University technological output and industrial specialization in Italian regions

Annals of Economics and Statistics, Number 153, March 2024

UNIVERSITY TECHNOLOGICAL OUTPUT AND INDUSTRIAL SPECIALIZATION IN ITALIAN REGIONS

ANTONIO DE MARCO[a] AND FEDERICO CAVIGGIOLI[b]

Regional specialization is a complex evolutionary process in which new industries and technologies evolve from existing ones following a non-ergodic path-dependent branching process. Although the scientific literature acknowledges the role of universities in shaping both the industrial and technological trajectories of geographical regions, empirical studies analyzing the link with the emergence of a local industrial specialization are relatively few. Our work contributes to filling this gap by investigating the relationship between the stock of patents developed by universities in a specific technology and the subsequent industrial specialization of the hosting region in the same domain. The empirical setting focuses on all Italian provinces (i.e., the geographical areas at the third level of the NUTS classification) in the years from 1995 to 2018. We examine the effect of the local and the neighboring knowledge stocks on subsequent industry specializations identified through the revealed technology advantage index. The results indicate the presence of a positive and significant correlation, robust to the inclusion of multiple fixed effects and several alternative model specifications. Instrumental variable regressions suggest that a causal relationship is likely to exist. Patent stocks of universities located in neighboring geographical areas have also a positive impact on the specialization, although of a smaller magnitude. Moreover, the patenting activity of local universities has an additional positive effect in both southern geographical areas and academies with lower internationalization levels whereas no significant premium or penalty is detected for high-tech and low-tech patent fields.

JEL Codes: O32, O33, O34, R10, R12.
Keywords: University Patents, Regional Branching, Technological Specialization, Spillover Effect, Knowledge Stock.

1. INTRODUCTION

This study provides further empirical support to the claim that the technological output of academies is positively correlated to the specialization of firms within the same region: universities can have a role in shaping the process of technological specialization locally. We use geolocalized patent data to precisely measure and characterize both the innovation output of local academic institutions and the specialization of companies. To this goal, we focused on Italy, which represents a useful case study for several reasons[1]: the choice of a single country provides a homogenous environment in terms of national innovation policies, while, at the same time, the Italian context is characterized by heterogeneous innovation development stages across regions and is well known for its industrial districts in traditional industries (Becattini, 2017). Also, previous studies have empirically documented the existence of a link between university institutions and the local economic

[a]Politecnico di Torino, Interuniversity Department of Regional and Urban Studies and Planning. `antonio.demarco@polito.it`
[b]Politecnico di Torino, Department of Management and Production Engineering. `federico.caviggioli@polito.it`

[1] Further details are reported in Section 2.3 of the paper.

context in Italy (Carree et al., 2014; Colombelli et al., 2019).

In recent years, scholars and policy makers have devoted increasing attention to studying the processes through which geographical areas develop and specialize over time as a tool to boost innovation activities and economic growth. Regions evolve via a branching process in which new industries, technologies, and scientific domains are created from the related existing ones (Boschma and Frenken, 2012; Frenken and Boschma, 2007). Under this perspective, specialization is considered a path-dependent process stemming from accumulated and related technological competencies: this theoretical framework has been confirmed in different geographical contexts (e.g., Boschma et al., 2013; Colombelli et al., 2014; Neffke et al., 2011). For these reasons, regional branching has been gradually adopted as the scientific background of numerous European policies based on the concept of *smart specialization strategies* (Boschma, 2014; Boschma and Gianelle, 2014), with the objective to detect areas of intervention, leverage local strengths, increase the levels of innovation activities, and support the economic growth (Foray, 2014).

Several types of key actors participate in the local innovation ecosystems: firms, regulators, financial institutions, venture capitalists, business angels, universities, and startup incubators (De Vasconcelos Gomes et al., 2018; Dias Sant'Ana et al., 2020; Mason and Pierrakis, 2013; Sun et al., 2019). Within such ecosystems, the *anchor tenant* plays a central role in spurring the innovation activities (Agrawal and Cockburn, 2003) and often coincides with the local university system (Tötterman and Sten, 2005). Universities support local innovation by transferring the knowledge they generate through different channels, such as scientific publications, education of skilled individuals, and research collaborations with companies (D'Este and Patel, 2007; Gunasekara, 2006).

The relationship between the technological specializations of academies and regions has been investigated in a limited number of studies (Caviggioli et al., 2022). The findings of the few empirical works that approach the topic quantitatively are mixed. Calderini and Scellato (2005) analyzed 33 regions located in European member countries and specialized in the ICT sector and showed that there is a causal relationship between scientific articles and the patenting activity of local companies in ICT-related domains. Braunerhjelm (2008) documented a positive statistical correlation between the specialization in *Medicine* and *Engineering* of 4 universities and the industrial specialization of Swedish regions. Acosta et al. (2009) reported no correlation between the specializations of the university patent portfolio and that of the industry in 200 regions of the EU. Coronado et al. (2017) focused on reverse spillovers indicating that an aggregate measure of specialization based on employment in high-tech sectors has a causal impact on the number of subsequent university patents in similar technological fields, but they did not find any significant relationship for mid-tech and low-tech sectors. Finally, the recent work from Caviggioli et al. (2023) analyzed the patenting activities of 250 geographical areas in Europe hosting the top universities by funding received from the EU and discovered a positive and significant correlation between the entry of academic institutions into a technological field, proxied by a new-to-the-sector patent filing, and the subsequent technological specialization in the same domain.

With respect to extant studies, we contribute to the literature on several grounds. First, we introduce variables that capture two important characteristics of knowledge: cumulativeness and stickiness. Concerning the former, we rely on the technology-specific patent stock of universities to evaluate the subsequent industrial specialization in the same field, using the same classification. As regards the latter, our econometric models consider the technological output of neighboring spatial units, introducing also the geographical dimension into the analyses. Moreover, the empirical setting covers the years from 1994 to 2018 and examines the patenting activities in a specific technological field of all the Italian provinces at the third level of the NUTS system[2] as well as all the Italian universities, identified by scanning the applicants. Extending the approach of previous studies, our econometric specifications incorporate multiple fixed effects which support the robustness of the results on top of the unobserved regional and technological specificities, time trends, and their combinations. Finally, we also considered instrumental variable regressions to account for potential endogeneity and reinforce the interpretation of the findings in terms of causality.

We document the presence of a positive causal relationship between the stock of university patents, generated by academic institutions located in the the focal geographical area (with a larger magnitude) and those found in neighboring ones (with a smaller magnitude), and the subsequent technological specialization of local firms. The empirical results are robust to several tests with different fixed effects, region-level time-variant controls, lagging the dependent variable, and focusing on another regressand based on the number of patents instead of industrial specialization. We have performed additional analyses with the aim to provide further clarifications on potentially relevant regional characteristics, i.e., comparing Northern and Southern provinces (the most heterogenous areas in Italy), the degree of international orientation of the local universities, and the level of technological complexity, i.e., high-tech versus low-tech sectors.

