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# Beyond local search: Bridging platforms and inter-sectoral technological integration

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ABSTRACT

This paper explores the dynamics of inter-sectoral technological integration by introducing the concept of bridging platform as a node of pervasive technologies, whose collective broad applicability may enhance the connection between 'distant' knowledge by offering a technological coupling. Using data on patents obtained from the CRIOS-PATSTAT database for four EU countries (Germany, UK, France and Italy), we provide empirical evidence that bridging platforms are likely to connect more effectively innovations across distant technological domains, fostering inter-sectoral technological integration and the development of original innovation. Public research organisations are also found to play a crucial role in terms of technological integration and original innovation due to their higher capacity to access and use bridging platforms within their innovation activities.


## 1. Introduction

Building on remarks by Schumpeter (1934) on the 'combinatorial' function of entrepreneurs and the conceptualisation of innovation as a combinatorial activity (Schumpeter, 1947; Nelson and Winter, 1982; Henderson and Clark, 1990; Arthur, 2007), the literature on innovation and technological change argues that technological spillovers among different industries crucially impact on the development of long term innovation activities (Rivera-Batiz and Romer, 1991; Klevorick et al., 1995). In particular, processes of exploration and search across distant knowledge domains have been associated with the development of discontinuous solutions and, ultimately, with novel technological trajectories (March, 1991; Gavetti and Levinthal, 2000; Fleming, 2001). These processes of knowledge exchange are especially relevant within a context characterised by an increasingly intricate and interconnected innovation environment leading to the multidimensional nature of emerging technological paradigms (Granstrand et al., 1997).

The fundamental issue inherent to the integration of distant knowledge is related to the complexity in the search process when opportunities reside in unrelated technologies and sectors defined by rather different characteristics in terms of knowledge and competencies required for innovation (Pavitt, 1984; Breschi et al., 2000), as prior related knowledge is crucial in defining the ability of firms to use and assimilate new information (Cohen and Levinthal, 1990). Thus, as firms' absorptive capacities are bounded by the cumulative and path dependent nature of learning within determined technological trajectories (Nelson and Winter, 1982), the exploration and the combination of knowledge outside firms' own industry increase substantially the uncertainty and risk inherent to the process of invention (Fleming, 2001). When this is achieved, rewards can be extraordinary. In particular, the integration of knowledge from different technology domains is associated with the development of radical and original inventions, constituting a fundamental element in the emergence of new technological trajectories and industries (Fleming, 2001; Schoenmakers and Duysters, 2010; Guerzoni et al., 2014). Similarly, it may represent an important element in fostering resilience across mature technologies. Notable examples include the application of technologies related to the internal combustion engine as well as lasers and synthetic fibres to a wide array of high tech and low tech industries (Mowery and Rosenberg, 1998), or the creation of completely new fields such as optoelectronics through the fusion of optics and electronics technologies (Kodama, 1992).

Notwithstanding the emphasis on the benefits and importance of inter-sectoral cross-fertilisation and distant search, there is surprisingly little evidence on the elements shaping technolog-

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ical integration as well as patent originality and the dynamics underpinning this process remain under researched. Economic scholars have provided empirical evidence of the importance of inter-sectoral technology spillovers using different approaches and data (Scherer, 1982; Verspagen, 1997). Yet, this strand of research has mainly focused on trying to quantify the process of knowledge flows in order to explore the impact of sectoral spillovers on productivity and economic growth (Griliches, 1992 Nadiri, 1993). Studies at the firm level have discussed the use of novel and original technologies in the development of radical innovations (Ahuja and Morris Lampert, 2001). Others have considered the role of original inventions departing from established technological trajectories in studying different elements of firm performance, like growth and survival (Cohen et al., 2002; Jaffe et al., 2005). Scholars have also looked at the role of external knowledge acquisition and collaboration (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Nooteboom et al., 2007). However, the evolution and the specific dynamics of technological integration and synthesis at the micro level have received much less attention, with fundamental and abstract inventions representing a fusion of divergent ideas being traditionally associated with basic science in the form of public research (Nelson, 1959; March, 1991; Trajtenberg et al., 1997).

This study contributes to the strand of research on the combinatorial nature of innovation and the process of invention offering a novel perspective on the dynamics underlying inter-sectoral technological integration and the development of original inventions departing from extant technological trajectories. To this end, we introduce the theoretical notion of bridging platforms (BPs), defined as a conceptual extension of those key enabling technologies that have recently attracted much attention from policy makers (European Commission, 2012; TSB, 2011). In particular, we show that nodes of technologies defined by a broad downstream applicability may operate as bridging platforms across distant knowledge landscapes, exerting a coupling effect across seemingly unrelated technologies. Hence, using all patent applications to the European Patent Office between 1996 and 2006 for four large industrialised EU countries, i.e. Germany, United Kingdom, France and Italy, we offer empirical evidence that BPs enhance the level of inter-sectoral technological spillovers and enable synergies across distant technologies, thus generating new innovation opportunities and more original patents that break previous technological trajectories. Additionally, we explore the hypothesis that the capacity of public research organisations to access, use and integrate BTs in their innovation processes might be at the very base of their capability to develop more original patents than private companies.

The remainder of the paper is organised as follows. Section 2 offers a review of the literature and explores the concept of BPs. The dataset, main variables and model specification are described in Section 3. Section 4 presents some stylised facts regarding originality and BPs across the four EU countries investigated and a discussion of the main findings. Section 5 concludes the paper with some final remarks.

## 2. Literature review and hypotheses

In the literature on technological change, invention is often described as a process of recombinant search where either new and/or existing elements are combined in a novel manner or previous combinations are rearranged into new ones (Schumpeter, 1934; Nelson and Winter, 1982; Henderson and Clark, 1990). In the same way, it has been argued that new technologies can be described as new combinations of existing innovations (Arthur, 2007).

