. The relative frequency of the stability was 73.3% (the sum of the diagonal gray area values which is 88 on the total 120 cases). The stability is more characterized by the low centrality of environmental

[2] Package igraph for R was the software used to calculate the Page Rank.

technologies (relative frequency of 61.4%), which is compatible with its novelty as path to explore new business opportunities. However, there is some evidence that these technologies are gaining centrality. The sum of the values below the diagonal is 21, which means that there was gain of centrality in a 17.5% of the cases. Alternatively, the sum of the values above the diagonal was 11, that is, there was loss of centrality in 9.2% of the cases.

Table 4– The evolution of E-UTK centrality

		2000-2016					
		High	Relative	Absolute	Low	No competences	Total
1969-1999	High	19	2	0	4	0	25
	Relative	4	9	1	3	0	17
	Absolute	5	0	4	1	0	10
	Low	2	2	6	54	1	65
	No competences	0	0	0	2	1	3
	Total	30	13	11	64	2	120

(shaded)	Stability
(blank)	Gains/Losses of centrality

*'No competences' cases also included.

Source: Author calculations based on data from EPO PATSTAT / EPO (2020), Orbis / BvD (2016).

Table 5 reports the centrality of the five environmental UTKs (E-UTKs) in 1969-1999 and 2000-2016 in 24 manufacturing industries grouped according to the representative environmental issue, that is, GHG and Waste in process and products, GHC in products, Waste in products, High energy intensity consumers and Low pollutants. There are two observations in relation to the test of the proposition 1, one transversal and one temporal. The transversal observation shows that E-UTK tend to acquire some centrality in industries according to the relative relevance of the environmental issue, and this propensity tend to be stable between periods. For example, Waste Management, which includes technologies to reduce GHG emissions, and Transportation are central in the two industries of the GHG pollutant in products (transport industries). This is also the case of Alternative Energy Production in the group of High intensity consumers. The other E-UTKs, Energy Conservation and Agriculture/Forestry acquire a low propensity to remain central in each group, which means that those are environmental technologies not specifically associated with any specific environmental issue. A second observation is the pervasive character of the Alternative Energy Production, that is, no matter what the main environmental issue is, the propensity to be central in the industry is quite high. A third observation is a different pattern by product and processes, that is, the centrality of E-UTKs tend to rise between periods when they affect production efficiency (costs reduction) like Alternative Energy Production.

The temporal observation shows the stability of the E-UTKs centrality between periods. Nevertheless, some interesting facts emerge. The pervasiveness of the Alternative Energy Production and Energy Conservation centrality grows, especially in the industrial groups where the environmental issue is referred to processes; and whatever the environmental issue is, Alternative Energy Production gains centrality in the industry strongly. There are also some interesting movements of the E-UTKs centrality between periods. Waste Management loses centrality in industries pollutant in GHG and Wastes in processes, that become more focused in the energy issue, but also in the Low pollutant industries.

In resume, the centrality analysis seems to confirm the propositions one and two. In general terms, E-UTKs tend to be more central when the environmental affects more to the reduction of production costs than to the reduction of social costs or negative externalities.

Table 5. The centrality* of environmental technologies in the industry by environmental issue

		1969-1999					2000-2016				
	Nº industries	Alternative Energy Production	Energy Conservation	Waste Management	Agriculture / Forestry	Transportation	Alternative Energy Production	Energy Conservation	Waste Management	Agriculture / Forestry	Transportation
GHG and Wastes in processes	7	5	1	4	2	1	6	3	3	1	1
High intensity consumer of energy	7	6	1	5	2	-	7	3	6	3	-
GHG in products	2	1	2	2	0	2	2	1	2	0	2
Waste in products	8	6	2	2	3	1	7	2	2	4	1
Low-Pollutant	6	4	4	4	1	2	5	3	2	1	2
Total	24	17	10	14	5	6	21	11	11	5	6

(*) Number of industries in each group where E-UTKs have high, absolute, or relative centrality.
Source: Author calculations based on data from EPO PATSTAT / EPO (2020), Orbis / BvD (2016).

