Technology Platforms in Europe: an empirical investigation

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Technology Platforms in Europe: an empirical investigation

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Contribution to the Project

MS67 Research paper on the development and anchoring of new technological platforms.

The Report reviews the policy and scholarly literature on GPS, KET and technology platforms. Drawing on this it introduces and discusses the main elements characterising technology platforms and the specific qualities of the underlying technology. It also presents the framework for the empirical investigation shaping the relationship between technology platforms and the development of original innovation and technology shifts. Patent data from 27 member states are used to test our hypothesis formulated in an econometric model.

Using patent data from the EPO for the period between 1996 and 2006, we have first offered some stylised facts regarding the level of generality and originality across technological classes for EU country members, also exploring differences across types of inventors (companies, universities and governmental not-for-profit organisations). Our findings show that there is a significant heterogeneity across technologies, and this seem to be country-invariant. Moreover, we have confirmed previous studies pointing out the higher levels of generality and originality for patents generated by universities as against private companies, and the positive correlation among these characteristics. Then, we have provided empirical evidence that inventions are more likely to be original if they have technological antecedents characterised by the specific qualities of technology platforms, that is, a broad and swift applicability across a wide range of different technological applications.

This research attempts to address the central question of how technological innovations can be supported to contribute to EU competitiveness – socio-economic sustainability. This related to what policy can be designed and what actors can be mobilised to support such technological shifts so as to reset and sustainably sustain EU growth. To this end, our research has addressed related issues such as: what innovation process generates technological innovations? How technological innovations can generate shifts in the technological trends? What integrated policy can drive the anchoring of the anchoring of technology platforms in Europe and how these can propel the technological upgrading of EU firms?

We investigate the role played by technology platforms in enhancing cross-fertilisation across different technological domains, thus fostering the development of more original and radical inventions that combining a number of different but related technologies enables technological shifts or technological trajectory leapfrogging.

Our results have relevant policy implications. In particular, they suggest that technology platforms play an important role in fostering technology flows across sectors, ultimately leading to the emergence of innovation that are more radical in nature and that technological breaks and leapfrogging on new technological trajectory.

Keywords: Clusters, ecological innovation, industrial innovation, innovation, innovation policy, new technologies, patents, socio-ecological transition, sustainable growth

Jel codes: O3, O31, O32, O33, O38

Abstract

In the last decades, innovation activity has been defined by an increasing complexity and a faster pace of the underlying technological change. Accordingly, several studies have shown that competitive systems of innovation benefit from being able to build upon a wide but integrated spectrum of technological capabilities characterised by a sustained dynamism in the level of inter-sectoral technology flows. In this context, technological platforms – defined as knowledge and scientific launching pads that spin out of key enabling and bridging technologies (KEBTs) - may create the opportunity for technological externalities to take place across distant technological domains, thus fostering the development of more original and radical inventions.

In this report, we look at the presence and determinants of these technological platforms across EU Countries and explore the mechanisms through which these influence inter sectoral technology spillovers, thus fostering technological shifts and technological synthesis within the broader economy. Using data on patents and patent citations obtained from the PATSTAT-CRIOS database, covering all patent applications made to the European Patent Office (EPO), we try to model the systemic nature of technology platforms. In particular, our aim is to provide empirical evidence that the presence of key enabling and bridging technologies at the base of the platform may lead to a more sustained interaction across second tier innovations characterised by a "distant" knowledge base. Then, we endeavour to investigate the relationship that may take place between this process, the research conducted within public organisations, and the role played by the national dimension.

1. Introduction

One of the most important determinants behind the heterogeneity in the level of innovation activities across different industries is constituted by the level of technological opportunities (Scherer, 1980). According to Klevorick et al. (1995), there are three main sources of technological opportunities: advances in basic science or, more generally, scientific knowledge; previously accumulated knowledge impacting on the next wave of technological opportunities of the same industry, and finally, technological spillovers from different but related industries. In particular, the role of the technological advance of related industries and the resulting inter-sectoral technology spillovers exert a most important role in the development of long term innovation activities (Rivera-Batiz and Romer, 1991), especially within a context characterised by an increasingly complex and interconnected innovation environment leading to the multidimensional nature of emerging technological paradigms (Granstrand et al., 1997). Not surprisingly, this inter-sectoral flow of new technologies has been a central element in 20th century invention and innovation (Mowery and Rosenberg, 1998; Arthur, 2007).

The scholarly debate has provided empirical evidence of the importance of inter-sectoral knowledge spillovers using different approaches and data (Griliches, 1992; Nadiri, 1993; Verspagen, 1997). However, this strand of research has mainly explored the effects on productivity and economic growth, while the evolution and the dynamics of technological change have received much less attention.

The novelty of this report is to present empirical evidence of the mechanisms that lie at the base of technological shifts and technological synthesis by exploring the concept and the characteristics of technology platforms, which have recently attracted much attention by policy makers (European Commission, 2012; TSB, 2011; 2012). Underpinned by key enabling and bridging technologies (KEBTs), technology platforms are defined as technologies with wide and swift applicability across a range of related and unrelated sectors. We explore the mediating role that KEBTs may exert in enhancing inter-sectoral technology flows and sustaining communication across technologies that may lead towards new innovation opportunities and new technological trajectories. In particular, we analyse patents applications to the European Patent Office to address the hypothesis that KEBTs may lead to more original patents that break previous technological trajectories, and whether there is a spatial effect in the dynamics of technology platforms.

The findings from this research lead to crucial business and policy implications. From a business perspective, understating whether KEBTs are characterised by a broad sectoral applicability may enhance the flow of technological spillovers across sectors. This offers useful insights in the processes that may lead to increased technological diversification and *technology trajectory leapfrogging*, and more importantly, to a broader absorptive capacity. From a policy perspective, reaching a better understanding of the role of KEBTs in the innovation capacity of the wider economy, addresses the issue of how to support the adoption and anchoring of such new innovations that may be considered of particular social value across different sectors. In other words, the effective action of technology platform may be seen as constituting a valid instrument for technology leapfrogging and for shifting technological trajectories towards more sustainable and socially valuable direction, a notable example being represented by the current interest in environmental – or green - technologies.

The remainder of the report is organised as follows. Section 2 introduces and discusses the main elements characterising technology platforms and the specific qualities of the underlying technology. Section 3 presents a short overview of the relationship between technology platforms and the spacial dimension. Data for the analysis are reviewed in Section 4, along with the specification for the main model variables. Section 5 presents some stylised facts regarding originality and generality across EU member states, followed by a discussion of the results from the regression analysis. Section 6 concludes with the policy implications drawn on our findings, along with some final remarks.

2. Technology integration and synthesis: the role of technology platforms

Since the remark of Schumpeter (1934) on the ‘combinatorial’ function of entrepreneurs, technological integration and synthesis has held a most important place within the literature on innovation and technological change. Combinative capabilities create linkages internal and external to companies which exert a fundamental role in the creation of new knowledge (Nelson and Winter, 1982; Kogut and Zander, 1992), so that it is possible to identify technologies as combinations (Arthur, 2007). Accordingly, technological trajectories and, ultimately, industry dynamics might be described by a process of cumulativeness in firms’ knowledge capabilities and the integration of the technological opportunities available (Nelson and Winter, 1982; Dosi, 1982).

To identify and create new knowledge, technological opportunities must overlap to some extent with the technological space of established capabilities. However, as firms' innovative activity is characterised by processes of knowledge relatedness (Breschi et al., 2003), the intersection between these elements is often significant and the resulting pattern of technological change usually displays an incremental and path dependent structure. Similarly, knowledge spillovers are also highly technology specific and, for the most part, intra-sectoral (Malerba et al., 2013).

Conversely, inter-sectoral technology spillovers are established through a process of technological integration defined by innovations that span across a broader set of technological classes, thus pushing towards a shift in the established technological trajectory. As „distant" technologies are integrated together, wider technological shifts and inter-sectoral cross-fertilisation are more likely to occur, so that a "technology that has less immediate precedents in its technology class is likely to be more radical innovation" (Hicks and Hegde, 2005: 708). Technologies characterised by higher levels of technological integration are not necessarily related to greater economic value (Nair et al, 2011), yet they represent an important competitive advantage providing companies with the potential to explore as well as exploit new opportunities, and engage in a wider and more articulated combination of resources. In this sense, the ability to recognise and absorb these new opportunities is a fundamental capability for the long-term survival of firms (Fai and von Tunzelmann, 2001). Similarly, the ability to integrate firms' established technologies with innovations from a different technological domain may also represent an important element in fostering resilience across mature technologies.

It is possible to identify two main processes through which technological integration and synthesis may take place. The first is related to the expansion of firms' absorptive capacities through technological diversification, whereas the second is related to the presence of enabling and bridging technologies.

2.1. The role of technological diversification

Large corporations and small serial innovators as well engage in processes of technological diversification to broaden the range of their absorptive capacity and knowledge competencies (Granstrand et al., 1997; Patel and Pavitt, 1997; Corradini et al., 2012). In this sense, technological diversification prevents innovative firms from being locked in a specific technology (Susuki and Kodama, 2004). Broad-based knowledge capabilities act as a platform enabling the expansion and the diversification of firms' technological trajectory in derived technologies along a wide range of new opportunities (Kim and Kogut, 1996). Hence, they increase the level of potential exploration and reconfiguration of existing knowledge into new fields of research, allowing for a more fruitful exploitation of firms' combinative capabilities (Kogut and Zander, 1992).

Similarly, the role of basic scientific research in fostering technological integration lies in the broader technological base which is usually related to its development, so that public research has often been associated with more original innovation (Nelson, 1959; Trajtenberg et al., 1997). An analogous rationale holds for innovation activity carried out by a larger group of inventors, although in this case the competencies involved are more likely to present a certain degree of relatedness (Petruzelli, 2011).