The remainder of the paper is structured as follows. A short account of the theoretical background underpinning the empirical analysis is provided in Section 2. Section 3 describes the framework and formulates the hypotheses. Section 4 presents data, methodology, and descriptive statistics on the sample whereas the results of the econometric models are reported in Section 5. The conclusion in Section 6 summarizes the findings and explores their implications.

[2] The *Nomenclature of Territorial Units for Statistics* (NUTS) classification is a hierarchical system used for dividing up the economic territory of both the EU and the UK where the third level regards the small regions for specific diagnoses. It is available online at `https://ec.europa.eu/eurostat/web/nuts` (last accessed in May 2023).

2. THEORETICAL BACKGROUND

2.1. *Regional specialization*

The scientific literature on regional branching and specialization found that technological development trajectories are driven by the *ex-ante* available capabilities (Boschma, 2017; Frenken and Boschma, 2007; Heimeriks and Balland, 2016; McCann and Ortega-Argilés, 2015; Neffke et al., 2011; Rigby, 2015; Van Den Berge and Weterings, 2014). In this framework, regions build their competitive advantages in economic sectors and technology fields for which they possess an existing knowledge base, leveraging their capabilities to jump into new and related activities more easily (e.g., Boschma et al., 2015; Guevara et al., 2016; Neffke et al., 2011). Such a perspective is grounded on the application of the recombinant knowledge theory to the regional domain (Fleming, 2001; Fleming and Sorenson, 2004). Accordingly, the knowledge base of a geographical area is the result of the combination of many different factors, which are much related to one another, reflecting the cumulative nature of innovation, the path-dependency (Dosi, 1993), and the existence of geographically bounded knowledge spillover mechanisms (Jaffe et al., 1993). Local dynamics involving individuals and organizations build around technological capabilities, competencies, and well-established routines that accumulate over time. In this context, regional ecosystems develop new fields of technological specialization not randomly but via the recombination of existing knowledge assets as building bricks (Hidalgo and Hausmann, 2009).

2.2. *Universities and local innovations*

The three key missions of academic institutions are teaching, research, and the activities that foster social, cultural, and economic growth. The development of the third mission (for a review, see Compagnucci and Spigarelli, 2020) is connected to the ratification of the Bayh-Dole Act in the US. Its approval in 1980 enabled universities to legally commercialize their research output (including patented inventions) resulting from governmental funds and encouraged them to convert their research into commodities and services to increase social development. These provisions influenced universities worldwide: many countries have since adopted a similar legislation (Link and van Hasselt, 2019) and progressively institutionalized the knowledge transfer process (Geuna and Muscio, 2009) in internal (technology transfer offices, also known as industrial liaison offices) and external organizational arrangements (science parks, business incubators, or accelerators) to locally bridge the gap between the university system and the industry. Etzkowitz and Leydesdorff (2000) define these new institutional arrangements as *triple helix* in which university, industry, and government assume overlapping roles and duties. Accordingly, modern entrepreneurial (Forliano et al., 2021) or engaged (Gunasekara, 2006) universities have been performing activities which traditionally belonged to the industry such as patenting and the creation of new ventures. Academic institutions seek to leverage their outputs (e.g., scientific papers, patents, spin-offs, talented graduates) to positively impact the industry in terms of productivity gains and business innovation (Goldstein and Renault, 2004). According to this conceptualization, academies integrate the three missions for being more adaptive and responsive to local needs (Uyarra, 2010) and for getting closer to regional economic development trajectories through the constant update of the educational offer, formal and informal mechanisms of technology transfer, the creation of networks involving the local industry, as well as via social and cultural development

(Piqué et al., 2020).

The extant literature addressed the relationship between the output of academic research and regional innovation performances and found positive results, either with direct or indirect role played by local universities. Academic knowledge can boost industrial development through formal collaborations with companies, technology transfer, and the foundation of spinoffs (Apa et al., 2021; Bragoli et al., 2024; García-Vega and Vicente Chirivella, 2020). At the same time, indirect knowledge spillover can flow via scientific papers, the education of skilled individuals (D'Este and Patel, 2007; Gunasekara, 2006; OECD, 2019), and the enhancement of capabilities exploited by firms (García-Vega and Vicente Chirivella, 2020; Kim et al., 2005).

Both quantitative studies that rely on the knowledge production functions (Acs et al., 1994; Fritsch and Slavtchev, 2007; Griliches, 1979; Leten et al., 2014) and qualitative approaches that are mainly based on data from surveys (e.g., Cohen et al., 2002; Laursen et al., 2011; Mansfield, 1991; Mansfield and Lee, 1996), provide robust evidence of the importance of geographical proximity between firms and universities to spur the innovation process. Spatial closeness is indeed crucial because the exchanged knowledge is cumulative, localized, and often tacit in nature (Antonelli, 1994). Companies can more easily access the results of academic research when they are in the same geographical area (Mansfield and Lee, 1996).

Moreover, geographical proximity may also strengthen other forms of closeness, such as cognitive, organizational, scientific, and technological proximity (Boschma, 2005; Hansen, 1999), that are essential to the learning process, the successful generation and exploitation of knowledge via recombination and exchange among organizations. Laursen et al. (2011) found that spatial closeness increases the likelihood of collaboration between universities and companies in general, especially for firms characterized by lower absorptive capacity. Hence, proximity can compensate for limited absorptive capacity, which is a catalyst for the identification and exploitation of new knowledge (Boschma, 2005).

2.3. *Italy*

Italy provides a useful and insightful case to empirically test the presence of a correlation between the technological output of academies and the subsequent industrial specialization of regions. The focus on a single country reduces the asymmetries due to different national innovation policies that may influence the statistical comparison in a cross-country setting (as in Caviggioli et al., 2023; Coronado et al., 2017). At the same time, Italy is characterized by a level of internal heterogeneity, especially comparing the areas located in the North with those in the South. Such internal differences are historically rooted (Felice, 2018) and deal with both institutional, social, and cultural aspects (Bigoni et al., 2019; De Santis et al., 2021). In particular, the South is associated with lower values in several measures of industrial productivity (Di Giacinto et al., 2014; Di Liberto et al., 2008; Felice, 2018), innovation, R&D (Cowan and Zinovyeva, 2013; Medda et al., 2004), and the scientific performance of universities (Abramo et al., 2016).

The country also provides a few distinctive features. In addition to the presence of industrial districts (Becattini et al., 1990), Italian regions exhibit a variety of both technological and industrial specializations that are associated with a broad range of idiosyncratic knowledge. The industrial structure is mostly composed of small and medium enterprises (SMEs). Although both large companies and start-ups benefit from academic research (Cohen et al., 2002), some studies highlighted that SMEs take more advantage of academic research than their larger counterpart since they rely on fewer R&D internal resources and competencies (Acs et al., 1994). In the Italian context, universities act as knowledge brokers for both SMEs and large companies, as highlighted in the case of Torino, where the local university system has played a crucial role in both the economic and industrial transformation of the region (Colombelli et al., 2019).