4. Centrality, relatedness, and paths of diversification.

The third proposition formulated in this paper establishes an association between (i) the relatedness between E-UTK and the industry's central technological competences (C-UTK); and (ii) the diversification towards E-UTKs. The indicator used for relatedness between two UTK *a* and *b* in period *t* ($R_{a,b,t}$) is the *cosine index*, defined by Breschi et al (2003) and Yan & Luo (2017). The cosine index captures similarities between vectors representing the relations of a UTK to each other UTK in the co-occurrence network for the whole industrial knowledge base, that is, for all kinds of applicants and not only the manufacturing network, as $R_{a,b,t}$ represents a technological link between technical knowledge and shouldn't depend on applicant type (Appendix A).

$$R_{a,b,t} = \frac{\sum_j CO_{a,j,t} CO_{b,j,t}}{\sqrt{\sum_j CO_{a,j,t}^2}\sqrt{\sum_j CO_{b,j,t}^2}}$$

where $CO_{a,j,t}$ is the edge size or the co-occurrence frequency of UTK *a* and *j* in the period *t* co-occurrence network.

Table 6 - Relatedness index (mean of $R^{h}_{C,et,t}$ by industry)

Industry	1968-1999						2000-2016					
	Alternative Energy Production	Energy Conservation	Waste Management	Agriculture / Forestry	Transportation	All E-UTK (mean)	Alternative Energy Production	Energy Conservation	Waste Management	Agriculture / Forestry	Transportation	All E-UTK (mean)
Computer, electronic and optical products	0.18	0.53	0.21	0.12	0.27	**0.26**	0.21	0.36	0.18	0.11	0.28	**0.23**
Electrical equipment	0.21	0.55	0.28	0.15	0.32	**0.30**	0.26	0.39	0.32	0.17	0.39	**0.31**
Printing and reproduction of recorded media	0.25	0.53	0.33	0.24	0.27	**0.32**	0.26	0.40	0.28	0.21	0.27	**0.28**
Machinery and equipment n.e.c.	0.25	0.55	0.36	0.21	0.37	**0.35**	0.37	0.48	0.44	0.24	0.43	**0.39**
Tobacco products	0.35	0.42	0.43	0.37	0.26	**0.36**	0.37	0.37	0.40	0.36	0.27	**0.35**
Leather and related products	0.28	0.52	0.41	0.26	0.37	**0.37**	0.34	0.41	0.41	0.29	0.31	**0.35**
Motor vehicles, trailers and semi-trailers	0.24	0.55	0.37	0.17	0.52	**0.37**	0.34	0.53	0.37	0.16	0.46	**0.37**
Other transport equipment	0.25	0.55	0.41	0.18	0.48	**0.37**	0.34	0.53	0.40	0.19	0.42	**0.38**
Furniture	0.26	0.50	0.38	0.21	0.48	**0.37**	0.35	0.45	0.39	0.23	0.41	**0.37**
Beverages	0.44	0.36	0.44	0.45	0.21	**0.38**	0.47	0.31	0.39	0.47	0.20	**0.37**
Textiles	0.36	0.47	0.45	0.37	0.26	**0.38**	0.39	0.41	0.45	0.40	0.28	**0.39**
Wearing apparel	0.31	0.50	0.44	0.27	0.41	**0.38**	0.36	0.45	0.42	0.29	0.36	**0.38**
Wood and of products of wood and cork (exc. furniture); Articles of straw […]	0.29	0.45	0.42	0.26	0.47	**0.38**	0.38	0.41	0.45	0.29	0.46	**0.40**
Basic pharmaceutical products and pharmaceutical preparations	0.56	0.23	0.43	0.60	0.10	**0.38**	0.53	0.21	0.31	0.55	0.09	**0.34**
Rubber and plastic products	0.30	0.49	0.42	0.28	0.41	**0.38**	0.38	0.48	0.43	0.31	0.38	**0.40**
Repair and installation of machinery and equipment	0.31	0.51	0.41	0.28	0.40	**0.38**	0.35	0.47	0.39	0.22	0.40	**0.37**
Paper and paper products	0.39	0.47	0.47	0.36	0.27	**0.39**	0.43	0.41	0.44	0.39	0.27	**0.39**
Coke and refined petroleum products	0.40	0.33	0.47	0.58	0.15	**0.39**	0.38	0.35	0.40	0.50	0.23	**0.37**
Chemicals and chemical products	0.47	0.34	0.49	0.51	0.15	**0.39**	0.43	0.37	0.41	0.52	0.21	**0.39**
Fabricated metal products, exc. m. & eq.	0.28	0.51	0.45	0.23	0.49	**0.39**	0.35	0.46	0.45	0.25	0.47	**0.40**
Food products	0.55	0.28	0.46	0.57	0.14	**0.40**	0.53	0.25	0.37	0.59	0.13	**0.37**
Other non-metallic mineral products	0.35	0.48	0.48	0.34	0.36	**0.40**	0.40	0.44	0.46	0.38	0.36	**0.41**
Basic metals	0.35	0.56	0.52	0.33	0.34	**0.42**	0.40	0.50	0.52	0.34	0.38	**0.43**
Other manufacturing	0.49	0.47	0.46	0.40	0.27	**0.42**	0.52	0.37	0.38	0.38	0.26	**0.38**
Computer, electronic and optical products	0.18	0.53	0.21	0.12	0.27	**0.26**	0.21	0.36	0.18	0.11	0.28	**0.23**