To a first approximation, the search for novel components and combinations is defined by the tension between processes of exploitation and exploration rooted in local and distant search (March, 1991). Reuse and refinement of cumulated knowledge along processes of local search offers significant advantages in innovation, such as the development of firm-specific technological capabilities strengthening tacit organisational knowledge, reduced inventive uncertainty and learning economies shaped by established search routines (Cyert and March, 1963; Nelson and Winter, 1982; Altschuler, 1998; Fleming, 2001). However, some scholars have long underlined important limitations as well. Notably, the path-dependency resulting from processes of exploitation may result in missed opportunities along different technological trajectories and, ultimately, core rigidities and technological lock-in. More broadly, decreasing returns to technological search may occur as the set of available combinations is exhausted (Kim and Kogut, 1996; Fleming, 2001) or increasingly considered to be as such (David 1985; Henderson, 1995). In line with this, many scholars have proposed that both exploration and cognitive search are central to the development of new technologies (March, 1991; Gavetti and Levinthal, 2000), with the integration of distant technologies being associated with more breakthrough and even radical innovation. Firms that extend technological scope and distance within their explorative search are more likely to reach a broader set of technological opportunities and increase variation in the cumulated knowledge, adding new components and possibilities to the process of recombinatory search (Fleming and Sorenson, 2001; Katila and Ahuja, 2002).

Identifying and integrating distant knowledge constitutes a complex challenge. As learning dynamics and knowledge competencies are bounded within specific sectors and technological fields (Nelson and Winter, 1982; Pavitt, 1984; Breschi et al., 2000), the fundamental role played by absorptive capacities and combinative capabilities in generating new knowledge is often characterised by an incremental and path dependent structure (Cohen and Levinthal, 1990; Kogut and Zander, 1992). Accordingly, technological trajectories and, ultimately, industry dynamics have been described as processes where the available technological opportunities are interwoven with the cumulativeness inherent to firms' knowledge capabilities (Nelson and Winter, 1982; Dosi, 1982). In other words, innovation often results from local search defined by the exploitation of the latent potential of technologies available within accumulated technological competencies, with firms' innovative activity being characterised by processes of knowledge relatedness (Breschi et al., 2003). Similarly, knowledge spillovers are also highly technology specific and, for the most part, intra-sectoral (Malerba et al., 2013).

On the other hand, as new technologies are developed using a set of components from progressively distant and seemingly unrelated knowledge domains, departing from the extant technological trajectories, their potential to generate radical novel combinations augments significantly, ultimately leading to less derivative, more original innovation (Ahuja and Morris Lampert, 2001; Fleming, 2001; Schoenmakers and Duysters, 2010; Datta and Jessup, 2013). Following this perspective, patent originality has been measured as the synthesis of divergent ideas defined by technological sourcing from a broad spectrum of technology domains (Trajtenberg et al., 1997; Jaffe et al., 2005).

The literature points to different ways through which innovative firms may engage in explorative search and be able to develop the competencies necessary to recognise, absorb and effectively integrate distant knowledge into novel combinations. Both large corporations and small serial innovators have been found to 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., 2016). The resulting broad-based knowledge capabilities of firms act as a platform that enables the expansion and the diversification of firms' technological trajectory in derivative technologies across a wide range of new opportunities (Kim and Kogut, 1996). This may prevent innovative firms from being locked in a specific technology (Suzuki and Kodama, 2004). In this sense, the ability to integrate firms' established technologies with knowledge located in a different technological domain is fundamental for the long-term survival of innovative firms (Kodama, 1992; Fai and Von Tunzelmann, 2001). An analogous rationale holds for innovation activity carried out by groups of inventors, whose different background may provide a wider knowledge base for the inventive process (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003), though the competencies involved are more likely to present a certain degree of relatedness (Petruzelli, 2011). Hence, such discovery processes 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).

### 2.1. Enabling technologies and bridging platforms

A different perspective on search processes leading to inter-sectoral technological integration may be considered looking at the characteristics of technology itself.

Previous studies have emphasised how important the degree of interaction or independence of technologies can be in shaping the inventive process (Fleming and Sorenson, 2001, 2004). In particular, a fundamental characteristic of technologies in relation to inter-sectoral knowledge spillovers is *pervasiveness*. Pervasiveness was indeed introduced in the literature as the founding quality of general purpose technologies (GPTs) (Bresnahan and Trajtenberg, 1995). According to this framework, GPTs are technologies that can be applied across different sectors, fostering the introduction of related or complementary new products (Bresnahan and Trajtenberg, 1995; Helpman, 1998; Torrisi and Granstrand, 2004). While this strand of research is mainly focused on social returns and economic growth, the element of pervasiveness has been adopted by the innovation literature to measure the basicness and generality of invention (Trajtenberg et al., 1997; Jaffe et al., 2005). In particular, this element is also used to define key enabling technologies (KETs), which have recently attracted much attention from policy makers for their potential applicability across a wide range of technological fields (European Commission, 2012; TSB, 2011). Similar to GPTs, KETs can act as a platform for the diversification of firms' competencies into a broader set of technologies (Kim and Kogut, 1996). In other words, KETs have been studied for the impact and the novel opportunities they create along a vertical dimension over subsequent derivative innovations in diverse technological fields.

Considering the relationship between pervasiveness and inter-sectoral technological integration, we argue that enabling technologies may also present a horizontal dimension. Key enabling technologies can be both *enabling* and *bridging* technologies in view of the fact that their broad applicability across different technological fields is not limited to generating 'technological cascades', with an enabling effect along the innovation process (vertical dimension). Most importantly, they also activate channels of cross-technological coupling thanks to a bridging effect that fosters connections between distant technologies (horizontal dimension).

In line with this, this study introduces the concept of *bridging platform* (BPs) as a node of enabling technologies defined by a pervasive nature across diverse technological fields. As a bundle of enabling technologies is connected around such a node, it forms a platform that allows the technological integration across seemingly unrelated technologies by bridging the gaps across different knowledge landscapes. In other words, as the aggregate pervasiveness of the platform increases, the distance across distant knowledge is effectively reduced. Consider the case of optoelectronics discussed by Kodama (1992). If two technologies in the fields of optics and electronics were to be independent and specific, the distance between the underlying knowledge would strongly hinder their integration in any derived combinatorial technologies. Conversely, a broad applicability in either one of them – or both – would increase the likelihood of the two technologies – and others necessary for the integration – to be connected, creating a bridging effect across distant technological fields.

Just as greater absorptive capacity would enable innovators to access and utilise a wider range of distant knowledge, nodes of technologies that present broader or more general applicability may increase the opportunities for integrating different fields since they present elements that can overlap and be more easily connected to other technological domains. Therefore, innovations based on BPs are more likely to integrate ideas from a wide spectrum of technology classes.

