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University of Cadiz (Spain)

2018

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Abstract: Technological diversity, or the breadth of technological knowledge embedded in patented inventions, refers to the range of different technological or economic fields covered by a patent. This paper explores the role of diversification scope in encouraging the production of new patents in European universities by including the diversification scope as an explanatory variable in a patent production function. We hypothesize that the more diversified the patented technology in the university, the greater the production of new patents in subsequent periods. To test this hypothesis we rely on a cross-sectional sample of patents owned by 141 European universities across Europe in 2001-2004. Our empirical findings support the hypothesis of diversification, which means that the production of new patents can be spurred by promoting or stimulating greater levels of technological diversification. This result is robust to both the use of various measures of diversification and to different econometric specifications.

Keywords: University patenting, technological diversification, entropy index, multilevel negative binomial model, knowledge production function, European universities.

JEL Classification: O31, O32

This is an original manuscript of an article published by Springer in Journal of Technology Transfer in 2018, available at https://doi.org/10.1007/s10961-015-9414-y

Please, quote as:
Acosta, M., Coronado, D., & Martínez, M.A. (2018). Does technological diversification spur university patenting? *The Journal of Technology Transfer*, *43*, 96-119.

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1 Introduction

University patenting is one of the roles that universities conduct as part of the "third mission", conceptualised as an additional function to teaching and research (Etzkowitz et al., 2000). Other activities include a variety of technology transfer mechanisms such as spin-offs, licensing, entrepreneurial education, publications with industry scientists, etc. (Etzkowitz and Zhou, 2006; Rothaermel et al. 2007; Link et al. 2007). Although patents are a small part of the knowledge produced by universities, the analysis of university patenting is relevant because of its consequences for both the productive system and the university.

On the one hand, the positive effects of university patenting on industry stem from at least three separate but complementary factors. Firstly, there is a direct contribution when a university produces useful patented technologies with some application to industrial processes and transfers them to private firms, thereby increasing private innovation and inducing regional economic growth (e.g. Bercovitz and Feldmann, 2006; Carlsson et al. 2009). Secondly, the production of a patent may affect innovation in surrounding areas because of the flow of technological knowledge between universities and firms. This flow of knowledge can occur through a variety of interaction channels between academics and firms (such as by reading the patent, or via direct conversation or informal meetings with the inventors). This situation may induce localized spillovers from university to industry, with effects on firms' innovative outputs (Anselin et al. 1997, 2000; Feldman and Florida, 1994; Fischer and Varga, 2003; Jaffe, 1989; Varga, 1998) or new company formation across geographical areas (Acosta et al. 2011; Audretsch and Lehmann, 2005; Di Gregorio and Shane, 2003; Woodward et al. 2006; Zucker et al. 1998, Bonaccorsi et al. 2014). Thirdly, academic researchers may use patents to exploit these technological outputs by creating new companies (spin-offs) that will increase the technological capacity of neighbouring areas (Chiesa and Piccaluga, 2000; Mustar et al., 2006, Djokovic and Souitaris, 2008; O'Shea et al. 2008; Zahra et al. 2007).

On the other hand, patenting also has positive consequences for universities. Patents have great potential as a source of licensing revenues for academic institutions (Siegel et al. 2004, Link et al., 2007). Universities benefit from patenting when they gain revenue through licensing or by participating in spin-offs to exploit the results of a patent (Geuna and Nesta, 2006; Sterckx, 2011, include some recent data for the US and Europe). Moreover, in some contexts, there is evidence that researchers can tap into technological knowledge to develop new ideas for research in related scientific fields; for example, Stephan et al. (2007) found that patenting US academic researchers publish more than do members of a non-patenting control group. Carayol (2007) and Breschi et al. (2007) obtained similar results using data from Europe. Van Looy et al. (2006) concluded that inventors publish significantly more than their colleagues (non-inventors), which suggests that the two activities - research and patenting - may actually reinforce each other. A recent paper by Crespi et al. (2011) indicates that in the UK academic patenting may complement publishing, at least up to a certain point. However, patenting and licensing have caused some concern about the extent to which the use of proprietary protections for knowledge detracts from their primary mission as creators of public knowledge. According to Hall and Harhoff (2012), this is one of the main reasons for the enormous interest in this topic by academic researchers, raising questions about the effects of patenting on the quantity and quality of research, the changes in its nature towards other types of investigations focused on commercial ends, or the consequences of university patenting on the diffusion of knowledge by privatizing some of it. Although some literature also points to a substitution effect, most of the empirical evidence reveals no such trade-offs and even signals positive effects (Franzoni, 2009, Van Looy et al. 2011, Franzoni and Scellato, 2011).

This previous literature suggests several arguments that support the importance of analysing patenting activities in universities. Particularly, providing insight into the causes encouraging or hindering the capacity of universities to produce patents would help to design policy measures in order to foster the production of university patents. In this respect, an important consideration in managing technology in universities is technological diversification, which has an implication on how widely a technology can be applied (Lerner, 1994; Leten et al. 2007; Toh, 2014). More specifically, technological diversity, or the breadth of technological knowledge, refers to the antecedent quality of the body of knowledge, which allows creativity and generates new perspectives and insights into a given problem (Lettl et al. 2009). The extent to which the production of university technology is diversified or specialised can have consequences on the academic outputs. The scarce empirical research on this topic suggests, for example, that the breath of knowledge embedded in patents affects the quality of the patent (Tantiyaswasdikul, 2012), the probability of commercialization (Nerkar and Shane, 2007), or its value (Jaffe, 2000), which in turn is relevant for technology transfer. Moreover the immediate consequence of widening or narrowing the scope of technology produced in universities may go beyond the university itself. According to Rosell and Agrawal (2009), university flows of knowledge are narrowing (even only those associated with patented inventions in certain fields), and this fact could throw into question the traditionally conceived arrangement between academia and society, affecting policies and economic growth.

In this study, we examine the role of technological diversification in the production of patents by including the diversification of technology at university level as an explanatory factor in a patent production function. By doing so, we add an additional aspect to the literature on the factors affecting university patent production that, to our knowledge, has not been analysed so far. Furthermore, our approach differs from previous econometric studies with respect to the empirical framework. While previous works have applied one level of analysis (e.g. university), we put forward a multilevel model in which the dependent variable is the number of universities, and the independent variables include university characteristics (the technological scope along with other variables) and control for regional factors at a second level. For testing the role of technological diversification in the production of patents we use the university as unit of analysis. Based on a knowledge production function, we estimate several empirical models using a cross-sectional sample of university-owned patents for 141 European universities located in 74 European regions.