Source: EPO PatStat and Orbis. Author's calculation.

After finding the relatedness between all pairs of technical fields, the relatedness between each E-UTK and the C-UTKs set of the industry h in period t ($R^h_{C,et,t}$) is calculated as:

$$R^h_{C,et,t} = \frac{\sum_{j \in C^h} R_{et,j,t} O^h_{j,t}}{\sum_{j \in C^h} O^h_{j,t}}$$

where C^h is the C-UTK set of sector h and $O^h_{j,t}$ is the number of occurrences of UTK j in sector h's knowledge base in period t. This indicator measures how similar the central technologies in a specific industry (C-UTKs) and the E-UTKs co-occur with other UTKs. If the way in which both co-occur with others is similar, then both are indirectly related. When $R^h_{C,et,t}$ is relatively higher, the E-UTK constitutes a coherent path of diversification by knowledge interdependencies in the industry h and public policies would play a complementary role. Alternatively, relative low $R^h_{C,et,t}$, means that the way the E-UTKs relates to other technologies is dissimilar to the way the C-UTKs do in a specific industry and, therefore, the E-UTKs does not constitute a *natural* path of diversification in the firms. In this case, the probability to develop eco-innovation from technological diversification is low and eco-innovation must be fostered by other incentives, as regulation.

The relatedness index between E-UTK and central technologies by sectors shows similar distributions for both periods, 1968-1999 and 2000-2016. Energy conservation and Waste management are more related to central technologies in different sectors than others E-UTK are. This is a consequence of its transversal character that can be associated to investments in innovation projects to adapt to regulatory standards and to attain the millennium goals. Alternative energy production becomes more related to the core technologies in almost all industries which reveals investments efforts for reducing carbon emissions and energy costs (Table 6). Therefore, these E-UTK represent strong candidates for path of technological diversification, what will be observed in the next step.

In addition, the numbers show some heterogeneity between sectors in both periods. On the one hand, there are pollutant sectors, such as Other non-metallic mineral products, Basic metals, and Fabricated metal products (except machinery and equipment) in the group of sectors with central competences more related to E-UTK. On the other hand, other pollutant sectors, such as Computer, electronic and optical products, and Electrical equipment are in the lowest central competences-E-UTK relatedness indexes group. Both are examples of pollutant sectors due to wastes by its products and have C-UTK weakly related with 4 of 5 E-UTK, including waste management. The former group includes sectors for which relatedness is expected to be associated to diversification towards E-UTK due to technological coherence. In the latter, relatedness does not configure a driver for technological diversification and eco-innovation.

