Technological Forecasting & Social Change 188 (2023) 122216

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

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

F. Caviggioli [a], A. Colombelli [a,c], A. De Marco [b,d,*], G. Scellato [a,c,d], E. Ughetto [a,c,d]

[a] Politecnico di Torino, Department of Management and Production Engineering, Italy
[b] Politecnico di Torino, Interuniversity Department of Regional and Urban Studies and Planning, Italy
[c] Collegio Carlo Alberto, Bureau of Research on Innovation, Complexity and Knowledge, Italy
[d] Politecnico di Torino, Future Urban Legacy Lab, Italy

ARTICLE INFO

JEL classification:
O32
O33
O34
R10
R12

Keywords:
University patents
Regional specialization
Technological distance
Knowledge spillovers
Technological co-evolution processes
Innovation

ABSTRACT

This study investigates the relationship between the entry of universities into a new technology field and the innovative activities of firms located in the same geographical area. We aim to assess the presence of a significant correlation between academic research and technological specialization. The empirical setting is based on a dataset of 846,440 patent families, the output of 256 European regions and 428 local universities. The results of the fixed-effect models indicate a robust and positive relationship between the technological entry of academic institutions and the specialization of the region in the same domain. Furthermore, the technological distance between the portfolio of inventions filed by universities and that of co-localized firms is negatively correlated with the subsequent specialization of the hosting region, and this relationship is amplified by the entry of local academies. Several robustness checks have been performed. In particular, the results are tested on sub-samples that distinguish technology fields with lower and higher complexity and geographical regions with lower and higher innovative performance. The technological entry of universities has an additional positive effect for the strong and leading innovators whereas no significant premium or penalty was found for high and low-tech areas. This suggests that the entry of academic institutions into new technology fields occurring in a highly developed innovation ecosystem is more conducive to subsequent industrial specialization thanks to existing collaborations and transmission channels.

1. Introduction

In recent years, increasing attention from both academics and policy makers has been devoted to understanding the processes by which regions develop and specialize over time. In this line of research, the economic geography literature has focused on the determinants and the specific characteristics of the regional branching pathway leading to the industrial and technological specialization of regions (Frenken and Boschma, 2007; Boschma and Frenken, 2011). This literature has revealed that knowledge and technological competencies cumulated over time in a local context exert a crucial role in the path-dependent process of regional specialization (e.g., Neffke et al., 2011; Boschma et al., 2013; Colombelli et al., 2014; van den Berge and Weterings, 2014).

Although the importance of universities for the production of new technological knowledge and the development of local ecosystems for innovation has been widely recognized for many years (Agrawal and Cockburn, 2003; Calderini and Scellato, 2005; Cassia and Colombelli, 2008; Colombelli et al., 2019; Tötterman and Sten, 2005), their role in regional branching and diversification patterns has been almost neglected by the extant scientific literature. Only a few empirical papers have analysed the linkages between academic research and the technological trajectories of regions, providing mixed results on the presence, direction, and magnitude of the relationship between university activities and the industrial specialization of local firms (Acosta et al., 2009; Braunerhjelm, 2008; Calderini and Scellato, 2005; Caviggioli et al., 2022; Colombelli et al., 2021; Coronado et al., 2017).

The objective of this study is to shed further light on the role of local academic institutions in the technological specialization processes of regions. More precisely, the paper aims at analysing the dynamics of co-

* Corresponding author at: Corso Duca degli Abruzzi, 24, 10129 Torino, Italy.
E-mail addresses: federico.caviggioli@polito.it (F. Caviggioli), alessandra.colombelli@polito.it (A. Colombelli), antonio.demarco@polito.it (A. De Marco), giuseppe.scellato@polito.it (G. Scellato), elisa.ughetto@polito.it (E. Ughetto).

https://doi.org/10.1016/j.techfore.2022.122216
Received 23 December 2021; Received in revised form 11 October 2022; Accepted 17 November 2022
Available online 5 January 2023

evolution between the technological specialization of European regions and the patenting activities of their co-localized universities. To this end, we exploit a large dataset made of 846,440 patent families that are linked to 256 different geographical areas in the EU and 428 academic institutions. The paper contributes to the relevant scientific literature on regional branching in three main respects. First, we extend previous empirical studies to 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) sub-class to account for the heterogeneity of the examined technology fields. Second, we exploit a novel dataset that merges information from several sources: i) the CORDIS database collecting all R&D projects funded by the EU under the *Seventh Framework Programme*; ii) the ETER repository providing data on higher education institutions (HEIs) in Europe; iii) the PATSTAT database reporting worldwide patent information; iv) the REGPAT database containing georeferenced patent applicants and inventors; and v) the ARDECO database with regional economic statistics. This rich dataset allows us to map the full technology portfolios of the largest patenting academic institutions in the EU as well as that of all the firms located in their geographical areas with additional region-level and university-level controls. Third, we also examine the moderating role of the technological distance between the two portfolios of inventions developed by academic institutions and co-localized firms to understand whether it significantly affects the relationship between the entry of universities in a patent domain and the subsequent specialization of the region in that field.

Our findings reveal a significant and positive correlation between the technological entry performed by local universities and the subsequent specialization of the hosting region. We also find that the technological distance negatively moderates such a relationship, meaning that lower coherence between the portfolio of patented technologies filed by firms and that of the related academic institutions diminishes the probability of becoming relatively more specialized for a region. Results are robust to different model specifications and tests.

The rest of the paper is organized as follows. In Sections 2 and 3, we discuss the theoretical background on the dynamics of technological specialization processes of regions, with an emphasis on the role of universities. In Section 4, we illustrate the data collection method and the empirical design. In Section 5, we present the results of the econometric analysis as well as all the performed robustness checks. Section 6 concludes and puts forward some policy implications.

2. Research framework

Scholars investigating regional branching and technological specialization processes have shown a growing interest in studying the development trajectories of regions and the different patterns that are activated (Boschma et al., 2017). The economic geography literature on the dynamics of regional branching has already highlighted that regions are conditioned by their extant local capabilities when diversifying into novel products and new technologies (e.g., Frenken and Boschma, 2007; Heimeriks and Balland, 2016; Neffke et al., 2011; Rigby, 2015; van den Berge and Weterings, 2014). Therefore, the dominant bulk of know-how and capabilities embedded in a territory, which have been developed slowly over time, influence the new areas of technological entry and the productive activities to be developed within regions. As a result, diversification is seen as a path-dependent branching process that drives the creation of new activities.

This interpretative framework is at the core of the smart specialization concept, which reflects a vision of regional development built around existing local capabilities (Foray et al., 2009; McCann and Ortega Argilés, 2015). According to this view, regions need to build their competitive advantage in products and technologies for which they possess an existing strength, leveraging these capabilities to diversify into related activities. This approach can benefit from the application of the *recombinant knowledge* theory (Fleming and Sorenson, 2004; Fleming, 2001) to a regional domain. Accordingly, the knowledge base of a region is the final result of the combination of different ideas and bits of knowledge, which are much related one to another, reflecting the cumulative nature of innovation, the presence of learning effects in knowledge generation, as well as the existence of localized knowledge spillovers (Jaffe et al., 1993). Local dynamics involving individuals and organizations build around technological capabilities, skills, and well-established routines that accumulate over time. Within this context, the entry into new technological domains is not random but instead reflects the capability of regions to recombine existing knowledge assets for blazing new technological spaces.

The main result of this literature is that relatedness is an important driver of regional diversification as a branching process (Boschma et al., 2013; Colombelli et al., 2014; Essletzbichler, 2015; Frenken and Boschma, 2007; Neffke et al., 2018; Rigby, 2015; Kummitha, 2020). More precisely, the underlying idea that the production of knowledge is conceived as a process of recombination of existing knowledge enables to understand how the emergence of new industries and the entry into new technological domains is linked to the current technological base of the region.

Furthermore, the growing awareness that regional performance is intrinsically related to the set of localized capabilities and locally embedded knowledge has spurred debate among policymakers (Maskell and Malmberg, 1999). Recent policy prescriptions have progressively endorsed the idea of regional specialization based on branching arguments and revolving around the concepts of heterogeneity and path dependence in regional know-how bases, variety, and specialization strategies (Boschma, 2014; Colombelli et al., 2013; Frenken et al., 2007; Rigby and Essletzbichler, 1997). Such policies have built on the identification of strategic areas of intervention by leveraging the role of industrial actors, the accumulated knowledge base, and the distinctive assets of the territory (Foray, 2014). However, some criticism has been raised that the future development of regions as a function of locally embedded skills and capabilities guiding new activities, industries, and technologies cannot be effectively operationalized into concrete policies (Foray et al., 2011) and that lock-in effects might hamper related diversification.

An emphasis on regional development dynamics as driven by territorial agents collectively acting to create distinctive technological and industrial capabilities has been advanced by several approaches, ranging from *Regional Innovation Systems* (Braczyk et al., 1998; Cooke et al., 1997), to *Triple Helix* (Etzkowitz and Leydesdorff, 2000), and *Entrepreneurial Ecosystems* (Colombelli et al., 2019; Isenberg, 2010; Spigel, 2017). This literature can provide useful insights for understanding the dynamics of regional branching. While the role of relatedness is nowadays quite well established in evolutionary economic geography, the relative contribution of the different kinds of locally available institutional actors is less debated. For example, the balance between local and non-local agents, such as the multinational corporations, has been proposed as key to the entry into brand-new specializations (Crescenzi et al., 2022; Elekes et al., 2019; Neffke et al., 2018). The implication of universities in local innovation dynamics has also been indicated as a crucial factor shaping regional diversification, deserving much careful study (Tanner, 2015). In Section 3, we will elaborate on the role that academies can play in regional branching dynamics, stressing the importance of the technological proximity between university-based research and the direction of local diversification trajectories.