The paper is organised as follows. Section 2 summarises the relevant literature. Section 3 describes the data and the patterns of university technological diversification in university-owned patent production across European universities. Section 4 presents the models, explaining the effects of technological diversification on the production of new patents. Section 5 provides the results and robustness checks. We briefly summarise the conclusions and provide some policy implications in Section 6.

2 Literature review

In recent years an increasing number of studies carried out both in Europe and in the US has contributed to our knowledge on the factors affecting the production of patents in universities. We know which universities produce more patents, which receive more revenues in licensing, in which fields patents are being issued, who is patenting in the university and how patent activity relates to personal characteristics (Stephan et al., 2007; Azoulay et al., 2007). We also know something about certain institutional and regional factors encouraging academic patent activities and others that are hampering the production of patents. For example, prior empirical research on the determinants of university patenting has largely evaluated regulatory changes such as the US Bayh-Dole Act (e.g., Henderson et al., 1998, Mowery et al. 2001) or IPR regulatory policies in Europe (Geuna and Rossi 2011). Other research has focussed on university-specific factors (for example, the size, prestige of the university, universities' policies, etc.) and whether the economic environment can affect the production of patents at university level (Coupe, 2003; Payne and Siow, 2003; Saragossi and de la Potterie, 2003; Azagra-Caro et al. 2003; Dai et al., 2005; Geuna and Nesta, 2006; Baldini, 2006; Acosta el al. 2009; Rizzo and Ramaciotti, 2014). However, the question of whether the breadth of the technologies embedded in university patents can contribute to or hinder the production of new patents remains unanswered. In the following paragraphs we advance some positive and negative consequences of technological diversification.

Universities, as with other organisations, can develop knowledge in a variety of technological domains; they can make choices about the knowledge fields in which they want to develop their research and technological activities. By deciding upon the development of knowledge in one technological domain (or discipline), they reduce their options to develop expertise in other domains, and hence decisions regarding the knowledge depth and breadth become strategic questions with consequences in the long run (Moorthy and Polley, 2010). Therefore, there are two alternatives. On the one hand, universities may follow a technological diversification strategy expanding the production of technology base embedded in patents into a wide range of fields. On the other hand, universities may promote specialisation by reinforcing and stimulating the production of technology in a small number of areas. Both options could produce different outcomes. While the final decision about university research might remain centred on the individual researcher, some studies show that these decisions are influenced by the university environment, societal forces, and policy (Dai et al., 2005).

In order to provide clues about which hypothesis (diversification or concentration) would be more compatible with the increase of patent performance at universities, there are two questions to address. First, we discuss some advantages and drawbacks of one or another strategy. Second, we summarise some empirical background.

With respect to the first question, while the role of technological diversification has been studied at company level, there is not much research at university scope. Some literature has analysed the advantages of diversifying the production of technology. For example, Wade and Gravill (2003) argue that it reduces the risks of innovation and creates synergy in cross-disciplinary technology integration (Gambardella and Torrisi, 1998), thereby enhancing the sources of competitive advantage. Henderson and Cockburn (1996) point out the benefits of diversity in the research agendas of pharmaceutical firms. They suggest that having a range of research approaches and expertise within firms permits the cross-fertilization of ideas through knowledge spillovers between units and therefore greater innovative output. Granstrand (1998) argues that a technological diversification strategy can help firms to enhance innovation efficiency because diversification can stimulate firms to generate innovative ideas through the combination and recombination of various technologies. By maintaining a broad technology portfolio, firms can explore and exploit new opportunities emerging from scientific and technological breakthroughs (Lin et al. 2006). Some drawbacks are also inherent in technological diversification. Coordination costs may increase exponentially with higher levels of technological diversification because more diversified firms are more likely to encounter difficulties in combining mature, or exploitative, technologies with explorative trajectories (Leten et al. 2007). Uncertainty in conducting sometimes unrelated activities (Brown, 1992) is another of the main negative consequences. Some of these advantages and drawbacks at company level can be observed at university level. For example, in academic circles, a relationship between the diversity of knowledge and information accessed via network connections during the various stages of the research process should positively influence both an actor's creativity and the knowledge creation quality since knowledge diversification offers opportunities to exploit and combine inputs from different sources (Chen and Liu, 2012). The costs of co-ordination are probably higher for a technological diversification strategy compared to a concentration option. For example, diversification in university research sometimes stems from the incorporation into a project of researchers from different universities, working in related fields. Many (though not all) European funding opportunities require some sort of collaboration with partners in other European countries; for example, most of the funding in the framework of the European strategy Horizon 2020 require organisations from at least three different countries. When several universities are involved in a project, some face-to-face contact between researchers is necessary for co-ordination and exchange of ideas, increasing the displacement costs. Another risk is uncertainty; there is no guarantee that technological diversification will increase the likelihood of generating technological outputs in the form of patents. Sometimes, attempts to cope with several fields of research result in fewer outputs because of lack of expertise in some of them, or perhaps there is the same quantity of outputs, but of worse quality than in a specialisation scenario.

With regard to the empirical background, the consequences of technological diversification has been widely analysed at firm level (e.g. Breschi et al. 2003; Lin et al. 2006; García-Vega, 2006; Quintana-García and Benavides-Velasco, 2008; Chiu et al. 2010). Overall, this literature confirmed the positive impact of technological diversification on firms' technological performance. However, the question of whether the scope of technological knowledge embedded in university patents affects the production of new patents remains quite unexplored. Only a few number of papers have dealt with a related topic about the breadth (knowledge diversification) created in universities with several outcomes, such as the quality of patents and commercialisation. The research by Rosell and Agrawal (2009) examined the technological breadth of university inventions, which are more likely to be cited by a more concentrated set of subsequent patent owners. Their results suggest that the rapid rise in patenting during the 1980s in the US was associated with a narrowing of knowledge flows both to and from universities, but only in specific technology fields. Tantiyaswasdikul (2012) investigated the effect of the breadth of patent protection – including both of the number of IPC classes and the number of claims - to account for breadth or diversification on the value of patents measured with patent citation. Using a sample of 1120 Japanese university patents the author found a significant effect and concluded that patent diversification does influence the value of university patents. Nerkar and Shane (2007) examined the effect of the attributes of inventions on their commercialisation, particularly technology scope. Using patents assigned to the Massachusetts Institute of Technology between 1980 and 1996 and licensed to a private firm, their work supports the hypothesis that the greater the scope of the invention's patent, the greater the likelihood of its commercialisation. These two papers show the positive effects of technological diversification of university patents on its quality and commercialisation, but not on the subsequent performance.