Concerning the patenting activities of academic institutions, they did not always occur with the same intensity, and only in the last two decades, the system started to be equipped with technology transfer offices, rules, and policies aiming at the valorization of innovations with a more industry-oriented approach[3].

Although the results from this empirical setting cannot be generalized globally, the focus on Italy allows to exclude potential time-varying country-specific differences, such as changes in innovation policies and patenting behaviors while, at the same time, maintain a certain degree of intra-national heterogeneity to analyze the relationship between university and industry technological orientation which could be similar in other geographical contexts.

In terms of spatial units, the Italian areas at the third level of the NUTS classifications are provinces[4]. Each geographical area is surrounded by neighboring ones, i.e., the provinces that share at least a border (i.e., either a vertex or an edge) with it[5]. Figure 1 provides an example of the employed characterization of contiguity.

Finally, our empirical approach in the identification of university patents in Italy reduces the risk of false positive results since patents are not assigned to technology transfer offices with no indication of the parent academic institution and the observed figures can be easily compared with those reported in both the PATIRIS repository[6] and with the aggregated counts of the self-reported data in the NETVAL surveys[7].

3. FRAMEWORK AND HYPOTHESES

3.1. *The relationship between university research and technological specialization*

The extant scientific literature provides mixed results on the relationship between academic research and industrial specialization. The examined frameworks, the operationalization of the main variables and the empirical tests are very different. Table I provides a summary of the findings and a direct comparison of the empirical contexts[8].

---

[3] The *Network for the Valorization of Research* (NETVAL) was established in 2002. It now includes more than 60 different higher education institutions. Furthermore, in the same year the so-called professor privilege was introduced (see Lissoni et al., 2013). Please note that our identification strategy for Italian universities does not seem to be affected by the introduction of such a rule, since, in almost all the cases, academics transfer their intellectual property rights to the university they are affiliated to.

[4] We use this term as a synonym for NUTS3 area in the rest of the article.

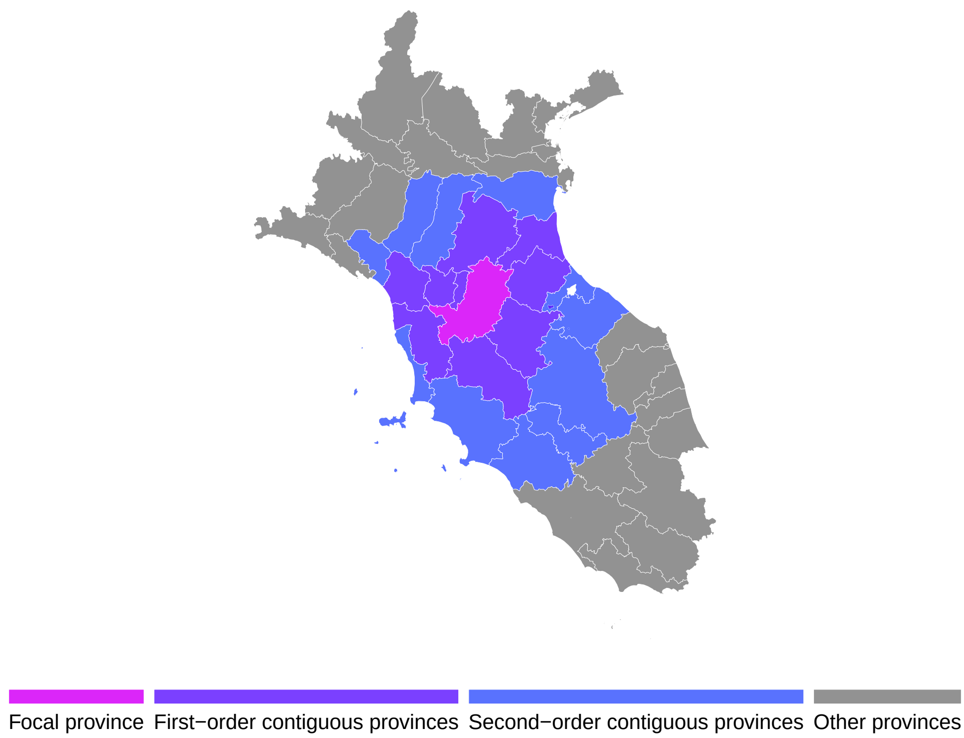
[5] Maritime areas and international borders are not considered.

[6] A permanent observatory collecting all patent applications filed by Italian universities and public research centers. The platform has been developed by the *Italian Patent and Trademark Office* (UIBM) in collaboration with the *Network for the Valorization of Research* (NETVAL) and the University of Bologna. Its micro data is available online at `https://patiris.mise.gov.it` (last accessed in October 2023).

[7] They aim to continuously monitor technology transfer processes implemented by all Italian universities through a questionnaire along with a specific annual report. Although individual micro data from each academic institution is not publicly disclosed, the overall self-reported trend of university patenting over time is available.

[8] The selected articles focus on the relationship between university and industry specializations and introduce specific variables to operationalize such measures. Additionally, two recent studies are worth

Figure 1: example of first and second-order queen contiguities



Calderini and Scellato (2005) analyzed industrial patenting activities in the ICT sector for a sample of 33 regions in EU member countries. The concept of specialization is introduced via the selection process that considered only geographical areas that were among the top recipients of EU funding in *Telecommunications* and with a relevant track of specific research papers. The authors found the presence of a causal relationship between the number of scientific publications and the subsequent patenting activity of local firms.

Braunerhjelm (2008) analyzed 70 labor markets in Sweden between 1975 and 1999 and focused on four economic sectors (i.e., *Drugs and medicines*, *Office and computing machinery*, *Professional and scientific instruments*, and *Metal products*). The study investigated the presence of universities and found a positive statistical correlation between specialized academies (in terms of the share of staff in medicine or engineering) and the corresponding industrial specialization of the region where the academic institution is located.

Acosta et al. (2009) found no significant correlation between university and industrial specializations (measured using the patent technological classification) in their descriptive statistics on a sample of 202 European regions during the years from 1998 to 2004.

mentioning as they address similar research questions, but their empirical settings do not investigate the link between the specializations directly. Aksoy et al. (2022) found a positive and significant association between the diversification of state-level patent portfolios and the aggregate count of licenses generating income and granted by a co-located academic institution (a proxy of successful knowledge transfer and patent commercialization). Caviggioli et al. (2022) proposed a measure of university technological push on the co-located firms by comparing the entries of academia in new fields and industrial specializations: this variable is studied with respect to university and region-level characteristics.