3. Role of universities

While previous research has largely confirmed that regions diversify into economic activities related to their current knowledge bases (see Boschma, 2017 and Kogler, 2017 for both a review and research agenda), what remains unclear is the contribution of universities to the definition of regional diversification trajectories and technological change. Academic institutions are recognized as important players in territorial economic development as they represent a key source of knowledge for the local ecosystem (Ponds et al., 2009) and the development of regional innovation capabilities. They act as *anchor tenants* for local growth (Agrawal and Cockburn, 2003; Colombelli et al., 2019; Tötterman and Sten, 2005), being the source of both a highly educated and skilled workforce and scientific knowledge production that underpins technological innovation to be transferred to the industrial ecosystem (D'Este and Patel, 2007; Gunasekara, 2006).

However, their role in regional branching and diversification patterns remains an under-researched issue (Caviggioli et al., 2022). The regional innovation systems approach underlines the relevance of localized interactions (both formal and informal) between universities and industrial partners, as affecting the development of technological trajectories at the regional scale and the local dynamics of creation, diffusion, and adoption of new technological knowledge (Asheim et al., 2011; Cooke, 2001; D'Este and Patel, 2007; Perkmann and Walsh, 2007). The core argument of the *Triple Helix* framework is that academic institutions play a key role at the regional level, particularly in facilitating knowledge spillovers from research and educational activities (Etzkowitz and Leydesdorff, 2000) and in favouring innovation dynamics and the setup of technological trajectories. Moreover, universities promote the diffusion of the entrepreneurial culture among both students and academics and stimulate the birth of novel firms within the ecosystem (Bonaccorsi et al., 2013; Carree et al., 2014; Forliano et al., 2021; Shane, 2004; Zucker et al., 1998). The processes of knowledge recombination and creation that originate from academic institutions affect regional innovation dynamics. Several quantitative articles have confirmed the existence of i) a positive and significant relationship between university research and innovation within a geographical area, pointing to spillover effects (Anselin et al., 2000; Fritsch and Slavtchev, 2007); ii) positive outcomes related to the introduction of technological innovations in various industries; iii) the decrease in time lags between investments in scientific research and the industrial exploitation of its outputs (Arundel and Geuna, 2004; Caviggioli et al., 2020; Laursen et al., 2011; Mansfield, 1998).

Despite the importance of the knowledge production and diffusion processes associated with the academic institutions, the contribution of university research to the evolution of regional specialization has almost been neglected. Only in recent years, scholars have redirected their attention towards the role of academies in tracing technological trajectories and their impact on regional diversification, using variegated methods to compute the specializations of regions and universities (e.g., scientific publications, patents, employees, or researchers). According to the findings of Aksoy et al. (2022), academic institutions can actively spur innovation and local economic growth, thus regions would benefit from reducing the technological and cognitive gap between the university and industry. Nonetheless, prior empirical studies have provided mixed results concerning the presence, direction, and magnitude of the relationship between academic and industrial specialization. Calderini and Scellato (2005) found that scientific research favours the patenting activity of local firms in the ICT field. Similarly, in Braunerhjelm (2008) university outputs are shown to be positively and significantly related to the industrial specialization of the hosting region, although this impact depends upon the commercial environment in which the academic institution is embedded. Potential moderators of the university-industry relationship in this context are linked to the size of the academia and the presence of STEM courses (Caviggioli et al., 2022) as well as the degree of focus on internal goals (i.e., scientific papers) rather than external ones (Acosta et al., 2009). Therefore, the nexus between the underlying processes of knowledge production by the universities and innovation at the regional level remains somewhat unexplored. Neither geographers nor economists have managed to empirically unveil whether the entry of academic institutions into a new technology domain is correlated to the cross-fertilization of ideas and innovation processes between previously unconnected knowledge bases or rather to the dominance of processes grounded in local capabilities.

This work aims to contribute to such an underexplored field of research by investigating whether the entry of universities into a new technological domain is correlated to the subsequent specialization of the firms operating in the same geographical area.

Furthermore, we aim to improve understanding of the relationship between technological entry of universities into a new sector and specialization of the co-localized industrial activities by considering additional elements. First, we expect a moderating negative effect of the distance between the two portfolios of technologies patented by academic institutions and neighbouring firms. When the distance is relatively larger, university-industry relationships might not be so tight to favour a subsequent specialization. Second, there may be substantial differences because of the idiosyncratic characteristics of the examined technological domains. Hence, the analyses will be replicated by focusing on high-tech versus low-tech fields, the former being more complex and harder to transfer. Finally, we aim to disentangle the effects at the regional level and distinguish between geographical areas with a higher propensity to innovate and less performing ones, to assess the role of existing local innovation ecosystems that might favour specialization from knowledge transmission.

4. Methodology

4.1. Data collection and sample description

We have generated a novel dataset that contains information on both European academies and regions, starting from a number of different sources. At first, a sample of universities was selected by considering those academic institutions that are located in EU countries having substantial research activities and track records in gaining EU funds from competitive projects. The aim was to include universities active in applied research. Thus, the largest recipients of FP7 funds[1] among European academies were identified by disambiguating their names in the CORDIS[2] database. We selected a sample made of the 528 largest universities in the EU: they account for around 90 % of the total FP7 funding to academic institutions. Each of them was geolocalized at the third level of the *Nomenclature of Territorial Units for Statistics* (NUTS), which identifies, for example, provinces in Italy and Spain, prefectures in Greece, landkreise in Germany, and departments in France (Fig. 1). Precise NUTS information was retrieved from the ETER dataset.[3]

The patents associated with each academic institution in the sample and the corresponding NUTS3 area were collected for all the years from 1990 to 2018. The search strategy for university patents examined both the assignee field in PATSTAT[4] and the standardized names that are available in the HAN[5] repository. A semantic approach was considered for academic institutions: it relied on the fuzzy comparison and

[1] The *Seventh Framework Programme for Research and Technological Development* (FP7) was run by the EU from 2008 to 2013 with a budget of about 55 billion euros.

[2] The *Community Research and Development Information Service* (CORDIS) is the major online data source on EU-funded research and innovation projects. Its public repository is available at http://cordis.europa.eu/projects (last accessed in November 2021). CORDIS denotes universities as *Higher Education Institutions* (HEIs).

[3] The *European Tertiary Education Register* (ETER) collects detailed information on all HEIs in the EU, e.g., their basic characteristics and precise geographical position, staff, finances, educational and research activities. It is available at http://eter-project.com (last accessed in November 2019).

[4] The *Worldwide Patent Statistical Database* (PATSTAT) is a comprehensive patent data repository maintained by the *European Patent Office* (EPO). We used the *Autumn Edition* of 2018.

[5] The *Harmonised Applicant Names* (HAN) database is maintained by the *Organization for Economic Co-operation and Development* (OECD). The examined tables are those included in the selected version of PATSTAT.

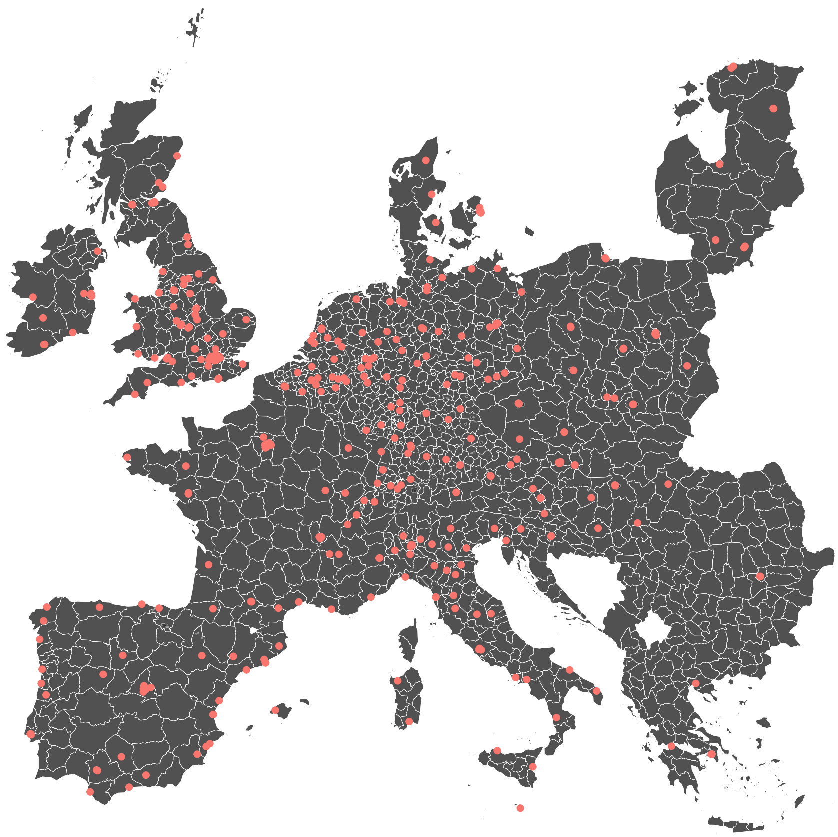

Fig. 1. Geographic location of the selected universities.

matching in order to account for spelling variations, and web searches to identify TTOs or ad-hoc entities (e.g., *Oxford University Innovation*) managing intellectual property for universities.[6] The authors iteratively and meticulously controlled all the names resulting from each query to avoid false-positive identifications. Finland, Sweden, and Norway were then excluded from the analysis since the so-called *professor's privilege* was in force during the selected time frame and the total number of their patent filings appears to be extremely low, suggesting a high chance of underestimation[7] (see Lissoni et al., 2008, 2013). University patents having multiple assignees (e.g., collaborations with firms, individuals, and other research organizations) are considered university ones.[8]

Regional patent portfolios were generated from the residence addresses of all the inventors using the georeferenced data available in REGPAT. Note that the previously identified university patents were excluded from the patent portfolios of local firms and the corresponding calculation of specialization indexes.