2.2 The role of technology platforms in technological integration

Just as innovators may increase their absorptive capacity in order to access and utilise a wider range of „distant‟ technologies, technologies that present a broader or more general applicability may be more easily accessible by firms, as if they were closer to inventors in other technological domains. Discussing the characteristics of general purpose technologies (GPTs), usually identified by a general nature defined by technological pervasiveness leading to „innovational complementarities‟, previous literature has underlined their role as key enabling technologies (Bresnahan and Trajtenberg, 1995), that is, technologies whose impact is exerted on the productivity of a wide range of sectors.

Whilst the literature limits its analysis to explain the impact of key enabling technologies along the innovation process -vertical dimension-, we argue that some of these enabling technologies may also present a horizontal dimension as they act as bridges across „distant‟ technologies. Thus, we propose an extension to the concept of key enabling technology and suggest that some technologies are indeed key enabling and bridging technologies (KEBTs) in view of the fact that their broad applicability across different technological fields is likely not only to generate innovation cascades –enabling effect-, but most importantly to foster connections between „distant‟ technologies by offering a technological coupling –bridging effect-. KEBTs are therefore able to generate a web of related and unrelated synergies across distant technologies that have disruptive effect on firms' technological trajectories.

Building upon the conceptualisation of KEBTs, we introduce the concept of technology platform as set of KEBTs that are able to generate intra and inter-sectoral technology spillovers. In this sense, we define technology platforms as being crucially underpinned by a broad – and yet interconnected - technological base characterised by high technological dynamism generating positive technological externalities across a wide range of sectors, thus increasing inter-sectoral linkages within the innovation system. In this sense, technology platforms developed around key enabling and bridging technologies (KEBTs) can be argued to play a fundamental role in sustaining communication across diverse technological fields, generating high levels of dynamism and pervasiveness through processes of technological integration. Taking into account the inter-firm dimension that is inherent to innovation networks and the rise of „open innovation" (See Freeman, 1991; Chesbrough, 2003), technology platforms increase the opportunities that companies might have to access and learn from „distant" technologies and to integrate these within their knowledge competencies. This is possible because KEBTs allow firms to exploit complementarities across the wide range of technological fields that are distant albeit technologically connected. Increasing the likelihood of inter-sectoral technology spillovers, technology platforms exert a displacing effect on the path-dependent nature of technological change and propel firms onto new technological trajectories. In line with these arguments, we hypothesize that technology platforms underpinned by KEBTs are more likely to be conductive to original innovation characterised by processes of technological integration from a broad range of related and unrelated technologies. Thus, our first hypothesis is the following:

H1. KEBTs exert a positive effect on the likelihood to develop more original technologies.

3. Technology platforms and the national dimension

The discourse associated with technological platforms is clearly associated with another level of analysis rooted in a spatial perspective. Cooke and De Laurentis (2010, p 273) write about 'platforms of innovation' where a platform "consists of a number of businesses and quite possibly knowledge or training and support services, agencies and firms that cross typical sectoral and even cluster boundaries. Comparable to clusters but not to the same extent, there is spatial contiguity in the notion of platform." Robinson et al. (2007) note that "because of the coordination [...] that is involved, there is a proximity effect and some clustering will occur". Hence, high-tech clusters and districts might be argued to comprise an external technological platform defining the contours of the cluster's technological proximity. Cooke and Leydesdorff (2006) develop a regional innovation policy framework, incorporating the concepts of related variety and differentiated knowledge bases, that embraces a 'platform' approach. Producing the co-location of different scientific and technological fields, the shared pool of technological capabilities which define these platforms creates technological externalities across a set of related sectors, thus fostering regional economic growth (Cooke and De Propris, 2011).

With respect to technology platforms, one important difference is identifiable: while high-technology clusters are usually defined in terms of sectoral proximity, the distinctive element in the agglomeration effect defined by the presence of a technological platform is the underlying core technology (Robinson et al., 2007), around which spillovers arise and are exchanged (Iammarino and McCann, 2006). As Maurseth and Verspagen (2002) have shown, knowledge spillovers in Europe are often confined within a national dimension. Thus, innovations that are based on 'distant' technologies may have a higher likelihood of success if the knowledge required for their development is characterised by a geographical proximity.

Our second hypothesis builds upon these arguments to explore the presence of a national dimension in the process of knowledge synthesis carried out by technology platforms, where proximity in knowledge spillovers exert a positive effect on the integration of 'distant' technologies.

H2. Innovations which are spatially related are more likely to foster the development of original technologies.

4. Empirical analysis

4.1. Data

The analysis presented is based on patent data from the EP-CRIOS[1] database covering all patent applications made at the European Patent Office (EPO), whose priority date[2] is comprised in the period between the year 1996 and 2006 included. The use of patents as measure of innovation has been adopted for a long time, and strengths and weaknesses are well known (see Pavitt, 1988, Griliches, 1990). Patent data are used extensively in the innovation literature for they have a wide coverage of innovative activity in almost all technological sectors, while ensuring the presence of a significant inventive step. Moreover, they are available for long periods of time and provide detailed and fine information on the technological characteristics of the patented invention, as well as inter-sectoral knowledge flows as provided by citations (Jaffe et al., 1993).

Focusing on all patent applications for all 27 member countries of the European Union, the sample obtained accounts for 490444 patent applications. Data are obtained merging information from two related databases. The first is the EP-CRIOS database, which contains information on all patent documents from the EPO. Among these, the most relevant to our studies are:

- Patent publication date, priority date, International Patent Classification (IPC) technological class;
- Applicant data, such as names, addresses, NUTS3 level location and type (i.e.: private company, or public research organization);
- Standardised inventor data, including all information available for applicants.

The second database is the PATSTAT database, based on the EPO master documentation database (DOCDB), which is used to collect information on all forward and backward EPO to EPO citations for all the patents analysed in this report.

As we focus on EPO to EPO patent citations to build our indexes and carry out our analysis, a couple of considerations are in order. First, EPO patents do not represent the

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[1] For a detailed description, see Lissoni et al. (2006).

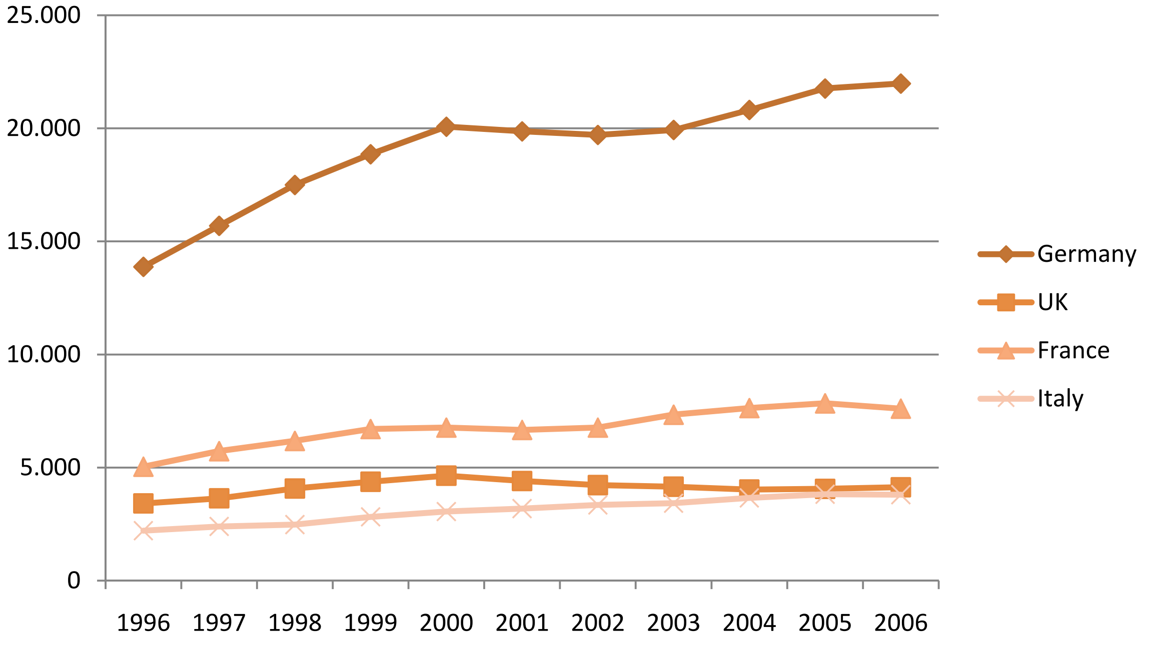
[2] The priority date refers to the year of worldwide first filing. Being the first date in the application process, this data can be considered as the closest to the date of invention.

whole population of patent applications in Europe, as must first apply for the patent in their national patent office. However, we may expect patents with higher quality to be filed also at the European level. Second, patent examination at the EPO differs significantly form other offices such as the USPTO. In particular, while under the US patent system the applicant is required to list all citations relevant to the patent applied for, at the EPO the large majority of citations are added by the patent examiner. Thus, it is possible the applicant may be not aware of some of the technologies included in the document citations (Maurseth and Verspagen, 2002). This does not imply that a citation link in EPO patents cannot be used as an indicator of technological relatedness. In fact, Criscuolo and Verspagen (2008) suggest the opposite may be true, as EPO citations have been scrutinised by patent examiners to be closer in technological relevance and time to the filed invention.