Coronado et al. (2017) studied the effects of the reverse spillover, i.e., whether a previous industrial specialization affects the subsequent university patenting in the same region. They found a positive causal relationship in high-tech sectors and no relationship in medium-low tech sectors. The analysis was carried out by considering universities as units in cross-sectional models with no regional fixed effects. Furthermore, the technological dimension is collapsed to the distinction between high-tech and mid/low-tech: the considered dependent variables were the average regional specialization in high-tech sectors only and mid/low-tech only respectively, thus aggregating many sectors in a single indicator.

The recent work from Caviggioli et al. (2023) found a significant and positive correlation between regional specialization in a technology domain and the previous entry of local universities into the same field, where the entry is measured through a new patent filing. The examined sample includes 256 European regions (NUTS3) selected as those hosting universities that are among the top receivers of EU funding.

TABLE I

SUMMARY OF PREVIOUS ARTICLES EMPIRICALLY INVESTIGATING THE RELATIONSHIP BETWEEN UNIVERSITIES AND CO-LOCATED FIRMS IN TERMS OF SPECIALIZATION

Article	**Geographical scope**	**Unit of analysis**	**Time frame**	**Industry measure**	**University measure**	**Results**
Calderini and Scellato (2005)	33 administrative regions (NUTS2) located in 15 European countries	Political region (all spatial units host at least a university)	Years from 1992 to 2001	Count of granted patents in ICT-related technical fields	Count of scientific papers in ICT-related research fields	Weakly significant causal link between university research and industry patents in ICT-related fields
Braunerhjelm (2008)	70 functional regions (local labor market areas) all located in Sweden	Labor market region (only 4 spatial units host universities)	Years from 1975 to 1999	Employee-based productive specialization in four sectors	Share of university staff in medicine and engineering	Positive and significant correlation between university research and industry specialization
Acosta et al. (2009)	202 administrative regions (NUTS2) located in 16 European countries	Region-technology (only 148 spatial units host universities)	Years from 1998 to 2004	Employee-based productive specialization of companies	Technological specialization based on university patents	No correlation between technological specialization of universities and industry specialization
Coronado et al. (2017)	360 universities located in European administrative regions (NUTS2)	Region-university (all spatial units host at least a university)	Years from 2001 to 2004	Industry specialization in high or mid-low tech fields	Count of university patents in high or mid-low tech fields	Significant causal link between university patents and industry specialization only in high-tech fields
Caviggioli et al. (2023)	256 administrative regions (NUTS3) located in 26 European countries	Region-technology (all spatial units host at least a university)	Years from 2002 to 2018	Patent-based technological specialization of companies	Technological entry (first patent filing) of universities	Positive and significant correlation between the entry of universities and industry specialization

Notes: the sample of Calderini and Scellato (2005) includes the best-performing regions by ICT funding; the empirical models of Braunerhjelm (2008) do not contain any fixed effects; Acosta et al. (2009) document the presence of a univariate correlation with a sample of 378 universities; Coronado et al. (2017) estimate models with cross sectional data and no regional fixed effects; Caviggioli et al. (2023) collect data on the 428 best-performing universities by EU funding in FP7.

Starting from the extant scientific literature, we formulate the first hypothesis that academic institutions do play a key role, acting as anchor tenants of the innovation ecosystem. We use the stock of university patent families to gauge the technological output of academic institutions. We argue that it provides a precise indication of the accumulated technical knowledge, thus representing a more comprehensive proxy in this context than the simple presence of a university in a given province or the filing of the first patent in a specific technology field. It also considers the evolutionary aspects and the potential delays in the knowledge flows between academic institutions and local companies. Hence, our first hypothesis is:

HP1: *the accumulated stock of academic technical knowledge in a technological domain (university patent families) is expected to be positively related to a subsequent specialization in the same field by the firms located in the same geographical area.*

A number of empirical studies have found a positive correlation between geographical distance and surrounding accumulated knowledge. In particular, the results of Moreno et al. (2005) suggest that both geographic proximity and technological similarity are important moderating factors in regional knowledge diffusion processes. Externalities originating from innovation activities and R&D efforts performed by firms in neighboring regions are found to matter, despite the marked presence of a spatial decay effect. Similarly, Paci et al. (2014) analyze the effect of different proximity dimensions (i.e., geographical, technological, social, and organizational) on the innovative capacity of European regions. All forms of closeness are proven to have a complementary function in explaining the flow of knowledge across space. By using data on patent citations with a gravity-like model, the study of Figueiredo et al. (2015) investigates the role of geographical distance on the diffusion of spillovers from innovation activities and finds that they are more likely to occur between geographically close patents.

According to such results, we extend the analyses by introducing the spatial dimension with the aim to disentangle the role of neighboring innovation ecosystems in the relationship between the local industry specialization and university patent stock. This element assumes particular relevance when considering small reference spatial units as the Italian provinces (the average size of these geographical areas is 2,740 squared kilometers).

Concerning the stock of knowledge generated by the universities neighboring the focal geographical area, we formulate the following two hypotheses:

HP2A: *the industrial specialization in a province is expected to be positively related to the patenting activities in the same technological field of universities located in neighboring provinces.*

HP2B: *the magnitude of the relationship between the technological specialization of companies and the patent stock of neighboring universities is expected to be smaller than the one with the academic institutions located in the focal province due to the increased geographical distance.*

Additionally, previous research suggests that both international collaboration and exposure to different cultures and ideas can lead to increased knowledge spillover (Civera et al., 2020; Iacobucci and Perugini, 2023; Ponds et al., 2009). The inward-looking perspective suggests that universities with a higher level of internationalization are expected to bring additional knowledge in the territory and favor its absorption locally. Hence, technological specializations should be observed more frequently. At the same time, internationally open and innovative academic institutions could favor the circulation of their own knowledge outwards the regional boundaries, reducing the chances of achieving local specialization in the same technological area where the university is patenting. Therefore, we propose the following hypothesis:

HP3: *the presence of highly internationalized local universities is more likely to induce technological specializations of firms in general; however, the mediating effect of academic internationalization on the university patent stock is expected to be negative.*

Geographical areas are characterized by heterogeneous propensity to innovate with respect to the presence of local innovation ecosystems (EC, 2023). In the framework of this study, Northern and Southern regions provide different contexts: knowledge spillovers from universities to industry is expected to be more effective and lead to a local specialization where companies are in general less likely to be on the innovation frontier, i.e., in the Southern provinces (Cowan and Zinovyeva, 2013). The contribution of university institutions in a technological sector can be a flywheel for the local development. Hence, we translate this expectation into the following hypothesis:

HP4: *knowledge from university patenting is more likely to trigger industrial specialization in the Southern provinces.*