The identified patent filings (domestic and international) were selected and consolidated in their INPADOC patent families, which provide a more accurate measure of inventive activities. Each invention is then associated with a specific year according to its earliest priority date. Note that 56 regions and 64 universities (i.e., about 16.6 % and 12.1 % of the initial sample, respectively) having a particularly small patent portfolio were not included in the analyses because they would have yielded inaccurate specialization values (more details on the calculation of these indexes in the following Section 4.2).

The final sample includes 428 universities located in 256 regions at the third level of the NUTS classification and 846,440 patent families (see Table 8 in the Appendix for country-level statistics). These data provide the ground for the definition of the metrics described in the next sections. Note that in 22.7 % of the cases the focal area contains two universities whereas in 13.7 % three or more. All these instances were treated by merging the patent portfolios of local academies into a single entity, representing the university research system co-localized with the regional industries.

We matched additional information to describe the examined regions. The geographical areas were characterized by the demographic indicators available in the ARDECO database.[9] We also collected data on regional innovation systems from the Regional Innovation Scoreboard (RIS).[10]

[6] Examples of search queries are *((*FEDER* or *EIDGEN*) and (*INST* or *HOCHSCH*) and (*TECH*) and (*ZURICH* or *ZUERICH* or *ZÜRICH*)) or ((*ETH*) and (*ZURICH* or *ZUERICH* or *ZÜRICH*)) not *TRANSPOR** for the *Eidgenoessische Technische Hochschule Zuerich* and *((*UNIV* and *NAPOLI* and *FEDERIC*) or (*UNIVE* and *FEDERICO*)) not *MAR** for the *Università degli Studi di Napoli Federico Secondo*.

[7] The countries where the rule was in force in the examined years are Sweden (from 1949), Norway (until 2003), Germany (until 2001), Austria (until 2002), Finland (until 2007), Denmark (until 1999), and Italy (from 2002). However, the search results seem to underestimate the results only for Finland, Sweden, and Norway. This exclusion criterion dropped 36 universities and 25 regions.

[8] If any impact on the analysis has to be expected from this choice, it would be on reducing the correlation between the technological entry of universities and industrial specialization. In fact, in the extreme scenario where the majority of patents leading to specialization are inventions jointly developed by academic instituions and local firms, they would be associated with the university and the industrial specialization would not be observed.

[9] Statistics on socio-economic indicators of EU member countries for all three different levels of the NUTS classification system are found at: https://knowledge4policy.ec.europa.eu/ardeco-database (last accessed in February 2021).

[10] A comparative assessment of the research and innovation performance for all European regions. It is available online at: https://ec.europa.eu/info/research-and-innovation/statistics/performance-indicators/regional-innovation-scoreboard (last accessed in November 2021).

4.2. Region technological specialization

The revealed technology advantage (RTA) is employed as an indicator of specialization for regions (Balassa, 1965). RTA provides information about the relative technological strengths of a geographical area (Soete, 1987), showing whether the share of patent families associated with the region in a technology field is larger than the corresponding proportion of patent families filed in the same domain by all the regions over the considered time frame (D'Agostino et al., 2013; Malerba and Montobbio, 2003; Soete and Wyatt, 1983).

We computed the RTA indicator by taking into consideration all the IPC codes at the four-digit level (i.e., the sub-classes) that correspond to 639 different patent domains. They act as a proxy for the presence of the related technological knowledge in the region[11]:

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

where p_{ijt}^{R} is the count of patent families developed in region i, having technology j, and priority year t, excluding university patents. The RTA indicator is then normalized to its symmetric version, the NRTA (Laursen, 2015):

$$NRTA_{ijt} = \frac{RTA_{ijt} - 1}{RTA_{ijt} + 1}$$

It provides a continuous measure of technological specialization, ranging between minus and plus one. Positive values of $NRTA_{ijt}$ indicate the level of specialization in technology j with respect to other geographical areas. This measure of technological specialization for regions (RTS) is the dependent variable of the empirical models.[12]

4.3. University technological entry

The university technological entry (UTE) is an indicator meant to capture the entry of academic institutions in a new field relative to previous technology development activities, while considering potential delays for the conversion into industrial follow-ups. Hence, the UTE dummy variable is initially set to one (i.e., start) if the university has filed a patent in the IPC sub-class j and year t for the first time during the previous five years. Note that the $start_{ijt}$ dummy variable can be equal to unity twice or more in the considered time frame:

$$start_{ijt} = \begin{cases} 1 & \text{if } \sum_{1}^{5} p_{ijt-k}^{U} = 0 \text{ and } p_{ijt}^{U} > 0 \\ 0 & \text{otherwise} \end{cases}$$

where p_{ijt}^{U} is the number of patent families filed by university i, in technology j, and year t.[13] Our implementation considers an oblivion time after every five consecutive years of no-patenting in that technology field. The operationalization of UTE includes a persistence of four additional years after the preliminary identification in order to allow some time for industrial specialization:

$$UTE_{ijt} = \begin{cases} 1 & \text{if } \sum_{k=0}^{4} start_{ijt-k} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Alternative definitions of UTE with different persistences are also tested in the econometric models and reported in Appendix A.

Table 1
Description of the variables.

	Description
Dependent variable	
Region technological specialization (RTS)	Continuous variable (i.e., normalized revealed technology advantage) that takes positive values if the region is specialized in the focal technology sub-class and year, and negative values otherwise; larger values describe higher specialization relative to other geographical areas in the same period
Independent variables	
University technological entry (UTE)	Dummy variable that equals one if the university system has filed a patent in a technology field for the first time in the previous five years; once set to one, it remains so for the next four years
Euclidean technological distance (ETD)	Euclidean distance computed between the technological specialization vectors of the focal region and the co-localized university system in the focal year
Cumulated university patent families	Cumulated number of patent families filed by the university system between 1992 and the focal year computed in thousand units
Population	Population of the region computed in million persons
Regional GVA per capita	Gross value added of the region computed in million purchasing power standards per capita

4.4. Euclidean technological distance

The Euclidean technological distance (ETD) measure is meant to capture the evolution of the overall technological proximity between the two portfolios of patented inventions for a given university-region pair. We computed the standard index of Euclidean distance (Jaffe, 1989) in each year of analysis. The variable gauges the technological proximity between the vectors representing the percentage sectoral decompositions of patent activities (i.e., all sub-classes are considered jointly) for a region and its local university system with a scalar between zero and one:

$$ETD_{it} = \sqrt{\sum_j \left(s_{ijt}^{R} - s_{ijt}^{U}\right)^2}$$

where s_{ijt}^{R} is the relative frequency of patent families associated with region i, technology sub-class j, and year t. Likewise, s_{ijt}^{U} is the corresponding share computed for the co-localized academic institutions. Whenever the proportions of patented inventions in all fields are similar for the focal region and its university system, ETD_{it} will approach zero and vice versa.[14]

We also computed other standard measures of technology proximity to perform robustness tests, such as the angular separation, ATD (Jaffe, 1986), as well as the min-complement distance, CTD (Bar and Leiponen, 2012; Benner and Waldfogel, 2008; Breschi et al., 2003; Simon and Sick, 2016). Further details are reported in Appendix A.

4.5. Description of the variables

The generated data have a longitudinal structure with 17 time periods (i.e., the years from 2002 to 2018) and 163,584 units (i.e., the combination of 256 regions and 639 patent domains). Thus, the defined panel has 2,780,928 observations in total.

The description of the dependent and independent variables, their summary statistics, and the correlation matrix are shown in Tables 1, 2, and 3 respectively.

[11] Coherently with this approach, patent families associated with more than one IPC sub-class have been counted multiple times, once for each technology field when computing the RTA.

[12] We also ran a series of logit models in which the dependent variable has been transformed into a dummy variable (i.e., equal to one when the industrial activities in the region are specialized in the focal technology field, and zero otherwise).

[13] See Table 15 in the Appendix for some examples.

[14] Note that the maximum distance is reached when both specialization vectors have a different component with unitary value and zeros in all the others. The indicator has been normalized to vary between zero and one.

Table 2
Summary statistics.