Diversification seems to bring benefits for technology transfer as well. Some research has shown that broader scope of patented inventions provides a wider range of alternative inventions that can be blocked by the patent. The size of the region of technology space may exclude other patentees from operating, and then a broader patent is more valuable to the patentee (Jaffe, 2000). This idea suggests that a diversification patent generates greater appropriateness and increases the value of the patented invention (Merges and Nelson, 1990; Lerner, 1995; Shane, 2001). To summarise, the empirical research on technological diversification in other institutions (firms) shows some benefits on technological performance, and the limited research of this topic at university level also points in the same direction: a positive relationship between diversification and some indicators such as the patent quality and patent commercialisation. This similarity with respect to the empirical research between firms and universities is not surprising, given that universities have become entrepreneurial in their inner dynamic as well as through external connections with business firms in research contracts and transfer of knowledge and technology (Etzkowitz, 2003). Moreover, although the intra-organisational processes of these academic units are relatively nascent and fragmented (Hunter et al. 2011), some similarities between the production of knowledge in firms and universities are clea,r to the extent that universities are divided into research groups that operate as firm-like entities; they lack only a direct profit motive to make them companies (Etzkowitz, 2003). On these grounds, we expect a positive causal relationship between technological diversification and the production of university patents in subsequent periods.

3 Patent specialisation across European universities

3.1 University-owned patents across European universities

Following the terminology in Lissoni et al. (2008), 'academic patenting' comprises both university-owned patents, in which the property is retained by the universities that employ the academic inventors, and university-invented patents, where at least one of the inventors is from a university but the owner of the patent is a firm. This latter category of patents consists of inventions arising from collaboration with industry, with three actors involved in negotiations over the intellectual property: the academic inventor, his/her business partner, and the university administration (Lissoni et al, 2013)[1]. In this paper we consider university-owned patents. Lissoni (2012) suggests that, by looking solely at university-owned patents, we may end up losing sight of a substantial amount of inventing activity that is registered under a company's or an individual's heading. However, although our choice might be seen as a partial view (we exclude invented patents), the fact is that university-owned patents fit better to the objective of this paper for the

[1] Geuna and Nesta (2006) concluded that the number of university-invented patents is higher than the number of patents owned by universities. Lissoni et al. (2008) provide figures to show that university-owned patents in France, Italy and Sweden constitute no more than 10% of all academic patents (most patent ownership lies with firms), although this can be as high as 69% in the US. Recently, some European countries have introduced legislative changes in an attempt to retain the rights of invention where universities produce the information included in patents; see Geuna and Rossi (2011) for a discussion.

following reason. Our research question on how diversification of knowledge embedded in university patents can produce additional, subsequent technological knowledge is an issue that, if corroborated, would require university competence to put in practice measures affecting the diversification or specialisation of patented technology. This control competence over technological research is easier for university-owned patents than for university-invented patents because the former relies on university's resources while the latter are totally or partially funded by the firms that end up owning the intellectual property. Some empirical research supports this idea; for example, university-owned patents have been found to be more responsive to public funding and university-invented patents more responsive to private funding (Azagra-Caro et al. 2006; Azagra-Caro, 2014).

In order to construct our sample of university-owned patents we used the following criterion. A patent was assigned to a university when the name of the university appeared in the list of applicants[2]. When there was more than one university applicant, each was assigned a patent. To avoid national distortions arising from differing patent application requirements in different countries, we included only European Patent Office patents in our sample. We examined the institutions named in the European Indicators, Cyberspace and the Science–Technology–Economy–System (EICSTES) Project and in the Worldwide Web of Universities (http://univ.cc, a web site with links to 7,884 universities in 190 countries).

Our search resulted in 3,330 European university-owned patents (obtained from the Derwent Innovation Index) related to 391 universities located in Europe-15 (before the 2004 enlargement) for the period from 2001 to 2004[3]. Of the 391 universities, 31 have no university-owned patents; 192 universities have between one and five such patents; 89 have between six and 10; 37 have 11 to 20; 18 have 21 to 30; and 24 universities own more than 30 patents. On average, there are 8.5 patents per university for the whole period.

Table 1 presents the top 10 universities with the highest number of owned patents. Three British universities lead the ranking, accounting for 17.5% of all patents. That Table also shows that owned patents appear to be concentrated in a few universities; only ten universities (2.5% of the sample) account

[2] There are two issues that we had to solve. First, sometimes the college appears as applicant instead of the university. Second, it is common that different names and/or abbreviations for the university appear as applicant of the patent. To avoid losing information we elaborated a complete list of universities (and colleges) considering different abbreviations as well. (This list is available upon request).

[3] Although the first search was performed using the Derwent Innovation Index, we have recently checked and compared the entire information with another database (PATSTAT), with little change with respect to our original data.

for 25.6% of patents. University-owned patents can be analysed by looking at the distribution across technological fields. For this purpose, we have classified all patents in the sample according to the technological subclasses of the International Patent Classification (IPC) at four digit-level. The IPC offers a means of obtaining an internationally-uniform classification of patent documents of which the primary objective is the establishment of an effective search tool for the retrieval of patent documents. Researching the IPC codes is a way to find out the various technologies embodied in a patent because each classified 'thing' in a patent is made according to its nature, function, purpose or application (Guide, 2012)[4]. The last column in Table 1 shows the number of different technological subclasses for all the patents owned by each university and Table 3 exhibits the ten most dynamic technological subclasses of the IPC in which European universities have patented in 2001-2004. As this table depicts, more than a half of all university-owned patents include at least one of those IPC codes.

Table 1. Top Universities by number of university- owned patents (2001-2004)

University	Country	University-owned patents No.	%	Cum. %	No. IPC (*)
University of London	GB	243	7.30	7.30	114
University of Oxford	GB	168	5.05	12.34	99
University of Cambridge	GB	89	2.67	15.02	81
Ghent University	BE	61	1.83	16.85	48
University of Southampton	GB	50	1.50	18.35	42
Catholic University of Leuven	BE	49	1.47	19.82	51
Universitat Politecnica de Valencia	ES	49	1.47	21.29	39
University of Bristol	GB	48	1.44	22.73	46
Delft University of Technology	NL	48	1.44	24.17	59
Leiden University	NL	47	1.41	25.59	27
University of Manchester	GB	46	1.38	26.97	44
Eberhard-Karls-Universitat Tubingen	DE	45	1.35	28.32	32
University of Glasgow	GB	45	1.35	29.67	27
Catholic University of Louvain	BE	43	1.29	30.96	45
Utrecht University	NL	40	1.20	32.16	20
Others		2259	67.84	100	
All Universities in the sample (391)		3330	100	100	

(*) Number of different technological fields (IPC codes at four digit-level).
Source: Derwent Innovation Index.