Finally, high-tech inventions are characterized by higher R&D intensity and are located on the very edge of the scientific frontier: they are more complex, involve larger teams, multiple labs, and rely on more diversified competences. The accumulation of a patent stock is not trivial and specialization is more likely to occur in high-tech domains (Caviggioli et al., 2023; Coronado et al., 2017). A higher level of complexity is also related to hurdles in the full codification and transmission of knowledge: geographical distance is expected to weight more for more complex technologies (Lyytinen et al., 2001). We thus formulate the following hypothesis:

HP5: *the patenting activity of universities in high-tech sectors is not expected to be related to an increase in industrial specialization.*

4. DATA AND METHOD

This study contributes to the literature by analyzing the co-evolution of technological trajectories of universities and of the co-located firms in Italy. We combine some of the characteristics of previous studies into a novel empirical setting while also introducing novel dimensions of analysis. Industry specialization and university technical output are both operationalized via patent-based measures, which makes it possible to compare them in the same technological space and at the patent-field-and-province level of analysis (Caviggioli et al., 2023). The analysis is conducted at the geographical level of the province, according to the NUTS classification. All spatial units are considered, regardless of the presence of universities. The areas without academic institutions represent a relevant control group (as in Acosta et al., 2009; Braunerhjelm, 2008).

Data on the patenting activities of academic institutions and provinces has been extracted from the PATSTAT[9] and REGPAT[10] databases, which provide detailed bibliographic and georeferenced patent information. The unit of analysis is the patent family, the reference year is derived from the earliest priority, and the georeferencing of industrial patents is based on the address of the inventors. This setting is advised when studying

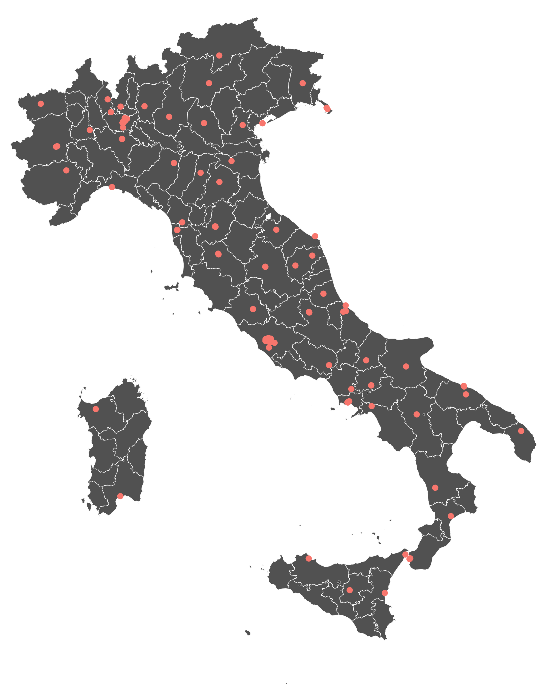
[9] The *Worldwide Patent Statistical Database* is published by the *European Patent Office* (EPO) and contains procedural and legal information on patent documents (we used the 2022 spring release).

[10] A database maintained by the *Organisation for Economic Co-operation and Development* (OECD) that geo-localizes patent data (we used the 2022 release).

inventive activity (e.g., OECD, 2009). Collected data range between 1985 and 2019. We consider the first ten years as a reference ground for the creation of technology stocks: the examined sample focuses on the years from 1995 to 2018.

For each Italian province, we distinguish between industry and university patent families. First, we identify all the worldwide patents having Italian academic institutions in the list of their assignees and exclude them from the rest of the local patenting activities[11]. The list of the 98 universities officially recognized by the Italian higher education system is available on the *Ministry for Education, Universities, and Research* (MIUR) website[12]. University patent families have been searched in the applicant and assignee fields in PATSTAT: we adopted a fuzzy comparison and matching technique which accounts for variations and non-exact matches of names, as well as semantic query searching procedures[13]. University patent families are then geolocalized according to the NUTS3 code of the main campus available in the ETER database[14]. This approach merges the patent portfolios of universities located in the same province.

Figure 2: geographic location of the selected universities



[11] Patents co-assigned to academic institutions and firms are considered as university patents only.

[12] Found at `http://ustat.miur.it/dati/didattica/italia/atenei` (last accessed in July 2022). See Abramo et al. (2016) for further details.

[13] Examples of search queries are the following: `(UNIVERSIT* and ((CAMPANIA and L*VANVITELLI*) or (SECONDA and NAPOLI)))` for the *Università degli Studi della Campania Luigi Vanvitelli*; `(UNIVERSIT* and (SALERNO or FISCIANO)` for the *Università degli Studi di Salerno*; `((LIBER* and UNIVERSIT* and STUD*SOCIAL*) or (LUISS* and ROMA))` for the *Libera Università Internazionale degli Studi Sociali Guido Carli di Roma*.

[14] The database provides information on all higher education institutions in Europe. It is available online at `https://eter-project.com` (last accessed in July 2022).

The second step is the identification of the industrial patent families generated in each geographical area. The REGPAT repository and the residence addresses of the inventors are employed to geolocalize EPO patents, which are then linked to their INPADOC families in PATSTAT. The previously identified university patent families are not considered as industrial output and are excluded from this sample.

In our empirical setting, the *International Patent Classification* (IPC) codes are employed to identify all the diverse technological fields. The granularity of the analysis is set at the level of patent sub-classes (i.e., four-digit codes), representing 635 different technological domains[15]. The IPC codes are useful to identify technological clusters of activities (i.e., low-tech and medium-low-tech, medium-high-tech, and high-tech). This was possible by relying on both the ARDECO repository on regional economic statistics[16], the concordance table that connects economic sectors to technological fields proposed by Van Looy et al. (2014) and the Eurostat classification of manufacturing industries according to their R&D intensity.

Finally, in ETER we collected the number of foreign graduates of each university: their share on total count of graduates is considered a proxy for the level of internationalization of universities, capturing how much a university is locally or globally oriented.

4.1. *Industrial patenting in Italian provinces*

After excluding university patents, data in Table II show that 57.5% of the total patenting activities are concentrated in 15 provinces out of 110 units. The most innovative areas are in Northern Italy, and, especially, in Lombardia (31.9% of all the patent families in our sample) and include some of the largest cities (e.g., Milano, Torino, Bologna, and Roma), jointly accounting for 27.9% of all patenting activities.

[15] The choice of four-digit domains as unit of analysis is in line with previous works (Acosta et al., 2009; Beaudry and Schiffauerova, 2009; Caviggioli et al., 2023).

[16] The *Annual Regional Database* of the *European Commission Directorate General for Regional and Urban Policy* is available at `https://knowledge4policy.ec.europa.eu/territorial/ardeco-database` (last accessed in July 2022).

