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Technology Platforms in Europe: an empirical investigation

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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 technologies - may create the opportunity for technological externalities to take place across a set of related sectors through a swarm of increasingly applied and incremental innovations.

In this paper, 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 shaping technological shifts 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 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 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 a context characterised by an increasingly complex and interconnected innovation environment leading to a multidimensional nature of emerging technological paradigms (Granstrand et al., 1997), the role of the technological advance of related industries and the resulting inter-sectoral technology spillovers has become even more relevant for the development of long term innovation activities. Accordingly, 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 paper is to present robust evidence of the mechanisms that lie at the base of technological shifts 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 technologies (KETs), 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 KETs 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 address the hypotheses that KETs may lead to more original patents that break previous technological trajectories, and whether there is a spatial effect in the dynamics of technology platforms. To this end, we analyse patents applications to the European Patent Office controlling for the mediating effect of coherence in the technological base of new applications and the level of technological diversification and knowledge stock of patent applicants.

The findings from this research lead to crucial business and policy implications. From a business perspective, understating whether KETs 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 KETs 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 paper 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. Conversely, technological shifts occur when ‘distant’ technologies are integrated together, 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).

2.1. The role of technological diversification

In a context where there is an increasing complexity in innovation and a faster pace within technological activity, opportunities from different but related industries become fundamental elements that hold the potential to increase innovation productivity due to cross-fertilisation and innovation complementarity. In this sense, the ability to recognise and absorb these new opportunities is a fundamental capability for the long-term resilience of firms (Fai and von Tunzelmann, 2001). Thus, capabilities of technological synthesis represent an important competitive advantage allowing companies to explore and exploit new opportunities. Moreover, the ability to integrate firms’ established technologies with innovations technologically different 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 technologies. 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).

Although technological diversification represents an important strategy for the horizontal exploitation of technological opportunities across the innovation environment, it requires resources and competencies that are often scattered across heterogeneous and dissimilar

companies. In this sense, the creation of new technological paradigms resulting from the integration of ‘distant’ innovative capabilities requires a wider set of different actors to trigger the positive feedbacks that generate technological progress and economic growth. These may encompass public research institutions undertaking basic research (Nelson, 1959; Trajtenberg et al., 1997), large incumbent firms and new technology-based companies, communicating together through a common, coherent knowledge base (Teece et al., 1994; Breschi et al., 2003).

2.2. Technology platforms: towards a definition

In this paper, we argue that the specific qualities of technology may also create the opportunities for similar processes of knowledge integration and synthesis of ‘distant’ technologies. Discussing the characteristics of general purpose technologies (GPTs), usually identified by a general nature defined by technological pervasiveness leading ‘innovational complementarities’, previous literature has underlined their role as enabling technologies (Bresnahan and Trajtenberg, 1995), that is, technologies whose impact is exerted on the productivity of a wide range of sectors.

Building upon the idea of enabling technology, we introduce the concept of technology platforms to underline the role that technologies with a broad applicability across different technological fields may play not just in generating innovation cascades, but most importantly in fostering a web of linkages across ‘distant’ technologies.

In the current scholarly literature, the term technological platform is related with “a set of instruments which enables scientific and technological production: it allows exploration and exploitation of a variety of options, for strategic research, technology development, and sometimes also product development” (Robinson et al., 2007). Taking into account the inter-firm dimension that is inherent to innovation networks and the rise of ‘open innovation’ (See Freeman, 1991; Chesbrough, 2003), technological platforms can be defined as “building blocks that act as a foundation upon which an array of firms (sometimes called a business ecosystem) can develop complementary products, technologies, or services” (Gawer, 2010).

More generally, platforms are characterised by a core underlying technology which serves as a pivot around which the different actors are interconnected. Cooke (2007, p. 188), for example, argues that the key feature of industry platforms, “... is that a single significant innovation may travel swiftly across the platform, earning surplus profits as it is applied to different but related technologies by 'communities of practice' sharing a high degree of 'absorptive capacity' across the platform strands”. As such, industry platforms represent more

than a collective use of common resources, rather they define and constrain future research efforts. Accordingly, Robinson et al. (2007) argue that technological platforms can be seen as 'intentional opportunity structures' which play an essential part in emerging techno-industrial networks.