*H1: Bridging platforms have a positive effect on the integration of distant knowledge.*

### 2.2. Public research and technological integration: the role of BPs

Looking at the role of the characteristics of technology itself in inter-sectoral technological integration offers a novel perspective on the relationship between public research organisations and originality. Notwithstanding the potential benefits of developing original innovations, the incentives for firms to engage in explorative search and technological integration of distant knowledge remain somehow limited. Distant combinations are complex and costly, while the outcome remains uncertain (Martin and Scott, 2000). Furthermore, as original innovations may not offer immediate commercial value and, more generally, the new knowledge generated may not be used directly by the innovator, returns to investment in research present issues of limited appropriability (Nelson, 1959; Arrow, 1962; Agrawal and Henderson, 2002).

The literature has engaged in a significant debate over the quality of public research and the differences with respect to private companies as well as the role of the institutional settings in creating incentives for the development of original and basic research (Henderson et al., 1998; Trajtenberg et al., 1997; Sampat et al., 2003; Thursby et al., 2009; Guerzoni et al., 2014). Previous studies have associated the more original innovation developed by public research institutions with the broader technological base and explorative nature of basic scientific research (Nelson, 1959; Trajtenberg et al., 1997). While private research is constrained by the practical problems firms need to solve, public research is usually more basic in nature, thus following a less certain direction of explorative patterns (Nelson, 1959; March, 1991). This enhances recombinatory innovation characterised by higher search scope (Fleming and Sorenson, 2001; Katila and Ahuja, 2002). Such effect is reinforced by the nature of scientific knowledge, whose theory-driven approach supports a more effective identification of novel combinations (Fleming and Sorenson, 2004).

Integrating distant technology is likely to be the result of searching across bundles of basic knowledge, so that public research organisations may have an advantage over private companies. However, a broader search scope is still likely to be bounded by inventors' field of expertise (Cohen and Levinthal, 1990; Fleming, 2001). Indeed, such search process does not resolve the difficulties inherent to the integration of distant technologies (Fleming and Sorenson, 2001), so much so that only by overlapping different technological fields new and breakthrough associations may occur. While the explorative and serendipitous nature of basic research does not imply higher capabilities to directly create such connections, it can be seen as an important element for identifying and accessing technologies with a broad applicability that may facilitate

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linkages to other domains, such as BPs. In this sense, the scientific nature of public research may offer an advantage in directing inventors to nodes of pervasive elements that may act as bridges across distant knowledge in the quest for discontinuous recombinations (Fleming and Sorenson, 2004). Accordingly, considering this higher capacity of public research organisations to effectively identify and use BPs within their innovation activities, we posit the relationship between public research and original innovation may be explained through the role of BPs in generating a bridging effect for inter-sectoral technology integration.

*H2: Bridging platforms mediate the positive relationship between public research organisations and the integration of distant knowledge.*

## 3. Empirical analysis

### 3.1. Data

The analysis presented is based on patent data. The use of patents as measure of innovation has been adopted for a long time, and strengths and weaknesses are well known (Griliches, 1990; Archibugi and Pianta, 1996). 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 a view on inter-sectoral knowledge flows as provided by citations (Jaffe et al., 1993).

Our data is obtained from the CRIOS-PATSTAT[1] database, based on the EPO master documentation database (DOCDB), which contains information on all patent applications made at the European Patent Office (EPO). Among these, the most relevant to our studies are patent publication date, priority date, EPO-to-EPO citations, International Patent Classification (IPC) indicating the specific technological class and applicant data, such as names, addresses, NUTS3 level location and type (i.e.: private company and public research organisations, or PROs).

In the context of this study, the use of EPO data offers some additional features with respect to other sources such as US Patent and Trademark Office (USPTO). In the USPTO system, inventors are legally required to include all relevant citations in their application, often resulting in the tendency "to quote each and every reference even if it is only remotely related to what is to be patented" (Michel and Bettels, 2001; p. 192) in order to avoid potential legal issues or the patent being revoked. This may introduce significant noise in the use of citations as proxies for technological scope or generality, potentially leading to biased indicators (Thompson and Fox-Kean, 2005).

In the EPO system, however, it is the patent examiner who is responsible for including all the documents necessary to define prior art of the filed invention, reducing the incentives for inventors to add unnecessary citations. EPO citations are thus scrutinised and chosen by patent examiners only on the basis of strict technological relevance between backward citations and the citing patent. This is reflected in the much smaller number of citations compared to USPTO patents, since USPTO examiners often do not filter citations added by applicants or their attorneys (Michel and Bettels, 2001). Accordingly, recent studies have argued EPO citations represent a less noisy indicator of knowledge flows compared to USPTO (Criscuolo and Verspagen, 2008; Schoenmakers and Duysters, 2010), thereby offering a more robust foundation for the development of our analysis. Additionally, as discussed by Criscuolo and Verspagen (2008), EPO search reports provide information on the specific citation category assigned by the examiner reflecting the relevance of the documents cited in the application. This allows to conduct further robustness checks with respect to potential noise in knowledge flow indicators.

Focusing on patent applications whose priority date is comprised in the period between the year 1996 and 2006 included, our dataset accounts for 355065 patent applications by firms and public research organisations[2] across the four largest countries in terms of both GDP and number of EPO patents in Europe: Germany, United Kingdom, France and Italy. With respect to the technological classification of patents, we adopt a reclassification[3] constituted by 30 different technological classes, developed by Fraunhofer Gesellschaft-ISI (Karlsruhe), Institut National de la Propriété Industrielle (INPI, Paris) and Observatoire des Sciences and des Techniques (OST, Paris).

### 3.2. Variables

To capture innovations generating inter-sectoral technological integration, we make use of two different but related dependent variables, labelled respectively ORIGIN and TECHWIDTH.

