EPO Academic Research Programme

University Research funding, Patenting and Technological Impact

Final Report

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1 Summary of research output

The research project includes two main activities: the first deals with the technological specialization of a sample of European universities and of the regions where they are located; the second focuses on the identification of those patents associated to projects financed by the European Union (EU).

The first line of research is developed in three articles in different publication stages (see sections: 1.1, 1.2, 1.3), while the second is currently included in one scientific working paper (1.4). All the data developed in the project will be published on an open platform at the beginning of 2021 (1.5)

a. Pattern of co-evolution of university patenting and technological specialization in European regions

Authors: Federico Caviggioli, Alessandra Colombelli, Antonio De Marco, Giuseppe Scellato & Elisa Ughetto

Abstract: This paper provides novel evidence on co-evolution patterns of the technological specialization of innovation activities of firms and academic institutions located in the same European region during the years between 2003 and 2014. We exploit a novel and unique dataset merging data on EU-funded R&D projects, universities, patents, and economic region-level data for a large sample of universities and firms co-located in NUTS3 European regions. Our results indicate the presence of substantial heterogeneity across the analyzed EU regions with respect to the co-evolution of industry and academia specializations. In particular, we find that the specialization into a new technological domain is led by the local academic research system only in a few cases. We also find that a number of factors, at both the university and regional levels, are associated with convergent or divergent processes in the relative specialization of the innovation activities carried out by firms and universities co-located in the same region.

Status:

- Submitted to Technological Forecasting & Social Change.
- EPO support will be acknowledged

b. University technology transfer and the evolution of regional specialization: the case of Turin

Authors: Alessandra Colombelli, Antonio De Marco, Emilio Paolucci, Riccardo Ricci & Giuseppe Scellato

Abstract: The paper is aimed at obtaining a better understanding of the role played by universities in the technological development and specialization of the territories in which they are located. Our methodology adopts both quantitative and qualitative techniques. First, we provide evidence of the interplay between the technological specialization of universities and the evolution of the technological trajectories of firms located in Italian NUTS3 regions. We also propose an original taxonomy of university-region technological evolution processes that leads to the identification of four possible models and reveals substantial heterogeneity in university-region specialization processes. Finally, we analyze the underlying mechanisms of university technology transfer activities in more detail, by using the Politecnico di Torino as a single case study. The case examines how the university has changed its strategy by modifying the mix of exploitation and exploration strategies to continue increasing the technological proximity with the local ecosystem under conditions of

rapid and radical change. Our work offers important implications for both regional technology policies and the management of universities.

Status:

- Published as: Colombelli, A., De Marco, A., Paolucci, E., Ricci, R., & Scellato, G. (2020). University technology transfer and the evolution of regional specialization: the case of Turin. The Journal of Technology Transfer, 1-28.
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c. The impact of university patenting on the technological specialization of European regions: a technology-level analysis

Authors: Federico Caviggioli, Alessandra Colombelli, Antonio De Marco, Giuseppe Scellato & Elisa Ughetto

Abstract: The paper aims at estimating the impact of university patenting on the subsequent dynamics that characterize the innovative activities of firms located in the same geographic areas. We exploit a large dataset of 827.627 patent families that are linked to 263 different European regions and 528 academic institutions. We set up an original framework in which the unit of analysis is the individual IPC code to account for the heterogeneity of the examined fields. The econometric modeling of technological diversification processes is implemented by using fixed-effect models with binary outcome response where the likelihood that a region becomes specialized in a specific sector is a function of the entry performed by the university system in that field. We also examine the moderating role of the technological distance between the portfolios of inventions filed by academic institutions and co-localized firms. We find a significant positive effect of the technological entry and a negative impact of the technological distance on the subsequent specialization of the hosting regions. We decompose such overall results by considering sub-samples based on the nature of the technology and the innovative performance of the region. Our findings are robust to alternative specifications of the models that include alternative measures of technological distance, different lags or decays for the regressors, and the presence of interactions between the entry and the technological distance.

Status:

- Working paper.
- EPO support will be acknowledged

d. The effects of public research funding on publications and patents: a validation assessment of ERC research grants

Authors: Federico Munari, Herica Morais Righi, Maurizio Sobrero, Laura Toschi (Department of Management, University of Bologna); Elisa Leonardelli, Stefano Menini, Sara Tonelli (Fondazione Bruno Kessler)

Abstract. In order to provide an innovative contribution to the debate about the effects of publicly supported research activities on technological developments, we analyzed the impact of public funding for scientific research on the generation of subsequent patents by developing and validating a new methodology to identify patents relying on the knowledge (as captured by scientific publications) generated through the grant

programs. We used as a context of the study the set of projects funded by the European Research Council (ERC) in the Life Sciences (LS) and Physical Engineering (PE) sectors during the FP7 program The new data allows the focus on several key research questions related to the role and impact of patents as a tool to foster the direct and indirect deployment of academic research outcomes to benefit society and firms' innovation potential. As a result of our analyses, we were able to identify 3.697 FP7 ERC grants awarded in the LS and PE domains, generating over 86 thousand scientific publications cited by 12.918 unique patents. Overall, we found that about 30% of ERC grants are associated to granted patents citing their publications in the NPL (non-patent literature) section. We compared such figures with those related to projects where the principal investigators declared patents as project outcomes in the final technical reports for the ERC. We also provide evidence on the factors explaining the likelihood to observe linkages between grants and patents, showing that the approach based on patents-publications-grants matches is not particularly appropriate in identifying patents linked to projects with a translational nature, and it provides stronger results for projects with higher age, duration, budget level and number and quality of associated publications.

Status:

- Working paper.
- Presented on the 5th October 2020 (in an online meeting) at the European Research Council (to representatives managing the ERC Proof of Concept Program and the analysis of data on publications and patents) in order to share results and receive a feedback.
- EPO support will be acknowledged

e. Data disclosure

Concerning the dissemination of the project results, the project objectives and activities are summarized on the PoliTO team webpage (http://innovationstudies.polito.it/epo-academic-research-project).

The databases generated by the projects will be made available to the public in 2021 in open online repositories, so to facilitate replications studies and subsequent research work. We will include explanatory files providing information about the data files and the metadata, in order to ensure that the data can be correctly interpreted.

2 Introduction

This project studies the interplay between universities and co-localized firms when considering their innovation activities and the evolution of their technological portfolios. It undertakes two different lines of research. The first aims at analyzing the evolution of technological trajectories of universities and the specialization of co-localized firms in European NUTS3 regions in the period 2003-2014, by also taking into account the moderating role of the nature of the funding received by universities. The second, and more experimental line of research analyzes the impact of funding on subsequent patents (both directly produced and indirectly affected), focusing on a specific research funding scheme, and collecting data at the level of awarded research projects.

The findings of this study contribute to several streams of the existing scientific literature on the economic effects of public funding for science and research, on the assessment of the impact of research grants, on the determinants of university patenting and of university commercialization activities.

The project builds on the generation and the analysis of a new original dataset that integrates data at European level from different sources (patent data, FP7 funding levels, university and NUTS3 level data).

The research project also devotes a considerable effort to the improvement of methods for linking research projects and subsequent patents. The new data are exploited in order to address a number of key research questions related to the role and impact of patents as a tool to foster the direct and indirect deployment of academic research for the benefit of society and the innovation potential of firms.

In the next sections, we report the results of the research which are included in four articles, three regarding the technological specialization of European universities and the interplay with the local firms, and one concerning the the link between EU projects and patents. Each article is reported in a separate section.

3 Pattern of co-evolution of university patenting and technological specialization in European regions

The analyses of the different drivers that affect the process of transformation of the knowledge bases within local innovation systems has important implications for the understanding of the long-run dynamics in economic performance across different regions. Several streams of empirical studies have addressed this issue, focusing on the role of different endogenous and exogenous factors that can have an impact on the capability of the economic and institutional actors in a regional economic system to develop and apply new technological and scientific knowledge.

In particular, the transformation of the knowledge base has been addressed by previous studies with reference to endogenous branching processes based on the recombination of previously accumulated knowledge in different industrial domains, on the localized nature of knowledge spillovers, and on the presence of learning effects in the generation of new knowledge (Antonelli, 1995; Boschma and Frenken, 2011; Frenken and Boschma, 2007; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999). Yet, the role of local universities in the regional specialization processes has been almost neglected. This is surprising given that, over the past two decades, there has been a growing consensus on the key role of academia in sustaining innovation capabilities through technology transfer activities (Good et al. 2019), and related policies have been introduced to support more effective industry-university interactions.

In this chapter, we contribute to the literature on regional technological specialization in three main respects. First, we provide new evidence on the co-evolution patterns of the technological specialization of innovation activities of firms and academic institutions located in the same European region, defined at NUTS 3 level, during the years between 2003 and 2014. More specifically, the work aims at exploring to what extent and under what conditions there have been in place convergent or divergent processes in the relative specialization of the innovation activities carried out by co-located firms and universities. Our focus is on the patenting activities of universities, rather than their scientific publications, as patents can be assumed as a more precise proxy for more applied knowledge developed locally, as well as a more technology-transfer oriented activity. Second, we exploit an original and unique dataset that has been built by merging data from four different sources: i) the European Commission CORDIS dataset, reporting EU funded R&D projects under FP7, ii) the ETER database reporting information on Higher Education Institutions in Europe, iii) the PATSTAT database containing worldwide patent information and iv) Eurostat database reporting economic region-level data. The dataset allows us to map the full patent portfolios of about 500 European universities and the patent portfolios of all firms in their region with additional region-level and university-level controls. Third, we apply the conceptual framework for the identification of alternative co-evolution patterns developed by Colombelli et al. (2020). This taxonomy and its operationalization offer interesting evidence and call for the investigation of the location-specific factors that might have influenced the emergence of diverse patterns of technological evolution. The literature has indeed emphasized that many factors, at different levels of analysis, may affect the effectiveness of knowledge transfer from universities to firms (Muscio and Vallanti, 2014; Bruneel et al., 2010). Thus, we provide an empirical test of the four possible models of university-region technological evolution processes illustrated in the taxonomy, linking such patterns to both region-specific and university-specific structural characteristics.