Variables	Count	Mean	Median	SD	Min	Max
RTS	2,593,456	−0.811	−1.000	0.496	−1.000	1.000
UTE	2,780,928	0.050	0.000	0.218	0.000	1.000
ETD	2,556,639	0.257	0.224	0.130	0.068	0.866
Cumulated university patent families	2,780,928	0.172	0.077	0.277	0.000	2.653
Population	2,780,928	0.777	0.575	0.760	0.000	6.557
Regional GVA per capita	2,704,887	0.028	0.025	0.013	0.008	0.166

Note that it is not possible to compute the Euclidean technological distance for 224,289 observations (8.1 %) since in those instances there is no patent family associated with the university or the corresponding region.

We included in the regressions additional time-varying covariates at both the university and region levels, i.e., the cumulated number of patent families filed by the academic institutions to measure the intensity of the innovative activities performed by local universities, the population of the region as a proxy of size, and the gross value added defined at current market prices in purchasing power standards (the latter two variables were collected from the ARDECO database).

4.6. Model specification

A balanced panel data structure is then defined to study the relationship between the entry of universities into a new technology field and the industrial specialization of the corresponding region in the same domain. Although we collected longer time series for patent data (i.e., from 1992 onwards), we only consider the years between 2002 and 2018 to minimize the potential issues due to left censoring in the technological entry of local academic institutions. The model specification is the following:

$$RTS_{ijt} = \beta_1 UTE_{ijt-1} + \beta_2 ETD_{it-1} + X_{it-1}\delta + \alpha_{ij} + u_{ijt}$$

The dependent variable representing the technological specialization for regions (RTS) is based on the $NRTA_{ijt}$. This is a continuous variable taking positive values in the presence of specialization for region i, patent sub-class j, and year t (as described in Section 4.2). UTE is the dummy that captures the entry of universities located in region i into the technology field j (more details are reported in Section 4.3). Since UTE is lagged and has a persistence of five years, the model is testing whether an entry of academic institutions occurring between one and five years prior to the focal one is correlated to RTS.[15] ETD is the Euclidean technological distance between the university and the industrial system in region i the year before t. Furthermore, X is a vector of time-variant controls (in logarithm) that include the cumulated number of patent families filed by the university system, the population, and the gross value added per capita in region i the year before t. Note that α_{ij} is defined as the sum of the unobserved time-invariant individual effect and the general intercept of the model. Finally, u_{ijt} is the error term. The econometric model includes year dummies and is estimated using fixed-effects regressions for panel data to control for region-specific unobserved heterogeneity.[16]

The baseline model is first extended by introducing an interaction

[15] Robustness tests with other persistence durations are reported in Appendix A. We have also performed tests with lags of two and three years and the results are robust. They are not included for sake of brevity but can be made available upon request.

[16] We employ the *xtreg* command of Stata 17.2. According to the specification tests based on the Hausman statistic, a fixed-effect regression is more appropriate in our case.

Table 3
Correlation matrix.

#	Variable	(1)	(2)	(3)	(4)	(5)
1	RTS	1.000				
2	UTE	0.108	1.000			
3	ETD	−0.100	−0.108	1.000		
4	Cumulated university patent families	0.051	0.123	−0.409	1.000	
5	Population	0.094	0.060	−0.221	0.304	1.000
6	Regional GVA per capita	0.104	0.042	−0.272	0.293	0.011

between UTE and ETD, to capture the moderating role of the technological distance. Then, the baseline specification is tested on different clusters of regions and technological domains. Concerning the latter, patent sub-classes were distinguished between high and low-tech according to the classification provided by Eurostat that relies on NACE fields grouped into four clusters along R&D intensity and share of tertiary educated persons. We employed the concordance schema proposed by Van Looy et al. (2014) to link economic sectors and technological domains.

Concerning the propensity to innovate of a region, we tested the models on two different sub-samples by distinguishing between geographical areas having a higher propensity to innovate and territories with a lower one. To this aim, we use data from the latest release of the RIS which classifies regions into four groups of innovators: emerging, moderate, strong, and leaders.[17] In our analyses, we compare two sub-samples of regions, one including the top innovators (i.e., strong and leader geographical areas) and the other with the emerging and moderate innovators.

Several additional robustness tests are performed, and the corresponding tables are reported in Appendix A.

5. Results

All the estimates of the baseline regressions are reported in Table 4. Considering the results of the correlation matrix (in Table 3), we tested two sets of models without and with the cumulated number of university patent families as a control in models from (1) to (3) and from (4) to (6), respectively.

Results show the presence of a significant and positive relationship between the entry of local universities and the subsequent technological specialization of the hosting region. Note that the computed marginal effect of UTE is small in all the models (including the robustness checks). Nonetheless, its interpretation refers to the measure of specialization (RTS). Moving the analysis to the regional level and hypothesizing the entry of academic institutions for those cases when it is not actually observed, the estimated RTS would change to a positive value (i.e., the hosting region would then be specialized) in 184 geographical areas: this represents a large variation as 72 % of the regions would count one (or more) additional specializations in their technology portfolios.

There is evidence of a negative partial correlation between the technological distance and the dependent variable, meaning that geographical areas characterized by lower coherence between the portfolio of patented technologies filed by local firms and that of co-located universities have a lower probability of becoming relatively more specialized in the focal technology field.

Several robustness tests have been performed. First, we included the lagged dependent variable (RTS) among the regressors (Table 11 in the Appendix) for disentangling the presence of a potential *bandwagon effect* with the universities following the specialization trends of the local industry in a specific technological domain. Results are robust to this

[17] RIS provides data for European member states at the NUTS2 level only. We linked this upper level of information to our NUTS3 regions.

Table 4
Relationship with the region technological specialization (RTS), baseline specifications.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UTE	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ETD	−0.020***	−0.020***	−0.017***	−0.015***	−0.015***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Cumulated university patent families (log)				0.005***	0.005***	0.005***
				(0.001)	(0.001)	(0.001)
Population (log)		−0.018	0.015		−0.013	0.019
		(0.011)	(0.012)		(0.012)	(0.012)
Regional GVA per capita (log)			0.050***			0.050***
			(0.004)			(0.004)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,238,718	2,179,168	2,179,168	2,238,718	2,179,168	2,179,168
Average group size	13.954	13.964	13.964	13.954	13.964	13.964
R-squared within model	0.0004	0.0004	0.0005	0.0004	0.0004	0.0005
R-squared between model	0.0716	0.0078	0.0744	0.0261	0.0003	0.0697
R-squared overall model	0.0049	0.0020	0.0278	0.0072	0.0001	0.0269

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 5
Relationship with the region technological specialization (RTS), specifications with the interaction between UTE and ETD.

Model	(1)	(2)	(3)	(4)
UTE	0.019***	0.018***	0.019***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)
ETD	−0.019***	−0.016***	−0.014***	−0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
UTE × ETD	−0.046***	−0.045**	−0.047***	−0.046**
	(0.018)	(0.018)	(0.018)	(0.018)
Cumulated university patent families (log)			0.005***	0.005***
			(0.001)	(0.001)
Population (log)		0.015		0.019
		(0.012)		(0.012)
Regional GVA per capita (log)		0.050***		0.050***
		(0.004)		(0.004)
Year dummies	Yes	Yes	Yes	Yes
Observations	2,238,718	2,179,168	2,238,718	2,179,168
Average group size	13.954	13.964	13.954	13.964
R-squared within model	0.0004	0.0005	0.0004	0.0005
R-squared between model	0.0722	0.0744	0.0263	0.0696
R-squared overall model	0.0051	0.0278	0.0074	0.0269

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

inclusion and thus confirm the prior role of the entry of local academic institutions in favouring technological specialization. Second, because the distribution of RTS is right skewed and contains 80.2 % of values equal to minus one (i.e., no patent families in a certain region, technology field, and year), the models in Table 12 introduce a dummy variable that is set to one when the lagged dependent variable is equal to minus one. Once again, the results are robust.[18]

In further robustness checks, we consider alternative measures of technological distance and different persistences of UTE. Moreover, model specifications with random effects have been employed to control for time-invariant geographical dummies. The estimated results are reported in Tables 13, 14, and 15 of the Appendix, respectively. No substantial deviations from the baseline were found. Finally, with the aim to analyse more in depth the potential differences across academic institutions (as in Fisch et al., 2015), the models were tested on subsamples of universities split in terms of orientation towards technical disciplines (Table 16). The findings are coherent with the baseline model and show that the marginal effect of UTE is higher when considering those academies with a higher share of STEM graduates. Further research could investigate deeper the university-level characteristics that may correlate more with industrial specialization.

The second set of econometric analyses extends the investigation on the role of technological distance as moderating factor to the entry of universities into new patent fields with respect to the technological specialization of co-localized firms (Table 5). The results indicate that the negative correlation between technological distance and regional specialization is amplified in the case of entry by local universities. To get a better understanding of this relationship, we estimated the marginal effect of UTE for all deciles of the ETD distribution in the sample. Up to its 70th percentile, the computed marginal effect of UTE is positive and significant and gradually decreases in magnitude as ETD increases. For all the percentiles located after this threshold, the marginal effect of UTE is still decreasing but no longer statistically different from zero. In other words, the relationship between the technological entry of academic institutions and the specialization of the region gradually loses its positive sign with the increasing technological distance computed between universities and the local industry and becomes statistically irrelevant when the two systems are technologically too far.[19]

In the following alternative specifications, we aim to disentangle the

[18] Furthermore, we tested the robustness of the models by considering the dependent variable in the exponentiated form. Results hold and are available on request from the authors.