ORIGIN represents the intuitive and well established index of patent originality. Following Trajtenberg et al. (1997), the index is calculated as the inverse of a Herfindahl index measuring the dispersion across technological classes in the backward citations. Including the correction presented in Hall (2005) for small sample bias (i.e. $N_{bp}/N_{bp}-1$), we have:

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

where K is the number of different technological classes in the backward citations included in the patent, $N_{bp,k}$ is the number of backward citations made to the *k* sector and $N_{bp}$ the total number of backward citations.[4]

The second variable we use, labelled technological width (TECHWIDTH), offers the advantage of explicitly accounting for the technological 'distance' across backward citations. TECHWIDTH is based on the concept of knowledge-relatedness suggested by Breschi et al. (2003). Knowledge-relatedness is measured by the cosine index $S_{ij}$, which measures the similarity between two technological classes i and j with respect to their relationship with all other technological classes.[5] Formally, we have:

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

where $C_{i,j}$ represents the number of patents that have been classified in both sectors i and j using information on all EPO patents between 1996 and 2006. This process generates a 30 × 30 square matrix M that can be used to measure the level of knowledge relatedness between patents. Thus, the index TECHWIDTH is given by

[1] For a detailed description, see Lissoni et al. (2006) and Coffano and Tarasconi (2014).

[2] Patentees' sector allocation has been obtained following the KU Leuven and Eurostat method for sector allocation. For the full methodology, see Du Plessis et al. (2010).

[3] For more information on the concordance, see Schmoch et al. (2003).

[4] Patents with only one backward citation have the index set equal to 0 by construction (Hall and Trajtenberg, 2004)

[5] For a detailed description, see Breschi et al. (2003).

the inverse of the average value of knowledge-relatedness between the technological class of the original patent and those of each backward citation:

$$TECHWIDTH_p = 1 - \frac{1}{B}\sum_{b=1}^{B} S_{pibj} \tag{2b}$$

where $B$ is the number of backward citations of patent $p$, and $S_{pibj}$ is the cosine index for technological class $i$ of patent $p$ and technological class $j$ of the backward citation $b$.

To capture the effect of BPs on current innovations, we propose an index representing the level of generality across backward citations. As BPs are a conceptual extension of key enabling technologies, we start calculating the generality index first proposed by Trajtenberg et al. (1997). This index provides a measure of the spread across different technological fields of follow-up innovations, and for this reason it 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. Including the same correction introduced for the dependent variable ORIGIN, the generality index is an inversed Herfindahl index defined for each patent p as follows:

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

where K is the number of different 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 citations. Thus, the value for the variable BP is defined as the average level of GENERALITY across the backward citations of each patent application:

$$BP_p = 1 - \frac{1}{B}\sum_{b=1}^{B} GENERALITY_b \tag{3b}$$

where $B$ is the total number of backward citations of patent $p$. The variable BP refers to the generality level in the backward citations of patents, thus identifying a clear direction of dependence – from BP to originality – in the regression model.

To capture companies' technological diversification, we use the index TECHDIV. It is calculated as the inverse of the Herfindahl index, confronting patents for each technological class against the total number of patent of a given company. Correcting for small sample bias (Hall, 2005), the index is formally defined as follows:

$$TECHDIV_p = \frac{N_p}{N_p - 1}\left(1 - \sum_{k=1}^{K}\left(\frac{N_{p,k}}{N_p}\right)^2\right) \tag{4}$$

where $N_{it}$ is the total number of patents for the ith company in year t, while k represents the technological class 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.

Next, we add the dichotomous variable PROs to analyse the role of patents owned by public research organisations, which have often been associated with more original patents. Private firms' patents are used as base group.

Finally, NINVENTORS captures the number of inventors that registered the patent. The rationale behind this variable is that as the number of inventors involved in the innovation process increases, the technology being developed is more likely to benefit from higher opportunities for cross-fertilisation of competencies and, in turn, higher originality.

To control for the R&D intensity in the innovation process, we use the knowledge stock of applicants (KSTOCK). This variable is calculated as the patent stock of the inventor up to time t. In line with previous literature (Lanjouw and Schankerman, 2004; Hall et al., 2005), we measure the knowledge stock (KSTOCK) as:

$$KSTOCK_{it} = P_{it} + \left(1 - \delta\right) KSTOCK_{it-1} \tag{5}$$

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). KSTOCK enters the equation after being log-transformed.

In addition, we include a dummy variable indicating whether the patent has more than one applicant (NAPPL), which is usually associated with higher quality patents. Similarly, we also add controls for the numbers of backward citations (CITATIONS), the number of forward citations after 8 years (FCIT8) and the average number of patent claims (AVGCLAIMS). Finally, time and technological class dummy variables, as well as Country variables where appropriate, have been included.

**Table 1**
Patent applications by country and type of applicant (%).

| | Patents | Companies (%) | PROs (%) |
|---|---|---|---|
| DE | 208,040 | 96.77 | 3.23 |
| UK | 43,244 | 91.28 | 8.72 |
| FR | 70,588 | 90.76 | 9.24 |
| IT | 33,193 | 97.45 | 2.55 |

### 3.3. Estimation method

In the regression analysis, both originality and coherence indices represent our dependent variables and have 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 account for this issue, we make use of the fractional response model suggested by Papke and Wooldridge (1996). Modeling the conditional expectation of the fractional response variable as being defined by a cumulative distribution function such as the logistic function G(z) = exp(z)/(1 + exp(z)), which confines z to the open bounded interval I = (0, 1), they extend the generalized linear model literature showing that quasi-maximum likelihood estimation (QMLE) can be used to obtain asymptotically robust estimators of the conditional mean parameters of the fractional response through ordinary logit or probit regression (Papke and Wooldridge, 1996; Wooldridge, 2010). To follow this approach, we estimate a Generalised Linear Model (GLM) using a logit link function and specifying a Bernoulli distribution for the dependent variable.

## 4. Results and discussion

In Table 1, we report the distribution in the number of patent applications to the EPO across the four countries over the considered time, along with the percentage of applications from private companies and public research organisations (PROs). While the vast majority of applications comes from private companies for each of countries considered, the differences in the percentage of applications from PROs across the four countries offers a view on the important specificities of the various national systems of innovation. For example, UK and French PROs account for about 9% of all applications as opposed to an average of 3% for the other two countries.