Our results indicate the presence of substantial heterogeneity across the analyzed EU regions with respect to the co-evolution of industry and academia specializations. For a subset of regions, we observe in the years from 2003 to 2014 a diverging pattern of technological specialization between the co-localized industrial and academic systems, while other regions show a dynamic of convergence in their specialization patterns. Although we do not address direct causality in the specialization structure of industry and universities, the data provide useful policy insights about the contextual factors that are associated with different co-evolution patterns. The overall evidence suggests that, only in a few cases, the specialization into a new technological domain is led by the local academic research system. The prevalence of a university-push configuration is in place when universities are large and have a STEM orientation. Instead, the regional specialization is more frequent in the case of pre-existing R&D and innovation activities of private firms, which contribute to the further development of applied research in the region. Regression analyses show that the overall innovation performance of a region is associated with a divergence pattern in the co-evolution of industry and academic technological portfolios, while a dynamic of convergence in the specialization patterns of industry and academia is revealed when local universities are large and have a STEM orientation. The study elaborates on such empirical findings and suggests implications for the design of policy approaches in line with the so-called smart-specialization strategies.

The chapter is organized as follows. In Section 2, we discuss the theoretical background and provide an overview of the main empirical contributions that have addressed the drivers of technological specialization in regional innovation systems, with a focus on those specifically accounting for the role of universities. We also illustrate the taxonomy we draw upon to operationalize the empirical analysis of co-evolution dynamics. Section 3 illustrates the data collection process and the methods adopted to measure university-region technological specialization and technological distances. In section 4, we present summary evidence on the patterns of university-industry specializations in European regions and econometric models on the factors associated with specific co-evolution patterns across regions. Section 5 concludes and puts forward some policy implications.

f. Universities and the local technological system

The recent economic geography literature on regional branching and technological specialization shows that regions stay close to their existing capabilities when diversifying into new products and technologies (Boschma and Frenken, 2011; Frenken and Boschma, 2007). These dynamics are engendered by the cumulative nature of innovation processes, the existence of learning economies in knowledge generation, and the localized nature of knowledge spillovers (Antonelli, 1995; Jaffe et al., 1993; Jaffe and Trajtenberg, 1999). Such a thesis has been confirmed in different geographical contexts (e.g., Boschma et al., 2013; Colombelli et al., 2014; Neffke et al., 2011). This evidence has stimulated the debate, in both policy and academic circles, about the role of technological specialization on regional performance and has contributed to the adoption of Smart Specialization Strategies in the latest wave of regional policies (Boschma, 2014). These policies are aimed at identifying strategic areas of intervention to sustain regional innovation activities, by building on cumulated knowledge, collective intelligence, and distinctive assets of the territory (Foray, 2014). However, the debate on regional diversification patterns has started questioning the desirability of these strategies because of path-dependence and lock-in effects. Understanding the factors that help regions sustain their competitive advantage through technological specialization dynamics becomes of paramount importance. Universities may exert a crucial role in this process, as they are key sources of knowledge for the local ecosystem. Yet, the literature on regional branching has neglected the role of universities so far.

On a parallel ground, the regional economics literature has instead provided a great deal of evidence on the crucial role of universities in the creation and development of local ecosystems for innovation. Different frameworks like Regional Innovation Systems (RIS) (Braczyk et al. 1998; Cooke et al. 1997), Triple Helix (Etzkowitz and Leydesdorff, 1995; 2000), industrial district (Becattini 1990; Marshall 1920), clusters (Porter, 1998), entrepreneurial ecosystems (Isenberg, 2010; Spigel, 2017) and innovation ecosystems (Granstrand and Holgersson, 2020) have been conceived to emphasize the active role of territorial actors within regional development dynamics and to give relevance to the institutional foundations of the competitive advantage of regions. Although this literature is broad and heterogeneous, scholars largely converge on the idea that the local development is spurred by a central player, i.e., the *anchor tenant* (Agrawal and Cockburn, 2003; Totterman and Sten, 2005), which is usually fulfilled by local universities (Agrawal and Cockburn, 2003; Calderini and Scellato, 2005; Colombelli et al. 2019; Totterman and Sten, 2005). Universities indeed are key sources of new knowledge, which can be transferred to the local ecosystem through a variety of channels (d'Este and Patel, 2007). First, universities nurture the local ecosystem with highly educated and skilled individuals, support the regional skill upgrading through life-long learning programs and attract talents to the local ecosystem (Bramwell and Wolfe, 2008; d'Este and Patel, 2007). Academic institutions also interact with local industrial partners in order to transfer the results of their internal R&D through formal mechanisms such as patenting, licensing, and research collaboration, in addition to informal mechanisms such as consulting, networking, and face-to-face communication (Bonaccorsi and Piccaluga, 1994; Cohen et al., 2002; Friedman and Silberman, 2003; Link et al., 2007; d'Este and Patel, 2007; Perkmann and Walsh, 2007). Moreover, universities promote the diffusion of an entrepreneurial culture among students and academics and stimulate the creation of new firms within the ecosystem (Bonaccorsi et al., 2013; Carree et al., 2014; Shane, 2004; Zucker et al., 1998). Despite this evidence, the contribution of academic knowledge to the evolution of regional specialization has almost been neglected.

Within these domains, the empirical literature has examined the impact of academic research on the innovation dynamics at the regional level. More precisely, a number of empirical analyses have investigated the spillover effects of academic research by adopting the knowledge production function approach (Acs et al., 1992; Anselin et al., 1997; 2000; Fritsch and Slavtchev, 2007; Griliches, 1979; Jaffe, 1989; Leten et al., 2014). These quantitative analyses have provided evidence of a positive relationship between academic research and the innovative activities that occur within a geographical area and have confirmed the importance of proximity between firms and universities for the innovation process. Other studies have studied the effects of academic research on regional innovation dynamics through qualitative analyses mainly based on surveys (Arundel and Geuna, 2004; Cohen et al., 2002; Laursen et al., 2011; Mansfield, 1991; 1998; Mansfield and Lee, 1996). These works have revealed that universities positively contribute to the introduction of technological innovations in various industries, and the decrease in time lags between investments in scientific research projects and the industrial utilization of their findings (Mansfield, 1991; 1998). Moreover, these empirical analyses have shown that firms are more willing to collaborate with universities based on proximity and research quality (Arundel and Geuna, 2004; Laursen et al., 2011; Mansfield and Lee, 1996).

However, only a few scholarly works have empirically tested the impact of academic research on the technological trajectories of geographical areas and vice versa (Acosta et al., 2009; Braunerhjelm, 2008; Calderini and Scellato, 2005; Coronado et al., 2017). Overall, these contributions have provided mixed results concerning the existence, the direction, and the causal relationship between academic research and industrial specialization. Moreover, these studies have adopted different empirical models and implemented different variables to compute the technical specialization of regions and universities (e.g., scientific publications, patents, employees, and researchers). Calderini and Scellato (2005) studied the wireless sector and found a causal effect of academic research specialization on the patenting activity of local firms. Braunerhjelm (2008) found a positive impact of a university's research specialization on the industrial specialization of the region where the university was located, with this impact depending upon the commercial environment in which the university was embedded. Acosta et al. (2009) showed a strong correlation between university and industry specialization only in few regions and no significant result emerging at the sector level. This evidence was explained referring to two possible reasons: i) universities tend to satisfy only a fraction of the demand for technological knowledge; ii) academic research is more focused on internal objectives (i.e., scientific publications) and therefore does not consider the external demand for knowledge. Finally, Coronado et al. (2017) studied the effects of reverse spillovers in high-tech sectors and found that the productive specialization of a region has a significant effect on the patenting activity of universities located in the same area. Overall, these contributions provide mixed results concerning the existence, the direction, and the causal relationship between academic research specialization and industrial specialization. More recently, Colombelli et al. (2020), in order to obtain a better understanding of the role played by universities in the technological development and specialization of the territories in which they are located, have developed an original taxonomy composed of four models of university-region technological evolution processes.

g. Co-evolution patterns of industry and academic innovation activities

Our analysis aims at gathering novel evidence on the relative dynamics of the specialization of innovation activities carried out by firms and universities, which are co-localized in the same region. In this regard, we use the composition over time of their patent portfolios as a proxy for the specialization of the innovation activities within a region. Patent technological classifications allow mapping on a sufficiently fine scale the set of competencies and the innovative knowledge available in a specific local area. In order to analyze the determinants (at the university, firm, and ecosystem levels) of university-region technological evolution processes, we adopt the taxonomy adopted in the work by Colombelli et al. (2020). The taxonomy is based on two dimensions: i) the direction of the technological evolution process that allows divergent processes to be distinguished from convergent ones and ii) the leading role of local universities versus firms in the entry of a new technology, that allows region-pull versus university-push processes to be identified. In divergent processes, the technological specialization of universities and local firms follows different trajectories (Acosta et al., 2009), while convergent processes are characterized by increasing technological proximity over time between local firms and universities. In the case of region-pull processes, local firms exert the leading role and guide the evolution of the local technological specialization (Coronado et al., 2017), while in university-push processes, regional technological trajectories are driven by local universities through their entry into new technological fields (Braunerhjelm, 2008; Calderini and Scellato, 2005).

The combination of the two dimensions of the taxonomy leads to identifying four possible models of university-region technological evolution processes (illustrated in Table 1). In line with the previous literature, we argue that each of these models is influenced by the specificities of the local universities (university exploitation versus exploration strategies), the degree of innovation capabilities and absorptive capacity of the local firms (high versus low absorptive capacity) and the strength of the links between the local firms and universities (tight versus loose innovation ecosystems).