TABLE II

TOP 15 ITALIAN PROVINCES BY COUNT OF PATENT FAMILIES (UNIVERSITY PATENTS ARE EXCLUDED)

Province (identifier)	Patent families	Percentage	Cumulated percentage
Milano (ITC4C)	15,196	11.9%	11.9%
Torino (ITC11)	8,375	6.6%	18.4%
Bologna (ITH55)	7,142	5.6%	24.0%
Roma (ITI43)	4,889	3.8%	27.9%
Varese (ITC41)	4,596	3.6%	31.4%
Monza e Brianza (ITC4D)	4,448	3.5%	34.9%
Bergamo (ITC46)	3,934	3.1%	38.0%
Treviso (ITH34)	3,894	3.0%	41.1%
Vicenza (ITH32)	3,744	2.9%	44.0%
Modena (ITH54)	3,702	2.9%	46.9%
Padova (ITH36)	3,281	2.6%	49.4%
Brescia (ITC47)	3,107	2.4%	51.9%
Como (ITC42)	2,511	2.0%	53.8%
Reggio Emilia (ITH53)	2,379	1.9%	55.7%
Firenze (ITI14)	2,354	1.8%	57.5%
Others	54,266	42.5%	100.0%
Total	**127,818**	**100.0%**	

Notes: one patent family can be attributed to multiple geographical areas if the addresses of its inventors are regionalized in more than one province; the residual category includes 95 provinces.

The technological specialization of the provinces is measured via the revealed technology advantage index (RTA). It provides quantitative information on the technological strengths (or weaknesses) of a given geographic area (Soete, 1987) and is computed as follows:

$$RTA_{ijt} = \frac{RP_{ijt}}{\sum_j RP_{ijt}} \cdot \frac{\sum_j EP_{jt}}{EP_{jt}}$$

where RP_{ijt} is the number of industrial patent families that are associated with region i, technology j (identified by the four-digit IPC sub-classes), in year t. Each patent family in a given field signals an increase in the competences and skills associated with the local technological portfolio. Patents with multiple IPC sub-classes contribute equally to each of them. EP_{ijt} is the number of patent families developed by all European regions[17] in technology j and year t. In other words, the index compares, for a specific technological field, the share of patent families in the portfolio of each Italian province with the same share of inventions computed at the European level to provide a continuous measure of relative specialization. Values of the RTA above (or below) one for a year suggest that the focal province is over-specialized (or under-specialized) in that technology area with respect to all other regions in Europe. The RTA is transformed into the regional technology specialization (RTS) dummy that represents the dependent variable of all empirical models. It is equal to one when the industrial activities located in a region are over-specialized in the examined technological field and year, and zero otherwise (see, for instance, Boschma et al., 2013; Caviggioli et al., 2023; Cicerone et al., 2023; Montre-

[17] We include 21 countries with the largest patenting activity at the EPO: 18 are EU member states (i.e., Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Poland, Portugal, Slovenia, Spain, and Sweden), 2 are EFTA member states (i.e., Norway and Switzerland), and the remaining one is the United Kingdom.

sor and Quatraro, 2017):

$$RTS_{ijt} = \begin{cases} 1, & RTA_{ijt} > 1 \\ 0, & RTA_{ijt} \leq 1 \end{cases}$$

4.2. *University patenting*

As of 2018, the sample includes 56 provinces with no university (50.9%) and 18 geographical areas hosting more than one academic institution (16.4%). Among the Italian provinces with at least one university, seven (13.0%) never patented in the examined years. Table 3III reports some details for the first 5 provinces (i.e., NUTS3) ranked by the total number of university patent families. The single five organizations with the largest portfolios of patent families are *Politecnico di Milano*, *Politecnico di Torino*, *Università degli Studi di Bologna*, *Università degli Studi La Sapienza di Roma*, *Università degli Studi di Milano*. The total of their inventions represents 39.1% of all university patent families.

TABLE III

TOP 5 PROVINCES BY COUNT OF UNIVERSITY PATENT FAMILIES IN ITALY

University	**Patent families**	**Percentage**	**Cumulated percentage**
Politecnico di Milano	508	14.0%	
Università degli Studi di Milano	198	5.5%	
Università degli Studi Bicocca	118	3.2%	
Università Cattolica del Sacro Cuore	22	0.6%	
Humanitas University	2	0.1%	
Milano (ITC4C)	**830**	**22.8%**	**22.8%**
Politecnico di Torino	272	7.5%	
Università degli Studi di Torino	92	2.5%	
Torino (ITC11)	**357**	**9.8%**	**32.7%**
Università degli Studi La Sapienza	219	6.0%	
Università degli Studi Tor Vergata	59	1.6%	
Università Campus Bio-Medico	22	0.6%	
Università degli Studi Roma Tre	18	0.5%	
Università Telematica Niccolò Cusano	2	0.1%	
Roma (ITI43)	**316**	**8.7%**	**41.4%**
Università degli Studi di Bologna	239	6.6%	
Bologna (ITH550)	**239**	**6.6%**	**47.9%**
Scuola Superiore Sant'Anna di Pisa	122	3.4%	
Università degli Studi di Pisa	92	2.5%	
Scuola Normale Superiore di Pisa	9	0.2%	
Pisa (ITI17)	**218**	**6.0%**	**53.9%**
Others	1,673	46.1%	100.0%
Italy	**3,633**	**100.0%**	

Notes: in this table only, the percentages of the single universities do not necessarily sum up to the sub-total at the province level since patent families assigned to more than one university in the same geographical area are counted once at the province level; the residual category includes 48 universities located in 43 provinces.

4.3. *Patent stocks of local and contiguous areas*

The knowledge generated by universities in a specific technological field is proxied by the stock of university patent families (UPS) associated with the corresponding IPC subclass. Patent stocks have been operationalized by counting patent families and considering a declining balance formula with a yearly depreciation rate of 15% (as in Hall et al., 2005):

$$UPS_{ijt} = (1 - \delta) \cdot UPS_{ijt-1} + UP_{ijt}$$

where UPS_{ijt} is the stock of university patent families, δ is the depreciation factor, and UP_{ijt} is the count of new inventions developed by all the academic institutions located in province i during year t and associated with technology j. A second set of variables considers the knowledge stock developed in the geographical areas around each focal province (as in Moreno et al., 2005). One of the computed measures evaluates the stock of inventions generated by the universities located in the contiguous geographical areas:

$$C1UPS_{ijt} = (1 - \delta) \cdot C1UPS_{ijt-1} + C1W_i \cdot UP_{jt}$$

where $C1UPS_{ijt}$ is the stock of university patent families of the areas neighboring the focal province i, in technology j and year t. Also, $C1W_i$ is a binary spatial-weighting row vector with i components representing the first-order contiguities for province i, and UP_{jt} is a (conformable) column vector whose entries are the counts of university patent families. δ is the depreciation factor. Similarly, the stock of inventions filed by firms located in the neighboring provinces is computed as:

$$C1RPS_{ijt} = (1 - \delta) \cdot C1RPS_{ijt-1} + C1W_i \cdot RP_{jt}$$

where $C1RPS_{ijt}$ is the stock of inventions generated by firms in contiguous provinces and RP_{jt} is a column vector whose i components represent the counts of regionalized patent families in technology j and year t.