4.2. EPO applications: some stylised facts

Before exploring the relationship between technology platforms and their binding effect on different technologies, in this Section we offer a broad overview of the data used in the analysis to offer a descriptive snapshot of the innovation activity in the European Union as depicted by EPO patent applications. In terms of total patent applications, there are

Figure 1 – Patent applications per year for selected countries.



well-known significant differences across Countries. This is shown for some of the largest Countries in Figure 1, where we report the number of patent applications to the EPO per year[3].

Substantial differences also take place across different IPC classes, reflecting the inter-sectoral heterogeneity in the pace of technological change. At the same time, these differences are strongly country variant, in line with the technological specialisation of EU member states and the important specificities of the various national systems of innovation. This is reported in Figure 2, which shows the percentage of patent applications for each IPC class with respect to the total number of applications from some selected Countries. While it is important to take into account that sectors have a different propensity to patent inventions[4], some stylised facts emerge from Figure 2. The IPC classes with the highest percentage of patenting across the EU are class 3 (Telecommunications) and class 7 (Technologies for Control/Measures/Analysis), followed by class 1 and class 27 (respectively Electrical engineering and Transport technology). Conversely, lower values are presented by class 9 (Nuclear technology), class 8 (Space technology) and 21 (Environmental Technologies).
Interestingly, we can also observe significant differences across the selected Countries. For example, Germany presents higher specialisation in sectors such as Transport technology and Technologies for Control/Measures/Analysis, while France is stronger in Telecommunications and Electrical engineering. The UK is also strong in Technologies for Control/Measures/Analysis, but it also shows strong specialisation in Biotechnologies and Pharmaceuticals. Quite different is the case of Italy, whose higher values are associated with Handling and Printing technologies, Consumer goods and Civil engineering. Other countries are even more specialised. Sweden[5], for example, holds almost a quarter of all its patent in the Telecommunications class, while for Finland this value goes up to around 40%. For the Netherlands, more than a third of all patents are in classes 2, 3 and 4.

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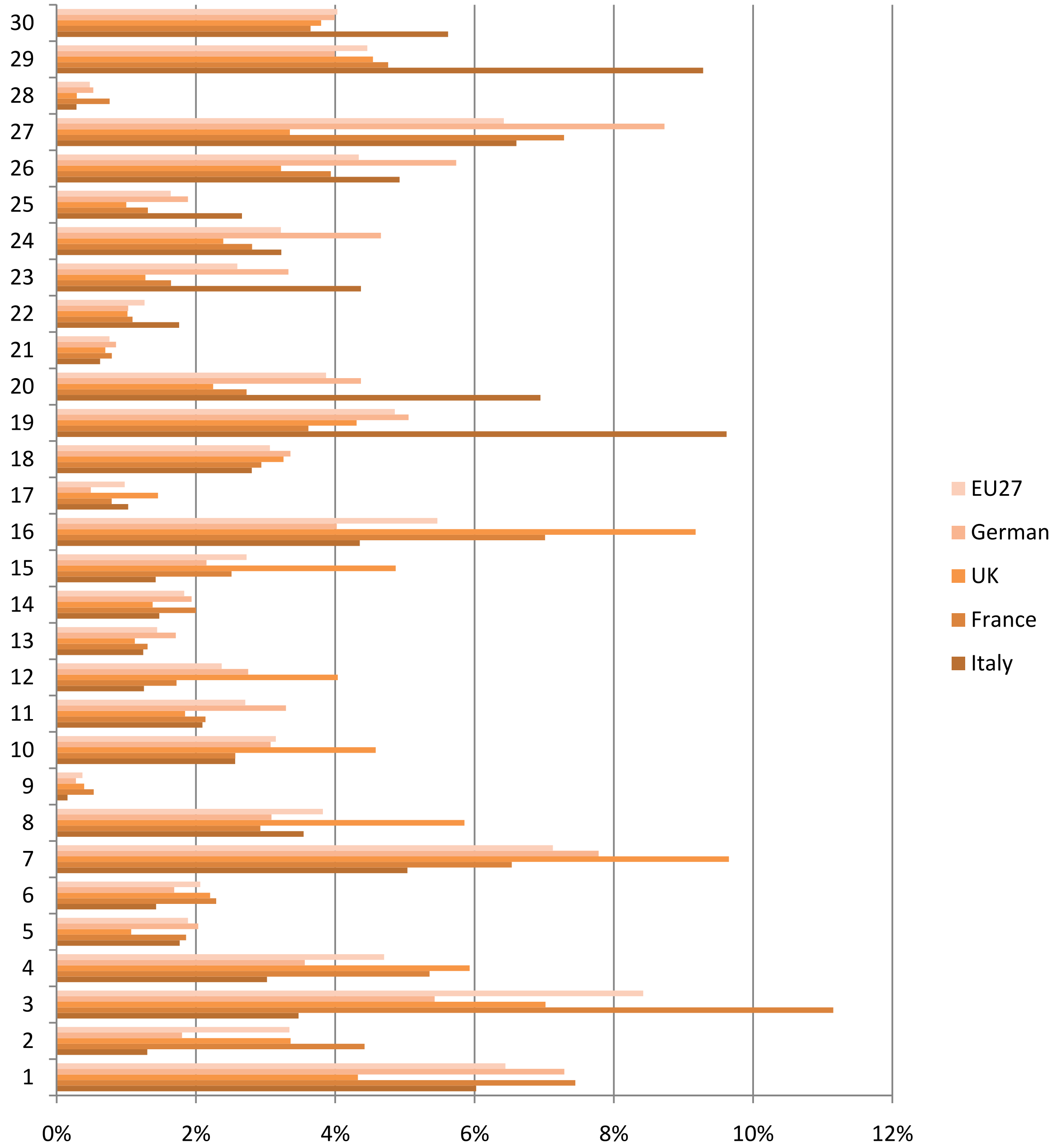
[3] We note that as the EPO is located in Germany, the number of applications from this Country may be over-represented.

[4] See, for example, Arundel and Kabla (1998).

[5] Data are not reported here, but they are available upon request.

Figure 2 – Percentage of EPO applications per IPC class.



4.3. Econometric approach

In this Section, we try to model the effect of technology platforms. Our aim is to provide empirical evidence that the presence of KEBTs that form technology platforms leads to a more sustained interaction across technological fields, leading to innovations characterised by a "distant" knowledge base (H1), and that this effect may be stronger within a national dimension (H2). In other words, we try to test the hypothesis that innovations whose effects take place in a wide range of technological fields might increase the likelihood of developing more original innovations that may shift away from previous technological trajectories, and whether there is a regional dimension related to this process. Thus, our model may be defined as follows:

ORIGIN = f(KEBT, INTER, N_INVENT, TECHDIV, KSTOCK, UNIV, FCIT8, CITATIONS)

4.3.1. Dependent variable

In this report, we analyse patents escaping the path dependency inherent to the cumulative nature of technological change, which can be seen as 'shifting technologies' that broaden the spectrum of the technological frontier. Such patents can be also related to original and more radical innovations.

An intuitive and well established proxy for these characteristics is offered by the 'originality' index, labelled ORIGIN, which is a measure of the sector dispersion of backward citations. Following Trajtenberg et al. (1997), the index is calculated as the generality index, except that citations received are replaced by citations made by the company. Including the correction presented in Hall (2005) for small sample bias (i.e. N_{bp} / N_{bp} - 1), we have:

$$ORIGIN_p = \frac{N_{bp}}{N_{bp} - 1}\left(1 - \sum_{k=1}^{K}\left(\frac{N_{bp,k}}{N_{bp}}\right)^2\right) \quad (1)$$

where K is the number of different IPC technological classes where the patent made citations, $N_{bp,k}$ is the number of backward citations made to the *k* sector and N_{bp} the total number of citations made.

We also analyse our model using a related variable, which reflect the technological distance in the backward citations of patents, so that the presence of KEBTs may allow technologies to be connected to a wider set of technological domains. To do so, we define the variable TECHWIDTH as a measure of the technological distance within the backward citations underpinning the original patent. Following the concept of knowledge-relatedness suggested by Breschi et al. (2003), we proceed calculating the knowledge-relatedness matrix whose elements are given by the cosine index S_{ij}, that measure the similarity between two technological classes i and j with respect to their relationship with all other IPC classes (For a detailed description, see Breschi et al., 2003). Formally, we have:

$$S_{ij} = \frac{\sum_{k=1}^{30} C_{ik} C_{jk}}{\sqrt{\sum_{k=1}^{30} C_{ik}^2} \sqrt{\sum_{k=1}^{30} C_{jk}^2}} \tag{2}$$

where Si,j represents the number of patents that have been classified in both sectors i and j using information on all UK patents between 1996 and 2006. This process generates a 30X30 square matrix M[6] that can be used to measure knowledge-relatedness between patents and patent citations in time t. Thus, the index TECHWIDTH is given by the inverse of the average value of knowledge-relatedness between the IPC of the original patent and those of each backward citation.

4.3.2. Independent variables

To capture the presence of key enabling and bridging technologies, represented by the variable KEBT, we make use of the generality index first proposed by Trajtenberg et al. (1997) to capture the generic nature of academic patents. This index provides a measure of the spread across different technological fields of follow-up innovations, and for this reason has been adopted as a proxy for the quality of enabling technology in the seminal paper by Hall and Trajtenberg (2004) on the measurement of general purpose technologies. To calculate this variable, we follow the approach proposed by Trajtenberg et al. (1997), who construct the index as an inversed Herfindahl index, with values closer to 1 for patents with citations from a large spread across different technological classes and values close to 0 for patents cited in a small number of technological classes. Including the same correction

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[6] Values for the matrix are available upon request.

introduced for the dependent variable, the generality index is defined for each patent p as follows:

$$GENERALITY_p = \frac{N_{fp}}{N_{fp}-1}\left(1-\sum_{k=1}^{K}\left(\frac{N_{fp,k}}{N_{fp}}\right)^2\right) \tag{3}$$

where K is the number of different IPC technological classes where patent p was cited, $N_{fp,k}$ is the number of forward citations for the k sector and N_{fp} the total number of forward citations7. The value for our variable, KEBT, is defined as the average level of GENERALITY across the backward citations of each patent application.