Quadrant A in Table 1 refers to a context in which universities enter into new technological fields, and that is characterized by a loose innovation ecosystem and firms with a low absorptive capacity. This configuration leads to divergent technological evolution processes. Quadrant B refers to convergent university-push processes where local universities follow an exploration approach. Convergence is allowed because of a tight local innovation ecosystem and the high absorptive capacity of local firms. Quadrant C relates to convergent region-pull processes. In this configuration, characterized by a tight local innovation system mostly pulled by local firms with high innovation capabilities, universities adopt exploitation strategies, thus fostering convergent technological evolution processes at the regional level. Divergent region-pull processes are illustrated in Quadrant D. In this configuration, local firms endowed with high innovation capabilities operate in a loose innovation ecosystem, and universities leverage on the local accumulated knowledge and technological specialization.

Table 1: Taxonomy of university-region technological co-evolution processes

Co-evolution process	Convergent	Divergent
University-push	Quadrant B Exploration role of university Local firms with high absorptive capacity Tight innovation ecosystem	Quadrant A Exploration role of university Local firms with low absorptive capacity Loose innovation ecosystem
Region-pull	Quadrant C Exploitation role of university Local firms with high innovation capabilities Tight innovation ecosystem	Quadrant D Exploitation role of university Local firms with high innovation capabilities Loose innovation ecosystem

Source: Colombelli et al. (2020)

We will initially present evidence on the incidence of regions showing, alternatively, a convergent or divergent co-specialization process between local universities and co-localized firms. Following the theoretical framework presented above, we will provide an analysis of the distribution of such clusters with respect to university-push versus region-pull dynamics. Finally, we will investigate the characteristics associated with the different clusters and provide analyses of the factors (at regional and university level) that appear to be associated with convergent versus divergent and university-push versus region-pull dynamics in the evolution of the innovation specialization patterns.

h. Data and methods

The analyses presented build on two novel datasets that integrate data for European regions and universities.

The first step of the process was identifying a set of European universities that were involved in substantial research activities and with a significant performance in obtaining EU funds on competitive projects. The use of data about EU funds is motivated by the purpose of identifying those academic institutions that are not only active in research but have a good performance on collaborative (and mostly applied) projects, often involving collaboration with firms. Hence, we collected data on the largest recipients of FP7 funds among European universities. We disambiguated the names of the universities available in the CORDIS database[1]. We sorted universities according to the number of the awarded EU projects and selected those accounting cumulatively for 90% of the total funding to universities. We ended up with a sample of 528 largest universities. The universities were then geo-localized in the corresponding regions at the third level of the Nomenclature of Territorial Units for Statistics (NUTS) on the basis of on the information provided in the ETER dataset[2].

For each university and the corresponding geographical area, we collected all patents filed and identified the aggregate portfolio in the years between 1992 and 2014. The university patents were searched with queries that exploited the assignee field in PATSTAT[3], as well as the standardized names available in OECD HAN[4]. We

[1] The European Commission database of EU-funded research and innovation projects (CORDIS). It is available online at https://cordis.europa.eu/projects/en (last accessed in November 2019). Please note that CORDIS denotes Universities as Higher Education Institutions (HEIs).

[2] The European Tertiary Education Register (ETER) collects information on HEIs in Europe, their basic characteristics and geographical position, educational activities, staff, finances, and research activities. It is available online at https://eter-project.com (last accessed in November 2019).

[3] A patent data repository maintained by the European Patent Office (EPO). Please note that we use the autumn edition of 2018.

[4] A database maintained by the Organization for Economic Co-operation and Development (OECD) that harmonizes patent applicant names. For each university, we searched different spelling variations, integrated the patent filings

collected all patent filings (domestic and international) and then consolidated them into patent families to avoid double counting. Since we are attributing patents to universities based on the patent applicant name, we had to exclude from the sample Finland, Sweden, and Norway, as such country had in force during the examined years the so-called *Professor Privilege*[5] (see Lissoni et al., 2008 and 2013).

For each NUTS3 area where the universities are located, we collected the corresponding patent families filed by inventors residing in those geographical areas, using the methodology detailed in De Rassenfosse et al. (2019), excluding those patents attributed to the universities. These data will be used to compute industrial specializations patterns in the region.

Note that we excluded from the final sample the NUTS3 regions and the universities with very small patent portfolios to avoid problems in the computation of specialization indexes[6]. After such additional filtering process, we obtained a final sample composed of 428 universities located in 263 geographical NUTS3 areas. The patent-level dataset associated with this sample includes 827,627 patent families (Table A1). These data have been processed to derive specialization indicators according to the methods presented in section 4.1.

We also collected and matched additional data to characterize the universities and the regions. The selected universities were matched with the records available in the ETER database to collect information on types, presence of STEM courses, size, and other structural variables. The geographical areas were characterized by the economic indicators available in the Eurostat Regio Database[7]. We also collected data about the Regional Innovation Scoreboard (RIS)[8] to gather information on the regional innovation systems.

A single NUTS3 region included in the dataset can host more than one university. In these cases, we added up the patent portfolios of the different academic institutions within a specific region since we are interested in mapping the evolution of the relative specialization of industry and the co-localized academic research system[9]. We aggregated in a similar fashion the other quantitative measures relating to universities.

i. Methodology for assessing the evolution of specialization patterns

In this section, we present the methodology adopted to generate indicators to measure the technological specialization of both regions and universities, as well as the technological distances between their patent portfolios (consolidated into patent families). Table 2 reports a definition of the indicators employed, together with their specific target aim.

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managed by TTOs or ad-hoc companies (e.g., Oxford University Innovation), and controlled for false-positive results to refine the final identification strategy.

[5] The countries were the Professor's Privilege rule was in force in the years of the examined sample are Sweden (in force), Norway (ended in 2003), Germany (until 2001), Austria (until 2002), Finland (until 2007), Denmark (until 1999), Italy (in force from 2002). The search results seem to underestimate the results for Finland, Sweden, and Norway only. The application of the exclusion criterion dropped 36 universities and 25 NUTS3 areas.

[6] In particular, we excluded regions and universities with a number of new patent applications smaller than 24 and 3 patents in any of the two periods from 2003 to 2008 and 2009 to 2014, respectively. This excluded sample corresponds to 64 universities (16.5% of the initial sample) and 57 NUTS3 geographical areas (12.1% of the initial sample).

[7] Regional statistics on socio-economic indicators of EU member countries are available online for different levels of the NUTS classifications at https://ec.europa.eu/eurostat/web/regions/data/database (last accessed in November 2019).

[8] More information available online at https://ec.europa.eu/growth/industry/innovation/facts-figures/regional_en (last accessed in October 2019). Since the RIS is defined at NUTS1 and NUTS2 levels, we attributed such characteristics to our NUTS3 regions.

[9] About 22% of the sample are NUTS3 areas with two universities (included in the analysed top-performers) and 13% with more than two universities.

Table 2: Indicators to measure the technological specialization of regions and universities and the technological distances between their patent portfolios

Variable	Definition	Objective
Evolution of the technological distance	Variation of the Euclidean distance between the patent portfolios of the region and the local universities (consolidated into patent families)	Measuring the process of technological convergence or divergence over time
Entry ratio	Number of technologies in which the entry was led by the university divided by number of technologies in which the entry was led by the industry[10]	Measuring the prevalence of university-push or region-pull dynamics in the change of the knowledge base

The joint use of the indicator on technological entry and the indicator on the variation in time of the technological distance allowed us to classify a specific university-region technological evolution process in one of the four quadrants illustrated in Table 1.

a. Evolution of technological distance: the convergence-divergence process

The presence of a divergent or convergent process is obtained by comparing the relative technological distance between the patent portfolios of the firms and the universities co-localized in the same region. Technological distance is computed through a standard Euclidean distance measure proposed by Jaffe (1989). We computed the distance in a given period using the following specification:

$$D_t^{RU} = 1 - \sqrt{\sum_j \left(s_{jt}^R - s_{jt}^U\right)^2}$$

where D_t^{RU} is the technological distance between region r and the local university u, s_{jt}^R and s_{jt}^U are the share of patents of the region and the university for technology class j at time t, respectively. We used a normalized version[11] of the indicator that varies between 0 and 1. Also in this case we used 642 different technological classes. By observing the variation in the distance measure over time, we were able to classify the university-region evolution process as a convergent versus divergent one. In particular, we compared the two periods 2003-2008 and 2009-2013.

b. Entry ratio: measuring entry into a new technological field

We used the Revealed Technology Advantage (RTA) index, based on patent classifications, as a measure of technology specialization. The RTA index was defined as the proportion of patent applications filed in year t by firms located in region i with technology class j, divided by the total share of patents associated with the same region i with respect to the others. As such, the indicator was equal to zero if there were no patent filings in sector j for region i; it was equal to one when the share of region i in technology j equaled its proportion in all the domains (i.e., no specialization was observed); and larger than unity if any relative specialization was detected for region i. The indicator was computed for all regions (or academic institutions) i, all technologies j in specific periods t using the following specification:

$$RTA_{ijt} = \frac{p_{ijt}}{\sum_i p_{ijt}} \Big/ \frac{\sum_j p_{ijt}}{\sum_i \sum_j p_{ijt}}$$

[10] The cases in which both events occur simultaneously were considered in the numerator and denominator of the ratio.
[11] We compute it by dividing the technological distance D_t^{RU} by its maximum value, which is $\sqrt{2}$.

where p_{ijt} is the number of patent applications in region (or university) i in technology j during period t. We then computed the standardized version of the index, or $NRTA$, that is symmetric around zero, as in Laursen (2015):

$$NRTA_{ijt} = (RTA_{ijt} - 1)/(RTA_{ijt} + 1)$$

Therefore, positive values of the adjusted indicator denote that the focal region i is relatively strong (i.e., over-specialized) in the specific technological domain, compared to all the other areas in our sample (Soete, 1987). The $NRTA$ indicator is computed taking into consideration all the IPC sub-classes (at a four-digit level) that corresponded to 642 different technologies. The idea behind this approach is that a patent with a specific sub-class is a signal of the local presence of specific competencies and skills. The patents with more than one IPC code were double counted in the computation of the indicator for each of the corresponding technology sub-classes.