4.4. *Descriptive statistics of the variables*

Table IV and Table V describe all the variables employed in the econometric analysis. The correlation matrix is shown in Table VI. The empirical models include two controls for time-variant NUTS region characteristics: a measure of size (i.e., the population of the province in thousand inhabitants) and the gross value added measured at current market prices in thousand purchasing power standards per capita. Moreover, the pairwise correlation values suggest being cautious in considering jointly the following couples of variables: i) C1UPS and C1RPS; ii) GVA and the two regional variables (i.e., the share of foreign graduates and the Southern/Northern province dummy). Hence, they will not be employed jointly.

TABLE IV

DESCRIPTION OF THE VARIABLES

Variable	Description
RTS	Dummy variable that equals one if the industrial portfolio of the province is specialized in the technology (i.e., patent sub-class) and year and zero otherwise
UPS	Stock of patent families developed by universities in the technology (i.e., patent sub-class) and year
C1UPS	Stock of patent families filed by all the universities located in the first-contiguous provinces in the technology (i.e., patent sub-class) and year
C1RPS	Stock of patent families filed by all the firms located in the first-contiguous provinces in the technology (i.e., patent sub-class) and year
Population	Population of the province (in thousands)
GVA	Gross value added of the region at current market prices purchasing power standards per capita (in thousands)
Intl of university system	Internationalization as share of international students graduating from the local university system
High-tech/Low-tech sector	Dummy variable equal to one if the technology (i.e., patent sub-class) belongs to the cluster of high-tech domains, zero for low-tech
Southern/Northern province	Dummy variable equal to one if the province belongs to Southern Italy (including islands), zero otherwise

TABLE V

DESCRIPTIVE STATISTICS OF THE VARIABLES

Variable name	Count	Mean	Q1	Median	Q3	SD	Min	Max
RTS	1,676,400	0.054	0.000	0.000	0.000	0.226	0.000	1.000
UPS	1,676,400	0.019	0.000	0.000	0.000	0.309	0.000	43.958
C1UPS	1,676,400	0.109	0.000	0.000	0.000	0.892	0.000	59.995
C1RPS	1,676,400	3.933	0.000	0.232	2.298	16.225	0.000	934.882
Population	1,676,400	533.676	225.900	365.150	590.100	577.097	56.879	4,354.700
GVA	1,676,400	20.316	15.526	20.214	24.349	5.928	8.243	49.996
Intl of university system	777,240	0.040	0.005	0.029	0.041	0.081	0.000	0.556
High-tech/Low-tech sector	1,676,400	0.734	0.000	1.000	1.000	0.442	0.000	1.000
Southern/Northern province	1,676,400	0.573	0.000	1.000	1.000	0.495	0.000	1.000

TABLE VI

CORRELATION MATRIX

	Variable name	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	UPS	1.000						
2	C1UPS	0.269	1.000					
3	C1RPS	0.229	0.547	1.000				
4	Population	0.115	-0.017	0.014	1.000			
5	GVA	0.117	0.059	0.146	0.265	1.000		
6	Intl of university system	0.002	0.014	0.031	-0.033	0.312	1.000	
7	High-tech/Low-tech sector	0.023	0.030	0.027	0.000	0.000	0.000	1.000
8	Southern/Northern province	-0.038	-0.044	-0.166	-0.023	-0.638	-0.365	0.000

4.5. *Econometric models*

Our empirical setting is based on a balanced panel data structure where all the 69,850 units are the combinations of technologies and Italian provinces that are observed yearly from 1994 to 2018. The baseline estimating equation is the following:

$$RTS_{ijt} = \alpha + \beta \cdot UPS_{ijt-1} + \Gamma \cdot C_{it-1} + \delta_t + \eta_j + \vartheta_i + \varepsilon_{ijt}$$

where RTS_{ijt} and UPS_{ijt-1} are the technological specialization of the region and the university patent stock respectively, as explained in the previous Sections 4.1 and 4.3. Furthermore, C_{it-1} represents a set of lagged control variables, δ_t are the year dummies, η_j are the patent subclass dummies, ϑ_i are the province dummies, and ε_{ijt} is the error term. All the models are specified to consider the fixed effects of 25 years, 110 provinces, and 635 technology sub-classes by including the corresponding set of dummies in the specifications. Standard errors are adjusted for 69,850 clusters obtained by combining the spatial controls with the patent sectors to account for correlation in the error terms. We provide a set of robustness tests with additional fixed effects (more details in the corresponding Section 5.2).

With the aim to test the potential correlation with the knowledge spilling over from universities and firms that are located in neighboring regions, we also include the stocks of patent families developed in first-degree contiguous areas, i.e., $C1UPS_{ijt-1}$ and $C1RPS_{ijt-1}$.

All the equations have been estimated using linear regressions with high-dimensional fixed effects[18] where the independent variables are lagged by one year.

The results will be tested in several robustness analyses, such as considering multiple levels of fixed effects (i.e., spatial, technological, time-related, and their combinations), focusing on a measure of industrial output rather than specialization, and using instrumental variable regressions to account for potential endogeneity. These tests aim to shed light on the hypothetical existence of unobserved trends in the data that may jointly influence both specialization and university technical output. The Appendix reports the results of the analyses with the yearly number of industrial patents in each region-technology pair as the dependent variable. In line with this new count regressand, we adopt Poisson pseudo-maximum likelihood regressions with multi-way fixed effects[19].

5. RESULTS

5.1. *Baseline specification*

The baseline results are in Table VII. The stock of technical knowledge generated by the universities is positively and significantly related to the industrial specialization in the same technological field, hence confirming HP1. This finding is robust across all models even after controlling for the size (i.e., population) and the GVA of the province. The marginal effect of an increase in one additional unit of the local university patent stock on industrial specialization is equal to about 0.03, a magnitude consistent across the baseline and most of the robustness specifications.

The econometric analysis is extended to capture the potential role of the neighboring geographical provinces. The results for university and industry have consistent signs. We find a positive and highly significant association between the lagged stock of patents filed by universities located in contiguous areas and the specialization in the same technological field. This result supports HP2A.

The marginal effect of an increase of one unit in the local university patent stock on

[18] We used the `reghdfe` command in the latest version of Stata since it allows to estimate panel data regression models with multiple levels of fixed effects and robust standard errors (Correia, 2016). The choice of fixed-effects over random-effects modeling is supported by the results of the Hausman test.