To address our second hypothesis related to the degree of internationalisation of technology flows in the development of technology platforms (associated to the coordination across technologies and the localised effect of knowledge spillovers), we introduce a variable capturing the international dimension of knowledge flows (INTER), which is defined as the proportion of backward citations to the same Country as the original patent over the total number of backward citations[8].

The next variable, labelled N_INVENT, is given by the number of inventors that registered the patent. The simple idea behind this is that the broader the range of actors participating and therefore the elements of combinative capability involved, the higher the opportunities for cross-fertilisation of competencies and the broader the scope of new technologies.

A first set of control variables includes the R&D intensity and the technological diversification among applicants. To control for R&D intensity we use the knowledge stock of the owner of the original patent (KSTOCK)[9], which is based on the past history of innovation, as companies with more R&D capabilities have higher absorptive capacity and are more likely to pursue broader processes of technological search. The proxy for the R&D

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[7] It follows from the definition of GENERALITY, that the index is not defined for patents with zero backward citations. Patents with only one backward citation have the index set equal to 0 by construction.

8 Different levels of regional dimension have been explored, as patent data are available at the NUTS3 level. However, results are similar to the analysis conducted at the national level. Results are based on the NUTS3 level for the patent applicant, but similar findings are obtained using data on the NUTS3 of inventors.

9 For the formal definition, see previous Section.

intensity of the inventors is measured through the patent stock of the inventor up to time t. In line with the existing literature we measure the patent stock (KSTOCK) as:

$$KSTOCK_{it} = P_{it} + (1-\delta)KSTOCK_{it-1} \tag{4}$$

where P_{it} represents the number of patents at the beginning of year t and δ is the depreciation rate, which is usually assumed to be 15% (Hall et al., 2005)[10].

Then, we include a measure of the technological diversification within companies' innovation activity to control for the possibility that inventors characterised by a broader technological base might present higher 'combinative' capabilities (Kogut and Zander, 1992) and stronger absorptive capacity, leading to more original inventions. To measure technological diversification (TECHDIV) we make use of an index which is based on a measure of technological proximity. It is calculated as the inverse of the Herfindahl index, confronting patents for each IPC technological class against the total number of patent of a given company. Again, we correct the index using the bias correction indicated by Hall (2005) to account for observations with few patents per year. The index is formally defined as follows:

$$TECHDIV_p = \frac{N_p}{N_p - 1}\left(1 - \sum_{k=1}^{K}\left(\frac{N_{p,k}}{N_p}\right)^2\right) \tag{5}$$

where Nit is the total number of patents for the ith company in year t, while k represents the IPC category where the firm patented and K is the total number of technological classes where the company was active. It follows that due to the nature of the formula of TECHDIV, companies with less than two patents per year had to be omitted from the analysis.

We add a dichotomous control variable to capture the role of research done within Universities or other public research organizations (PROs), as these have often been associated with more original patents.

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[10] Given that our database contains information on all patent applications, we do not need account for the effect of missing initial conditions.

Finally, the variables FCIT8 and CITATIONS are introduced to control for the quality of the patent and the number of backward citations included in the application. Given the wide variance in the quality of the patents, accounting for the number of forward citations in the following 8 years ensures that the effect of technology platforms is consistent for both low and high quality patents, the latter being obviously more interesting as a case. The number of backward citations is included as an additional control for the propensity to add more citations in sectors where patents are traditionally used as a means of intellectual property protection.

4.3.3. Estimation method

In the regression analysis, the originality index that constitutes our dependent variable presents values that fall within the open bounded interval I = (0, 1). Hence, predicted values from OLS regression or spline methods may generate predicted values lying outside the unit interval. At the same time, modelling the log-odds ratio as a linear function is an inefficient solution as values for our dependent variable standing on the interval boundaries zero and one would not be handled. Adjusting such values is also inappropriate. To address this issue, we make use of the fractional response model[11] suggested by Papke and Wooldridge (1996), who show that quasi-maximum likelihood estimation (QMLE) can be used to obtain robust estimators of the conditional mean parameters.

5. Results

5.1. Descriptive Results

For a first understanding of possible differences at the Country level in the qualities of originality[12] and generality across different types of applicants, in Figure 3 and Figure 4 we report the average values of originality and generality across four selected Countries for patents developed by private companies and public research organisations (PROs).

Overall, we find that both measures of originality and generality seem to support previous findings from the literature indicating that patents owned by PROs are on average

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[11] Estimates are robust to more standard methods like logit or probit.

[12] Values for originality are calculated for patent applications with at least 2 backward citations.

more original and general than patents generated by private companies.[13] As we can see from the Figure 3, there are similar levels of originality observed across the four member Countries selected, and at the same time we see that PROs seem to develop patents characterised by higher levels of originality with respect to private companies[14], irrespective of the Country analysed.

Figure 3 – Average patent originality across selected EU members and type of applicant.

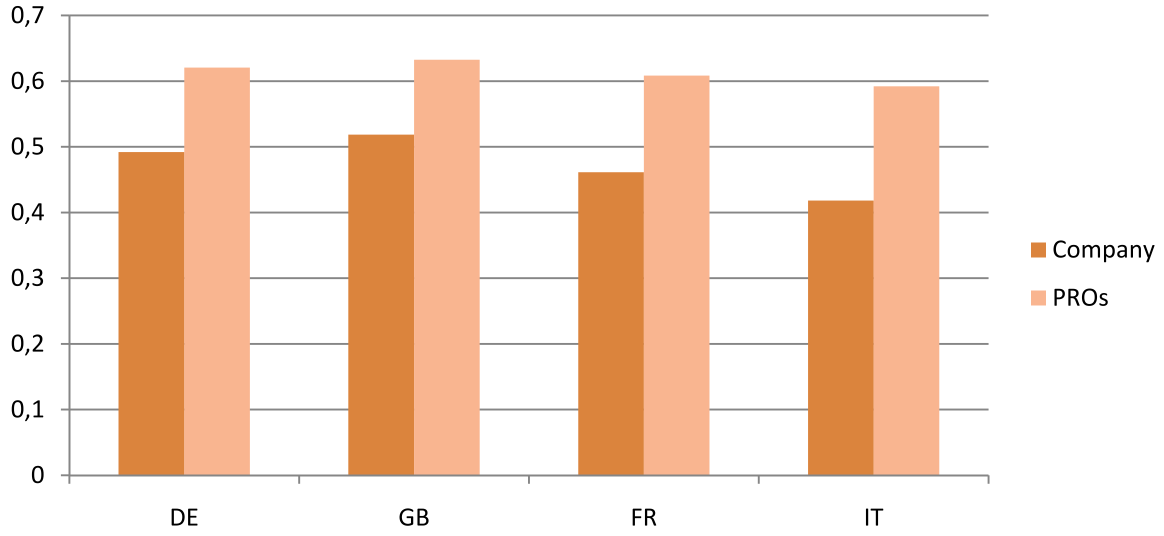

Figure 4 shows that the level of generality is more heterogeneous across type of applicant and Countries. Germany and the UK seem to develop more general inventions, but the wider differences take place across the two categories analysed. As observed for originality, companies present lower values than public research organisations[15]. Such findings are also confirmed by means of multivariate analysis where the dependent variable is the index for GENERALITY[16]. In particular, estimates for dummy variables representing PROs patents present positive and statistically significant values. Given that the base group for country variables is Germany, we find a positive sign for the UK, while the other countries all present negative coefficients.

The level of generality presents significant differences across technological classes. This is shown in Figure 5, where we report the average value for generality across IPC

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[13] For a broader discussion of the differences between university-owned and company-owned patents, see Lissoni and Montobbio (2012).

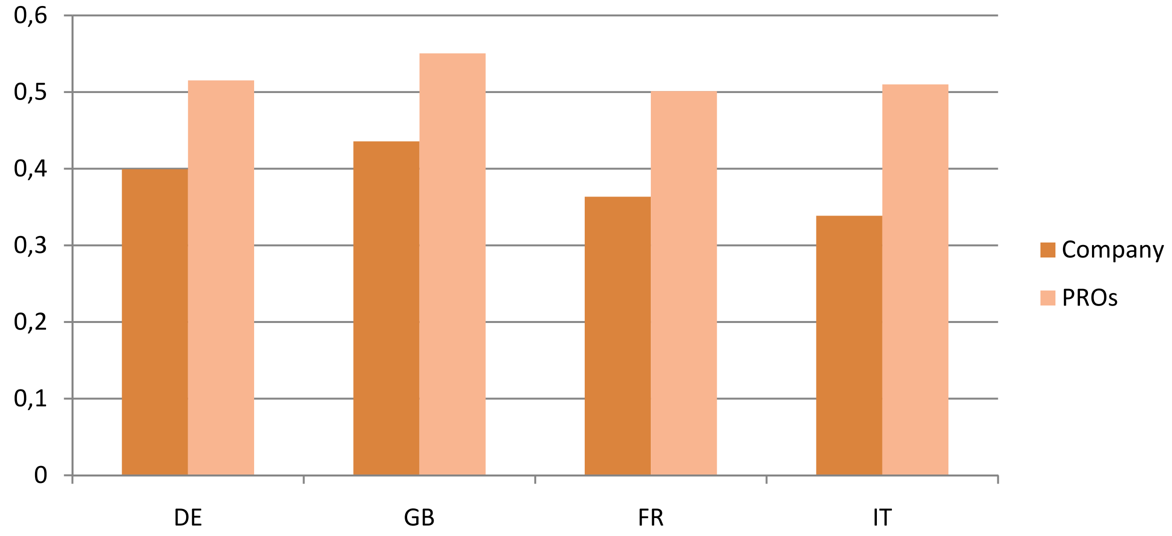
[14] T-tests for mean differences are significant at the .001 level.