The entry of region i in technology j is defined as the first year in which the vector of its $NRTA$ becomes greater than zero for the specific IPC sub-class j, thus indicating that region i is over-specialized for technological domain j. Given the limited number of patent applications filed by universities, we used the count of patents rather than the values of the $NRTA$ index for local academic institutions. Hence, the entry of a university in field j was defined as the first year in which it filed a new patent application associated with the specific IPC sub-class j. By comparing the timing of entry of the region and the university, we can assess, for each technological class, whether the entry was led by the local university or by the co-localized firms.

In order to move from a technology-class level to a region-level indicator, we then built a standardized indicator of technology entry for each region-university pair (i.e., the entry ratio), based on the ratio between the occurrence of cases over the observed years in which the technological entry was led by the university, divided by those in which it was led by the region. Using this measure, we can classify a specialization process as a region-pull versus university-push one.

j. Analyzing the patterns of university-industry specializations in European regions

This section provides a number of descriptive statistics on the sample of patent families that we employ for our empirical analyses. Figure 1 is a choropleth map representing the count of patent families for each NUTS3 region included in the sample. Note that we use a different color of the scale to identify the five quintiles of the distribution.

Figure 1: Distribution of the number of patent families by NUTS3 region

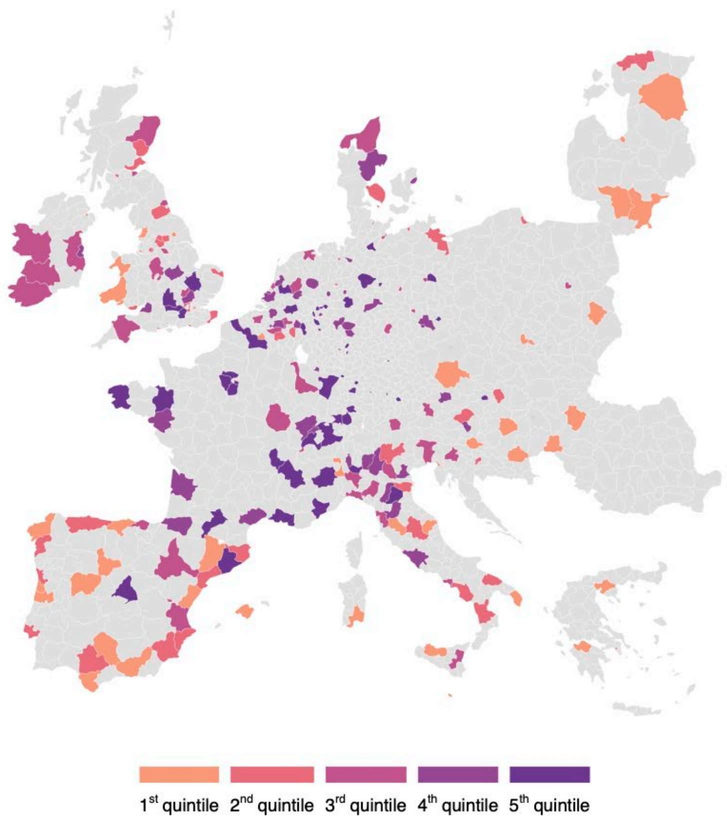


Table 3 illustrates the distribution of NUTS3 regions by the number of local university patent families. The 27% of NUTS3 regions total between 100 and 200 patent families, 24.3% more than 200 patent families, and 23.6% between 16 to 50 patent families. The aggregate number of patent families in the analyzed NUTS3 regions (excluding the corresponding university patent families) is increasing from 35.284 to 41.352 patent families in the considered years, namely from 2003 to 2014 (see Table A2). During the same period, the share of university patent families almost doubled in the same years, from 6.0% to 11.5%, confirming the increasing relevance of academic patenting activities in these economic systems. There is considerable variation across regions in the size of the patent portfolios attributed to the local universities.

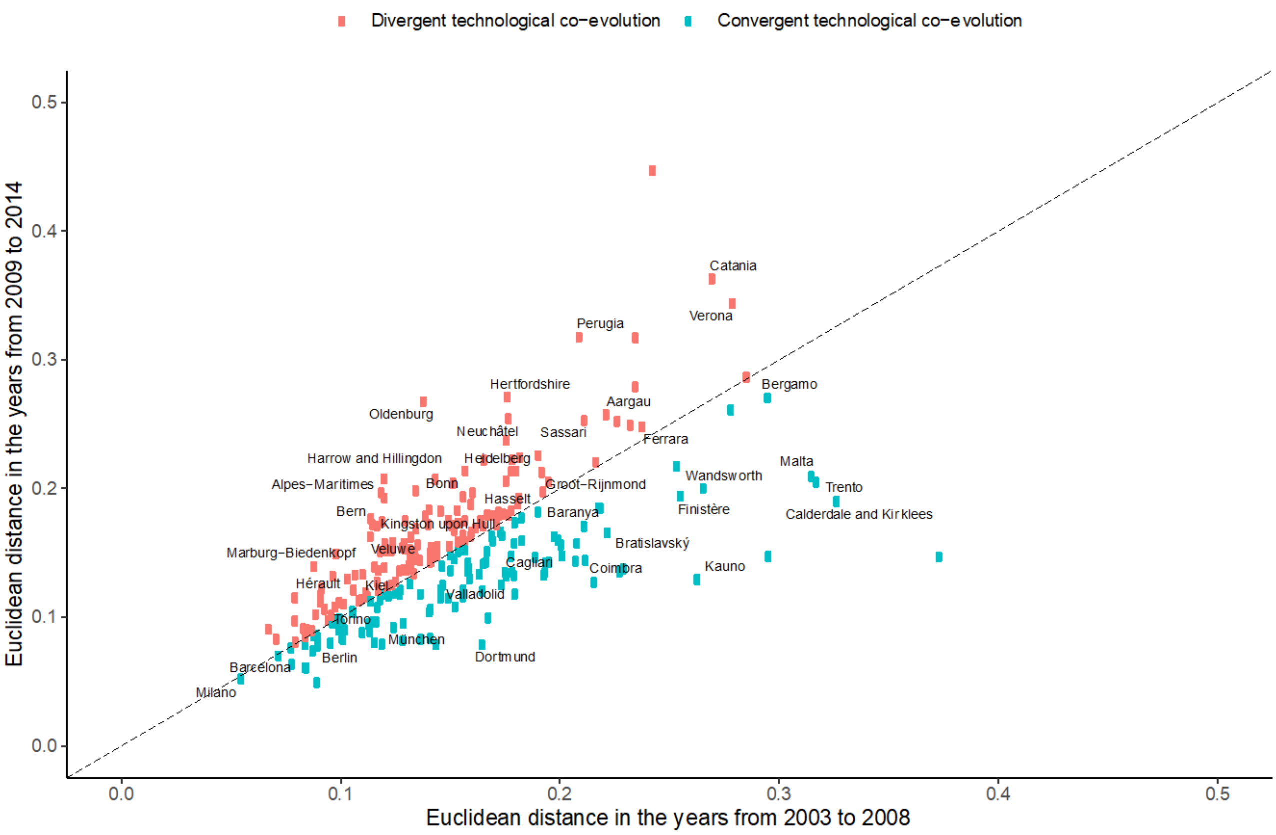
Table 3: Distribution of NUTS3 regions by class of local university patent families

Count of university patent families	Count of NUTS3 regions	Percentage of NUTS3 regions
From 1 to 15	17	6.5%
From 16 to 50	62	23.6%
From 51 to 100	49	18.6%
From 101 to 200	71	27.0%
More than 200	64	24.3%
TOTAL	**263**	**100.0%**

Figure 1 illustrates the incidence in the sample of regions showing, alternatively, a convergent or divergent co-specialization process between local universities and co-localized firms. The x-axis reports the values of the Euclidean distance index computed between the technological portfolio of the university system and the other patent families associated with the same NUTS3 region for the period from 2003 to 2008. The y-axis indicates the values of the same variable but for the subsequent time frame (from 2009 to 2013). The dots in the scatterplot represent pairs of university systems and regions. The NUTS3 regions positioned below the bisector (dots colored in blue) are characterized by a decrease in the technological distance between the university system and the local firms: their portfolios of technologies are converging (45.6% of the sample). For the universities and the regions that are located above the bisector (dots colored in orange), the technological distance is increasing and indicates the presence of a diverging process of technological co-evolution (54.4%). The university-region pairs closer to the origin are those with more similar technological portfolios in both intervals. We highlight that the dispersion of points around the diagonal of the quadrant gets larger as the distance between the technology specializations of the region and the local university increases.

Figure 2 provides the empirical distribution of the examined geographical areas according to the taxonomy proposed in the previous section. The horizontal axis measures the ongoing convergence (divergence) process between the university technological portfolio and all the regional innovation activities as the variation of the technological distance between the intervals of years 2003 to 2008 and 2009 to 2013. The vertical axis provides a measure of the ability of universities to enter a technological domain before the local industry gets to be specialized: this index is calculated as the number of entries in new technologies completed by the university and divided by the number of fields where the region is specialized earlier. The quadrants are identified by the median value for the y-axis and zero growth of the technological distance for the x-axis. Interestingly, we obtain a distribution of the examined universities across all four quadrants. Note that the vertical axis of the chart starts from zero since our technological entry measure can only assume positive values.