[19] As an example, imagine the case where the university "U1" and the industrial sectors in the region "R1" are unrelated, e.g., "U1" covers mainly chemicals and pharmaceuticals, while "R1" is innovating in the automotive domain. Given that "U1" and "R1" are technologically distant, there is a negative correlation with regional specialization in any field. At the same time, if "U1" enters a new technology field (e.g., computers), the degree of specialization of "R1" in the same domain will be on average higher. However, this specialization would be smaller with respect to the instance where "U1" and "R1" have similar technology portfolios.

Table 6
Relationship with the region technological specialization (RTS), specifications including a dummy for high-tech fields among the regressors.

Model	(1)	(2)
UTE	0.050***	0.048***
	(0.002)	(0.004)
High-tech sector dummy	0.025***	0.024***
	(0.002)	(0.002)
UTE × High-tech sector dummy		0.003
		(0.005)
ETD	−0.055***	−0.055***
	(0.003)	(0.003)
Cumulated university patent families (log)	0.002***	0.002***
	(0.001)	(0.001)
Population (log)	0.053***	0.053***
	(0.001)	(0.001)
Regional GVA per capita (log)	0.143***	0.143***
	(0.002)	(0.002)
Year dummies	Yes	Yes
Observations	2,105,026	2,105,026
Average group size	14.025	14.025
R-squared within model	0.0003	0.0003
R-squared between model	0.0802	0.0802
R-squared overall model	0.0314	0.0314

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 7
Relationship with the region technological specialization (RTS), specifications including a dummy for highly innovative regions (RIS) among the regressors.

Model	(3)	(4)
UTE	0.052***	0.033***
	(0.002)	(0.003)
Strong and leader innovator dummy (RIS)	0.077***	0.076***
	(0.002)	(0.002)
UTE × Strong and leader innovator dummy (RIS)		0.027***
		(0.004)
ETD	−0.046***	−0.046***
	(0.003)	(0.003)
Cumulated university patent families (log)	−0.001**	−0.001**
	(0.001)	(0.001)
Population (log)	0.069***	0.069***
	(0.001)	(0.001)
Regional GVA per capita (log)	0.118***	0.118***
	(0.002)	(0.002)
Year dummies	Yes	Yes
Observations	2,149,391	2,149,391
Average group size	13.998	13.998
R-squared within model	0.0003	0.0003
R-squared between model	0.0877	0.0884
R-squared overall model	0.0347	0.0349

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

potential moderating effects of technological and regional specificities. These models are tested with random effects since the potential moderators are time-invariant. With respect to the former, technology fields are classified as low-tech and high-tech types. This distinction highlights the potential role of technological complexity in transferring the results from academia to the business sector.

Table 6 shows that the baseline results hold, and there is a positive partial correlation between the high-tech sector dummy and regional specialization. This evidence might be due to the idiosyncratic characteristics of more sophisticated technologies: gaining a competitive advantage in those patent domains is positively associated with regional specialization. However, as the interaction term is not significant, there is no moderating effect of UTE and the entry of local universities in high-tech fields is similar to that into low-tech ones for industrial specialization.

In Table 7, the baseline models are tested with a dummy that is set to one when the region is among highly active innovators (i.e., strong and leader territories) according to the performance groups identified by the RIS. All previous results hold, and high-performing regions are correlated to a larger technological specialization. Furthermore, the interaction term is significant and positive meaning that the entry of academic institutions into new technology fields is more strongly correlated with local specialization when considering innovation ecosystems with strong and leader performance than less-performing ones. This might be due to the local presence of highly innovative firms that rely on scientific research of universities to a larger extent for guiding their processes of technological development.

6. Conclusion

This study investigated the relationship between the technological specialization of EU regions and the patenting activities of the universities located in the same geographical areas during the years from 2002 to 2018. The empirical analysis relied on a new and rich dataset with information on patents of EU academic institutions and regions at the third level of the NUTS classification, as well as regional economic data. The examined sample was a selection of EU regions having a patent portfolio that is sufficiently large to compute quantitative measures of specialization and hosting a patenting academic institution. Hence, the results should be interpreted with respect to such a selected sample and not to the whole Europe.

The aim of the work was to improve the understanding of the role of universities in influencing the branching process that leads to regional specialization. More precisely, our findings showed a positive and significant correlation between the specialization of regions in a technological sector and the previous entry of local academic institutions in that specific domain. The results of the robustness tests that control for prior specialization suggest the presence of a causal relationship, although further analyses are needed in future research to confirm it.

Some moderating factors are found to be relevant. First, the technological proximity between co-localized universities and firms plays a positive role in the statistical relationship. In general, a higher coherence between the portfolios of patented technologies owned by local firms and universities is positively correlated with the later specialization of the hosting region. The analysis of the technological distance as a moderator for the role of the technological entry performed by local universities indicates that such a positive relationship is amplified if industry and academia have a similar technology portfolio while it is no longer significant when the two portfolios are very different (for those cases in the top 30th percentile of the distribution). The technological distance can be interpreted as an indirect proxy of the technology transfer opportunities that are available locally. This result seems to corroborate previous evidence suggesting that the effective transmission of knowledge from one organization to another requires the recipient party to possess a high absorptive capacity for identifying, interpreting, and exploiting the new knowledge (Cohen and Levinthal, 1990; Boschma, 2005). Such processes tend to be easier if the involved organizations have a similar knowledge base, while it gets harder to transfer knowledge and skills in the absence of synergies and when the innovation ecosystem is not operating in domains shared by universities and local firms. This hints that where there is technological proximity, all the local mechanisms favouring knowledge transfer from academic institutions are correlated to industrial developments that lead to regional specialization. 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 industry is expected to be relatively greater.

To improve the understanding of the relationship between technological entry of universities and subsequent industrial specialization, we focused on the type of technologies (i.e., low and high-tech fields) and found no significant premium or penalty. Although in high-tech areas the chances of specialization are greater, the role of the technological entry performed by academic institutions is similarly positive both in high and low-tech, suggesting that the technology transfer between universities and firms is comparable regardless of complexity. This result could be explained by considering the role of physical distance: neighbours share tight relationships and cognitive proximity (Cooke and Morgan, 1999; Hansen, 1999) that favour local spillovers from academia to near firms. Hence, the entry of universities into new technology fields provides the conduit for knowledge spillovers from the source organization (i.e., the university) to firms located nearby, which will exploit such knowledge.

Concerning the comparison between geographical areas that are characterized by high or low innovative performance according to the RIS, we found a positive additional effect of the technological entry of academic institutions on the specialization of local firms for the former group of regions (i.e., the strong and leading innovators). We argue that this difference may be linked to the characteristics of highly innovative local firms that rely on university research to a larger extent in their technological development processes.

Our work has major implications for regional technology policy. Public policies aimed at supporting regions to sustain their competitive advantage by favouring branching processes should stimulate the investment of hosted universities in technology fields which are close to the local knowledge base. This empirical result provides support to the recent wave of regional policies implementing *smart specialization strategies* (Boschma, 2014). These policies aim to identify strategic areas of intervention to sustain regional innovation activities, by building on cumulated knowledge, collective intelligence, and distinctive assets of the territory (Foray, 2014).

Our results are in line with the premises of the *knowledge spillover* theory, according to which one relevant source of local development is the new knowledge generated by specific organizational contexts, such as university laboratories (Audretsch et al., 2006). This knowledge, which is frequently left uncommercialized because of its complex and poorly codifiable nature, generates entrepreneurial opportunities and specialization within a geographical area.

Future research can overcome some of the main limitations of this study, along different directions. First, non-patent-based technological measures might be employed to better assess specialization and expand the set of regions analysed. Second, prospect studies can delve deeper into those characteristics of academic institutions that might act as moderators and flywheel to industrial specialization (e.g., the size of TTOs or university-based incubators and accelerators, the intensity of spinoffs, and the involvement in collaborations with firms). Finally, the relationship with neighbouring regions and other university systems could be taken into account via spatial regression models.

CRediT authorship contribution statement

F. Caviggioli: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Validation, Supervision, Funding acquisition. **A. Colombelli:** Conceptualization, Writing – original draft, Writing – review & editing. **A. De Marco:** Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Validation. **G. Scellato:** Conceptualization, Methodology, Formal analysis, Validation, Supervision, Funding acquisition. **E. Ughetto:** Conceptualization, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Acknowledgements

This paper was supported by the research project entitled "*University research funding, patenting and technological Impact*" financed by the Academic Research Programme (ARP) of the European Patent Office (EPO) under grant no. 2018/8401. Any opinions, findings, conclusions, or recommendations expressed in this work are those of the authors and do not necessarily reflect the views of the EPO.

Appendix A

Table 8
Number of examined regions and universities by country and corresponding total portfolio of patent families.