**Table 2**
Descriptive statistics.

| | Description | Mean | St.Dev | Median | Max | Min | VIF |
|---|---|---|---|---|---|---|---|
| Origin | Originality index[a] | 0.48 | 0.37 | 0.59 | 1 | 0 | |
| TechWidth | Technological width across backward citations[a] | 0.25 | 0.27 | 0.19 | 0.99 | 0 | |
| BP | Index of generality across backward citations[a] | 0.46 | 0.28 | 0.52 | 1 | 0 | 1.96 |
| Techdiv | Technological diversification of applicant[a] | 0.63 | 0.25 | 0.70 | 1 | 0 | 1.43 |
| PROs | Applicant is a PRO. Yes = 1, No = 0 | 0.05 | 0.21 | 0 | 1 | 0 | 1.06 |
| Ninventors | Number of inventors | 2.49 | 1.76 | 2 | 49 | 1 | 1.08 |
| Kstock | Knowledge stock of applicant (log transformed) | 4.22 | 2.55 | 4.20 | 9.06 | 0 | 1.44 |
| Nappl | Patent has more than 1 applicant. Yes = 1, No = 0 | 0.05 | 0.23 | 0 | 1 | 0 | 1.04 |
| Citations | Number of backward citations | 3.29 | 3.25 | 3 | 128 | 1 | 1.05 |
| Fcit8 | Number of forward citations after 8 years | 1.43 | 2.61 | 1 | 129 | 0 | 1.05 |
| Avgclaims | Average number of patent claims | 7.71 | 7.23 | 6.50 | 202 | 0 | 1.01 |

[a] Index is bounded between 0 and 1.

Substantial differences also take place across different technological classes, reflecting the inter-sectoral heterogeneity in the pace of technological change. These differences are strongly country variant, in line with the technological specialisation of the four countries analysed. The technological classes with the highest percentage of patenting across the countries observed are Technologies for Control/Measures/Analysis, followed by Electrical engineering and Transport Technology. Conversely, lower values are found for Nuclear Technology, Space technology and Environmental Technologies. With respect to the differences across the selected Countries, Germany presents higher specialisation in sectors such as Transport Technology and Electrical Engineering, while France is strong in Telecommunications and Information Technology. The UK is strong in Technologies for Control/Measures/Analysis, but it also shows a 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.

We present descriptive statistics in Table 2, while the correlation matrix of the variables employed is reported in Table 3. With respect to the latter, we observe a medium-high positive correlation between the two dependent variables ORIGIN and TECHWIDTH, indicating they may function as alternative measures for patent originality in our model. These also correlate with the level of generality among backward citations (BP), providing initial evidence that patents that are based on distant technologies tend to rely on technologies characterised by a broad technological applicability. As expected, there is also a significant positive correlation between knowledge stock and the level of technological diversification. We note this does not generate issues of multicollinearity, also discarded by the VIF values in Table 2.

In Table 4, we report the estimates from the fractional response model with ORIGIN as dependent variable, while Table 5 shows the model with TECHWIDTH as dependent variable. In both Tables, Columns (1) and (2) report the results using applications from all four countries, with patents from Germany being the base group. The other columns show the results for each single country.

As shown in Table 4, we find positive and statistically significant coefficients for the variable BP across all different countries taken jointly or separately, in support of our first hypothesis. In other words, even after controlling for patents' technological class and technological diversification, patents based on BPs are significantly more likely to integrate components from a wider range of different technologies, leading to higher level of inter-sectoral technological integration. We obtain similar results when we explicitly account for the technological 'distance' among the technological classes of backward citations, captured by TECHWIDTH, as shown in Table 5. These findings extend existing perspectives on the role of key enabling technologies discussed in previous literature as innovations characterised by a broad vertical applicability across different technological sectors (Trajtenberg et al., 1997; Hall and Trajtenberg, 2004). Integrating insights from the theory on the combinatorial nature of technological change (Fleming, 2001; Fleming and Sorenson, 2004), our findings confirm our first hypothesis that the aggregate pervasiveness inherent to nodes of such technologies may also generate a horizontal effect, as they function as bridging platforms across distant technological fields.

With respect to the role of public research organisations, we report the average values of ORIGIN, TECHWIDTH and BP across the four countries for private companies and public research organisations (PROs) in Table 6. Overall, we find that our two measures of inter-sectoral technological integration seem to support previous findings from the literature indicating that PROs patents are on average more original than patents generated by private companies (Lissoni and Montobbio, 2012; Guerzoni et al., 2014). The average value for the index BP is also significantly higher across PROs than private companies in all four countries. Thus, our data show that PROs not only develop patents characterised by higher inter-sectoral technological integration, but they also use more extensively BPs within their innovation activities, providing initial evidence for our second hypothesis.

Results from the regression model support this. Looking at the models where the variable BP is not included in Table 4, we find a positive and significant effect for PROs, which indicates public research organisations are more likely to develop patents characterised by higher inter-sectoral technological integration. However, such results are not statistically significant when BP is included. This suggests the variability of ORIGIN associated with PROs is in fact reflecting their higher referencing to BPs within their innovation processes, in line with the data in Table 6. Once again, we obtain similar results in the model with TECHWIDTH, although in this case the coefficient of PROs is not significant in the regressions for France and Italy when we do not control for BP as well. Indeed, we even find a negative effect for PRO when BP is included in the model with all Countries (Column 1). These findings provide evidence for our second hypothesis that the function of public research organisations in developing more original technologies may reside in their ability to identify and access bridging platforms within their innovation activity. Adding to previous studies focused on the role of knowledge competencies and basic research (Nelson and Winter, 1982; Granstrand et al., 1997; Trajtenberg et al., 1997), our results underline the importance of considering the specific qualities of technology when analysing the dynamics of inter-sectoral technological integration and how technological trajectories shift. This implication extends to the analysis of the innovation activity of public research organisations, as differences with private companies in developing innovation defined by higher inter-sectoral technological integration seem to be related to a more extensive use of bridging platforms within their innovative activities.