[4] Available at http://www.wipo.int/classifications/ipc/en/general/

Table 2. Ten IPC codes with the greater number of university onwed-patents

IPC Codes	Patents including the IPC code(*) No.	%	Cum. %
A61K	1051	10.93	10.93
C12N	769	7.99	18.92
G01N	760	7.90	26.82
A61P	686	7.13	33.95
C07K	535	5.56	39.51
C12Q	509	5.29	44.80
C07H	217	2.26	47.06
B01J	199	2.07	49.13
C12P	198	2.06	51.19
H01L	194	2.02	53.20

A61K: Preparations for medical purposes; **C12N**: Micro-organisms or enzymes; compositions thereof; **G01N**: Investigating or analysing materials by determining their chemical or physical properties; **A61P**: Specific therapeutic activity of chemical compounds or medicinal preparations; **C07K**: Peptides; **C12Q**: Measuring or testing processes involving enzymes or micro-organisms; **C07H**: Sugars; derivatives thereof; nucleosides; nucleotides; nucleic acids; **B01J**: Chemical or physical processes, e. g. catalysis, colloid chemistry; their relevant apparatus; **C12P**: Fermentation or enzyme-using processes to synthesise a desired chemical compound or composition or to separate optical isomers from a racemic mixture; **H01L**: Semiconductor devices; electric solid state devices not otherwise provided for.

(*) When a same code appears for example in two patents, these data include both patents.
Source: Derwent Innovation Index

3.2 Relationship between technological diversification and patent production

To analyse how universities diversify their patented technology, we suggest an entropy index based on Jacquemin and Berry (1979), which measures the degree of technological diversification across technological fields:

$$entro = \sum_{i=1}^{n} P_{ij} \ln\left(\frac{1}{P_{ij}}\right),\cdot$$

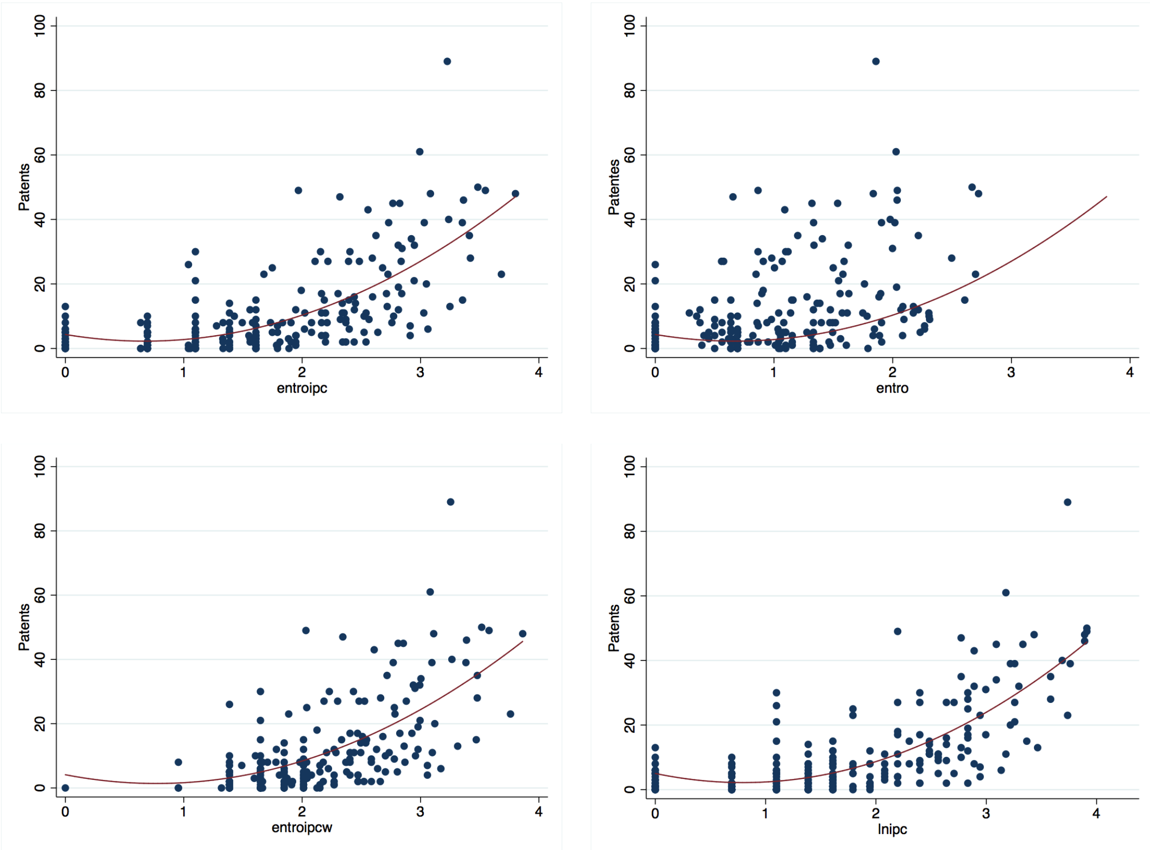
where P_{ij} is the proportion of patents in field j in university i, and $\ln(1/P_{ij})$ is the weight given to each field. This measure considers both the number of technological fields and the relative importance of these fields compared with all the patents owned by the university. Zero indicates the absence of diversity and ln (number of sectors) indicates the maximum extent of diversity.

In order to calculate the entropy index for each university we have followed two criteria. First, according to Lerner (1994) and other subsequent research (e.g. Nerkar and Shane, 2007; Huang and Murray, 2009; Czarnitzki et al., 2011), the technological diversification in university patenting is measured using the spread of a university's patent portfolio over technological subclasses of the International Patent Classification at four-digit level. Second, to avoid problems over the sensitivity of the results to changes in scale (that is, the number of technology fields used to calculate the entropy indexes), we have considered another way of classifying patents, using an industrial classification instead the IPC subclasses. For this purpose, we classified all the university-patented technology (by four-digit IPC codes) into 44 industrial sectors, applying an industrial concordance table developed by Schmoch *et al.* (2003). Using this equivalence table, we assigned the original IPC data (all the IPC at the four-digit level) for each university-owned patent to the Classification of Economic Activities in the European Community at the two-digit level based on the industrial sector where the patent originated. Once all the technologies were classified in industrial sectors, we used this information to obtain the entropy indexes for all universities in the sample for the period 1998–2000.