Sample	Regions			Universities		
Country	Count	Share	Patent families	Count	Share	Patent families
Austria (AT)	6	2.3 %	22,996	16	3.7 %	1153
Belgium (BE)	9	3.5 %	29,543	10	2.3 %	3059
Bulgaria (BG)	1	0.4 %	421	3	0.7 %	69
Switzerland (CH)	7	2.7 %	64,716	12	2.8 %	3273
Czechia (CZ)	2	0.8 %	1452	6	1.4 %	1112
Germany (DE)	57	22.3 %	281,131	79	18.5 %	16,764
Denmark (DK)	5	2.0 %	21,425	7	1.6 %	1598
Estonia (EE)	1	0.4 %	412	2	0.5 %	121
Spain (ES)	22	8.6 %	28,217	36	8.4 %	8190
France (FR)	21	8.2 %	174,007	44	10.3 %	9200
Greece (GR)	2	0.8 %	808	5	1.2 %	50
Croatia (HR)	1	0.4 %	465	4	0.9 %	42
Hungary (HU)	5	2.0 %	3732	9	2.1 %	387
Ireland (IE)	5	2.0 %	6887	11	2.6 %	1419
Italy (IT)	32	12.5 %	88,693	42	9.8 %	3464
Lithuania (LT)	1	0.4 %	210	2	0.5 %	205
Latvia (LV)	1	0.4 %	2700	1	0.2 %	78
Latvia (LU)	1	0.4 %	272	2	0.5 %	662
Malta (MT)	1	0.4 %	225	1	0.2 %	25

(*continued on next page*)

Table 8 (*continued*)

Sample	Regions			Universities		
Country	Count	Share	Patent families	Count	Share	Patent families
Netherlands (NL)	11	4.3 %	70,230	19	4.4 %	3071
Poland (PL)	6	2.3 %	3730	17	4.0 %	11,528
Portugal (PT)	4	1.6 %	2028	8	1.9 %	952
Romania (RO)	1	0.4 %	443	2	0.5 %	336
Slovenia (SI)	2	0.8 %	1403	2	0.5 %	311
Slovakia (SK)	2	0.8 %	566	4	0.9 %	505
United Kingdom (GB)	50	19.5 %	110,984	84	19.6 %	13,302
Total	256	100.0 %	917,696	428	100.0 %	80,876

Note that patent families have been counted multiple times when associated with more than one region or university.

Table 9
Examples of construction for the UTE variable.

Year	1	2	3	4	5	6	7	8	9	10	11	12	13
Technology A													
University patent families		2	1	5						3		1	9
Start of UTE	0	1	0	0	0	0	0	0	0	1	0	0	0
UTE (five-year persistence)	0	1	1	1	1	1	0	0	0	1	1	1	1
Technology B													
University patent families	3			2		4						2	9
Start of UTE	1	0	0	0	0	0	0	0	0	0	0	1	0
UTE (five-years persistence)	1	1	1	1	1	0	0	0	0	0	0	1	1

A.1. Measures of technological distance employed for robustness tests

The angular (or cosine) technological distance (ATD) is computed between the specialization vectors of the region and the university system in the focal year. ATD_{it} is defined as one minus the cosine of the angle between s^R_{ijt} and s^U_{ijt}:

$$ATD_{it} = 1 - \frac{\sum_j s^R_{ijt} s^U_{ijt}}{\sqrt{\left(\sum_j {s^R_{ijt}}^2\right)\left(\sum_j {s^U_{ijt}}^2\right)}}$$

The min-complement technological distance (CTD) is computed between the specialization vectors of the region and the university system in the focal year. CTD_{it} is given by one minus the sum of the minimum values for each component of the specialization vectors:

$$CTD_{it} = 1 - \sum_j min\left\{s^R_{ijt}, s^U_{ijt}\right\}$$

Table 10 reports the summary statistics for the two alternative measures of technological distance.

Table 10
Summary statistics.

Variable	Count	Mean	Median	SD	Min	Max
ATD	2,556,639	0.722	0.757	0.209	0.100	1.000
CTD	2,556,639	0.840	0.859	0.124	0.429	1.000

A.2. Robustness tests

In Table 11 we report the results of the models including the lagged dependent variable (RTS) among the regressors. This test is performed since the process of specialization is driven by the local accumulation of competencies and knowledge while our empirical approach considers the entry of universities as exogenous. The lagged RTS tries to disentangle the presence of a pre-existing endogenous local trend.[20]

[20] We thank one of the anonymous reviewers for suggesting the inclusion of this test.

Table 11
Relationship with the region technological specialization (RTS), specifications including the lagged RTS among the regressors.

Model	(1)	(2)
RTS (lagged)	0.002	0.002
	(0.001)	(0.001)
UTE	0.009***	0.009***
	(0.002)	(0.002)
ETD	−0.018***	−0.013***
	(0.003)	(0.003)
Cumulated university patent families (log)		0.005***
		(0.001)
Population (log)	0.014	0.018
	(0.012)	(0.012)
Regional GVA per capita (log)	0.052***	0.052***
	(0.004)	(0.004)
Year dummies	Yes	Yes
Observations	2,130,336	2,130,336
Average group size	13.759	13.759
R-squared within model	0.0005	0.0005
R-squared between model	0.0858	0.0796
R-squared overall model	0.0324	0.0311

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 12
Relationship with the region technological specialization (RTS), specifications including a dummy for observations having lagged RTS equal to minus one (i.e., no patent families) among the regressors.

Model	(1)	(2)
No region patent families dummy (lagged)	0.000	0.001
	(0.002)	(0.002)
UTE	0.009***	0.009***
	(0.002)	(0.002)
ETD	−0.020***	−0.012***
	(0.003)	(0.003)
Cumulated university patent families (log)		0.005***
		(0.001)
Population (log)		0.019
		(0.012)
Regional GVA per capita (log)		0.051***
		(0.004)
Year dummies	Yes	Yes
Observations	2,238,718	2,179,168
Average group size	13.954	13.964
R-squared within model	0.0004	0.0005
R-squared between model	0.0549	0.0670
R-squared overall model	0.0039	0.0259

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 13
Relationship with the region technological specialization (RTS), specifications with alternative technological distances.

Model	(1)	(2)	(3)	(4)
UTE	0.010***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
ATD	−0.012***	−0.009***		
	(0.002)	(0.002)		
CTD			−0.027***	−0.019***
			(0.004)	(0.004)
Cumulated university patent families (log)		0.006***		0.005***
		(0.001)		(0.001)
Population (log)		0.018		0.017
		(0.012)		(0.012)
Regional GVA per capita (log)		0.050***		0.050***
		(0.004)		(0.004)
Year dummies	Yes	Yes	Yes	Yes
Observations	2,238,718	2,179,168	2,238,718	2,179,168
Average group size	13.954	13.964	13.954	13.964
R-squared within model	0.0004	0.0005	0.0004	0.0005
R-squared between model	0.0792	0.0702	0.0569	0.0696
R-squared overall model	0.0053	0.0270	0.0053	0.0267

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. Models (1) and (2) include the angular technological distance (ATD), models (3) and (4) the min-complement technological distance (CTD). All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 14
Relationship with the region technological specialization (RTS), specifications with different persistences of UTE.

Model	(1)	(2)	(3)	(4)
Persistence of UTE	One year		Three years	
UTE	0.007**	0.007**	0.010***	0.009***
	(0.003)	(0.003)	(0.002)	(0.002)
ETD	−0.020***	−0.012***	−0.020***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Cumulated university patent families (log)		0.005***		0.005***
		(0.001)		(0.001)
Population (log)		0.019		0.019
		(0.012)		(0.012)
Regional GVA per capita (log)		0.051***		0.051***
		(0.004)		(0.004)
Year dummies	Yes	Yes	Yes	Yes
Observations	2,238,718	2,179,168	2,238,718	2,179,168
Average group size	13.954	13.964	13.954	13.964
R-squared within model	0.0004	0.0005	0.0004	0.0005
R-squared between model	0.0347	0.0649	0.0562	0.0676
R-squared overall model	0.0023	0.0251	0.0036	0.0261

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in the previous year in models (1) and (2) or in the previous three years in models (3) and (4). ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 15
Relationship with the region technological specialization (RTS), specifications with different sets of geographical dummies among the regressors and random effects.

Model	(1)	(2)	(3)	(3)
UTE	0.052***	0.053***	0.053***	0.053***
	(0.002)	(0.002)	(0.002)	(0.002)
ETD	−0.072***	−0.029***	−0.011***	−0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Cumulated university patent families (log)	−0.008***	−0.002***	0.003***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
Population (log)	0.055***	0.090***	−0.010	−0.010
	(0.001)	(0.001)	(0.011)	(0.011)
Regional GVA per capita (log)	0.127***	0.071***	0.027***	0.027***
	(0.002)	(0.002)	(0.003)	(0.003)
Country dummies	No	Yes	No	Yes
Region dummies	No	No	Yes	Yes

(continued on next page)

Table 15 (*continued*)

Model	(1)	(2)	(3)	(3)
Year dummies	Yes	Yes	Yes	Yes
Observations	2,179,168	2,179,168	2,179,168	2,179,168
Average group size	13.964	13.964	13.964	13.964
R-squared within model	0.0002	0.0002	0.0001	0.0001
R-squared between model	0.0808	0.1152	0.1465	0.1465
R-squared overall model	0.0308	0.0456	0.0584	0.0584

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Models (2) and (3) include respectively country and region dummies whereas model (4) includes both. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 16

Relationship with the region technological specialization (RTS), specifications on different clusters of universities by degree of technical orientation.