The key feature of technology platforms is a broad technological base characterised by high technological dynamism generating positive technological externalities across a wide range of sectors, thus yielding increasing returns to scale in the output of the innovation system. In other words, those key enabling technologies (KETs) that underpin technology platforms can also generate increasing the returns to R&D and a 'cascade' effect on all technologies pegged to the platform - similarly to the disruptive effect of the adoption of GPTs as technological applications across the wider economy.

Technology platforms increase the opportunities that companies might have to learn from distant technologies, and to exploit complementarities across a wide range of technological fields that are connected through a common enabling technology. Similarly, they increase the likelihood of inter-sectoral cross fertilisation to take place, thus generating a shift in current technological trajectories. In other words, technology platforms developed around KETs may play a fundamental role in sustaining communication across diverse technological fields, generating high levels of dynamism and pervasiveness through processes of 'innovational complementarity' and innovation synthesis.

In line with these arguments, our first hypothesis is that technologies which are based on technology platforms, here identified as KETS, are more likely to be original and be more disruptive with previous technological trajectories. Thus, our first hypothesis is the following:

H1. KETs 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 sectors, 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-CRIOS¹ database covering all patent applications made at the European Patent Office (EPO), whose priority date² is comprised in the period between the year 1996 and 2006 included. The use of patents as

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.

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, university or not for profit government 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 paper.

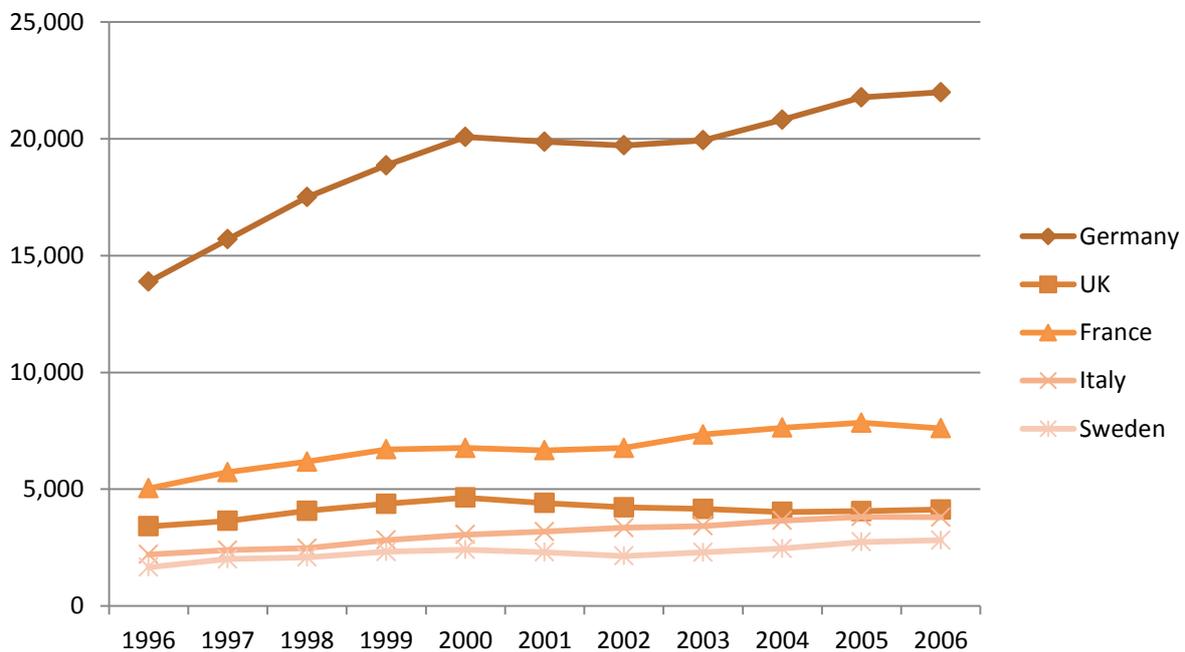
As we focus on EPO to EPO patent citations to build our indexes and carry out our analysis, a couple of considerations are in order. First, EPO patents do not represent the whole population of patent applications in Europe, as must first apply for the patent in their national patent office. However, we may expect patents with higher quality to be filed also at the European level. Second, patent examination at the EPO differs significantly from 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.