[15] Mean differences are significant at the .001 level.

[16] Estimates are reports in Table A.3.

classes for the EU as a whole and in the four selected countries. While we observe that generality is fairly country invariant, we see clear differences at the technological level.

Figure 4 – Average patent generality across selected EU members and type of applicant.



Sectors characterised by a higher level of generality (e.g.: > 0.5) include Organic chemistry (10), Macromolecular Chemistry (11), Surface technology (13), Biotechnology (15), Technical processes (18) and environmental technologies (21). Conversely, lower levels are found for Telecommunications (3), Medical engineering (8) and Civil engineering (21)[17]. These technological classes resemble those identified by both the European Commission and the UK Technology Strategy Board[18] as enabling technologies. Some differences remain, notably in a more prominent role of environmental technologies and a low level of generality for telecommunications.[19]

As our analysis is aimed at exploring the role of KEBTs in supporting technological synthesis or - more broadly - originality, we also start looking at the average generality within backward citations for patents across different applicants and selected countries. Means values are reported in Figure 5. These values resemble those identified for Generality when we consider differences between companies' patents or PROs patents, the latter group having

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[17] We are currently working on a network analysis to analyse technological flows across different technologies.

[18] See Appendix, Table A.1.

[19] We point out that other classes related to ICT present significant generality, such as Audiovisual technology (2), Information technology (4) and Semiconductors (5).

a significantly higher average for KEBT[20]. However, differences across the selected Countries are less marked, as they present similar means across the type of applicants. In other words, our data show that PROs not only make more general patents, but they also use more extensively these patents characterised by a wide applicability.

Figure 4 – Average generality across IPC classes.

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[20] A multivariate analysis is offered in Table A.4.

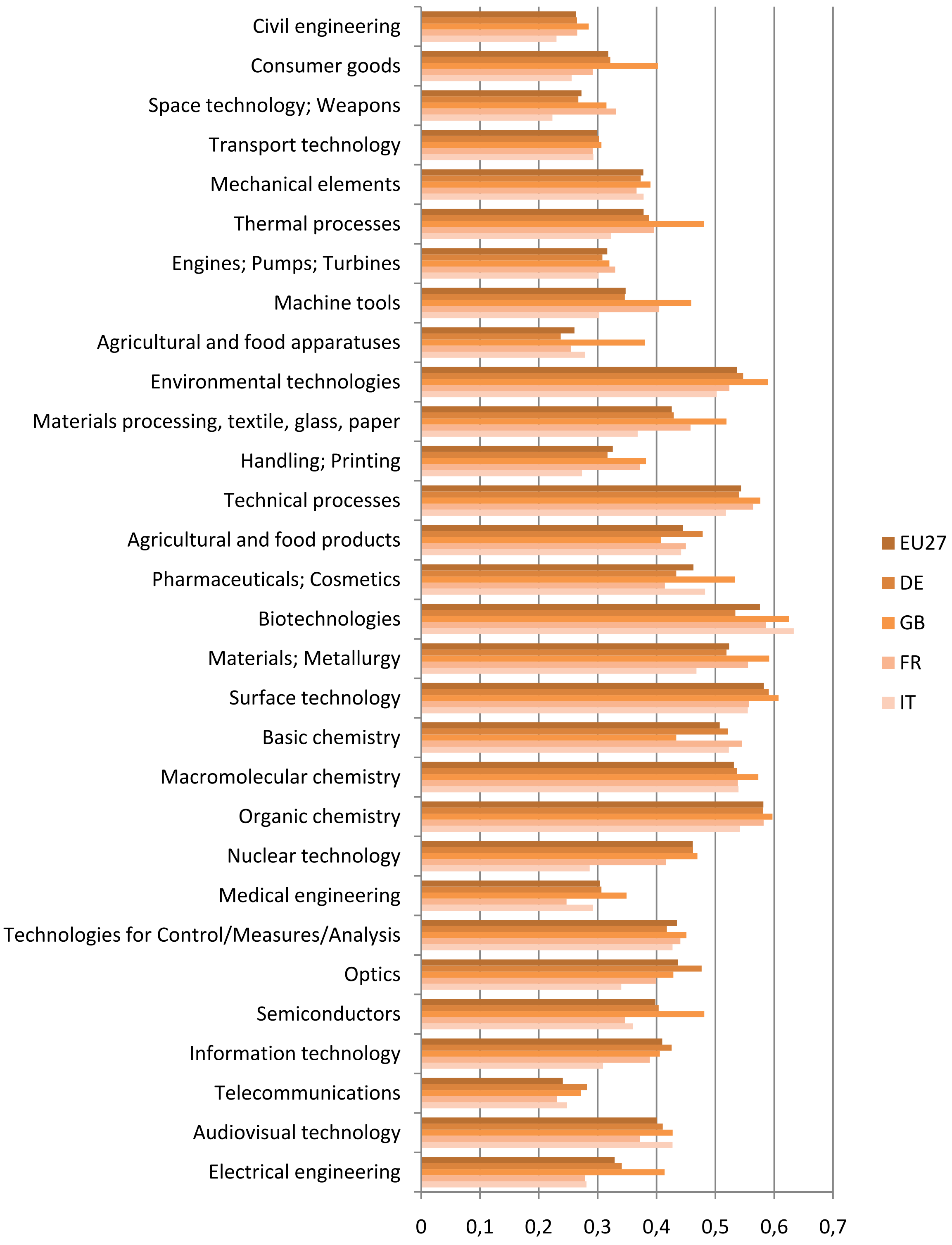
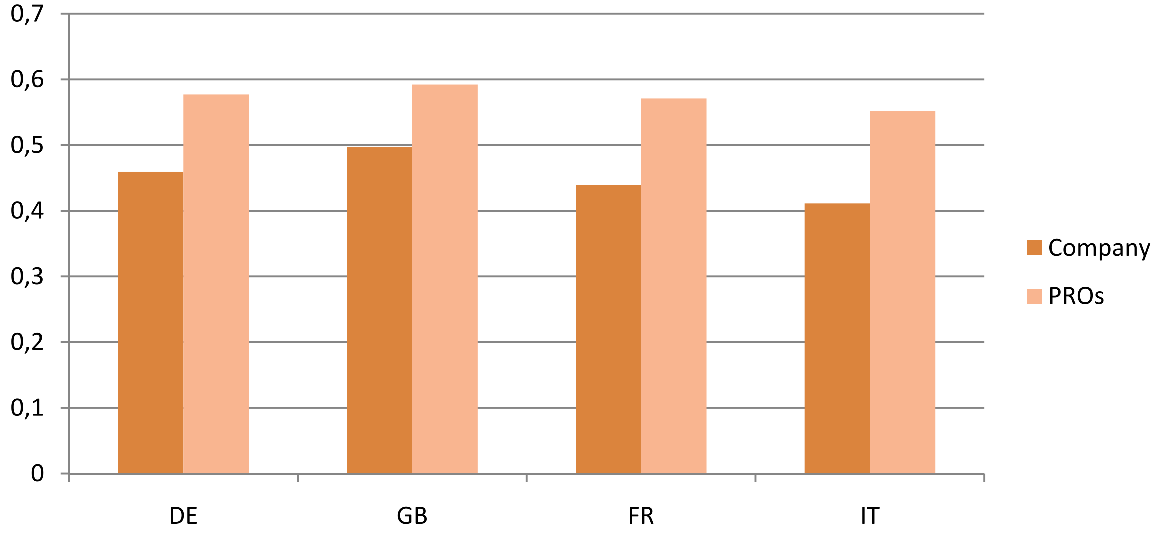


Figure 5 – Average value of KEBT across selected EU members and type of applicant.



5.2. Regression results

In this Section, we present the results based on our empirical framework. We present descriptive statistics in Table 1, while the correlation matrix of the variables employed is reported in Table 2. With respect to the latter, it is particularly interesting to see that there is a medium-high positive correlation between technological width across backward citations and the level of generality among these, indicating that patents that are based on distant technologies tend to rely on technologies that are characterised by a broad

Table 1 – Descriptive statistics.

	Obs	Mean	St.Dev	Median	Max	Min	VIF	Tolerance
Origin	370715	0.48	0.37	0.59	1	0		
Techwidth	370463	0.25	0.26	0.17	0.99	0		
KEBT	362612	0.46	0.28	0.52	1	0	1.97	0.51
Inter	362621	0.66	0.38	0.75	1	0	1.01	0.99
N_inventors	370755	2.46	1.75	2	49	0	1.05	0.95
Techdiv	283301	0.62	0.25	0.68	1	0	1.35	0.74
Kstock	370755	4.33	2.49	4.15	9.31	0.69	1.36	0.73
PROs	370755	0.04	0.20	0	1	0	1.05	0.95
Fcit8	370755	1.45	2.78	1	144	0	1.04	0.96
Citations	370755	3.28	3.31	2	128	1	1.05	0.96

Table 2 – Correlation matrix.