The next step is to point out sectors in which diversification towards E-UTK occurs, that is, when simultaneously:

(i) the share of E-UTK occurrences grows in the industrial knowledge base between periods *t-1* and *t* (ΔET^h) such as,

$$\Delta ET^h = \frac{\sum_{j \in ET} s_{j,t}^h}{\sum_{j \in ET} s_{j,t-1}^h} > 1,$$

where $$s_{j,t}^h = \frac{o_{j,t}^h}{\sum_j o_{j,t}^h}$$

and (ii) the share of E-UTKs is more diversified, contributing to a higher diversification and variety in the industrial knowledge base when the diversification index among E-UTK increases more than the diversification registered in the industrial knowledge base. The adjusted Theil Entropy index (TE) measures the diversification:

$$TE_{K,t}^h = \frac{-1}{ln(n)} \sum_{j \in K} s_{j,t}^h * ln\left(s_{j,t}^h\right)$$

where *n* is the number of UTK in the observed knowledge base, *K*. When calculating *TE* for the entire knowledge base (*Total-KB*) n=39 and when measuring diversification among E-UTK n=4 (*ET-KB*), as there is only 4 E-UTK. The adjusted version of this diversification index varies between 0 when the knowledge base of sector *h* is composed of only one UTK, and 1, which represents a knowledge base composed of all possible technical fields and in which each UTK has the same weight.

The diversification towards E-UTK in period *t* occurs when diversification among E-UTK ($TE^h_{ET\text{-}KB}$) grows at least equal to diversification in the entire knowledge base:

$$\frac{TE_{ET-KB,t}^h}{TE_{ET-KB,t-1}^h} \geq \frac{TE_{Total-KB,t}^h}{TE_{Total-KB,t-1}^h}$$

Considering those two movements, three diversification scenarios are possible for E-UTK: relative diversification, relative concentration, and importance reduction (Figure 3). According to the third proposition, the (relative) diversification towards E-UTK should be associated with higher relatedness between E-UTK and the industry central competences in the period before ($R^h_{C,et,t-1}$), as it would constitute a coherent diversification path.

The sectors where the diversification towards E-UTK occurs is presented in table 7. The E-UTK reduced its importance in the industrial knowledge bases in some sectors between 1968-1999 and 2000-2016 periods. However, in more than half of the industries, E-UTK not only increased its participation, but also contributed to the diversification of industrial competences. This last scenario took place in GHG pollutant sectors, pollutant sectors by waste, and in high intense energy consumer industries, such as chemicals, textile, motor vehicles, and coke and petroleum; but also in low pollutants sectors, reinforcing E-UTK's transversal character.

Figure 3 - Scenarios of diversification towards E-UTK in the industrial knowledge base.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Contribution of E-UTK to industry diversification</td></tr>
<tr><td>$\frac{TE^{h}_{ET-KB,t}}{TE^{h}_{ET-KB,t-1}} < \frac{TE^{h}_{Total-KB,t}}{TE^{h}_{Total-KB,t-1}}$</td><td>$\frac{TE^{h}_{ET-KB,t}}{TE^{h}_{ET-KB,t-1}} \geq \frac{TE^{h}_{Total-KB,t}}{TE^{h}_{Total-KB,t-1}}$</td></tr>
<tr><td rowspan="2">Evolution of E-UTK the participation in the industrial knowledge base between 1968-1999 and 2000-2016 periods</td><td>↑</td><td>Relative Concentration towards E-UTK</td><td>Relative Diversification towards E-UTK</td></tr>
<tr><td>↓</td><td colspan="2">E-UTK importance reduction</td></tr>
</table>

Table 7 – Industries and relatedness index (mean of $R^{h}_{C,ET,t}$ by industry) according to scenarios of diversification towards E-UTK

Scenario	Industry	$R^{h}_{C,\cancel{ET}et,t}$ (1968-1999)
Relative Diversification towards ET	Food products Textiles Wearing apparel Wood and of products of wood and cork, except furniture; Articles of straw and plaiting materials Paper and paper products Coke and refined petroleum products Chemicals and chemical products Rubber and plastic products Basic metals Computer, electronic and optical products Machinery and equipment n.e.c. Motor vehicles, trailers, and semi-trailers Other transport equipment Repair and installation of machinery and equipment	0.38
Relative Concentration towards ET	Printing and reproduction of recorded media Other non-metallic mineral products Fabricated metal products, exc. m. & eq. Electrical equipment	0.36
ET importance reduction	Beverages Tobacco products Leather and related products Basic pharmaceutical products and pharmaceutical preparations Furniture Other manufacturing	0.38

Source: EPO PatStat and Orbis. Author’s calculation.