Figure 1 – Patent applications per year for selected countries.



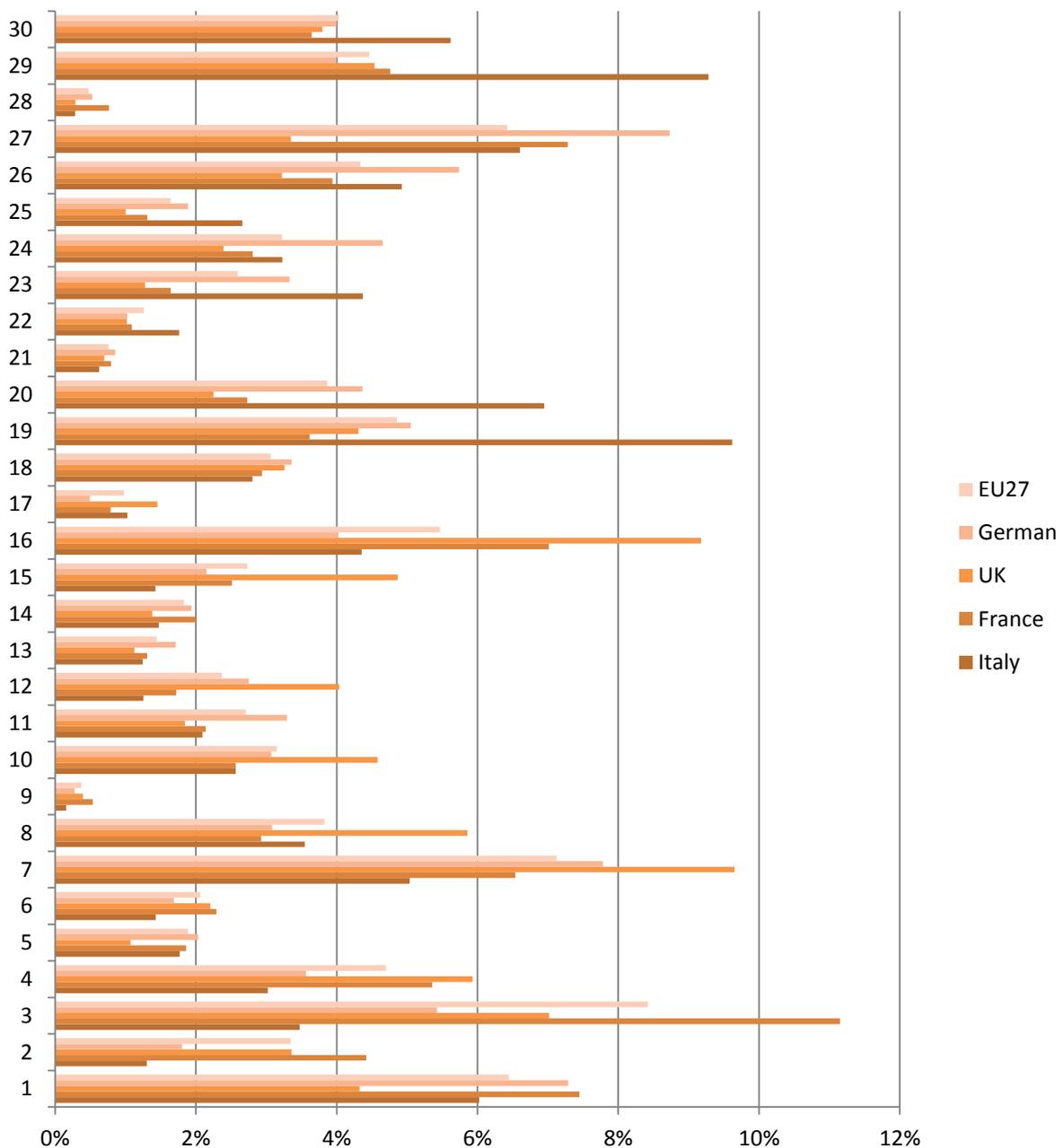
In terms of total patent applications, there are well-known significant differences across Countries. This is shown for some of the largest Countries – in terms of patents - in Figure 1, where we report the number of patent applications to the EPO per year³.