Figure 2: Evolution of the technological distance by NUTS3 region between the two considered time frames (2009-14 and 2003-08)



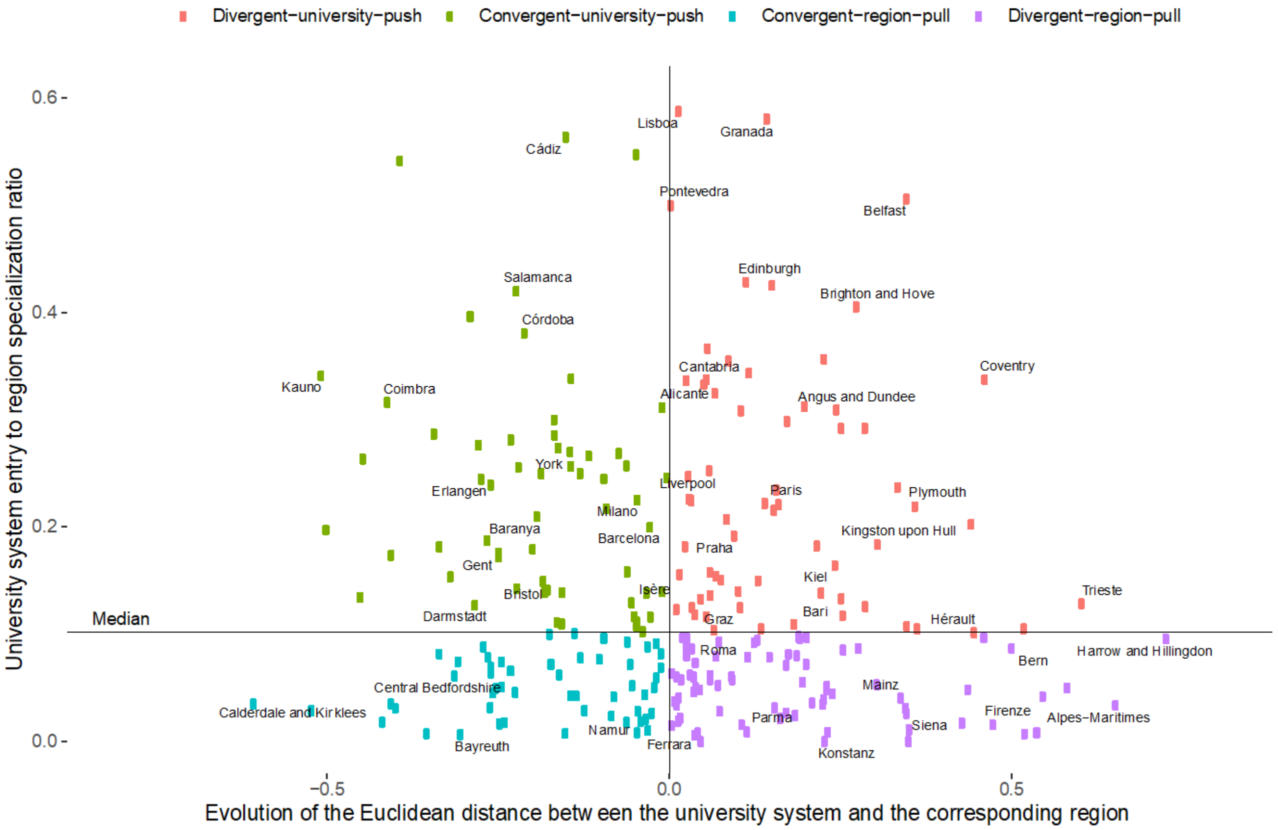
Quadrant A (top-right of the scatterplot) accounts for 24.7% of the sample. In these university-region pairs (e.g., Paris, Madrid, Dublin), the academic institution is more likely to enter new technologies than those in the lower quadrants, and the technology distance is increasing over time. Universities positioning in this quadrant lead the technological evolution process that is divergent from the one embedded in local firms.

Quadrant B (top-left of the scatterplot) accounts for 25.5% of all university-region pairs (e.g., Torino, Barcelona, Munich). According to our framework, such areas have a tighter innovation ecosystem, in which local firms show high innovation capabilities, and the academic institutions are more engaged in technology exploration activities. For local universities, it is more likely to push the entry in new technologies than those in the other NUTS3 regions. While academic institutions contribute to the development of new knowledge in the local ecosystem, the technology distance from the local industrial sector is decreasing.

Quadrant C includes areas where the university-region technological portfolios are converging. Academic institutions are more involved in technology exploitation efforts and interact within a tight innovation ecosystem where local firms tend to have a more leading role in the entry into new technologies. 20.2% of all university-region pairs are clustered here (e.g., Berlin, Hannover, Aachen).

Quadrant D represents 29.7% of the sample. Academic institutions (e.g., Bonn, Siena, Alpes-Maritimes) follow an exploitation approach, and local firms are characterized by a low absorptive capacity in a loose innovation ecosystem.

Figure 3: Taxonomy of university entry versus NUTS3 region specialization processes



k. Factors affecting the co-evolution of specialization patterns

Starting from the proposed taxonomy, we evaluated the significance of the impact of several variables on the distribution of the identified universities and regions across the four illustrated categories.

Table 4 reports descriptive statistics for the variables used in the empirical analysis. Variables refer to university-level and regional-level characteristics. Universities are characterized by their STEM orientation, the research intensity (proxied by the share of Ph.D. students), their size (measured in terms of total students), the propensity to rely on funding (i.e., the relative amount of awarded FP7 projects), and to collaborate with firms (i.e., the share of FP7 projects with industrial partners). The regional characteristics are determined using the openness or collaborativeness of the local companies proxied by the share of co-assigned patent families and the urbanization level (measured through the population density). Additionally, we derived from the Regional Innovation Scoreboard (RIS) two NUTS1 and NUTS2 level variables and matched them to the examined NUTS3: R&D investment of the business sector and the RIS innovation index. This latter index identifies innovation leaders, strong innovators, and moderate and modest innovators by combining various regional innovation metrics.

Table 4: Descriptive statistics of the regressors

Variable	Description	Count	Mean	Median	SD	Min	Max
STEM orientation	Share of STEM graduates on total graduates	258	0.228	0.217	0.145	0.000	0.969
Ph.D. intensity	Share of Ph.D. students on total undergraduate students	256	0.062	0.046	0.052	0.004	0.429
Univ. size	Total graduates (ISCED 5-7[12])	258	8.035	5.374	7.627	0.338	53.579
Univ. funding propensity	Ratio of financed costs for total FP7 projects over professors	252	1.678	0.887	2.244	0.077	18.801
Univ. collaborativeness	Ratio of financed costs for FP7 projects with firms over professors	252	0.940	0.502	1.314	0.035	9.049
R&D expenditure of the business sector	Value at the NUTS2 level from the RIS (2019)	259	0.888	0.840	0.333	0.169	1.693
Innovation index	Innovation index from the RIS (2019)	259	0.993	1.040	0.255	0.431	1.601
Technological openness of the region	Share of co-assigned patents developed by each NUTS3 area (univ. patents are excluded)	263	0.126	0.120	0.058	0.033	0.381
Population	Thousand inhabitants, value at the NUTS3 level (2019)	241	0.721	0.542	0.705	0.064	5.702
Population density	Thousand Inhabitants per square kilometer, value at the NUTS3 level (2019)	241	1.395	0.503	2.318	0.023	20.476

We performed a set of t-tests on the mean differences of the selected variables when there is a converging or diverging trend and when it is the university to enter a novel technological field before the region to specialize in the same area or the opposite (Table 5). The results show that the mean difference of some variables is statistically significant. In particular, a higher presence of STEM students is more frequently associated with a converging trend of technological portfolios and systems where the technological entry of the local university is relatively more frequent. Academic institutions with higher research intensity (i.e., the number of Ph.D. students) are associated with instances for which the technological specialization of the region occurs more frequently before the corresponding entry of the local university. The size of academic institutions (i.e., the number of graduates) is larger for cases where the entry of local universities is faster. Similarly, a higher technological openness of the region is typical of cases where the technological entry of academic institutions is much faster than the specialization of the local firms. On the contrary, a higher intensity in R&D expenditure of the business sector is associated with systems where the regional specialization is faster than the corresponding entry of universities. The RIS innovation index (i.e., a continuous measure combining several dimensions of regional innovativeness) is higher when the portfolios are diverging, and the region is faster in specializations.

[12] ISCED-5 are diplomas with a duration of fewer than three years, ISCED-6 are bachelor diplomas or equivalent levels, ISCED-7 are master diplomas or equivalent levels in the pre-Bologna system.

Table 5: Results of t-tests when comparing university-region pairs with a converging or diverging technological portfolio (column I); with a higher or lower frequency to observe the entry of universities in a new technological field (column II)

Variable	**I. Convergence / divergence of the technological portfolios**	**II. Relatively higher frequency of univ. entry in new tech field / region specialization**
STEM orientation	Convergence ***	University entry more frequent **
Ph.D. intensity	Difference is not significant	Region specialization more frequent **
Univ. size	Difference is not significant	University entry more frequent ***
Univ. funding propensity	Difference is not significant	Difference is not significant
Univ. collaborativeness	Difference is not significant	Difference is not significant
R&D expenditure of the business sector	Difference is not significant	Region specialization more frequent **
Innovation index	Divergence ***	Region specialization more frequent ***
Technological openness of the region	Difference is not significant	University entry more frequent ***

Tables 6 reports OLS regressions where factors affecting divergence patterns are investigated. Results show that a higher presence of STEM students and a greater university size is negatively and significantly associated with a divergence pattern of technological portfolios. The greater the RIS innovation index is, the larger the variation of the Euclidean distance between the patent portfolios of the region and the local universities, confirming a diverging trend.