After applying these two criteria explained above we obtained *introipc* (entropy index obtained from IPC codes) and *entro* (entropy index calculated from industrial sectors). Other alternatives consist of weighting the entropy index introducing a weight factor (p/p–1) similar to that proposed by Hall *et al.* (2001). This diversity index (entroipcw) accounts for the number of technology classes in which a university was involved and controls for the size of the patent portfolio by weighting for (p/p-1), which is correct for the small sample bias[5]. Finally, we use the log of the number of different IPC classes for all the technologies patented by each university. This is a rough measure (useful for comparing with the previous indexes) that takes into account only the technological scope of the patent (or number of technologies embedded in the patent). Fig. 1 shows the relationship between the production of university patents in the period 2001–2004 and the degree of technological diversification in the previous period (1998–2000) using the indexes described above. These graphs provide some intuition, showing that the data are consistent with the view that diversification is positively related to the production of patents. The graphs also suggest that diversification is important but, above a certain point, there is clearly a positive relationship with the production of patents in the subsequent period 2001–2004 when the values of the entropy indexes are larger than 1.5.

[5] For example, when the number of patents owned by the university is large, let us say 1000, the weight factor is near 1 (p/p-1 = 1000/999) and *entroipc* is equal to *entroipcw*; however, if the number of patents is small, e.g. 5, the weight factor is 1.25 (p/p-1 = 5/4), which means that *entroipcw* is larger than *entroipc* for universities with a small number of patents.

Fig. 1. Relationship between the number of university-owned patents in 2001-2004 and four measures of technological diversification 1998-2000 (*)



Note: entroipc is the entropy index computed from the number of IPC class at four-digit level for each university; *entro* is the entropy index obtained using the number of economic sectors; entroipcw is the entroipc index weighted by (n/n-1) where n is the number of all technological classes in each university; *lnipc* is the logarithm of the number of different IPC clases in each university.

4 Variables, data and method

4.1 Variables and data

4.1.1 Dependent variable

The dependent variable, *ownedpat,* is the number of European patents owned by university 'u' located in region 'r' in period 't'. As explained above, the data for this variable were obtained through a search using the Derwent Citation Index for the period 2001-2004.

4.1.2 Variable of main interest

Our main independent variable is the degree of diversification of the patented technologies produced in universities in a period before the patent production. We have used the four measures of diversification described above that were obtained at university level for the period 1998-2000: *entroipc, entro, entroipcw and lnipc*.

4.1.3 Control variables

 University size (*lnpub*). The empirical literature seems to support the view that large universities are more likely to produce technology outputs. For example, Schartinger et al. (2002), in a study of 309 Austrian university departments, found that department size is a significant determinant of industry–university knowledge and technology transfer. Likewise, Carlsson and Fridh (2002) investigated technology transfer in the US using data from 170 universities, hospitals and research institutes. One of their more important findings was the significant relation between institution size and the total number of patents. Friedman and Silberman (2003) also found that university size was a relevant factor in explaining the number of invention disclosures in 83 US universities. These references indicate the relevance of size to the production of more patents or other kinds of technology outputs, but including size in the model is also important for controlling by the fact that larger universities can count on more resources (such as researchers or facilities) and consequently have more opportunities to produce patents. For capturing the size of the university, we employed the number of scientific publications (*lnpub*). These data refer to the scientific articles containing at least one author affiliated with a European university for 1998–2000. The information was retrieved from the Science Citation Index Expanded (SCI) and includes papers from all scientific fields and engineering, which are the more related to the production of technology (fields in social sciences and humanities were excluded).[6]

 Collaborations with firms or universities in producing patents *(collabo)*. Collaboration provides benefits that include access to a wide variety of resources, to new foundations or instruments needed to solve complex problems, and to the creation of new knowledge or technologies (Belkhodja and Landry, 2007). To estimate the existence of spillovers, we need to assess the level of knowledge exchange or knowledge co-operation with other universities or firms. To capture this variable, an approximate indicator is the ratio between the number of university patents in collaboration with firms and other universities and the total number of patents (*collabo*) for each university in the period 1998–2000.

 University R&D expenditure (*rdexpend)*. This is one of the main variables suggested in the knowledge production function, and on which the empirical literature has focused most intensely. For example, Coupé (2003), Payne and Siow (2003), Azagra-Caro et al. (2003), Azagra-Caro et al. (2006),

[6] As is well known, the SCI is a bibliographical database produced by the Information Sciences Institute (ISI), which is in turn a part of Thomson Reuters' Web of Science. The main advantage of ISI citation indexes is that they provide a complete list of all authors and their affiliations. .

and Acosta et al. (2009) found a significant effect of university R&D expenditure on the production of university patents, although with different values for the coefficient depending on the context in which the knowledge production function was applied. This variable was measured using the logarithm of the annual average for 1998–2000 of Higher Education Expenditure on R&D (HERD) in millions of PPS—purchasing power standard, at 2000 prices. The source of HERD is Eurostat. We include regional instead of university data for two reasons. First, there are no available indicators of university R&D funds for a large sample of European universities, but we can take regional HERD, which is available at the regional level. This is the only method of control for university R&D expenditure. Second, our variable of interest is 'diversification'; we do not aim to obtain accurate estimates of the effects of R&D on patent production, although it is necessary to control for this factor. Methodologically, there should be no problem because we take into account the clustered nature of data in the specification (universities are grouped in regions and as regions for our analysis we chose the territorial units from Eurostat in each country at the NUTS 2 level of aggregation).

- Technological environment or demand side for university-patented technology (*rdgdp*). Regions with a strong industrial sector, supported by high-technology activities or with well-trained human resources, will demand more intensive university technology than regions with a much lower level of knowledge in technology and innovation. The inclusion in the model of a control variable capturing regional factors is important because of the spillovers theory reversed (Casper, 2013). This hypothesis suggests that the university's regional environment can significantly affect the university's success in producing and commercialising science and technology. However, the empirical literature does not offer a clear-cut conclusion about the effect of regional demand on university technology. For example, Baldini et al. (2006) analysed a set of 637 patent applications filed at the Italian Patent and Trademark Office, the European Patent Office, and the US Patent and Trademark Office between 1965 and 2002, with at least one applicant belonging to the official list of higher education institutions. They found greater university patenting activity in the north of Italy, where there is a higher level of industrial development. Using a longitudinal dataset of all public Italian universities for 2005-2009, Rizzo and Ramaciotti (2014) found that being embedded in an innovative region is a factor that exerts a positive influence on the university rate of application for patents. Acosta et al. (2009) found no evidence of the effects of industrial potential on the production of university patents in Europe. In our model this variable was captured by the ratio between firm R&D expenditure and regional gross domestic product. We obtain an annual average for 1998–2000. The source used to construct *rdgdp* was Eurostat.