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

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

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 inventions⁴, 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

Figure 2 – Percentage of EPO applications per IPC class.



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

(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. Sweden⁵, 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.

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 KETs that form the platform leads to a more sustained interaction across 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:

$$\text{ORIGIN} = f(\text{KET}, \text{INTER}, \text{N_INVENTORS}, \text{COHERENCE}, \text{TECHDIV}, \text{KSTOCK}, \text{OWN_TYPE}, \text{F_CIT}, \text{B_CIT})$$

4.3.1. Dependent variable

To investigate the presence of technology shifts, we analyse patents escaping the path dependency inherent to the cumulative nature of technological change, as these can be seen

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

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.

4.3.2. Independent variables

To capture the presence of key enabling technologies, represented by the variable KET, 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 introduced for the dependent variable, the generality index is defined for each patent p as follows:

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

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 citations⁶. The value for our variable, KET , 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 citations⁷.

The next variable, labelled $N_INVENTORS$, 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 coherence between the patents, the technological diversification among applicants and their R&D intensity.

The first variable of this group, defined as technological coherence ($COHERENCE$), is a measure of the technological distance within the backward citations underpinning the original patent. $COHERENCE$ is based on the concept of knowledge-relatedness suggested by Breschi et al. (2003). With this variable, we control for the fact that some technological fields are more likely to “communicate” to each other. 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:

⁶ 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.

⁷ 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.

$$S_{ij} = \frac{\sum_{k=1}^{30} C_{ik} C_{jk}}{\sqrt{\sum_{k=1}^{30} C_{ik}^2} \sqrt{\sum_{k=1}^{30} C_{jk}^2}} \quad (3)$$

where $S_{i,j}$ 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 $M8$ that can be used to measure knowledge-relatedness between patents and patent citations in time t . Thus, the index COHERENCE is given by the average value of knowledge-relatedness between the IPC of the original patent and those of each backward citation.

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 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:

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

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

⁸ Values for the matrix are available upon request.

⁹ For the formal definition, see previous Section.

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

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:

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

where N_{it} is the total number of patents for the i th 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 series of control variables to capture the role of University owned patents (UNIV_O), not for profit Government organizations (GNP) and others, as these have often been associated with more original patents.

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 model¹¹ 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 originality¹² and generality across different types of applicants, in Figure 3 and Figure 4 we report the average values of originality and generality across five selected Countries for private companies, universities, government non-profit agencies (GNP) and others. As we can see from the Figure 3, there are similar levels of originality observed across the five member Countries selected, and at the same time we see that the rankings between the four groups of inventors also presents similar patterns across them. In particular, universities and non-profit government organisations seem to develop patents characterised by higher levels of originality with respect to private companies¹³. However, whilst in Germany and the UK governmental non-profit organisations seem to produce patents with higher values of originality, in the other countries University generated patents present the higher values. These differences are likely to be related to the specific structure of the different national innovation systems. With respect to the public research system, it is important to underline the presence of differences in the role and the importance in terms of innovation output between universities and other types of public research organisations (For an introduction, see Lissoni and Montobbio, 2012). In this sense, our findings seem to suggest a closer relationship with fundamental research in Germany and the UK¹⁴. Finally, it is interesting to note a significantly high value for university generated patents in Sweden.

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.