The last question is if the diversification towards E-UTK verified in 2000-2016 is associated with the relatedness observed in the period before [1968-1999]. The results do not demonstrate a clear association that confirms the importance of technological coherence to explain paths of diversification and variety in the industrial knowledge base. The relatedness between E-UTKs and C-UTKs (index mean) in the group of sectors where relative diversification towards ET occurred [0,38] was like the one verified in the group where E-UTK reduced its importance (Table 7). Besides that, relative diversification towards E-UTK occurred in cases of low relatedness index, which means that E-UTK represent paths of diversification driven by other forces beyond the complementarities of knowledge into the industrial knowledge base, like complementary assets, reduction costs or environmental policy requirements. An example is Computer, electronic and optical products that presents the lowest relatedness between E-UTKs and C-UTKs among all sectors, 0.26 (Table 6). At the same time, E-UTK reduced its importance in the knowledge base of industries whose C-UTKs were close related to E-UTK, what indicates gaps of technological coherence in the new competences development process. This happened in other manufacturing, and Basic pharmaceutical products and pharmaceutical preparations, the last one a pollutant industry by its processes and products.

5. Conclusions

The theory of corporate coherence established that firm's growth is, in fact a process of evolution by transformation and adaption by diversification. In addition, productive diversification is not random but coherent to the set of firms' technological competences -technological diversification-. The relatedness of knowledge embedded in the technological competences of the firm determines its path of technological and productive diversification. Under this assumption, this paper aimed to test whether environmental technologies constitute a natural path of technological diversification in the industry, considering their relatedness to the core competences in each industry. To do that, the paper enounced three hypotheses: (1) on the coherence of ET in relation to the main environmental issues of the industry; (2) on the pervasiveness of the ET considering them in two groups: energy costs reducing ET, which involves private returns, and managing wastes ET, which involves social returns; (3) on the association between diversification towards ET and its relatedness to the core competences of the industry.

In relation to the first and second hypotheses, the paper shows, as expected, that ET are mainly marginal and stable between periods (1969-1999 and 2000-2016). However, a non-negligible part of the ET has a representative centrality in the industry and, even more, ET tend to gain centrality between periods. In addition, ETs use to be coherent (more central) in industry according to the main environmental issue, but gains of centrality are more relevant when ET provides private returns (case of alternative energy production and energy conservation). ET that provides social returns, those are the related to Waste management, does not reveal significant gains of centrality. This result is a first indication about the source of the motivation in the industry to invest in eco-innovation. As much as ET provide cost reduction, there is a motivation to innovate. However, there is low motivation in the industry to innovate in ET that provides social returns, especially technologies to resolve issues like the Waste generation in products (like in computers, pharma, chemicals, rubber and plastics, electrical equipment, wearing products, food, and beverages). In these cases, regulation and policy incentives must to stimulate eco-innovations in the industry. Respecting on the third hypothesis, the results reveal that the relatedness of environmental technologies to the core-competences of the industries does not drive the path of technological diversification in industry. This result is another indication that regulation and public policies are necessary to guide the rhythms and paths of ecoinovations in industry. It does not seem clear that ET represent a natural path of technological diversification, excepting maybe in the alternative energy paradigm.

Finally, the gaps of technological coherence observed in other manufacturing, and Basic pharmaceutical products and pharmaceutical preparations [the last one a pollutant industry by its processes and products] highlight cases that deserve more investigation and could contribute to understanding the role played by other factors pointed out in the literature as determinants for the development of new environmental competences and not considered in this paper, such as cost reduction and reputation. Additionally, it involves some relevant insights from an environmental policy perspective, as it draws attention to sectors where regulation and other instruments could be more important to foster eco-innovations more directly.

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