Note that our list of explanatory variables is comprised of data at two levels: our dependent variable (the number of university-owned patents, the main variables of interest (diversification) and the control variables capturing size and collaboration are obtained at university level. However, the control variables on R&D expenditure and the demand side for patented technologies are obtained at regional level. There are two reasons for this choice: first, according to the main empirical literature, R&D is a fundamental variable in explaining the production of patent, but this variable is unavailable at university level. Secondly, controlling for the university demand of the surrounding economic environment requires considering a variable that nests our dependent variable (universities are located in regions). The inclusion of these variables at regional level avoids a misspecification problem, and the combination of several nested structures can be dealt with the appropriate econometric specification. Unfortunately data about some the previous independent variables are not available for all the universities considered in the descriptive analysis (391). For some of them was impossible to obtain information about their characteristics and, on the other hand, information on several variables such as university R&D expenditure exists only for a specific number of European countries. Consequently, the number of observations (universities) to estimate the model was 141. Table 3 briefly summarises the variables and presents the descriptive statistics, while Table 4 shows the correlations among all variables involved in the analysis. Note that the linear correlations between the diversification indexes and the number of patents range between 0.32 and 0.56.

Table 3 Variables. Summary and Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min.	Max
ownedpat	Dependent variable. Nº of university-owned patents (2001-2004).	8.764	10.508	0	49
	Level 1: University data				
entroipc	Entropy index obtained using technological IPC classes. (1998-2000).	1.540	0.873	0	3.802
entro	Entropy index obtained using technological economic sectors. (1998-2000).	0.872	0.710	0	2.723
entroipcw	Entropy index weighted by the university patent activity (1998-2000).	1.763	0.858	0	3.862
lnipc	Log of the number of different IPC class for each university. (1998-2000)	1.592	0.928	0	3.892
lnpub	Log of number of JCR scientific papers published by each university (1998-2000).	6.730	1.761	0	8.856
collabo	Number of patents in 1998-2000 developed in collaboration with firms divided by the number of patents 1998-2000.	0.171	0.314	0	1.000
	Level 2: Regional data				
lnrduniv	Log of R&D University Expenses (average 1998-2000)	5.534	0.867	3.392	7.550
rdgdp	R&D expenses divided by the regional gross domestic product (average 1998-2000)	0.012	0.009	0.001	0.043

Table 4 Correlations

Variable	*ownedpat*	*entroipc*	*entro*	*entroipc*	*lnipc*	*lnpub*	*collabo*	*lnrduniv*	*lnrdfirms*
ownedpat	1.0000								
entroipc	0.5192	1.0000							
entro	0.3232	0.8055	1.0000						
entroipcw	0.4660	0.9893	0.8035	1.0000					
lnipc	0.5581	0.9959	0.7808	0.9783	1.0000				
lnpub	0.4142	0.3294	0.1228	0.3	0.3425	1.0000			
collabo	-0.0219	0.0262	-0.0017	0.0298	0.0227	0.0571	1.0000		
lnrduniv	0.2351	0.0809	0.0127	0.076	0.096	0.1294	0.1587	1.0000	
rdgdp	0.1297	0.1729	0.1175	0.1628	0.1814	0.0648	0.0942	0.4533	1.0000

4.2 Econometric model

This section establishes an econometric model to test the importance of diversification (along with other variables) in the production of subsequent university-owned patents. The standard starting point in the literature is a ‘knowledge production function’ (Griliches, 1979) in which knowledge is measured with a proxy variable (e.g., patents) and the inputs include university R&D funds and other variables. Several authors have used this empirical tool to analyse the production of university patents at various levels (e.g. Coupé, 2003; Foltz et al. 2000, 2003; Payne and Siow, 2003; Azagra-Caro et al. 2006; Baldini et al. 2006; Acosta et al. 2009; Gurmu et al. 2010).

Our framework is marked by two differences. First, we introduce the role of diversification as an explanatory factor, and, second, we take into account non-observable regional influences that can affect the production of university patents. The following paragraphs explain the empirical model, the variables and provide some details about the estimation procedure.

Given the nature of the dependent variable, a suitable framework for dealing with this type of data would be any of the family of the count models. The Poisson regression model is usually the starting point for the analysis of count data. However, the assumed equality of the conditional mean and variance functions is typically taken to be the major shortcoming of the Poisson regression model and thus observed data rarely, if ever, display this feature (Greene, 2012, p. 807). The most common is the negative binomial (NB) model, which is used to model overdispersion (the extra variability compared with the mean).[7] Additionally, we extend the standard NB model to incorporate normally distributed random effects at different hierarchical levels. More specifically, our base empirical specification is a count model in which the conditional mean explaining the production of university-owned patents depends on technological diversification along with a set of explanatory variables (Table 3) plus regional unobserved heterogeneity:

$$\begin{aligned} &E(ownedpat_{urt} \mid diversif_{urt-\mu}, \text{lnpub}_{urt-\mu}, collabo_{urt-\mu}\ \ln rduniv_{rt-\mu}, rdgdp_{rt-\mu}, \zeta_r^{(2)}) = \\ &\exp(\alpha + \gamma diversif_{urt-\mu} + \phi_1 \ln pub_{urt-\mu} + \phi_2 collabo_{urt-\mu} + \beta_1 \ln rduniv_{rt-\mu} + \beta_2 rdgdp_{rt-\mu} + \zeta_r^{(2)}) \end{aligned} \quad [1]$$

Where *diversif* is captured by one of the four diversification indexes put forward in Section 3.2 (see Table 3 for a summary) and $\zeta_r^{(2)} \mid X \approx N(0, \varphi^{(2)})$ is a random coefficient of unobserved heterogeneity over regions. This term should capture other characteristics of the regional innovation system (not explicitly included as explanatory factors in the model) that could affect the production of patents, such as incentives and other policy measures and interface centres.

All independent variables refer to a previous period, t–, in which the patents are produced, because it takes time for the factors included as independent variables to generate effects on the dependent variable. Because universities are grouped into regions, the model has two hierarchical levels. The first level of university effects considers the characteristics of universities affecting the production of patents. The second level clusters all universities in the same region. This hierarchical structure suggests the extension

[7] Other alternatives have been proposed in the literature, for example when the fraction of zeros is too high to be compatible with standard underlying count data, zero inflated models or hurdle models can be a good option. But in our analysis it is not appropriate to estimate this model as our sample contains 12.8% of zeros.

of the simple count regression to a grouped-data model with unobserved effects capturing regional heterogeneity. The adoption of a grouped-data model to analyse factors at two hierarchical nested levels has several advantages in avoiding potential endogeneity problems in simple cross-sectional regression models caused by the omission of variables and intragroup correlations. First, the grouped-data model takes into account unobserved factors affecting the production of university patents on a regional scale. Second, the geographical area where the patent is produced may have some influence. For example, patents produced in the same region may be influenced by identical incentives or transfer office characteristics (that is, we assume a high probability of intragroup correlation between universities in the same region). Consequently, the decision to use hierarchical analysis has the main objective of avoiding bias caused by both the omission of relevant variables and unobserved regional heterogeneity. Failure to consider clustering of data could result in serious bias when we estimate the effects of the aggregate explanatory variables on the individual-specific response variables (see, for example, Moulton, 1990; Antweiler, 2001; Wooldridge, 2003). Furthermore, this procedure makes it possible to estimate confidence intervals correctly for the estimated coefficient of diversification after controlling for regional unobserved heterogeneity.