¹³ T-tests for mean differences are significant at the .001 level.

¹⁴ Two notable examples may be the Cancer Research Institute in the UK and the Max Planck institute in Germany.

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

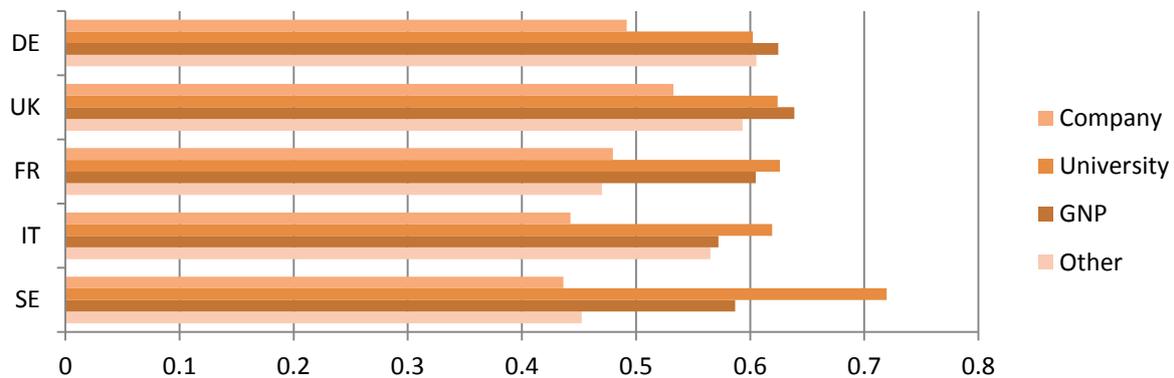


Figure 4 shows that the level of generality is more heterogeneous across type of applicant and Countries. Germany and the UK seem to develop more general inventions, but the wider differences take place across the four categories analysed. As observed for originality, companies present lower values than universities of governmental non-profit organisations¹⁵. The ranking among these two groups is once again mixed. In particular, for Italy and Sweden we note quite a gap between private companies' and universities' generality values: this can be explained by the sector specialised nature of innovation in companies in these countries as opposed to university research still much engaged with basic research.

Overall, we find that both measures of originality and generality seem to support previous findings from the literature indicating that university-owned patents and GNPs are on average more original and general than patents generated by private companies.¹⁶

The level of generality differs across technological classes. This is shown in Figure 5, where we report the average value for generality across IPC classes for the EU as a whole and in the five selected countries. While we observe that generality is fairly country invariant, we see clear differences at the technological level. 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

¹⁵ Mean differences are significant at the .001 level.

¹⁶ For a broader discussion of the differences between university-owned and company-owned patents, see Lissoni and Montobbio (2012).

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

identified by both the European Commission and the UK Technology Strategy Board¹⁸ as enabling technologies. Some differences remain, notably in a more prominent role of environmental technologies and a low level of generality for telecommunications.¹⁹