Table 6: Factors affecting divergence patterns; OLS regression results with clustered standard errors; the dependent variable is the Euclidean distance computed in the years from 2009 to 2014

Regressor	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Euclidean distance in the years 2003-2008				0.359***	0.363***	0.349***
				(0.052)	*(0.051)*	*(0.051)*
STEM orientation	-0.347***	-0.363***	-0.353***	-0.243***	-0.250***	-0.248***
	(0.058)	*(0.055)*	*(0.057)*	*(0.049)*	*(0.048)*	*(0.050)*
Ph.D. intensity	0.043	0.010	0.027	0.080	0.068	0.075
	(0.190)	*(0.182)*	*(0.179)*	*(0.147)*	*(0.138)*	*(0.136)*
Univ. size	-0.007***	-0.005***	-0.007***	-0.004***	-0.003**	-0.004***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*
Univ. funding propensity	-0.007	-0.008	-0.011	-0.005	-0.007	-0.009
	(0.011)	*(0.012)*	*(0.011)*	*(0.009)*	*(0.010)*	*(0.010)*
Univ. collaborativeness	0.000	0.004	0.006	0.009	0.013	0.014
	(0.019)	*(0.020)*	*(0.019)*	*(0.017)*	*(0.017)*	*(0.016)*
R&D expenditure of the business sector	0.048			0.038		
	(0.029)			*(0.025)*		
Innovation index		0.205***	0.188***		0.139**	0.133**
		(0.066)	*(0.064)*		*(0.057)*	*(0.055)*
Technological openness of the region	-0.102	-0.123	-0.118	-0.120	-0.136	-0.131
	(0.170)	*(0.163)*	*(0.165)*	*(0.138)*	*(0.134)*	*(0.135)*
Population	0.009	-0.005		0.009	0.001	
	(0.014)	*(0.017)*		*(0.014)*	*(0.015)*	
Population density	0.012***		0.010***	0.007**		0.005*
	(0.003)		*(0.003)*	*(0.003)*		*(0.003)*
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.579***	0.430***	0.452***	0.154***	0.094*	0.109**
	(0.042)	*(0.064)*	*(0.062)*	*(0.043)*	*(0.048)*	*(0.047)*
Observations	226	226	226	226	226	226
R-squared	0.475	0.469	0.490	0.610	0.611	0.616
Adjusted R-squared	0.409	0.406	0.430	0.559	0.562	0.568

Tables 7 reports Tobit models with clustered standard errors. The dependent variable is the ratio between the number of technological entries of the university and the number of technological specializations of the corresponding region. The STEM orientation of a university is positively and significantly (at 1% significance level) associated with the prevalence of a university-push configuration. The same pattern is envisaged for larger universities. Instead, regions characterized by a higher population and a greater innovation index are less frequently associated with the prevalence of technological entries by local universities.

Table 7: factors affecting university-push patterns; Tobit models with clustered standard errors; the dependent variable is the ratio between the number of technological entries of the university and the number of technological specializations of the corresponding region

Variable	Model 1	Model 2	Model 3
STEM orientation	0.218***	0.234***	0.223***
	(0.059)	*(0.056)*	*(0.057)*
Ph.D. intensity	0.092	0.145	0.145
	(0.193)	*(0.189)*	*(0.193)*
Univ. size	0.006***	0.005***	0.002**
	(0.002)	*(0.001)*	*-0.001*
Univ. funding propensity	0.019*	0.023**	0.023*
	(0.010)	*(0.011)*	*(0.012)*
Univ. collaborativeness	-0.031	-0.036	-0.036
	(0.020)	*(0.022)*	*(0.022)*
R&D expenditure of the business sector	-0.040		
	(0.029)		
Innovation index		-0.234***	-0.256***
		(0.064)	*(0.066)*
Technological openness of the region	-0.088	-0.071	-0.098
	(0.156)	*(0.153)*	*(0.154)*
Population	-0.052***	-0.045***	
	(0.013)	*(0.013)*	
Population density	-0.002		0.002
	(0.004)		*(0.004)*
Country dummies	Yes	Yes	Yes
Constant	0.139***	0.357***	0.392***
	(0.033)	*(0.074)*	*(0.075)*
Observations	226	226	226
Log-likelihood	187.321	192.791	188.431

I. Conclusion

We have investigated the issue of co-evolution patterns in the technological specialization of firms and universities located in the same European region during the years from 2003 to 2014. By relying on a unique and original dataset on patents, EU-funded R&D projects, universities, and economic data at the regional level, we have explored the dynamics characterizing the university-region technological evolution processes. We have offered insights into the role played by universities and firms in the evolution of regional specialization, disentangling between convergent or divergent processes and university-push versus region-pull dynamics to identify alternative co-evolution patterns. We have also explored the factors (at the regional and university levels) that might have influenced the emergence of such diverse patterns of technological evolution.

Our evidence shows the presence of differential patterns of co-evolution of industry and academia specializations across the analyzed EU regions. During the years from 2003 to 2014, we observe both diverging and converging specialization patterns between co-localized industrial and academic systems of sample regions. However, just in a limited number of cases, the specialization into a new technological domain is led by local universities. Empirical tests reveal that this happens when universities are large and have a STEM orientation. A region-pull configuration is more frequent in the case of pre-existing R&D and innovation activities of private firms, thus suggesting that the design of regional specialization policies should support the process of transformation of the knowledge bases within local innovation systems. The cumulative nature of the technological innovation process, the presence of learning, and local effects in knowledge generation and diffusion suggests that when regions stay close to their existing innovative capabilities, it is the local industrial ecosystem to lead technological specialization patterns. This is in line with the design of policy approaches that emphasize smart-specialization strategies that build upon distinctive regional assets and knowledge bases.

Public policies aimed at helping regions sustain their competitive advantage by favoring the convergence in technological specialization dynamics of industry and academia should instead support large academic institutions teaching technical subjects. The role of universities as sources of knowledge for the development and flourishing of the local ecosystem has to be endorsed by policymakers attempting to direct the technological trajectories of a specific geographical area. Policies aimed at promoting only the overall innovation performance of a region will likely lead to divergence patterns in the co-evolution of industry and academic technological portfolios. Instead, policies aimed at reinforcing the academic knowledge base in STEM disciplines might positively impact on the capability of local ecosystem actors to develop and apply new technological and scientific knowledge and favor industry-university interactions.

4 The impact of university patenting on the technological specialization of European regions: a technology-level analysis

m. Objective and empirical strategy

The aim of this chapter is to study the dynamics of co-evolution between the technological specialization of European regions and the patenting activities of the co-localized universities, extending the previous analyses at a more fine-grained level. Accordingly, we set up an original framework in which the unit of analysis is the single International Patent Classification (IPC) subclass to account for the heterogeneity of the examined technical fields.

We exploit the database created as indicated in the previous chapter to perform the analysis of such technological co-evolution processes. In particular, we rely on detailed patent information to generate indicators for measuring the technological specialization of regions and local universities as well as the technological distances between the related portfolios of patented inventions.

For each patent family[13], we collected structured data on application and publication dates, technology subclasses, list of assignees and inventors. Patent families provide a more precise measure of the innovative activity of universities and local firms. Each invention is associated to a specific year according to its priority date. We collected information of 827.627 unique patent families that are linked to 263 different EU regions and 528 universities and filed during the years between 1992 and 2014. We then used information on the residence address of all the inventors to regionalize each patent family and associate it to one or multiple geographic regions at the NUTS3 level using the approach proposed by De Rassenfosse et al. (2019). Patent applications filed by at least one academic institution have been tagged within the sample by means of a semantic approach that relies on the fuzzy comparison and matching to account for variations and non-exact matches of applicant names. Whenever multiple universities are located in the focal geographical area, we generate a consolidated entity that represent the patenting activities of academic institutions as a whole. Finally, we add time-variant characteristics extracted from the Eurostat database and the Regional Innovation Scoreboard (RIS).

The econometric modelling of technological diversification processes of regions is performed by implementing a set of logit regressions, which aim at estimating the impact of university patenting on the subsequent dynamics of specialization that characterize the innovative activities of firms located in the same geographic areas. The analyses also examine the moderating effects of the technological distance computed between the patenting activity of the academic institutions and those of the hosting regions in the relationship between the entry of universities into new sectors and the ensuing technological specialization of the co-localized firms. After estimating the models for the entire set of technologies and regions, we also decompose the sample according to two dimensions: a) the level of complexity of the studied technologies, b) the innovative performance of the considered regions.

With the aim of providing econometric evidence for the effects of the technological entry of academic institutions on the corresponding diversification processes of the co-located firms, we estimate a model in which the specialization of a geographical area is a function of the patenting activity of the university system as well as a number of regional specificities. We implement the Revealed Technology Advantage (RTA) as measure of specialization for regions. It provides information on the relative technological strengths (or weaknesses) of a geographic area (Soete, 1987). In the econometric estimations we use the normalized or

[13] We use the INPADOC definition of patent family.

symmetric version of the indicator that varies around zero. Positive (negative) values of the RTA for a specific year suggest that the focal region is over-specialized (under-specialized) in the technology with respect to other geographical areas. We computed the indicator by taking into consideration all the IPC codes at four-digit level that correspond to 636 different fields. By adopting such an approach, we implicitly assume that the presence in a region of a patent family associated with a specific technological subclass is the signal of the local availability of peculiar competences and skills. Whenever multiple technology subclasses are found, the related patent families have been double counted in the computation of the RTA for each of the corresponding IPC codes. We have developed two additional measures to better characterize the process of technological co-evolution of regions and universities. The first indicator is meant to capture the entry in a new field by the local academic institutions of a specific region. It is based on the filing of at least a new patent family by the university system in the corresponding IPC subclass. Since the entry into a new technological area by the university system could possibly generate a delayed impact on the specialization of co-localized companies even in a period subsequent to the first patent filing, we consider its occurrence for a certain number of years (e.g., 5), after which the variable returns to its initial state. This corresponds to saying that we allow for the presence of a decay in the process of technological exploration of academic institutions. The second indicator is meant to capture the evolution of the overall technological proximity between the portfolios of patented inventions for a given university-region pair. We again compute the standard measure of Euclidean distance (Jaffe, 1989) in each year of the observation period. We provide more details on the implementation of such measures in the following section.