A crucial issue for correctly identifying this relationship rests in the ability of our indexes to effectively capture knowledge flows between citing and cited patents and not simply reflect the scope

**Table 3**
Correlation matrix.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Origin | 1 | | | | | | | | | | |
| | (0.000) | | | | | | | | | | |
| TechWidth | 0.515 | 1 | | | | | | | | | |
| | (0.000) | | | | | | | | | | |
| BP | 0.559 | 0.621 | 1 | | | | | | | | |
| | (0.000) | (0.000) | | | | | | | | | |
| Techdiv | 0.090 | 0.022 | 0.078 | 1 | | | | | | | |
| | (0.000) | (0.000) | (0.000) | | | | | | | | |
| PROs | 0.082 | 0.044 | 0.094 | 0.166 | 1 | | | | | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | | | | | | | |
| Ninventors | 0.109 | 0.038 | 0.112 | 0.132 | 0.076 | 1 | | | | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | | | | | |
| Kstock | 0.022 | −0.016 | 0.001 | 0.497 | 0.027 | 0.209 | 1 | | | | |
| | (0.000) | (0.000) | (0.807) | (0.000) | (0.000) | (0.000) | | | | | |
| Nappl | 0.047 | 0.021 | 0.052 | 0.063 | 0.135 | 0.147 | 0.049 | 1 | | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | | | |
| Citations | 0.087 | 0.061 | 0.073 | 0.025 | −0.027 | 0.112 | 0.071 | 0.021 | 1 | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | | |
| Fcit8 | 0.050 | 0.043 | 0.071 | 0.033 | −0.011 | 0.099 | 0.052 | 0.026 | 0.186 | 1 | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | |
| Avgclaims | −0.005 | 0.006 | −0.009 | −0.078 | −0.015 | −0.022 | −0.061 | 0.007 | 0.045 | 0.046 | 1 |
| | (0.014) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |

**Table 4**
Fractional response model estimates for Originality.

| | Fractional response model – GLM robust SE estimates | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| origin | ALL | | DE | | GB | | FR | | IT | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| BP | 3.141$^{***}$ | | 3.160$^{***}$ | | 2.951$^{***}$ | | 3.129$^{***}$ | | 3.133$^{***}$ | |
| | (0.019) | | (0.024) | | (0.063) | | (0.044) | | (0.077) | |
| Techdiv | 0.400$^{***}$ | 0.715$^{***}$ | 0.453$^{***}$ | 0.823$^{***}$ | 0.191$^{***}$ | 0.286$^{***}$ | 0.462$^{***}$ | 0.861$^{***}$ | 0.309$^{***}$ | 0.397$^{***}$ |
| | (0.016) | (0.016) | (0.021) | (0.020) | (0.040) | (0.040) | (0.040) | (0.039) | (0.056) | (0.054) |
| PROs | 0.025 | 0.087$^{***}$ | 0.039 | 0.113$^{***}$ | 0.008 | 0.055$^{+}$ | 0.030 | 0.087$^{**}$ | 0.073 | 0.130$^{+}$ |
| | (0.015) | (0.015) | (0.024) | (0.024) | (0.032) | (0.032) | (0.029) | (0.028) | (0.088) | (0.088) |
| Ninventors | 0.009$^{***}$ | 0.011$^{***}$ | 0.009$^{***}$ | 0.011$^{***}$ | 0.015$^{**}$ | 0.020$^{***}$ | 0.006 | 0.006 | 0.013 | 0.024$^{*}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.004) | (0.005) | (0.005) | (0.005) | (0.009) | (0.010) |
| Kstock | −0.023$^{***}$ | −0.060$^{***}$ | −0.027$^{***}$ | −0.065$^{***}$ | −0.017$^{**}$ | −0.048$^{***}$ | −0.022$^{***}$ | −0.060$^{***}$ | −0.020$^{*}$ | −0.064$^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.006) | (0.006) | (0.005) | (0.004) | (0.009) | (0.009) |
| Nappl | 0.018 | 0.043$^{***}$ | 0.037$^{*}$ | 0.062$^{***}$ | −0.009 | 0.023 | 0.003 | 0.010 | 0.043 | 0.096 |
| | (0.013) | (0.013) | (0.018) | (0.018) | (0.028) | (0.029) | (0.031) | (0.031) | (0.064) | (0.065) |
| Citations | 0.018$^{***}$ | 0.020$^{***}$ | 0.023$^{***}$ | 0.025$^{***}$ | 0.002 | 0.003$^{*}$ | 0.015$^{***}$ | 0.019$^{***}$ | 0.016$^{***}$ | 0.020$^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) |
| Fcit8 | 0.005$^{***}$ | 0.000 | 0.006$^{***}$ | 0.002$^{+}$ | 0.004$^{*}$ | 0.002 | 0.002 | −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) |
| Avgclaims | 0.000 | −0.001 | −0.001 | −0.002$^{**}$ | −0.001 | −0.001 | 0.002$^{*}$ | 0.002$^{*}$ | 0.001 | 0.001 |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| GB | 0.033$^{**}$ | 0.051$^{***}$ | | | | | | | | |
| | (0.010) | (0.010) | | | | | | | | |
| FR | 0.014+ | 0.005 | | | | | | | | |
| | (0.008) | (0.008) | | | | | | | | |
| IT | −0.066$^{***}$ | −0.094$^{***}$ | | | | | | | | |
| | (0.014) | (0.013) | | | | | | | | |
| _cons | −1.901$^{***}$ | −1.249$^{***}$ | −1.943$^{***}$ | −1.335$^{***}$ | −1.592$^{***}$ | −0.702$^{***}$ | −1.949$^{***}$ | −1.325$^{***}$ | −1.865$^{***}$ | −1.213$^{***}$ |
| | (0.018) | (0.018) | (0.022) | (0.022) | (0.049) | (0.045) | (0.042) | (0.042) | (0.070) | (0.069) |
| Obs. | 215709 | 219108 | 133750 | 135650 | 23995 | 24426 | 43889 | 44496 | 14075 | 14536 |
| Country dummies | Yes | Yes | No | No | No | No | No | No | No | No |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Technological class dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

$^{+}$ $p < 0.10$.
$^{*}$ $p < 0.05$.
$^{**}$ $p < 0.01$.
$^{***}$ $p < 0.001$.

of the claims in the cited patent, as unobserved heterogeneity in the scope of patent claims might introduce a bias in the analysis. As discussed in Section 3, we note that differently from USPTO data EPO citations significantly reduce the incentives for inventors and their attorneys to add citations that are not relevant for patentability, as supplying a list of related documents remains optional. Moreover, "whether or not such a list has been filed, all references are screened and filtered by the EPO examiners in view of their direct relevance with respect to patentability" (Michel and Bettels, 2001; p. 192).