The log-likelihood of the multilevel count model (Poisson or NB) has no closed form, and so must be approximated. All the multilevel Poisson models in the next section are estimated by adaptive Gaussian quadrature, using the seven-quadrature points in the Stata statistical package, version 13. The technical details of the procedure can be found in Raudenbush and Bryk (2002), Pinheiro and Chao (2006) and Rabe-Hesketh and Skrondal (2012).

5 Results

5.1 Baseline results

Following our empirical specifications and the procedure proposed above, we estimated four negative binomial regressions with random cluster effects. These models are obtained from a process whereby the response is generated by counting the number of patents for each level-1 unit (university) and where, conditional on the fitted explanatory variables and higher-level terms (regions), the mean count for each university level-1 unit has a Poisson-gamma mixture distribution. This specification may capture some additional overdispersion stemming from unexplained heterogeneity between universities. Table 5 presents the results. The dependent variable *ownedpat* (number of university-owned patents in 2001–2004) is explained using four diversification indexes along with other variables that, according to the standard literature on this topic, affect the production of patents (see Table 3 for a short description of the variables and the descriptive statistics). Each model in Table 5 corresponds to one of the indexes capturing the diversification of patented technology. Model I includes the entropy index computed using IPC codes (*entroipc*); Model II uses the entropy index calculated from the number of industrial sectors; Model III is presented with the entropy index weighted by the size of the university portfolio (*entroipcw*); and Model IV considers the number of different IPC codes. The coefficient of overdispersion (*lnalpha*) is significant in all models, pointing to the gain of the NB model with respect to the Poisson regression for capturing the variability of the dependent variable. Analysing first the random part of the models, we find the regional variance is not significant and ranges from 0.03 to 0.11. On the other hand, the LR statistic that compares the two level random effect negative binomial models with standard NB regressions (last row in Table 5) is only significant at 10% in one model. This test suggests that there are no unobservable regional factors affecting the production of university-owned patents that had not been controlled for in all models, and consequently there is little difference with respect to standard NB regressions.

Focusing now on our main variables of interest, the indexes of diversification, their coefficients are positive and highly significant in all models. Consequently, the more diversified the number of patented technologies in a university in a period, the greater the number of new patents produced by the university in the subsequent period. In order to provide some direction about the magnitude of the effect of diversification, it can be noted that the estimated coefficients can be interpreted as semielasticities, or elasticities when the variable enters logarithmically in the exponential conditional mean (Cameron and Trivedi, 1998, pp. 80-81). The estimates suggest that 10% increase in technological diversification would lead to a rise in the number of patents ranging between 4 and 4.8%. For example, using the logarithm of the number of IPC codes as a diversification index (Model IV), a university which owns 9 patents (the average number of patents in the sample) over 8 different IPC codes at four-level digits (the average number of different IPC codes in the sample), doubling the number of technologies in which the university investigates in terms of number of IPC codes (or an increase of 100%) would lead to an increase of approximately 4 more subsequent patents (an increase of 48%). This result suggests diminishing returns, which means that the increase in the number of subsequent patents is less than the enlargement of the level of diversification. This is not surprising since part of the research in new knowledge may be fruitless in terms of future patents. The other coefficients for the indexes based on entropy have a similar interpretation (Models I, II and III), although it should be taken into account that the entropy indexes consider both the number of technological fields and the internal distribution of patents in each field (the increase in entropy can stem from both expanding the number of technologies and/or balancing the number of patents in each technology).

The other variables in the model present the following results. The variable *collabo* is not significant in any model; that is, collaboration with firms to produce new patented technologies in a period is not a significant variable when the objective is obtaining a greater number of patents in a subsequent period. Regarding the size of the university, the coefficient of the number of publications (*lnpub*) is highly significant. The elasticity of the R&D university expenditure is fairly stable around 0.25, showing decreasing returns to scale as the literature on university patents suggests. We find no significant effect from the demand side (captured by the ratio between firms R&D expenditure and GDP).

Table 5 Negative Binomial Models with Nested Random Effects

	MODEL I			**MODEL II**			**MODEL III**			**MODEL IV**		
	Coeff.		Std. E.	Coeff.		Std. E.	Coeff.		Std. E.	Coeff.		Std. E.
C	-2.420	***	0.607	-2.478	***	0.685	-2.565	***	0.996	-2.357	**	0.597
Level 1: University.												
entroipc	0.483	***	0.087									
entro				0.403	***	0.112						
entroipcw							0.449	***	0.091			
lnipc										0.477	***	0.080
lnpub	0.333	***	0.055	0.401	***	0.056	0.350	***	0.056	0.322	***	0.055
collabo	-0.233		0.260	-0.197		0.278	-0.247		0.269	-0.218		0.254
Level 2: Region												
lnrduniv	0.255	**	0.110	0.237	*	0.122	0.248	**	0.111	0.249	**	0.107
lnrdfirms	-8.696		10.098	-3.799		11.218	-7.527		10.345	-9.118		9.882
lnalpha	-0.604	***	0.224	-0.570	***	0.221	-0.548	***	0.221	-0.647	***	0.224
Lev 2 (region) Variance RE	0.032		0.078	0.112		0.098	0.033		0.084	0.031		0.073
Log-Likelihood	-409.537			-416.741			-412.091			-407.702		
No. of Level 1 units (universities)	141			141			141			141		
No. of Level 2 units (regions)	74			74			74			74		
LR test ML vs. nbinomial regression:	0.19			1.65	*		0.18			0.21		

***, **, * denote coefficients statistically different from zero at the 1%, 5% and 10% levels, respectively. Dependent variable (pat) is the number of university-owned patents produced in 2001-2004. All independent variables refer to the period 1998-2000.

5.2 Robustness check

As pointed out above, the main coefficients do not change substantially when the technological diversity is captured using different indexes, which means that the results are robust to four alternative measures of diversification. In this Section we provide additional robustness checks in several ways. First, by carrying out a sensitivity analysis to determine any possible change in the coefficients of either diversification indexes as a consequence of omitting variables from the main models; secondly, by estimating different count data specifications (Poisson models with robust standard errors); and thirdly, by choosing Tobit models as an alternative specification to the count models.