n. Variables definition

We employ a panel data structure to study the effect of the entry by the university system into new technological sectors on the probability that the hosting region becomes specialized in the same field. We define geographical regions based on the third level of the Nomenclature of Territorial Units for Statistics (NUTS) classification[14] whereas technologies are identified using the IPC codes truncated at four digits (i.e., subclasses) which identify about 650 distinct patent fields. The dependent variable of the empirical models is a dummy that equals one if the normalized measure of the revealed technology advantage indicator is greater than zero for a specific region and patent subclass, indicating that the share of patents associated with the examined geographical area and technology in the focal year is larger than the corresponding share of patents filed jointly in all regions and related to the same field. The main regressor is a dummy used to measure the technological entry of an academic institution into a new patent domain, it equals one if the first patent family having the focal technology subclass has been filed by the university system in the five years[15] prior to the focal one (i.e., we consider a decay after 5 years) and zero otherwise. After such a period, we set the indicator variable to zero again if the university has not recently filed any patent application associated with the specific IPC subclass. We also control for the Euclidean technological distance computed in each year between the entire specialization vector of the focal region and that of its university system. Such a measure represents the proximity between the two percentage sectoral decompositions of the patent activities (that jointly consider all patent subclasses) for a region and its university system with a scalar between zero and one. Whenever the relative shares of patented inventions in all fields are similar for the focal region and its university system, the technological distance indicator will approach zero and vice versa. In a set of econometric models, we test for the presence of significant interaction between the entry of the local academic institutions into new patent sectors and the overall technological distance between the region and its universities. Moreover, we include in the regressions additional time-varying covariates at the region

[14] The selected level identifies, for instance, the provinces in Italy and Spain, the prefectures in Greece, the *landkreise* in Germany, and the departments in France.

[15] We test the econometric models with alternative time decays for the technological entry of the university system.

level, such as its population as a measure of size and the gross domestic product computed at current market prices in purchasing power standards. The description of all variables, their summary statistics, and the correlation matrix are shown respectively in Tables 8, 9, and 10.

Table 8: Description of the variables

Variable	Description
Technological specialization of the region	Dummy variable that equals one if the region is specialized in the focal technology subclass (i.e., its normalized revealed technology advantage is greater than one) and year (i.e., a time decay is 1 year) and zero otherwise
Technological entry of the university	Dummy variable that equals one if the first patent family associated with the focal technology subclass has been filed by the university system in the five years prior to the focal one (i.e., a time decay of 5 years) and zero otherwise
Cumulated patent families of the university	Cumulated number of patent families filed by the university system between 1992 and the focal year and computed in thousand units
Euclidean technological distance	Euclidean distance computed between the vectors of technological specialization of the focal region and university system in the focal year
Angular technological distance	Angular distance computed between the vectors of technological specialization of the focal region and university system in the focal year
Min-complement technological distance	Min-complement distance computed between the vectors of technological specialization of the focal region and university system in the focal year
Population	Population of the region computed in million persons
Gross domestic product	Gross domestic product of the region computed at current market prices in million purchasing power standards

Table 9: Correlation matrix

#	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Technological specialization of the region	1.000						
(2)	Technological entry of the university	0.110	1.000					
(3)	Euclidean technological distance	-0.075	-0.146	1.000				
(4)	Angular technological distance	-0.079	-0.114	0.586	1.000			
(5)	Min-complement technological distance	-0.061	-0.153	0.676	0.909	1.000		
(6)	Cumulated patent families of the university	0.061	0.200	-0.446	-0.411	-0.559	1.000	
(7)	Population	0.052	0.088	-0.200	-0.295	-0.299	0.399	1.000
(8)	Gross domestic product	0.053	0.035	-0.148	-0.120	-0.121	0.175	-0.070

Table 10: Descriptive statistics of the variables

Variable	Count	Mean	Median	SD	Min	Max
Technological specialization of the region	2,038,776	0.180	0.000	0.384	0.000	1.000
Technological entry of the university	2,038,776	0.079	0.000	0.269	0.000	1.000
Cumulated patent families of the university	2,038,776	0.132	0.066	0.190	0.000	1.936
Euclidean technological distance	1,885,028	0.244	0.215	0.121	0.068	0.776
Angular technological distance	1,885,028	0.740	0.765	0.186	0.039	1.000
Min-complement technological distance	1,885,028	0.857	0.873	0.110	0.143	1.000
Population	1,952,858	0.752	0.550	0.742	0.063	6.474
Gross domestic product	1,604,018	0.033	0.028	0.027	0.008	0.363

The cumulated patent families of the university system are computed in thousand units, the population of the regions is computed in million persons, the GDP is computed at current market prices in million purchasing power standards.

We decompose the overall effects with different sub-samples that are selected based on the nature of the technology (i.e., high versus low-tech) or the innovative performance of the region[16]. Finally, we test the robustness of the results by considering alternative lags for the regressors, various time frames (i.e. decays) for detecting the impact of the technological entry referred to the patenting activity of local academic institutions, and different measures of technological distance (i.e., angular, min-complement).

Our baseline specification is the following:

$$RTS_{i,j,t} = \beta_1 UTE_{i,j,t-1} + \beta_2 TD_{i,t-1} + \mathrm{UCP}_{i,t-1} + \beta_3 \mathrm{X}_{i,t-1} + \alpha_{i,j} + u_{i,j,t}$$

where the dependent variable RTS_{ijt} is the dummy indicating the presence of a technological specialization for region i, patent subclass j, and computed in year t. The main regressor is a dummy variable $UTE_{i,j,t-1}$ technological entry of the university system in region i. Moreover, $TD_{i,t-1}$ is the Euclidean distance computed between the portfolios of patented technologies for region i and its local universities, $\mathrm{UCP}_{i,t-1}$ is the cumulated number of patent families attributed to the university system, and $\mathrm{X}_{i,t-1}$ is a vector of time-variant controls measured for the focal region i, including population and GDP per capita.

Note that each term $\alpha_{i,j}$ in the equation is defined as the sum of the unobserved time-invariant individual effect, $\eta_{i,j}$, and the general intercept β_0:

$$\alpha_{i,j} = \eta_{i,j} + \beta_0$$

Finally, $u_{i,j,t}$ is the error term. All the regressors are lagged one period[17] (i.e., they are measured in year prior to t). The equation is estimated using fixed effect models with binary outcome response[18].

o. Results

The estimates of the baseline models are reported in Table 11. Results show a significant positive effect of technological entry performed by the universities on the subsequent specialization of the hosting regions. There is also evidence of a negative impact of the Euclidean distance, meaning that geographical areas characterized by lower coherence between the portfolios of patented technologies filed by local firms and those of the related university institutions have a lower probability of becoming relatively more specialized in the focal patent subclass.

[16] We employ data from the latest release of the Regional Innovation Scoreboard (RIS) and approximate the innovative performance of the region at the NUTS3 level by using the information reported for its reference NUTS2.

[17] We also test the robustness of results using different lags for the independent variables.

[18] We use the xtlogit command in Stata.

Table11: Factors affecting the technological specialization of the regions; logit regression results (baseline models)

Regressor	**(1)**	**(2)**	**(3)**	**(3)**	**(4)**	**(5)**
Technological entry of the university	0.015***	0.014***	0.011***	0.010***	0.011***	0.010***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Euclidean technological distance	-0.051***	-0.040***	-0.019**	-0.041***	-0.036***	-0.019*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Cumulated patent families of the university				0.089***	0.089***	0.014
				(0.007)	(0.009)	(0.012)
Population		0.092***	0.081***		-0.021	0.066***
		(0.015)	(0.017)		(0.021)	(0.021)
Gross domestic product			-0.172			-0.247
			(0.178)			(0.191)
Observations	967,673	920,127	720,401	967,673	920,127	720,401
Log-likelihood	-359,654	-342,205	-265,452	-359,578	-342,154	-265,451
Chi-squared	60.978	81.164	36.696	213.463	182.457	38.105

Average marginal effects are reported in the table. The dependent variable is a dummy the equals one if local firms are specialized in the technology subclass and the focal year (i.e., decay of 1 year). The technological entry of the university system is a dummy variable that equals one if the first patent family associated with the technology subclass has been filed by the university system in the five years prior to the focal one (i.e., decay of 5 years). Standard errors are reported in parentheses. All the regressors are lagged one period.

Interestingly, these results are robust to alternative specifications of the models in which the technological entry is interacted with the Euclidean distance (see Table 12). In the presence of fewer technological connections between the university system and the co-localized industrial sectors, there is on average a lower effect of entry into new patent subclasses by the academic institutions on the probability of specialization by the region in the same technology area. Such a result seems to indicate that if the firms of a region are focused on sectors that are relatively more distant from those developed within the local universities, the introduction of new competencies by the academic institutions has a weakened effect on the likelihood that firms will specialize in the corresponding fields because it is more difficult to internalize the related skills. In this light, the technological distance could be interpreted as an indirect proxy of the technology transfer opportunities. The transformative mechanisms induced by university patenting on the local knowledge bases seem to be more effective whenever the density of relations between academic institutions and local industry is relatively greater.