While these arguments indicate EPO citations provide a reasonable representation of technological links across patents,

**Table 5**
Fractional response model estimates for Technological Width.

| | Fractional response model – GLM robust SE estimates | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| techwidth | ALL | | DE | | GB | | FR | | IT | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| BP | 3.071*** | | 3.140*** | | 2.800*** | | 3.010*** | | 2.857*** | |
| | (0.018) | | (0.024) | | (0.055) | | (0.042) | | (0.069) | |
| Techdiv | 0.229*** | 0.498*** | 0.268*** | 0.595*** | 0.178*** | 0.255*** | 0.247*** | 0.587*** | 0.197*** | 0.284*** |
| | (0.012) | (0.012) | (0.016) | (0.016) | (0.027) | (0.028) | (0.029) | (0.030) | (0.039) | (0.040) |
| PROs | −0.020+ | 0.056*** | −0.021 | 0.077*** | 0.003 | 0.049* | −0.031 | 0.036 | 0.028 | 0.109 |
| | (0.011) | (0.012) | (0.018) | (0.020) | (0.022) | (0.023) | (0.021) | (0.023) | (0.068) | (0.072) |
| Ninventors | −0.003* | −0.001 | −0.002 | −0.000 | 0.001 | 0.004 | −0.006+ | −0.005 | 0.007 | 0.018* |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.003) | (0.004) | (0.004) | (0.004) | (0.007) | (0.008) |
| Kstock | −0.025*** | −0.060*** | −0.024*** | −0.061*** | −0.043*** | −0.075*** | −0.024*** | −0.060*** | −0.061*** | −0.104*** |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.004) | (0.005) | (0.004) | (0.004) | (0.007) | (0.008) |
| Nappl | −0.014 | 0.013 | −0.010 | 0.020 | 0.031 | 0.056** | −0.027 | −0.008 | 0.016 | 0.045 |
| | (0.010) | (0.010) | (0.013) | (0.014) | (0.020) | (0.021) | (0.023) | (0.024) | (0.046) | (0.050) |
| Citations | 0.016*** | 0.013*** | 0.018*** | 0.014*** | 0.010*** | 0.008*** | 0.019*** | 0.016*** | 0.007*** | 0.005* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Fcit8 | −0.002** | −0.009*** | −0.002+ | −0.009*** | −0.003* | −0.007*** | −0.000 | −0.010*** | −0.003 | −0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) |
| Avgclaims | 0.001*** | −0.000 | −0.000 | −0.002*** | 0.001+ | −0.000 | 0.003*** | 0.003*** | −0.000 | −0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| GB | −0.037*** | −0.019* | | | | | | | | |
| | (0.007) | (0.008) | | | | | | | | |
| FR | −0.026*** | −0.036*** | | | | | | | | |
| | (0.006) | (0.007) | | | | | | | | |
| IT | −0.033** | −0.054*** | | | | | | | | |
| | (0.010) | (0.011) | | | | | | | | |
| _cons | −3.673*** | −2.753*** | −3.723*** | −2.830*** | −3.432*** | −2.338*** | −3.777*** | −2.906*** | −3.432*** | −2.602*** |
| | (0.015) | (0.014) | (0.019) | (0.018) | (0.040) | (0.034) | (0.034) | (0.032) | (0.059) | (0.055) |
| Obs. | 215715 | 219114 | 133758 | 135658 | 23996 | 24427 | 43886 | 44493 | 14075 | 14536 |
| Country dummies | Yes | Yes | No | No | No | No | No | No | No | No |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Technological class dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

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

**Table 6**
ORIGIN, TECHWIDTH and BP across countries and type of applicant.

| | ORIGIN | | TECHWIDTH | | BP | |
|---|---|---|---|---|---|---|
| | MEAN | *t*-Test | MEAN | *t*-Test | MEAN | *t*-Test |
| DE | | | | | | |
| Companies | 0.472 | −26.67 | 0.253 | −16.23 | 0.451 | −29.94 |
| PROs | 0.612 | | 0.315 | | 0.573 | |
| GB | | | | | | |
| Companies | 0.518 | −16.37 | 0.263 | −7.94 | 0.497 | −18.61 |
| PROs | 0.633 | | 0.302 | | 0.592 | |
| FR | | | | | | |
| Companies | 0.461 | −25.73 | 0.237 | −14.84 | 0.439 | −30.54 |
| PROs | 0.608 | | 0.296 | | 0.571 | |
| IT | | | | | | |
| Companies | 0.418 | −10.14 | 0.22 | −5.26 | 0.411 | −10.56 |
| PROs | 0.592 | | 0.284 | | 0.511 | |

All t-Tests are significant at the 0.01 level.

information on the specific category[6] of citations included in the EPO search reports allow us to conduct additional robustness checks to further explore their role as proxy for knowledge flows. In particular, documents that define the state of the art and the inventive step are assigned by patent examiners to Category A. These can be considered a more refined and precise measure of technological relatedness and relevance across citing-cited patent pairs. We recalculated our indexes and run our analysis on a sub-sample of the data based only on the citations added by the patent examiner in Category A. The results, reported in Table A1 (columns 1–4) for both models with ORIGIN and TECHWIDTH,[7] also support our hypotheses. As discussed, the majority of citations in Category A are added by the patent examiner, not the inventor. This does not imply a knowledge flow is not present (Schoenmakers and Duysters, 2010). Yet, considering only citations added by applicants – which are assigned to Category D – has been suggested to be a more conservative approach to capture knowledge flows across patents in the EPO system (Criscuolo and Verspagen, 2008; Schoenmakers and Duysters, 2010). While this involves a significant reduction in the sample size, results remain robust to estimates based only citations added under Category D (See Table A1, columns 5–8). However, one can note the positive effect of PROs in the model for ORIGIN without BP, reported in Column 6, is no longer statistically significant, which may reflect the loss of statistical power in the sub-sample.

Considering the other covariates in Table 4, we find a general positive effect for the number of inventors (N_INVERTORS) when we consider all four countries jointly. However, looking at each country individually, we observe that the positive effect is statistically significant only for Germany and the UK and, with respect to the model without BP, for Italy. Thus, these findings provide only a partial evidence for the notion that larger groups of inventors may add a wider set of technological competencies to the innovation process. When we consider TECHWIDTH (Table 5), we find a negative and significant effect only when all Countries are included and for France (Column 7). Conversely, a positive effect is found

[6] For a detailed discussion on EPO citation categories, see Criscuolo and Verspagen (2008).

[7] Estimates for individual countries are available upon request.

for Italy (Column 10), but results are not significant in all other columns. This suggests that teams of innovators may in fact come from related technological backgrounds so that TECHWIDTH is less sensible than ORIGIN and their effect results less clear.