	1	2	3	4	5	6	7	8	9	10
Origin	1									
Techwidth	0.500	1								
KEBT	0.558	0.634	1							
Inter	0.025	0.023	0.044	1						
N_invent	0.089	0.005	0.081	-0.040	1					
Techdiv	0.097	0.026	0.078	-0.014	0.117	1				
Kstock	-0.098	-0.171	-0.178	-0.037	0.109	0.450	1			
PROs	0.072	0.032	0.081	0.048	0.066	0.163	-0.033	1		
Fcit8	0.025	0.016	0.032	-0.007	0.086	0.009	0.031	-0.022	1	
Citations	0.062	0.043	0.048	-0.014	0.095	0.014	0.021	-0.036	0.182	1

technological applicability. As expected, there is a positive correlation between knowledge stock and the level of technological diversification, as well as between TECHWIDTH and originality.

The estimates from the fractional response model are reported in Table 3. Column (1) reports the results using applications from all 27 EU member states, while the other columns show the results for the four selected Countries. The estimates for KEBT are in line with our first hypothesis that key enabling and bridging technologies are positively related to the development of more original patent applications, with the relative coefficients being positive and statistically significant across all different columns. In other words, even after controlling for patents' technological class[21], patents based on general technologies - or KEBTs - are significantly more likely to be original and to integrate components from a wider range of different technologies[22]. Such technologies can be regarded as exerting a binding effect that may ultimately lead to technological shifts or innovation cascades.

The role of INTER, that is, the proportion of citations from countries other than the one of the citing patent, presents a mixed picture as coefficients are not always significant across the countries analysed. In particular, for the EU as a whole as well as for Germany and Italy, the coefficient of INTER is positive and significant, while for the United Kingdom is not significant but negative. Such results are likely to be related to both the characteristics of

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[21] Similar models have been also carried out for single IPC classes, but estimates are fairly robust to the different model specifications. Estimates are available upon request.

[22] While our model doesn't necessarily imply causation between KEBT and ORIGINALITY, we underline that the variable KEBT refers to the generality level in the backward citations of patents, thus providing a longitudinal dimension to the model.

the specific national systems of innovation and to the sector specialisation or diversification of the technological base in such countries. Overall, we have not found convincing evidence of a European innovation system. However, further analysis is needed to explore this possibility.

Control variables behave as expected. We find a general positive effect in the presence of a larger team of inventors (N_INVENT)[23], and a positive one for TECHDIV. With respect to this, our findings confirm that companies that are able to engage in different technological avenues present a higher likelihood of being able to benefit from and integrate distant technologies, thus developing more original innovations. A similar process may be generated by wider groups of inventors, which are more likely to encompass knowledge competencies from distant technological fields.

The role of universities and other public research organisations, like INTER, is less clear cut. Our results do not provide statistically significant results when KEBT is included. However, removing KEBT from the model makes the coefficient of PROs statistically significant, with the exception of the United Kingdom. Again, this difference might be explained in terms of different national systems of innovation. These findings seem to suggest that the level of originality usually associated with public research innovation may depend more on their ability to use KEBTs in their innovation processes. In other words, the function of public research in developing more original technologies lies in its ability to use and integrate enabling and bridging technologies within its innovation activity. This is supported by our findings on the mean value of KEBT across different types of applicants, reported in Figure 5, and the estimates from the multivariate analysis in Table A.4 where PROs are found to show a much higher coefficient for KEBT than private companies.

Finally, the remaining control variables related to backward and forward citations both show a positive coefficient in most of the columns of Table 3, with the exception of columns (5) and (6) based on Swedish and Italian patents. In these cases, though, estimates are not statistically significant.

Results from the robustness analysis, where the variable TECHWIDTH is used as dependent variable, are reported in Table 4. The estimates seem to confirm our main finding, with both KEBTS and INTER presenting significant and positive coefficients.

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[23] Estimates for Italy and Sweden are not significant at the .10 level.

Table 3 – Fractional response model estimates for Originality.

	Fractional response model - GLM robust estimates									
	(1) EU27		(2) DE		(3) GB		(4) FR		(5) IT	
KEBT	3.145***		3.159***		2.942***		3.133***		3.121***	
	(0.017)		(0.024)		(0.063)		(0.045)		(0.077)	
inter	0.022*	0.104***	0.031*	0.099***	-0.050	-0.023	-0.021	0.075***	0.171***	0.268***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.031)	(0.031)	(0.024)	(0.022)	(0.042)	(0.040)
N_invent	0.009***	0.012***	0.009***	0.012***	0.014**	0.020***	0.006	0.005	0.013	0.021*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)	(0.010)
techdiv	0.386***	0.686***	0.450***	0.831***	0.194***	0.286***	0.449***	0.861***	0.302***	0.432***
	(0.014)	(0.013)	(0.021)	(0.020)	(0.039)	(0.040)	(0.039)	(0.038)	(0.055)	(0.054)
Kstock	-0.021***	-0.058***	-0.027***	-0.067***	-0.019**	-0.050***	-0.020***	-0.060***	-0.017+	-0.068***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.005)	(0.005)	(0.010)	(0.010)
PROs	0.020	0.073***	0.039	0.118***	0.006	0.049	0.029	0.089**	0.062	0.146+
	(0.014)	(0.014)	(0.024)	(0.024)	(0.034)	(0.034)	(0.028)	(0.028)	(0.087)	(0.089)
fcit8	0.004***	-0.000	0.006***	0.002	0.005*	0.002	0.003	-0.005+	0.006	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
citations	0.014***	0.015***	0.023***	0.024***	0.002	0.002	0.016***	0.019***	0.016***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
_cons	-1.900***	-1.279***	-1.961***	-1.395***	-1.542***	-0.655***	-1.919***	-1.370***	-1.985***	-1.376***
	(0.017)	(0.016)	(0.023)	(0.023)	(0.054)	(0.051)	(0.045)	(0.045)	(0.077)	(0.076)
Obs.	278626		133759		23822		43889		14075	
Country dummies	Yes		No		No		No		No	
Time dummies	Yes		Yes		Yes		Yes		Yes	
IPC dummies	Yes		Yes		Yes		Yes		Yes	

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

Table 4 – Fractional response model estimates for Techwidth.

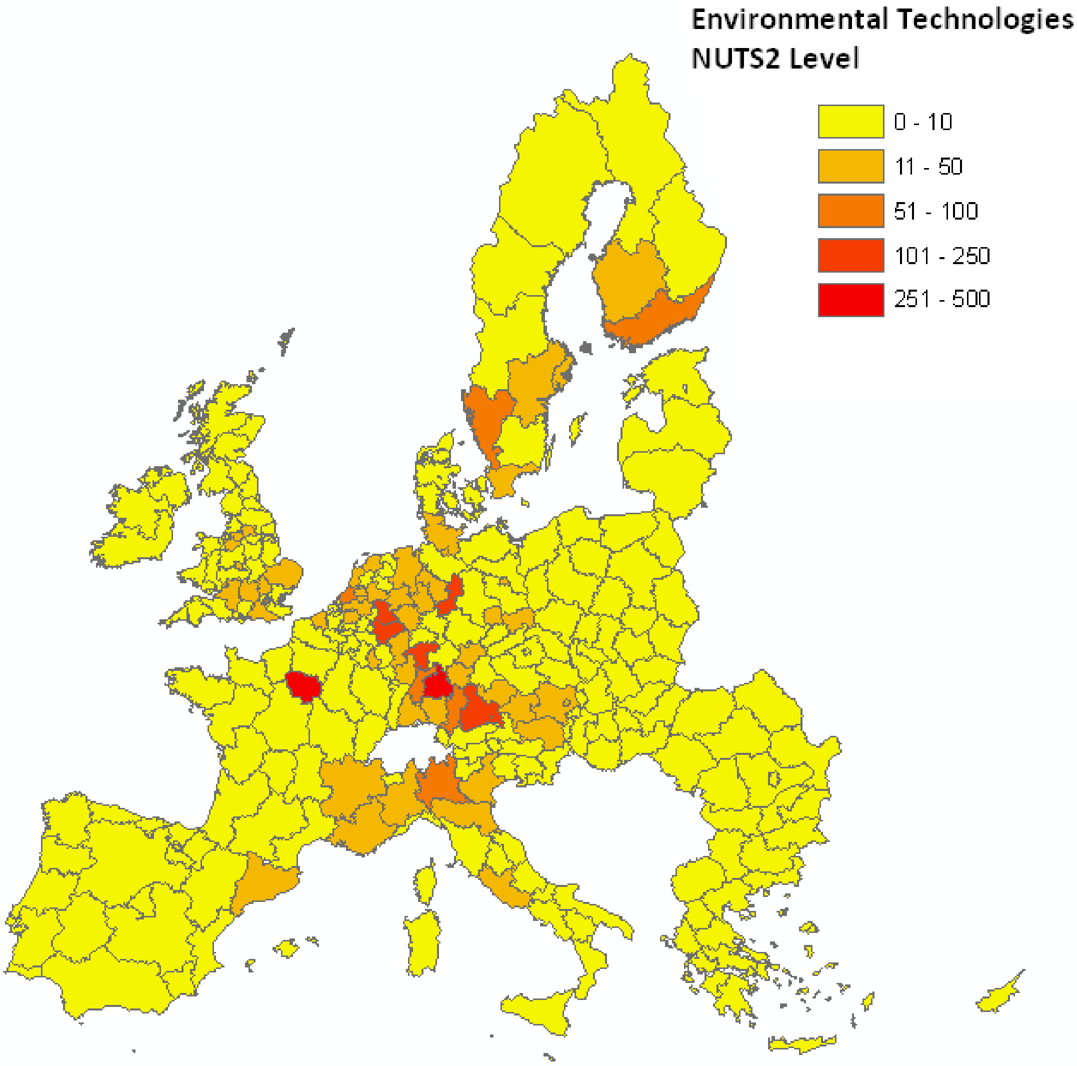
	Fractional response model - GLM robust estimates									
	(1)		(2)		(3)		(4)		(5)	
	EU27		DE		GB		FR		IT	
KEBT	3.043***		3.141***		2.800***		3.006***		2.853***	
	(0.016)		(0.024)		(0.055)		(0.042)		(0.069)	
inter	0.044***	0.105***	-0.001	0.055***	0.062**	0.065**	0.065***	0.127***	0.097***	0.173***
	(0.007)	(0.007)	(0.009)	(0.010)	(0.020)	(0.021)	(0.017)	(0.018)	(0.029)	(0.030)
N_invent	-0.002	0.000	-0.002	-0.000	0.003	0.005	-0.008*	-0.006	0.007	0.015+
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
techdiv	0.200***	0.443***	0.260***	0.588***	0.163***	0.230***	0.230***	0.576***	0.184***	0.278***
	(0.010)	(0.010)	(0.016)	(0.016)	(0.026)	(0.027)	(0.029)	(0.030)	(0.038)	(0.040)
Kstock	-0.024***	-0.058***	-0.024***	-0.061***	-0.043***	-0.073***	-0.021***	-0.059***	-0.063***	-0.109***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)	(0.008)
PROs	-0.030**	0.041***	-0.021	0.078***	0.001	0.057*	-0.038+	0.036	0.019	0.118+
	(0.010)	(0.011)	(0.018)	(0.020)	(0.023)	(0.024)	(0.021)	(0.022)	(0.067)	(0.072)
fcit8	-0.002***	-0.009***	-0.002*	-0.009***	-0.003*	-0.007***	0.001	-0.010***	-0.003	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
citations	0.015***	0.011***	0.018***	0.014***	0.010***	0.007***	0.019***	0.017***	0.007***	0.005*
	(0.000)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
_cons	-3.659***	-2.785***	-3.720***	-2.877***	-3.455***	-2.364***	-3.796***	-2.975***	-3.483***	-2.699***
	(0.014)	(0.013)	(0.020)	(0.019)	(0.043)	(0.038)	(0.036)	(0.035)	(0.063)	(0.061)
Obs.	278636		133767		23823		43886		14075	
Country dummies	Yes		No		No		No		No	
Time dummies	Yes		Yes		Yes		Yes		Yes	
IPC dummies	Yes		Yes		Yes		Yes		Yes	