Table 12: Factors affecting the technological specialization of the regions; logit regression results (interaction between the technological entry of the university and the technological distance)

Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Time decay of the technological entry		Decay of 5 years			Decay of 3 years	
Technological entry of the university	0.011***	0.008**	0.008**	0.014***	0.011***	0.008*
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Tech. entry of the univ. × Eucl. tech. dist.	-0.093***	-0.062**	-0.044	-0.103***	-0.073**	-0.070*
	(0.030)	(0.030)	(0.033)	(0.033)	(0.033)	(0.036)
Euclidean technological distance	-0.057***	-0.045***	-0.021**	-0.056***	-0.044***	-0.022**
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Cumulated patent families of the university		0.088***	0.013		0.088***	0.014
		(0.007)	(0.012)		(0.007)	(0.012)
Population			0.066***			0.066***
			(0.021)			(0.021)
Gross domestic product			-0.243			-0.241
			(0.191)			(0.191)
Observations	967,673	967,673	720,401	967,673	967,673	720,401
Log-likelihood	-359,649	-359,575	-265,450	-359,643	-359,570	-265,449
Chi-squared	70.777	217.818	39.930	82.189	229.664	43.477

Average marginal effects are reported in the table. The dependent variable is a dummy the equals one if local firms are specialized in the technology subclass and the focal year (i.e., decay of 1 year). The technological entry of the university system is a dummy variable that equals one if the first patent family associated with the technology subclass has been filed by the university system in the five years prior to the focal year (i.e., decay of 5 years) in models from (1) to (3) and in the three years prior to the focal year (i.e., a time decay of 3 years) in models from (4) to (6). Standard errors are reported in parentheses. All the regressors are lagged one period.

a. Robustness tests

Several robustness tests are performed and we report in the appendix (Tables A3 and A4) those that provide alternative definitions of the variables employed in the previous model specifications. Their results are coherent with the previous ones.

If we decompose the whole sample according to the complexity of the examined technologies (see Table 13), we find that the previous results hold only in the case of high-tech sectors whereas no significant impact of technological entry by universities on regional specialization is detected for the subset of low-tech patent subclasses. This evidence might be due to the idiosyncratic characteristics of the more complex technologies that often rely on the transmission of tacit knowledge from the academic institutions to the local firms.

Table 13: Factors affecting the technological specialization of the regions; logit regression results (sub-samples of high and low technology sectors)

Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sub-sample of technologies	Low-tech / mid-low-tech sectors			High-tech / mid-high-tech sectors		
Technological entry of the university	0.004	0.002	0.004	0.018***	0.013***	0.013***
	(0.007)	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)
Euclidean technological distance	-0.031*	-0.026	-0.014	-0.059***	-0.048***	-0.022*
	(0.018)	(0.018)	(0.019)	(0.011)	(0.011)	(0.011)
Cumulated patent families of the university		0.043***	-0.006		0.095***	0.016
		(0.014)	(0.024)		(0.009)	(0.014)
Population			0.006			0.087***
			(0.044)			(0.025)
Gross domestic product			-1.003***			-0.259
			(0.373)			(0.230)
Observations	236,093	236,093	173,990	662,946	662,946	494,459
Log-likelihood	-88,050	-88,046	-64,276	-245,005	-244,946	-181,116
Chi-squared	3.447	12.447	8.872	58.211	176.568	41.441

Average marginal effects are reported in the table. The dependent variable is a dummy the equals one if local firms are specialized in the technology subclass and the focal year (i.e., decay of 1 year). The technological entry of the university system is a dummy variable that equals one if the first patent family associated with the technology subclass has been filed by the university system in the five years prior to the focal one (i.e., decay of 5 years). Models from (1) to (3) refer to a sub-sample of low and mid-low-tech patent subclasses whereas in models from (4) to (6) the sample is restricted to high and mid-high-tech patent subclasses. Standard errors are reported in parentheses. All the regressors are lagged one period.

In the set of models where the sample is split based on the performance groups identified by the RIS (Table 14), the baseline results remain unchanged only for the regions that exhibit on average a modest or moderate innovation capacity. On the contrary, the entry of universities into new technical areas is not significantly affecting the probability of regional specialization for those instances where the local innovation ecosystem is associated with a leading or strong performance. In the latter geographical areas, there seems to be no direct relationship between the mechanisms underlying the technological specialization of firms and the patenting activity carried out by academic institutions. This might be due to the local presence of highly innovative firms that rely on university research to a lesser extent for guiding their processes of technological development.

Table14: factors affecting the technological specialization of the regions; logit regression results (sub-samples of regions with high and low innovative performance)

Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sub-sample of regions	Modest / moderate innov. perform.			Leader / strong innov. perform.		
Technological entry of the university	0.039***	0.025***	0.019***	0.007*	0.006	0.006
	(0.006)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)
Euclidean technological distance	-0.135***	-0.102***	-0.049***	-0.001	0.001	0.010
	(0.015)	(0.015)	(0.016)	(0.011)	(0.011)	(0.012)
Cumulated patent families of the university		0.189***	0.011		0.025***	0.010
		(0.012)	(0.026)		(0.009)	(0.014)
Population			0.039			0.146***
			(0.030)			(0.051)
Gross domestic product			1.850**			-0.414**
			(0.722)			(0.197)
Observations	244,850	244,850	203,206	715,506	715,506	509,878
Log-likelihood	-86,781	-86,653	-72,415	-270,391	-270,387	-190,578
Chi-squared	131.927	387.443	46.808	3.825	11.515	17.925

Average marginal effects are reported in the table. The dependent variable is a dummy the equals one if local firms are specialized in the technology subclass and the focal year (i.e., decay of 1 year). The technological entry of the university system is a dummy variable that equals one if the first patent family associated with the technology subclass has been filed by the university system in the five years prior to the focal one (i.e., decay of 5 years). Models from (1) to (3) refer to a sub-sample of regions characterized by modest and moderate innovative performance whereas in models from (4) to (6) the sample is restricted to regions with leader and strong innovative performance. Standard errors are reported in parentheses. All the regressors are lagged one period.

5 The effects of public research funding on publications and patents: a validation assessment of ERC research grants

This paper is currently under revision. It will be included soon in the report.

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7 Appendix

Table A1: Count of NUTS3 regions and local universities in the sample by country

Country	Count of NUTS3 regions	Count of local universities
Germany	56	78
United Kingdom	53	81
Italy	32	42
Spain	23	37
France	21	44
Netherlands	11	19
Poland	10	21
Belgium	9	10
Switzerland	7	12
Austria	6	16
Ireland	5	11
Hungary	5	9
Denmark	5	7
Portugal	4	8
Greece	3	6
Czech Republic	2	6
Estonia	2	4
Lithuania	2	4
Slovenia	2	2
Croatia	1	4
Latvia	1	2
Romania	1	2
Slovakia	1	2
Malta	1	1
Total	**263**	**428**

Table A2: Aggregate count of patent families of the NUTS3 regions and the university systems by priority year

Priority year	Patent families of the regions	Patent families of the university systems	Percentage
2003	35,284	2,131	6.0%
2004	39,010	2,214	5.7%
2005	40,702	2,531	6.2%
2006	43,881	3,041	6.9%
2007	45,405	3,315	7.3%
2008	47,445	3,641	7.7%
2009	45,708	3,820	8.4%
2010	46,574	4,153	8.9%
2011	46,178	4,702	10.2%
2012	47,387	4,734	10.0%
2013	47,836	4,825	10.1%
2014	41,352	4,756	11.5%
TOTAL	**798,676**	**57,077**	**7.1%**

Table A3: Factors affecting the technological specialization of the regions; logit regression results (robustness test with alternative time decays for the technological entry of the university system)

Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Time decay of the technological entry		Three years			Five years	
Technological entry of the university	0.018***	0.015***	0.011***	0.015***	0.010***	0.010***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Euclidean technological distance	-0.051***	-0.040***	-0.018*	-0.051***	-0.041***	-0.019*
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Cumulated patent families of the university		0.089***	0.015		0.089***	0.014
		(0.007)	(0.012)		(0.007)	(0.012)
Population			0.066***			0.066***
			(0.021)			(0.021)
Gross domestic product			-0.244			-0.247
			(0.191)			(0.191)
Observations	967,673	967,673	720,401	967,673	967,673	720,401
Log-likelihood	-359,648	-359,572	-265,450	-359,654	-359,578	-265,451
Chi-squared	72.206	224.659	39.724	60.978	213.463	38.105

Average marginal effects are reported in the table. The dependent variable is a dummy the equals one if local firms are specialized in the technology subclass and the focal year (i.e., decay of 1 year). The technological entry of the university system is a dummy variable that equals one if the first patent family associated with the technology subclass has been filed by the university system in the five years prior to the focal one (i.e., decay of 5 years) in models from (1) to (3) and in the three years prior to the focal year (i.e., decay of 3 years) in models from (4) to (6). Standard errors are reported in parentheses. All the regressors are lagged one period.

Table A4: factors affecting the technological specialization of the regions; logit regression results (robustness test with alternative measures of technological distance)

Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technological entry of the university	0.016***	0.011***	0.011***	0.015***	0.011***	0.011***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Angular technological distance	-0.019***	-0.017***	-0.000			
	(0.006)	(0.006)	(0.006)			
Min-complement technological distance				-0.052***	-0.031***	0.007
				(0.010)	(0.010)	(0.012)
Cumulated patent families of the university		0.092***	0.015		0.089***	0.015
		(0.007)	(0.012)		(0.007)	(0.012)
Population			0.068***			0.068***
			(0.021)			(0.021)
Gross domestic product			-0.233			-0.239
			(0.191)			(0.190)
Observations	967,673	967,673	720,401	967,673	967,673	720,401
Log-likelihood	-359,665	-359,584	-265,453	-359,658	-359,584	-265,453
Chi-squared	38.856	201.480	34.283	53.000	200.890	34.672

Average marginal effects are reported in the table. The dependent variable is a dummy the equals one if local firms are specialized in the technology subclass and the focal year (i.e., a time decay of 1 year). The technological entry of the university system is a dummy variable that equals one if the first patent family associated with the technology subclass has been filed by the university system in the five years prior to the focal one (i.e., a time decay of 5 years). In models from (1) to (3) the technological distance is computed with the angular distance measure whereas in models from (4) to (6) the technological distance is computed with the min-complement distance measure. Standard errors are reported in parentheses. All the regressors are lagged one period.