Model	(1)	(2)	(3)	(3)
University cluster	Lower technical orientation		Higher technical orientation	
UTE	0.007**	0.006**	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
ETD	−0.020***	−0.008	−0.021***	−0.015***
	(0.005)	(0.005)	(0.004)	(0.005)
Cumulated university patent families (log)		0.006***		0.005***
		(0.002)		(0.001)
Population (log)		0.070***		0.001
		(0.017)		(0.018)
Regional GVA per capita (log)		0.111***		0.011**
		(0.007)		(0.005)
Year dummies	Yes	Yes	Yes	Yes
Observations	1,022,567	982,077	1,197,687	1,178,627
Average group size	13.713	13.747	14.155	14.139
R-squared within model	0.0005	0.0009	0.0004	0.0004
R-squared between model	0.0318	0.0581	0.1072	0.0719
R-squared overall model	0.0026	0.0223	0.0069	0.0182

RTS is the dependent continuous variable based on NRTA that measures the technological specialization of local firms (per field and year). UTE is a dummy variable that captures the entry of universities into a technology field in any of the previous five years. ETD is the Euclidean technological distance between the portfolios of the region and the local university system. All the regressors are lagged one period. Models (1) and (2) refer to the sub-sample of universities with a lower degree of technical orientation whereas models (3) and (4) refer to the sub-sample of universities with a higher degree of technical orientation. Standard errors are reported in parentheses. Stars from one to three indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

References

Acosta, M., Coronado, D., León, M.D., Martínez, M.Á., 2009. Production of university technological knowledge in european regions: evidence from patent data. Reg. Stud. 43 (9), 1167–1181.

Agrawal, A., Cockburn, I., 2003. The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems. Int. J. Ind. Organ. 21 (9), 1227–1253.

Aksoy, A.Y., Pulizzotto, D., Beaudry, C., 2022. University-industry partnerships in the smart specialisation era. Technol. Forecast. Soc. Chang. 176, 121438.

Anselin, L., Varga, A., Acs, Z., 2000. Geographical spillovers and university research: a spatial econometric perspective. Growth Chang. 31 (4), 501–515.

Arundel, A., Geuna, A., 2004. Proximity and the use of public science by innovative european firms. Econ. Innov. New Technol. 13 (6), 559–580.

Asheim, B.T., Smith, H.L., Oughton, C., 2011. Regional innovation systems: theory, empirics and policy. Reg. Stud. 45 (7), 875–891.

Audretsch, D.B., Keilbach, M., Lehmann, E., 2006. Entrepreneurship and Economic Growth. Oxford University Press, New York.

Balassa, B., 1965. Trade liberalisation and revealed comparative advantage. Manch. Sch. 33 (2), 99–123.

Bar, T., Leiponen, A., 2012. A measure of technological distance. Econ. Lett. 116 (3), 457–459.

Benner, M., Waldfogel, J., 2008. Close to you? Bias and precision in patent-based measures of technological proximity. Res. Policy 37 (9), 1556–1567.

Bonaccorsi, A., Colombo, M.G., Guerini, M., Rossi-Lamastra, C., 2013. University specialization and new firm creation across industries. Small Bus. Econ. 41 (4), 837–863.

Boschma, R., 2005. Proximity and innovation: a critical assessment. Reg. Stud. 39 (1), 61–74.

Boschma, R., 2014. Constructing regional advantage and smart specialisation: comparison of two European policy concepts. Sci. Reg. 13 (1), 51–68.

Boschma, R., 2017. Relatedness as driver of regional diversification: a research agenda. Reg. Stud. 51 (3), 351–364.

Boschma, R., Frenken, K., 2011. Technological relatedness and regional branching. In: Bathelt, H., Feldman, M., Kogler, D. (Eds.), Beyond Territory: Dynamic Geographies of Knowledge Creation, Diffusion and Innovation. Routledge, New York, pp. 64–81 ch. 4.

Boschma, R., Minondo, A., Navarro, M., 2013. The emergence of new industries at the regional level in Spain: a proximity approach based on product relatedness. Econ. Geogr. 89 (1), 29–51.

Boschma, R., Coenen, L., Frenken, K., Truffer, B., 2017. Towards a theory of regional diversification: combining insights from evolutionary economic geography and transition studies. Reg. Stud. 51 (1), 31–45.

Braczyk, H.J., Cooke, P., Heidenreich, M., 1998. Regional Innovation Systems: The Role of Governances in a Globalized World. University College London Press, London.

Braunerhjelm, P., 2008. Specialization of regions and universities: the new versus the old. Ind. Innov. 15 (3), 253–275.

Breschi, S., Lissoni, F., Malerba, F., 2003. Knowledge-relatedness in firm technological diversification. Res. Policy 32 (1), 69–87.

Calderini, M., Scellato, G., 2005. Academic research, technological specialization and the innovation performance in european regions: an empirical analysis in the wireless sector. Ind. Corp. Chang. 14 (2), 279–305.

Carree, M., Della Malva, A., Santarelli, E., 2014. The contribution of universities to growth: empirical evidence for Italy. J. Technol. Transf. 39 (3), 393–414.

Cassia, L., Colombelli, A., 2008. Do universities knowledge spillovers impact on new firm's growth? Empirical evidence from UK. Int. Entrep. Manag. J. 4 (4), 453–465.

Caviggioli, F., De Marco, A., Montobbio, F., Ughetto, E., 2020. The licensing and selling of inventions by US universities. Technol. Forecast. Soc. Chang. 159, 120189.

Caviggioli, F., Colombelli, A., De Marco, A., Scellato, G., Ughetto, E., 2022. Pattern of co-evolution of university patenting and technological specialization in european regions. J. Technol. Transf. 1–22.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128–152.

Colombelli, A., Krafft, J., Quatraro, F., 2013. Properties of knowledge base and firm survival: evidence from a sample of french manufacturing firms. Technol. Forecast. Soc. Chang. 80 (8), 1469–1483.