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

5.3. The case of Environmental technologies

In this Section, we present a brief analysis of the role technology platform may play with respect to one of the most interesting technologies in terms of both sustainability and long-term innovation impact, that is, Environmental technologies[24]. We first present some descriptive statistics regarding Environmental technologies in Europe and their linkages with other technological classes. Then, we discuss the results of a modified version of the model presented in the previous Section where the dependent variable is substituted with a dichotomous variable representing whether the patent cited is a green technology.

Figure 6 – Total number of patents in Environmental technologies at the NUTS2 Level.



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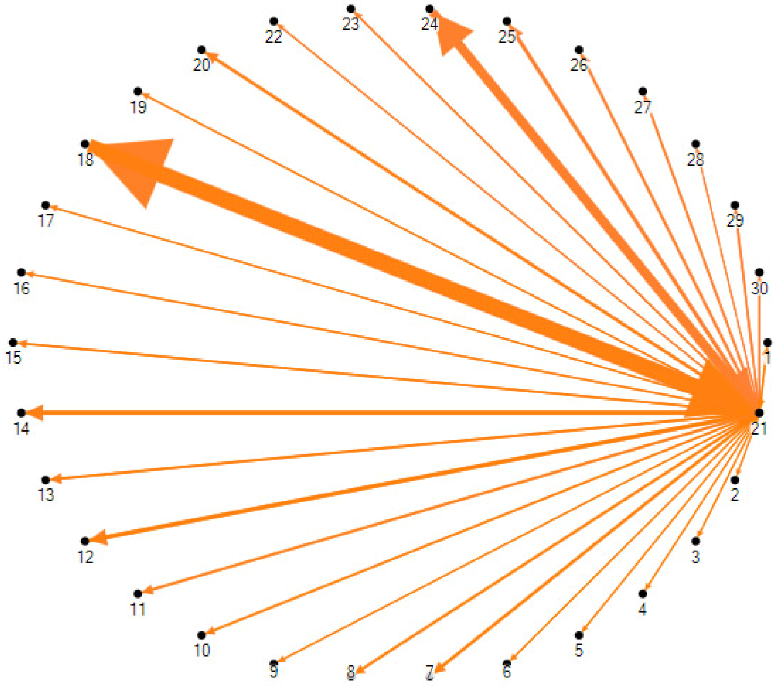
[24] As we have discussed in Section 5.1., Environmental technologies represent one of the IPC technological classes with the higher value of generality and hold a particular value in the recent discourse on sustainability in the EU.

In other words, we study whether the use of KEBTs may increase the likelihood of integrating green technologies in the development of innovation in other sectors.

The distribution of Environmental patents in Europe can be observed in Figure 6, where we map the total number of patents across NUTS2 regions for all 27 members of the EU. Development of Environmental technologies is characterised by a strong regional dimension, with four macro regions accounting for the majority of applications in this IPC class. These include the southern regions of Finland and the area around Helsinki, south-western Sweden, the district of Paris in France, the region between the Netherlands and the western part of Germany as well as the Bavaria.

With respect to inter-technology knowledge flows, Environmental technologies are characterised by a wide web of linkages with all other ICP classes. However, as for all technologies, some sectors are more important than others. Such relationships can be seen in Figure 7, where a network analysis of citations from and to Environmental technologies is represented through double-sided arrows. Each arrow is associated with a weight to show the relative importance, in terms of total number of citations, of the linkages between Environmental technologies and the other IPC

Figure 7 – Network analysis of technology flows for Environmental technologies.



classes[25]. Thus, we can see that two classes are particularly important. These are Technical processes (chemical, physical, mechanical) – IPC class 18 – and Engines/Pumps/Turbines – IPC class 24. Also relevant are Materials/Metallurgy (IPC 14) and Basic Chemistry (IPC 12).

To conclude this Section, we present the estimates from a probit regression for a modified version of the model discussed in Section 4.3. In this case, the dependent variable is a binary variable equal to 1 if the patent cited a green technology and 0 otherwise.

Table 5 – Probit model estimates for Environmental Technologies citation

	Environmental technology - probit estimates				
	(1) EU27	(1) DE	(1) GB	(1) FR	(1) IT
KEBT	0.935***	1.015***	0.723***	1.101***	0.666***
	(0.036)	(0.050)	(0.120)	(0.096)	(0.149)
inter	0.061**	0.007	-0.008	0.240***	0.275**
	(0.019)	(0.026)	(0.064)	(0.055)	(0.091)
N_invent	-0.000	-0.004	0.002	0.031*	-0.027
	(0.004)	(0.005)	(0.014)	(0.012)	(0.027)
techdiv	0.318***	0.378***	0.243*	0.301**	0.080
	(0.036)	(0.057)	(0.101)	(0.108)	(0.137)
Kstock	-0.023***	-0.022***	-0.019	0.002	0.0411
	(0.004)	(0.005)	(0.015)	(0.012)	(0.027)
PROs	0.022	0.084+	0.046	-0.128+	-0.133
	(0.032)	(0.051)	(0.082)	(0.067)	(0.247)
fcit8	-0.003	-0.001	0.000	0.002	-0.010
	(0.002)	(0.003)	(0.006)	(0.007)	(0.016)
citations	0.037***	0.037***	0.042***	0.039***	0.025***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
_cons	-2.600***	-2.643***	-2.413***	-2.952***	-2.782***
	(0.043)	(0.060)	(0.128)	(0.127)	(0.202)
Obs.	278607	133759	21560	43889	12128
Country dummies	Yes	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes
IPC dummies	Yes	Yes	Yes	Yes	Yes

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

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[25] Although arrows are not bound to be symmetrical, we can see a clear two-way relationship in the citation flows across the different pairs of the IPC technological classes.

Thus, this model allows us to investigate whether the use of KEBTs might increase the likelihood of integrating environmental technologies in the patent developed. In other words, innovations derived from any of the KEBTs are more likely to also draw on such environmental technologies, therefore breaking the existing technological trajectory and shifting onto one which has an ecological content.

As reported in Table 6, the coefficient for KEBT is positive and statistically significant across all columns, representing respectively estimates for the EU as a whole and for the selected Countries. This provides evidence in favour of the hypothesis that KEBTs enhance ‘shifting technologies’ and resilience. The other variables present similar signs as those observed in the previous model, with a positive effect for technological diversification (TECHDIV), while the coefficient for INTER is once again difficult to interpret, with a positive and significant sign only for the EU, France and Italy. This might indicate the international dimension of technology flows across green technologies or the fact that green technologies that integrate innovation from different sectors may require a set of inputs which are dispersed at the national level. Yet, the varying results across the different Countries call for a more focused analysis. Similarly, this analysis indicates that studies based on particular technologies rather than at the aggregate level may offer further evidence of technological change and the functioning of platforms. We believe these to be interesting possibilities for future research.

6. Conclusions

This research attempts to address the central question of how technological innovations can be supported to contribute to EU competitiveness – socio-economic sustainability. This related to what policy can be designed and what actors can be mobilised to support such technological shifts so as to reset and sustainably foster EU growth. To this end, our research has addresses related issues such as: what innovation process generates more original technological innovations? How technological innovations can generate shifts in the technological trends? What integrated policy can drive the anchoring of the anchoring of technology platforms in Europe and how these can propel the technological upgrading of EU firms? We investigate the role played by technology platforms in enhancing cross-fertilisation across different technological domains, thus fostering the development of more original and radical inventions that combining a number of different but related technologies enables inter-sectoral cross-fertilisation or technological trajectory leapfrogging.