With respect to the sensitivity analysis, we first assess potential multicollinearity computing the variance inflation factor (VIF) in the estimated NB models. The mean VIFs range between 1.14 and 1.19 with a maximum of 1.3. These levels are considerably lower than the usual threshold of 10, and consequently the results are not biased by multicollinearity. Additionally, we removed from the models the variable capturing the size of the university (*lnpub*, number of publications), which is the variable with the higher coefficient of correlation with the entropy indexes. Dropping this variable does not change the main result: the diversification variables remain significant with only small variations in the value of the coefficients.

The NB model is one way to model data in the presence of significant overdispersion, yet this commonly chosen specification is not the only one. As pointed out by Cameron and Trivedi (2009, p.561) we can simply use Poisson models with robust standard errors. We have followed this procedure to obtain four additional Poisson models (one model for each diversification index along with all other variables considered in the NB models) with robust standard errors and random effects to capture regional unobserved heterogeneity. The results do not change the significance of the four indexes of diversification. Although the values of the coefficients are slightly smaller than those obtained for our baseline models, all the coefficients of the diversification variables are statistically significant at the 1% level.[8]

Regarding the alternative specification, Table 6 presents four Tobit models including exactly the same variables as in the NB models and the same number of observations. These results show that all the

[8] The estimated models for the sensibility analysis and the additional Poisson models are not presented, but are available upon request.

coefficients of the diversification indexes remain highly significant, and the other significant coefficients are the same as in the previous NB models. Note however that the Tobit model should only be viewed as an approximation for these data. The dependent variable is a count, not a continuous measurement, and thus a count model is always a preferable modelling framework (Greene, 2012, p. 815).

Table 6 Tobit models

	MODEL V			MODEL VI			MODEL VII			MODEL VIII		
	Coeff.		Std. E.(1)	Coeff.		Std. E.(1)	Coeff.		Std. E.(1)	Coeff.		Std. E.(1)
C	-27.691	***	6.126	-28.676	***	6.871	-29.356	***	6.653	-26.794	***	5.820
Level 1: University.												
entroipc	5.529	***	1.286									
entro				4.555	***	1.203						
entroipcw							4.997	***	1.249			
lnipc										5.660	***	1.275
lnpub	1.967	***	0.410	2.651	***	0.485	2.166	***	0.425	1.834	***	0.398
collabo	-1.899		1.684	-1.891		1.591	-1.971		1.644	-1.789		1.706
lnrduniv	2.588	***	0.964	2.668	**	1.061	2.554	**	0.999	2.519	***	0.932
lnrdfirms	-21.642		111.610	16.097		115.381	-5.073		114.898	-31.654		109.889
Log-Likelihood	-456.55			-464.37			-459.82			-453.62		
F	9.125	***		8.849	***		8.601	***		9.464	***	
Pseudo R2	0.070			0.054			0.063			0.076		
No. Obs.	141			141			141			141		

***, **, * denote coefficients statistically different from zero at the 1%, 5% and 10% levels, respectively.
Dependent variable (ownedpat) is the number of university-owned patents in 2001-2004. All independent variables refer to the period 1998-2000.
(1) Robust standard errors allowing for intra-group correlation (regions were used as a grouped variable for the universities).

6 Conclusions

In this paper we have analysed the relationship between technological diversification and the production of new university patents. Our framework combines the literature on university patent production with other theoretical and empirical literature about the consequences of technological diversification. As noted in a previous section of the paper, several authors have shown the relevance of some particular university characteristics to the encouragement of patents production. This study extends these findings by including the role of technological diversification as an additional explanatory variable in a modified patent production function that controls for some university characteristics and unobserved regional factors. By analysing the effects of technological diversification to the framework on the factors affecting university patent production, this paper contributes a new aspect to our knowledge that has not been analysed so far at university level. Besides this, our research relates to several papers that have found a significant impact of technological diversification on variables such as the quality of university patents and their commercialisation.

Using a sample of university-owned patents distributed across 141 European universities, our findings provide empirical evidence which suggests that greater diversification of the technologies embedded in patents is relevant to spur the production of new patents. The estimations are robust as to the use of a variety of technological fields to compute several indexes of diversification as well as to alternative specifications. Other factors included in the models show evidence that variables usually analysed in the university patenting literature, such as university R&D expenditure and the size of the university (particularly the size of the research carried out in the university measured by the number of published papers), are relevant in explaining the production of university patents.

Our empirical findings should nonetheless be interpreted with caution because according to the broad classification of patents between university-owned patents and university-invented patents, we have considered only the first group (patents in which the name of the university appears as applicant) across Europe. Despite the fact that the use of university-owned patents is justified for the purpose of this paper, we have considered only one side of the story. Although most European countries have been moving away from inventor ownership of patent rights towards different systems of institutional ownership (Geuna and Rossi, 2011), there are still many university-invented patents where at least one of the inventors is a researcher affiliated to a university, but the applicant for the patent is a firm.

Bearing in mind the stated limitation, this study contributes by providing a new element for discussing policy steps regarding how universities should diversify their technology in order to strengthen the production of new university patents. Although a lengthy discussion of policy measures is beyond the scope of this paper, we suggest some ideas aimed at technological diversification which could be explored. For example, supporting projects with outcomes in multiple sectors, particularly with the involvement of the private sector; and intensifying network collaboration within and between universities and other public research institutes so that they share knowledge, resources and capabilities, thus enhancing technological diversification and the subsequent generation of new patented knowledge. Another course of action to be considered could consist of providing institutional encouragement for researchers towards a wider range of fields or activities in order to promote technology transfer in fields with greater industrial demand for university knowledge (e.g. introducing differences in the way in which patents are assessed in the professors' CVs; release from teaching time to develop complex patents with a wide range of technological applications, etc.).

Finally, there are other ways in which the role of technological diversification at universities can be explored. A natural extension of this research would be to analyse the effects of technological diversification of European university-invented patents and to compare them with our results based on university-owned patents. This contrast would provide a complete picture at European level on the role of technological diversification on the production of new patents. Other suggestions consist of using other objective variables such as the quality of the outputs or their commercialisation. The researcher and the research group as one unit of analysis to study the production of technology could also give an interesting perspective, given the recent debate about how patenting (or more generally, a greater involvement in technological commercialisation) may divert or delay the research agenda at individual or research-group level.

Acknowledgements

The authors highly appreciate the helpful comments of an anonymous Reviewer, which significantly contributed to improving the clarity and quality of the paper. We are also grateful for the financial assistance provided by Junta de Andalucía.

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