Colombelli, A., Krafft, J., Quatraro, F., 2014. The emergence of new technology-based sectors in European regions: a proximity-based analysis of nanotechnology. Res. Policy 43 (10), 1681–1696.
Colombelli, A., Paolucci, E., Ughetto, E., 2019. Hierarchical and relational governance and the life cycle of entrepreneurial ecosystems. Small Bus. Econ. 52 (2), 505–521.
Colombelli, A., De Marco, A., Paolucci, E., Ricci, R., Scellato, G., 2021. University technology transfer and the evolution of regional specialization: the case of Turin. J. Technol. Transf. 46 (4), 933–960.
Cooke, P., 2001. Regional innovation systems, clusters, and the knowledge economy. Ind. Corp. Chang. 10 (4), 945–974.
Cooke, P., Morgan, K., 1999. The Associational Economy: Firms, Regions, and Innovation. Oxford University Press, Oxford.
Cooke, P., Uranga, M.G., Etxebarria, G., 1997. Regional innovation systems: institutional and organisational dimensions. Res. Policy 26 (4–5), 475–491.
Coronado, D., Flores, E., Martínez, M.Á., 2017. The role of regional economic specialization in the production of university-owned patents. Ann. Reg. Sci. 59 (2), 513–533.
Crescenzi, R., Dyevre, A., Neffke, F., 2022. Innovation catalysts: how multinationals reshape the global geography of innovation. Econ. Geogr. 98 (3), 199–227.
D'Agostino, L.M., Laursen, K., Santangelo, G., 2013. The impact of R&D offshoring on the home knowledge production of OECD investing regions. J. Econ. Geogr. 13 (1), 145–175.
D'Este, P., Patel, P., 2007. University-industry linkages in the UK: what are the factors underlying the variety of interactions with industry? Res. Policy 36 (9), 1295–1313.
Elekes, Z., Boschma, R., Lengyel, B., 2019. Foreign-owned firms as agents of structural change in regions. Reg. Stud. 53 (11), 1603–1613.
Essletzbichler, J., 2015. Relatedness, industrial branching and technological cohesion in US metropolitan areas. Reg. Stud. 49 (5), 752–766.
Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: from national systems and mode two to a triple helix of university-industry-government relations. Res. Policy 29 (2), 109–123.
Fisch, C.O., Hassel, T.M., Sandner, P.G., Block, J.H., 2015. University patenting: a comparison of 300 leading universities worldwide. J. Technol. Transf. 40 (2), 318–345.
Fleming, L., 2001. Recombinant uncertainty in technological search. Manag. Sci. 47 (1), 117–132.
Fleming, L., Sorenson, O., 2004. Science as a map in technological search. Strateg. Manag. J. 25 (8–9), 909–928.
Foray, D., 2014. Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy. Routledge, New York.
Foray, D., David, P.A., Hall, B., 2009. Smart Specialisation: The Concept. Policy Brief. École Polytechnique Fédérale de Lausanne.
Foray, D., David, P.A., Hall, B.H., 2011. Smart Specialisation From Academic Idea to Political Instrument, the Surprising Career of a Concept and the Difficulties Involved in its Implementation. Working Paper. École Polytechnique Fédérale de Lausanne.
Forliano, C., De Bernardi, P., Yahiaoui, D., 2021. Entrepreneurial universities: a bibliometric analysis within the business and management domains. Technol. Forecast. Soc. Chang. 165, 120522.
Frenken, K., Boschma, R., 2007. A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. J. Econ. Geogr. 7 (5), 635–649.
Frenken, K., van Oort, F., Verburg, T., 2007. Related variety, unrelated variety and regional economic growth. Reg. Stud. 41 (5), 685–697.
Fritsch, M., Slavtchev, V., 2007. Universities and innovation in space. Ind. Innov. 14 (2), 201–218.
Gunasekara, C., 2006. The generative and developmental roles of universities in regional innovation systems. Sci. Public Policy 33 (2), 137–150.
Hansen, M.T., 1999. The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits. Adm. Sci. Q. 44 (1), 82–111.
Heimeriks, G., Balland, P.A., 2016. How smart is specialisation? An analysis of specialisation patterns in knowledge production. Sci. Public Policy 43 (4), 562–574.
Isenberg, D., 2010. How to start an entrepreneurial revolution. Harv. Bus. Rev. 88 (6), 40–50.
Jaffe, A., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. Am. Econ. Rev. 76 (5), 984–1001.
Jaffe, A., 1989. Real effects of academic research. Am. Econ. Rev. 79 (5), 957–970.
Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108 (3), 577–598.
Kogler, D.F., 2017. Relatedness as driver of regional diversification: a research agenda – a commentary. Reg. Stud. 51 (3), 365–369.
Kummitha, R.K.R., 2020. Why distance matters: the relatedness between technology development and its appropriation in smart cities. Technol. Forecast. Soc. Chang. 157, 120087.
Laursen, K., 2015. Revealed comparative advantage and the alternatives as measures of international specialization. Eurasian Bus. Rev. 5 (1), 99–115.
Laursen, K., Reichstein, T., Salter, A., 2011. Exploring the effect of geographical proximity and university quality on university–industry collaboration in the United Kingdom. Reg. Stud. 45 (4), 507–523.
Lissoni, F., Llerena, P., McKelvey, M., Sanditov, B., 2008. Academic patenting in Europe: new evidence from the KEINS database. Res. Eval. 17 (2), 87–102.
Lissoni, F., Pezzoni, M., Potì, B., Romagnosi, S., 2013. University autonomy, the professor privilege and academic patenting: Italy, 1996–2007. Ind. Innov. 20 (5), 399–421.
Malerba, F., Montobbio, F., 2003. Exploring factors affecting international technological specialization: the role of knowledge flows and the structure of innovative activity. J. Evol. Econ. 13 (4), 411–434.
Mansfield, E., 1998. Academic research and industrial innovation: an update of empirical findings. Res. Policy 26 (7), 773–776.
Maskell, P., Malmberg, A., 1999. Localised learning and industrial competitiveness. Camb. J. Econ. 23 (2), 167–185.
McCann, P., Ortega Argilés, R., 2015. Smart specialization, regional growth and applications to European Union cohesion policy. Reg. Stud. 49 (8), 1291–1302.
Neffke, F., Henning, M., Boschma, R., 2011. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. Econ. Geogr. 87 (3), 237–265.
Neffke, F., Hartog, M., Boschma, R., Henning, M., 2018. Agents of structural change: the role of firms and entrepreneurs in regional diversification. Econ. Geogr. 94 (1), 23–48.
Perkmann, M., Walsh, K., 2007. University-industry relationships and open innovation: towards a research agenda. Int. J. Manag. Rev. 9 (4), 259–280.
Ponds, R., van Oort, F., Frenken, K., 2009. Innovation, spillovers and university-industry collaboration: an extended knowledge production function approach. J. Econ. Geogr. 10 (2), 231–255.
Rigby, D.L., 2015. Technological relatedness and knowledge space: entry and exit of US cities from patent classes. Reg. Stud. 49 (11), 1922–1937.
Rigby, D.L., Essletzbichler, J., 1997. Evolution, process variety, and regional trajectories of technological change in US manufacturing. Econ. Geogr. 73 (3), 269–284.
Shane, S.A., 2004. Academic Entrepreneurship: University Spinoffs and Wealth Creation. Edward Elgar, Cheltenham.
Simon, H., Sick, N., 2016. Technological distance measures: new perspectives on nearby and far away. Scientometrics 107 (3), 1299–1320.
Soete, L., 1987. The impact of technological innovation on international trade patterns: the evidence reconsidered. Res. Policy 16 (2–4), 101–130.
Soete, L., Wyatt, S., 1983. The use of foreign patenting as an internationally comparable science and technology output indicator. Scientometrics 5 (1), 31–54.
Spigel, B., 2017. The relational organization of entrepreneurial ecosystems. Enterp. Theory Pract. 41 (1), 49–72.
Tanner, A.N., 2015. Regional branching reconsidered: emergence of the fuel cell industry in European regions. Econ. Geogr. 90 (4), 403–427.
Tötterman, H., Sten, J., 2005. Start-ups: business incubation and social capital. Int. Small Bus. J. 23 (5), 487–511.
van den Berge, M., Weterings, A., 2014. Relatedness in eco-technological development in European regions. Pap. Evol. Econ. Geogr. 14 (13), 1–30.
Van Looy, B., Vereyen, C., Schmoch, U., 2014. Patent Statistics: Concordance IPC V8-NACE R2. Eurostat, European Commission, Luxembourg.
Zucker, L.G., Darby, M.R., Armstrong, J., 1998. Geographically localized knowledge: spillovers or markets? Econ. Inq. 36 (1), 65–86.

F. Caviggioli is Associate Professor at the Department of Management and Production Engineering of Politecnico di Torino (Italy). He holds a Ph.D. in Economics and Management of Technology at the University of Bergamo (Italy). His research focuses on the economics of innovation, technology strategy, the market for technologies, patent data intelligence, and the quality of patent systems. Quantitative analysis and patent data treatment are among his main skills. He published in international journals such as Research Policy, Industry and Innovation, Technovation, and Technological Forecasting and Social Change. He contributed to research projects funded by the European Commission, national institutions, and companies.

A. De Marco holds a Ph.D. in Economics and Complexity from Collegio Carlo Alberto (Italy) and a M.Sc. in Management Engineering at Politecnico di Torino (Italy). He is Tenure-track Assistant Professor at the Interuniversity Department of Regional and Urban Studies and Planning of Politecnico di Torino. He contributed to research project funded by the European Patent Office, the Joint Research Center, and the European Commission. His research interests are in the areas of the economics of innovation, the markets for technology, the management of intellectual property rights, and the economics of technical standards. Such topics are investigated with an empirical perspective and micro-econometric techniques. His scientific works are published in refereed international journals such as Research Policy, Technological Forecasting and Social Change, Economics of Innovation and New Technology, and the Journal of Technology Transfer.

A. Colombelli is Full Professor at Politecnico di Torino, where she teaches strategy and organization and business management. She holds a Ph.D. in Economics and Management of Technology and a M.Sc. in Management Engineering from the University of Bergamo (Italy). She is member of the Entrepreneurship and Innovation Center (EIC) at Politecnico di Torino, Research Associate at the CNRS-GREDEG University of Nice Sophia Antipolis and the Bureau of Research on Innovation Complexity and Knowledge (BRICK) at Collegio Carlo Alberto. She serves as Technical Assessor at the Innovative Companies Incubator of Politecnico di Torino (I3P). She was formerly Marie Curie Fellow at the Manchester Business School, Research Associate at the University of Cagliari, Postdoctoral Fellow at the University Lumière Lyon 2 and the University of Torino.

G. Scellato holds a Ph.D. in Economics and is Full Professor at Politecnico di Torino, where he teaches corporate finance and economics and management of innovation. From 2015 to 2018, he has been the Vice Dean of the Faculty of Industrial Engineering and Management. Since 2018, he is the president and CEO of the Innovative Companies Incubator (I3P) of Politecnico di Torino. Since 2017, he is a member of the board of the Future Urban Legacy Lab (FULL) at Politecnico di Torino. Since 2008, he is research affiliate of the Bureau of Research on Innovation Complexity and Knowledge (BRICK) at Collegio Carlo Alberto. His main research interests are in the areas of economics and management of innovation, industry dynamics, the economic analysis of intellectual property rights, and the economics of science. His scientific publications have appeared in leading international journals, including Science, Nature, Journal of Management Studies, Journal of Corporate Finance, Research Policy, Journal of Banking and Finance, Journal of Business Research, and Cambridge Journal of Economics.

E. Ughetto is Full Professor at Politecnico di Torino, Department of Management and Production Engineering and Research Associate at the Bureau of Research on Innovation Complexity and Knowledge (BRICK), Collegio Carlo Alberto and at the Entrepreneurship and Innovation Center (EIC), Politecnico di Torino. She has a Ph.D. in Economics and Management of Technology from the University of Bergamo and teaches Accounting and Corporate Finance and Organizational Models and HRM at undergraduate level. She serves as Associate Editor for the Journal of Small Business Management and is a member of the Editorial Review Board of Small Business Economics. She has been visiting scholar at the Washington University in Saint Louis (US), the European Investment Fund (LU), and visiting professor at the University of Augsburg (DE). In April 2019, she was visiting professor at Iaelyon School of Management, Université de Lyon Jean Moulin.