Using patent data from the EPO for the period between 1996 and 2006, we have first offered some stylised facts regarding the level of generality and originality across technological classes for EU country members, also exploring differences across types of inventors (companies, universities and governmental not-for-profit organisations). Our findings show that there is a significant heterogeneity across technologies, and the degree of heterogeneity seems to be country-invariant. Moreover, we have confirmed previous studies pointing out the higher levels of generality and originality for patents generated by universities as against private companies, and the positive correlation among these characteristics. Then, we have provided empirical evidence that inventions are more likely to be original if they have technological antecedents characterised by the specific qualities of technology platforms, that is, a broad applicability across a wide range of different technological applications. The integration and use of such technologies within the innovation activity of public research organisations seems to be at the very base of their capability to develop more original patents than private companies.

Our results have relevant policy implications. In particular, they suggest that technology platforms play an important role in fostering technology flows across sectors, ultimately leading to the emergence of innovation that are more radical in nature and that may lead to technological breaks and leapfrogging on new technological trajectory.

Concrete policy recommendations can be formulated on three levels. Firstly, universities and other public research organisations play a crucial role in integrating a wide range of technological patents and by using them to produce also more radical innovations. Our results confirm what found in previous studies, that is, the higher level of originality and generality of patents developed by universities and governmental not-for-profit organisations. More interestingly, we have shown that the crucial role they play in terms of technological synthesis and radical innovation lies in their higher propensity to effectively adopt and use KEBTs within their innovation activity. For this reason, our results seem to suggest that public funded research may play a key role in driving radical innovation, acting as a boundary-spanner in connecting, translating and integrating different technological knowledge. This would seem to suggest that the Europe 2020 commitment to pushing R&D investment to 3% of GDP is crucially important to enable the EU to either maintain or gain a leading position in new technologies. Related to that, public government spending in R&D may be important for two additional reasons: one is to signal to companies where to direct their private R&D investment in a sort of risk-sharing bonding, and second is to inject in the wider innovation system original innovations from which firms can cherry-pick what technologies they need to be competitive in the market.

Secondly, from the most complete EU-wide patent database we have been able to derive what are those technologies that can be intrinsically defined as enabling technologies. These are those with higher level of generality (e.g.: > 0.5), including Organic chemistry (10), Macromolecular Chemistry (11), Surface technology (13), Biotechnology (15), Technical processes (18) and environmental technologies (21). These technologies are able to generate a spawning of patents spreading across different technological fields and for this reason they are enabling technology with the potentials to enhance the innovative capacity of other sectors. These technologies can be considered the root of a number of derivatives and applications that trickling down the innovation process will in the end produce products and services that will satisfy the changing needs of our society from aging to pollution. It is desirable for Europe to have a grip on such enabling technologies and to embed such enabling technologies in technology platforms that are located in European regions. Regional spillovers effects will work to diffuse such innovations across embedded regional innovation systems.

Finally, we have singled out patents related to green technologies and we have found that these impact more strongly on sectors such as Technical processes (chemical, physical, mechanical), Engines/Pumps/Turbines, Materials/Metallurgy and Basic Chemistry. Hence, we have offered empirical evidence that the use of KEBTs may enhance the integration of green technologies within innovations across related and unrelated technological classes.

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APPENDIX

Table A.1 - Enabling technologies identified by the European Commission and the UK Technology Strategy Board.

European Commission	**UK Technology Strategy Board**
Micro- and nanoelectronics	Electronics, sensors and photonics
Nanotechnology	*Nanotechnology is embedded in all themes where there are possibilities*
Photonics	*See above*
Advanced materials	Advanced materials
Industrial biotechnology	Biosciences
	Information and communication technology
Advanced manufacturing technologies (recognised as a "cross-cutting" KETs)	High value manufacturing (a competence to be applied to the technologies)
	Digital services (a competence to be applied to the technologies)

Table A.2 – International patent classification (IPC) technological classes

OST30-code	OST30-name
1	Electrical engineering
2	Audiovisual technology
3	Telecommunications
4	Information technology
5	Semiconductors
6	Optics
7	Technologies for Control/Measures/Analysis
8	Medical engineering
9	Nuclear technology
10	Organic chemistry
11	Macromolecular chemistry
12	Basic chemistry
13	Surface technology
14	Materials; Metallurgy
15	Biotechnologies
16	Pharmaceuticals; Cosmetics
17	Agricultural and food products
18	Technical processes (chemical, physical, mechanical)
19	Handling; Printing
20	Materials processing, textile, glass, paper
21	Environmental technologies
22	Agricultural and food apparatuses
23	Machine tools
24	Engines; Pumps; Turbines
25	Thermal processes
26	Mechanical elements
27	Transport technology
28	Space technology; Weapons
29	Consumer goods
30	Civil engineering

Table A.3 – Estimates for patents' generality. Selected countries.

Fractional response model - GLM robust estimates		
	B	SE
Univ	0.233***	(0.0256)
GB	0.093***	(0.0152)
FR	-0.098***	(0.0135)
IT	-0.107***	(0.0203)
Electrical engineering	0.515***	(0.0178)
Audiovisual technology	0.728***	(0.0286)
Telecommunications	0.271***	(0.0214)
Information technology	0.809***	(0.0242)
Semiconductors	0.590***	(0.0291)
Optics	0.727***	(0.0284)
Technologies for Control/Measures/Analysis	0.772***	(0.0161)
Medical engineering	0.370***	(0.0226)
Nuclear technology	0.657***	(0.0746)
Organic chemistry	0.987***	(0.0209)
Macromolecular chemistry	0.924***	(0.0196)
Basic chemistry	0.610***	(0.0214)
Surface technology	0.964***	(0.0277)
Materials; Metallurgy	0.888***	(0.0269)
Biotechnologies	0.938***	(0.0282)
Pharmaceuticals; Cosmetics	0.649***	(0.0182)
Agricultural and food products	0.640***	(0.0473)
Technical processes (chemical, physical, mechanical)	0.866***	(0.0200)
Handling; Printing	0.516***	(0.0206)
Materials processing, textile, glass, paper	0.644***	(0.0200)
Environmental technologies	0.965***	(0.0383)
Agricultural and food apparatuses	0.153***	(0.0462)
Machine tools	0.571***	(0.0278)
Engines; Pumps; Turbines	0.429***	(0.0212)
Thermal processes	0.705***	(0.0330)
Mechanical elements	0.703***	(0.0197)
Transport technology	0.486***	(0.0164)
Space technology; Weapons	0.467***	(0.0664)
Consumer goods	0.497***	(0.0222)
Civil engineering	0.339***	(0.0262)
_cons	-1.188***	(0.0179)
N		118268

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

Table A.4 – Estimates for the implementation of KEBTs. Selected countries.

	Fractional response model - GLM robust estimates	
	B	SE
Univ	0.207***	(0.0097)
GB	0.075***	(0.0059)
FR	-0.034***	(0.0052)
IT	-0.068***	(0.0079)
Electrical engineering	0.795***	(0.0073)
Audiovisual technology	1.059***	(0.0099)
Telecommunications	0.576***	(0.0081)
Information technology	1.094***	(0.0087)
Semiconductors	0.933***	(0.0113)
Optics	1.028***	(0.0100)
Technologies for Control/Measures/Analysis	1.092***	(0.0060)
Medical engineering	0.674***	(0.009)
Nuclear technology	1.029***	(0.0293)
Organic chemistry	0.964***	(0.0073)
Macromolecular chemistry	1.169***	(0.0076)
Basic chemistry	0.911***	(0.0083)
Surface technology	1.202***	(0.0105)
Materials; Metallurgy	1.052***	(0.0106)
Biotechnologies	1.083***	(0.0096)
Pharmaceuticals; Cosmetics	0.960***	(0.0068)
Agricultural and food products	0.973***	(0.0169)
Technical processes (chemical, physical, mechanical)	1.083***	(0.0076)
Handling; Printing	0.782***	(0.0082)
Materials processing, textile, glass, paper	0.939***	(0.0079)
Environmental technologies	1.179***	(0.0139)
Agricultural and food apparatuses	0.565***	(0.0210)
Machine tools	0.890***	(0.0106)
Engines; Pumps; Turbines	0.696***	(0.0085)
Thermal processes	1.014***	(0.0126)
Mechanical elements	1.013***	(0.0075)
Transport technology	0.733***	(0.0068)
Space technology; Weapons	0.760***	(0.0271)
Consumer goods	0.825***	(0.0095)
Civil engineering	0.630***	(0.0112)
_cons	-1.433***	(0.0084)
N		210556

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

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Project Information

Welfare, Wealth and Work for Europe

A European research consortium is working on the analytical foundations for a socio-ecological transition

Abstract

Europe needs change. The financial crisis has exposed long-neglected deficiencies in the present growth path, most visibly in the areas of unemployment and public debt. At the same time, Europe has to cope with new challenges, ranging from globalisation and demographic shifts to new technologies and ecological challenges. Under the title of Welfare, Wealth and Work for Europe – WWWforEurope – a European research consortium is laying the analytical foundation for a new development strategy that will enable a socio-ecological transition to higher levels of employment, social inclusion, gender equity and environmental sustainability. The four-year research project within the 7th Framework Programme funded by the European Commission was launched in April 2012. The consortium brings together researchers from 33 scientific institutions in 12 European countries and is coordinated by the Austrian Institute of Economic Research (WIFO). The project coordinator is Karl Aiginger, director of WIFO.

For details on WWWforEurope see: www.foreurope.eu

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ICLEI - Local Governments for Sustainability	ICLEI	Germany
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Ratio	Ratio	Sweden
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