When we look at the role of technological diversification (TECHDIV) with respect to both the dependent variables analysed, our findings provide evidence that companies engaged in different technological avenues present a higher likelihood of being able to benefit from and integrate distant technologies, thus developing more original innovations characterised by inter-sectoral technology linkages. Conversely, a negative effect is exerted by higher levels of knowledge stock, which underlines the relationship between accumulated knowledge capabilities and path-dependency.

## 5. Conclusions

This study contributes to the literature on the dynamics of technological integration of distant knowledge providing a novel perspective focused on the role of the specific characteristics of the technology itself. In particular, we argue that the generic and pervasive nature of specific technologies may act as bridge allowing inventors to connect components from seemingly unrelated knowledge landscapes. To this end, we introduced the concept of bridging platforms (BPs) as a conceptual extension of key enabling technologies in view of the fact that the aggregate pervasiveness of BPs across different technological fields is likely to generate, in addition to innovation cascades – enabling effect –, connections between distant technologies by offering a technological coupling – bridging effect –. Using EPO patent data for the period between 1996 and 2006, we show that nodes of technologies defined by a broad downstream applicability may operate as bridging platforms across distant knowledge landscapes, exerting a cross-technological coupling effect leading to more original innovation. This adds further evidence to the importance of considering the specific qualities of technology in addition to the scope of search processes when analysing the development of original innovations and how technological trajectories evolve. At the same time, our analysis suggests that the crucial role PROs play in terms of developing inter-sectoral technological integration and original innovation is related to their higher propensity to effectively access and use BPs within their inventive activity.

The findings from this research lead to relevant business and policy implications. From a business perspective, understating whether BPs create a bridging effect offers relevant information on how to foster the flow of technological spillovers across sectors and enhance distant search, thereby increasing firms' absorptive capacity. From a policy perspective, reaching a better understanding of the role of BPs in the innovation capacity of the wider economy addresses the important issue of how to support the adoption and anchoring of such new innovations that may be considered of particular social value across different sectors, a notable example being represented by the current interest in green technologies. This advocates in favour of public research being critical to ensure that original innovations are effectively pumped across the wider economy fostering cross-sector fertilisation.

The results from this analysis should be considered taking into account the usual caveats related to the use of patent data. More broadly, it is important to expand the analysis presented to the aggregated dynamics of technological integration across different sectors exploring the grid of related innovations connected by BPs and how these interact together. Future work may study such platforms through a wider approach, including firm-level elements such as R&D collaboration and innovation networks among companies, as well as companies and public research organisations, to identify the role they play in enhancing and diffusing the effect of BPs.

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## Appendix A.

**Table A1**
Fractional response model estimates for EPO citation categories A and D.

| | Fractional response model – GLM robust estimates | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | origin A | | techwidth A | | origin D | | techwidth D | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| BP | 1.581*** | | 1.712*** | | 1.315*** | | 1.389*** | |
| | (0.028) | | (0.024) | | (0.052) | | (0.059) | |
| Techdiv | 0.817*** | 0.828*** | 0.512*** | 0.536*** | 0.998*** | 0.978*** | 0.543*** | 0.490*** |
| | (0.033) | (0.032) | (0.026) | (0.026) | (0.069) | (0.066) | (0.072) | (0.073) |
| PROs | 0.049 | 0.091* | 0.084* | 0.138*** | 0.081 | 0.138 | 0.144 | 0.217* |
| | (0.047) | (0.045) | (0.038) | (0.037) | (0.094) | (0.090) | (0.103) | (0.103) |
| Ninventors | 0.005 | 0.007 | −0.013*** | −0.011** | 0.022* | 0.024** | −0.002 | 0.003 |
| | (0.005) | (0.005) | (0.004) | (0.004) | (0.009) | (0.009) | (0.008) | (0.008) |
| Kstock | −0.046*** | −0.059*** | −0.043*** | −0.062*** | −0.054*** | −0.069*** | −0.040*** | −0.051*** |
| | (0.004) | (0.004) | (0.003) | (0.003) | (0.008) | (0.008) | (0.009) | (0.009) |
| Nappl | −0.048 | −0.014 | −0.029 | 0.009 | −0.010 | 0.031 | 0.048 | 0.079 |
| | (0.034) | (0.033) | (0.025) | (0.026) | (0.065) | (0.063) | (0.065) | (0.065) |
| Citations | 0.009*** | 0.011*** | 0.006*** | 0.001 | 0.009* | 0.011** | 0.012** | 0.009* |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) | (0.004) | (0.004) |
| Fcit8 | 0.003 | 0.000 | −0.007*** | −0.012*** | 0.001 | −0.001 | 0.001 | −0.007 |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.005) | (0.005) | (0.004) | (0.004) |
| Avgclaims | 0.005*** | 0.004*** | 0.001+ | 0.001+ | 0.002 | 0.002 | 0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| GB | 0.023 | 0.027 | −0.008 | −0.003 | −0.077 | −0.053 | −0.192** | −0.170** |
| | (0.030) | (0.030) | (0.023) | (0.023) | (0.071) | (0.070) | (0.062) | (0.066) |
| FR | −0.008 | −0.004 | −0.054*** | −0.051*** | 0.079* | 0.064+ | −0.010 | −0.005 |
| | (0.017) | (0.017) | (0.014) | (0.014) | (0.037) | (0.036) | (0.042) | (0.043) |
| IT | −0.006 | −0.016 | −0.016 | −0.016 | 0.018 | −0.006 | 0.065 | 0.034 |
| | (0.026) | (0.025) | (0.020) | (0.020) | (0.059) | (0.057) | (0.064) | (0.062) |

Table A1 (*Continued*)

| | Fractional response model – GLM robust estimates | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | origin A | | techwidth A | | origin D | | techwidth D | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| _cons | −1.404*** | −1.521*** | −2.938*** | −2.868*** | −1.578*** | −1.770*** | −2.966*** | −2.899*** |
| | (0.037) | (0.037) | (0.030) | (0.030) | (0.078) | (0.077) | (0.087) | (0.087) |
| Obs. | 68722 | 70446 | 62046 | 63558 | 20411 | 21012 | 6699 | 6872 |
| Country dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| IPC dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

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

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