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

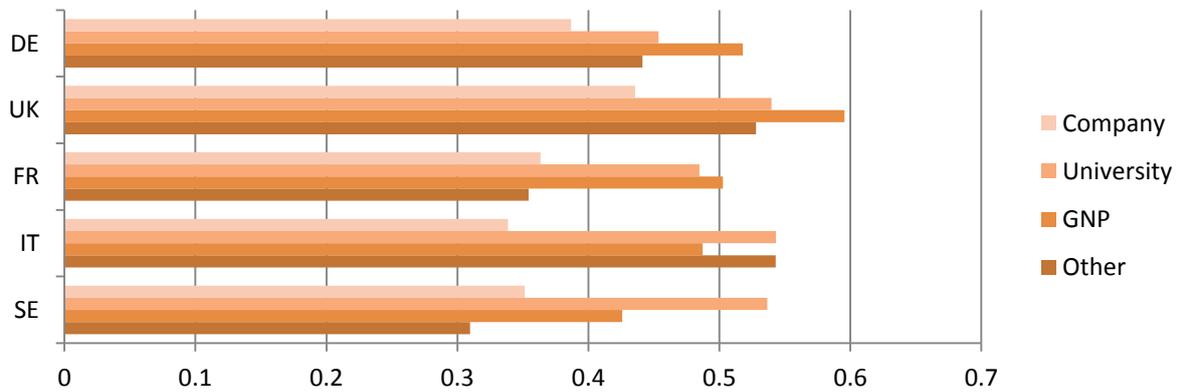
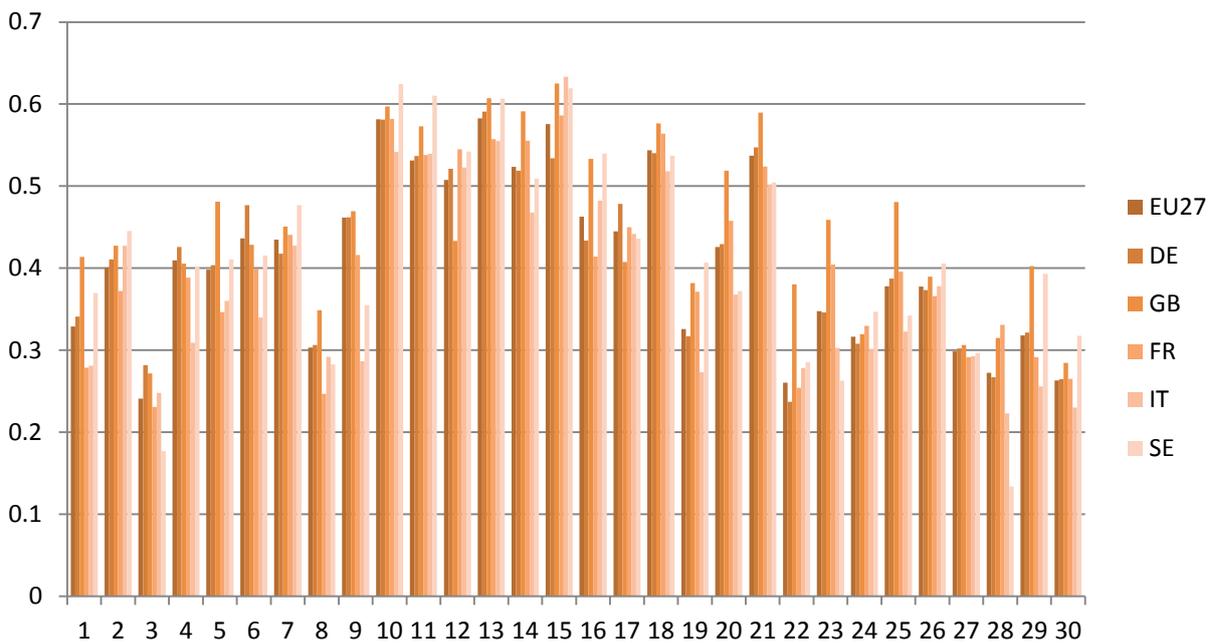


Figure 4 – Average generality across IPC classes.



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).

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 negative correlation between technological coherence 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 technological applicability. As expected, there is a positive correlation between knowledge stock and the level of technological diversification, while a negative correlation is present between coherence and originality.

Table 1 – Descriptive statistics.

	Obs	Mean	St.Dev	Median	Max	Min	VIF	Tolerance
Origin	379028	0.48	0.37	0.59	1	0		
Ket	370420	0.46	0.28	0.52	1	0	1.95	0.51
Inter	370429	0.66	0.38	0.76	1	0	1.01	0.99
N_inventors	379069	2.45	1.75	2	49	0	1.04	0.96
Coherence	378771	0.75	0.26	0.83	1	0.01	1.78	0.56
Techdiv	287041	0.62	0.25	0.68	1	0	1.15	0.87
Kstock	379069	876.16	2021.54	57.23	11091.8	1	1.14	0.87
Fcit8	379069	1.44	2.76	1	144	0	1.04	0.96
Citations	379069	3.27	3.29	2	128	1	1.05	0.96

Table 2 – Correlation matrix.

	1	2	3	4	5	6	7	8	9
Origin	1								
Ket	0.556	1							
Inter	0.026	0.045	1						
N_inventors	0.088	0.079	-0.039	1					
Coherence	-0.499	-0.633	-0.024	-0.003	1				
Techdiv	0.091	0.068	-0.017	0.116	-0.018	1			
Kstock	-0.062	-0.101	0.018	0.017	0.073	0.326	1		
Fcit8	0.024	0.031	-0.007	0.086	-0.015	0.011	-0.021	1	
Citations	0.061	0.047	-0.014	0.094	-0.041	0.015	-0.043	0.181	1

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 five selected Countries.

The estimates for KET are in line with our first hypothesis that key enabling technologies support 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 class²⁰ and coherence across backward citations, patents based on general technologies - or KETs - are significantly more likely to be original and to integrate components from a wider range of different technologies. 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 with different coefficients across the countries analysed. In particular, for Germany and Italy is positive and significant, while for Sweden is significant but negative²¹. Such results are likely to be related to both the characteristics of 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. 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_INVERTORS), a negative sign for COHERENCE and a positive one for TECHDIV. In this sense, our findings confirm that patent applications which are based on similar technologies are less likely to be disruptive. Conversely, 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.

The role of university and GNP patents, like INTER, is less clear cut. While for the EU overall the coefficient is statistically significant, Germany and France are the only countries where these variables present a positive and significant effect. Again, such differences might be explained in terms of different national systems of innovation. At the same time, these findings may also suggest that the level of originality usually associated with universities' patents depend more on their ability to use general technologies, or KETs, in their innovation

²⁰ Similar models have been also carried out for single ICP classes, but estimates are fairly robust to the different model specifications. Estimates are available upon request.

²¹ Negative coefficients are found also for France and UK, but they are significant only at the .10 level.

Table 3 – Fractional response model estimates for Originality.

Fractional response model - GLM robust estimates						
	(1)	(2)	(3)	(4)	(5)	(6)
	All countries	Germany	UK	France	Italy	Sweden
KET	2.339*** (0.0185)	2.323*** (0.0261)	2.136*** (0.0674)	2.375*** (0.0467)	2.353*** (0.0803)	2.484*** (0.0884)
INTER	0.0146 (0.00893)	0.0423*** (0.0122)	-0.0612+ (0.0313)	-0.0396+ (0.0233)	0.143*** (0.0418)	-0.0973* (0.0431)
N_INVENTOR S	0.00892*** (0.00151)	0.00796*** (0.00203)	0.0131** (0.00443)	0.00866+ (0.00507)	0.0119 (0.00899)	0.0108 (0.00662)
COHERENCE	-2.262*** (0.0204)	-2.252*** (0.0288)	-2.204*** (0.0708)	-2.297*** (0.0522)	-2.152*** (0.0900)	-2.675*** (0.105)
TECHDIV	0.300*** (0.0130)	0.344*** (0.0197)	0.146*** (0.0365)	0.331*** (0.0374)	0.267*** (0.0516)	0.355*** (0.0597)
KSTOCK	-0.000*** (0.000)	-0.000*** (0.000)	-0.000+ (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000*** (0.000)
GNP	0.0286+ (0.0167)	0.0433+ (0.0258)	-0.0902 (0.0681)	0.0131 (0.0288)	0.108 (0.117)	-0.499 (0.343)
UNIV_O	0.0465+ (0.0258)	0.0494 (0.0635)	0.0142 (0.0388)	0.176+ (0.0915)	0.0425 (0.138)	-0.151 (0.357)
OTHER	0.0508 (0.0346)	0.129+ (0.0705)	0.0339 (0.0860)	-0.0624 (0.0635)	0.0932 (0.0984)	0.767* (0.368)
FCIT8	0.00624*** (0.000751)	0.00858*** (0.00116)	0.00623** (0.00205)	0.00453* (0.00230)	0.00734 (0.00456)	0.00144 (0.00239)
B_CITATIONS	0.00872*** (0.000585)	0.0161*** (0.00103)	-0.00129 (0.00130)	0.00851*** (0.00168)	0.0126*** (0.00330)	-0.00313 (0.00207)
Constant	0.955*** (0.1209)	0.576*** (0.0417)	0.973*** (0.1617)	0.717*** (0.0742)	0.525*** (0.1308)	0.953 (0.628)
Obs.	277983	132872	23805	44217	14314	15301
Country dummies	Yes	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
IPC dummies	Yes	Yes	Yes	Yes	Yes	Yes

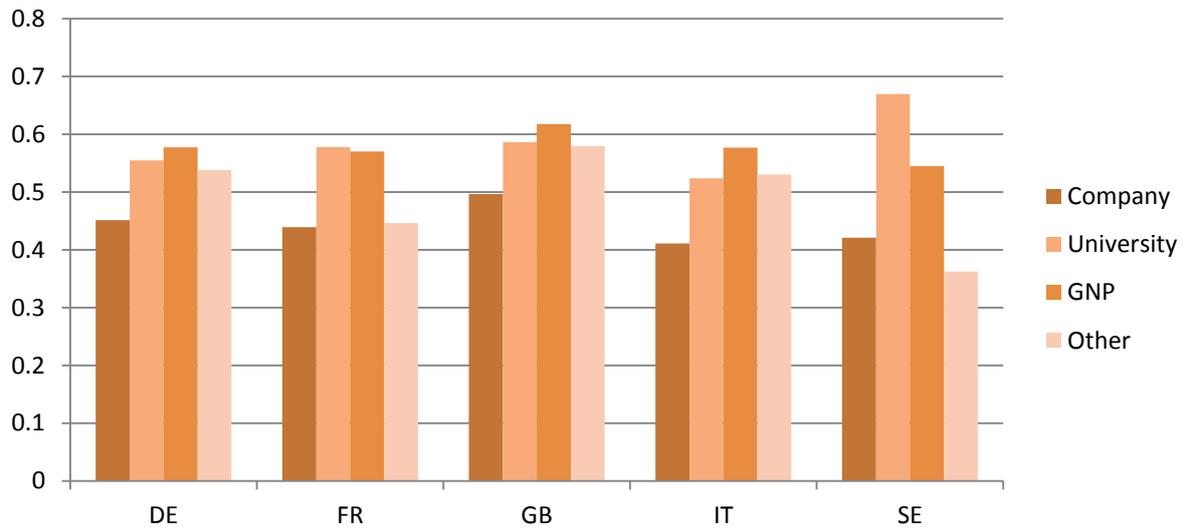
+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

processes. This is supported by our findings on the value of KET across different types of applicants, as reported in Figure 5, where universities and GNP organisations are found to show much higher value for KET 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. While it is not surprising that original patent are positively associated with more forward citations, the finding for CITATIONS is more interesting, as it suggests that previous knowledge is an important element in the development of more original inventions.

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



6. Conclusions

In this paper, we have investigated 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.

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 pattern 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

and swift applicability across a wide range of different technological applications. More generally, our findings suggest that technology platforms play an important role in fostering technology flows across sectors, ultimately leading to the emergence of innovations that are more radical in nature and that are more likely to be conducive to technological breaks and leapfrogging on new technological trajectory.

Our results have relevant policy implications. In particular, concrete policy recommendations can be formulated on two levels. Firstly, universities and to a lesser extent governmental not-for-profit organisations play a crucial role in integrating a wide range of technological patents and by using them to produce radical innovations. More interestingly, we have shown that the crucial role they play in terms of technological integration and radical innovation lies in their higher propensity to effectively adopt KETs within their innovation activity. Accordingly, public funded research can be seen as a key driver of basic research and radical innovations, as well as important as being 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.

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.

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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	<i>Nanotechnology is embedded in all themes where there are possibilities</i>
Photonics	<i>See above</i>
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