[19] We used the `ppmlhdfe` command in the latest version of Stata (Correia et al., 2020).

local industrial specialization is comparable to the effect of about 4.7 additional units in the aggregate stock of the neighboring academic institutions. The smaller effect of C1UPS is coherent with the expectation on the moderating role of physical distance in knowledge spillovers. This finding validates HP2B. To put the numbers in context, an additional patent family in the UPS corresponds to a shift of around three standard deviations, while the 4.7 units in the aggregate portfolios of neighboring universities to a shift of around two standard deviations.

Model (5) includes C1RPS, the patenting activities that are carried out by firms located in neighboring geographical areas: this last specification improves understanding of the magnitude of the results[20]. Even when considering the neighboring industrial output, we still observe a significant effect of the local university system on regional specialization. In terms of unit changes, C1RPS shows a smaller effect than the local university patent stock (6% of the effect of UPS): recall that the average C1RPS is larger than UPS and that one additional invention in the stock of local universities corresponds to a shift of about three standard deviations, while three standard deviations in C1RPS correspond to around fifty extra patents[21].

[20] For a broad comparison with the magnitudes of all the other controls, the average contribution of one university patent family to the specialization of local firms in the same technology field is similar to a population increase of approximately 370 thousand inhabitants (21% of the provinces have more inhabitants in 2018) or additional 29 thousand purchasing power parity in the GVA per capita (only two provinces have higher values of GVA).

[21] We computed the baseline models with standardized variables to compare more precisely the relative magnitudes of the marginal effects estimated for all the included regressors. In these models, the ratio between the marginal effects of UPS and C1UPS is 1.6, whereas the coefficient of C1RPS is about 3.8 times bigger than the UPS one. The first result is in line with those of the baseline models, the second finding seems to point towards the presence of a comparably more prominent role played by the accumulated stock of technological knowledge relating to companies in surrounding areas in driving regional specialization with respect to those of local and neighboring universities. However, the coefficient of UPS is still positive and significant. Detailed results are available on request.

TABLE VII

BASELINE MODELS ON THE REGIONAL SPECIALIZATION WITH HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS AND CLUSTERED STANDARD ERRORS

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
UPS (lagged)	0.03094***	0.03032***	0.03006***	0.02958***	0.02545***
	(0.00412)	(0.00409)	(0.00409)	(0.00406)	(0.00520)
C1UPS (lagged)				0.00636***	
				(0.00097)	
C1RPS (lagged)					0.00181***
					(0.00015)
Population (lagged)		0.00009***	0.00008***	0.00008***	0.00008***
		(0.00001)	(0.00001)	(0.00001)	(0.00001)
GVA (lagged)			0.00133***	0.00134***	0.00102***
			(0.00020)	(0.00020)	(0.00020)
Constant	0.05331***	0.00522	-0.01620**	-0.01625**	-0.01422**
	(0.00037)	(0.00569)	(0.00684)	(0.00684)	(0.00682)
Province dummies	Yes	Yes	Yes	Yes	Yes
Technology sub-class dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.1149	0.1150	0.1151	0.1155	0.1265
Number of clusters	69,850	69,850	69,850	69,850	69,850

Notes: RTS is the binary dependent variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces, respectively. Standard errors are reported in parentheses, they have been adjusted for 69,850 clusters obtained by combining the 110 spatial controls (i.e., provinces) with the 635 technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

5.2. *Robustness tests*

In this section, we introduce several robustness tests with the aim to clarify potential issues in the empirical setting. First, we introduce multiple fixed effects in the econometric models to control for potential unobserved trends that might drive the technological output of both universities and firms in the same areas. Second, we address the potential endogeneity of the main independent variable, i.e., the university patent stock, by including the lagged dependent variable as regressor and testing instrumental variable regressions. In addition, the Appendix reports the estimates of a set of models that focus on the number of industrial patents in a province as the dependent variable to test the relationship between UPS and the main component of the RTS.

The first issue is addressed in the estimates shown in Table VIII. The baseline specifications are tested with different sets of time, geography, and technology dummies. The selected fixed effects in these regressions exclude time-varying regional features such as population and GVA. Models (1) and (2) include all the interaction terms between year (i.e., 25 time periods) and province (i.e., 110 geographical units) dummies, that correspond to 2,750 indicator variables, therefore controlling for potential unobserved characteristics at the geography-time level. Models (3) and (4) are computed by absorbing the effects of all the interactions between years, technology sections (i.e., the 8 main patent domains represented by one-digit IPC sections), and province indicator variables. The aim is to control for potential unobserved local orientations towards a certain technological area in both university and industry. All the models confirm the results obtained in the previous baseline regressions.

TABLE VIII

MODELS ON THE REGIONAL SPECIALIZATION WITH HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS, CLUSTERED STANDARD ERRORS, AND DIFFERENT SETS OF TIME, GEOGRAPHY AND TECHNOLOGY DUMMIES

Model	**(1)**	**(2)**	**(3)**	**(4)**
UPS (lagged)	0.03004***	0.02582***	0.02901***	0.02493***
	(0.00412)	(0.00527)	(0.00402)	(0.00520)
C1UPS (lagged)	0.00660***		0.00651***	
	(0.00099)		(0.00098)	
C1RPS (lagged)		0.00180***		0.00174***
		(0.00015)		(0.00014)
Constant	0.05267***	0.04650***	0.05270***	0.04674***
	(0.00038)	(0.00061)	(0.00037)	(0.00060)
Province dummies	Yes	Yes	Yes	Yes
Technology sub-class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Year × Province dummies	Yes	Yes		
Year × Section × Province dummies			Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.1169	0.1279	0.1305	0.1405
Number of clusters	69,850	69,850	69,850	69,850

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are respectively the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces. Models (1) and (2) include interaction terms between year and province dummies, Models (3) and (4) include interaction terms between technology fields (i.e., patent sections) and province dummies. All the regressors are lagged one period. Standard errors are reported in parentheses, they have been adjusted for 69,850 clusters obtained by combining the 110 spatial controls (i.e., provinces) with the 635 technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Secondly, the following tests address the potential endogeneity of UPS. The first set of tests includes the lagged dependent variable in the model specification (Table IX). As expected, it is positively and significantly related to the current industrial specialization of provinces. This result may confirm that the technological evolution processes analyzed have distinct characteristics of non-ergodicity and path-dependency. Once the effect of the prior specialization of local firms is partialled out of the data, the regression estimates are still consistent with those reported in the baseline specifications both in terms of signs and statistical significances, but the magnitude of the coefficients of UPS is slightly reduced. As one can reasonably expect, the marginal effect of the lagged specialization is larger than that of UPS (around six times), therefore, indicating that the main driver of technological specialization is in the industrial system. However, the residual contribution from the universities is not negligible.

TABLE IX

BASELINE MODELS ON THE REGIONAL SPECIALIZATION WITH HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS, CLUSTERED STANDARD ERRORS, AND CONTROLLING FOR PREVIOUS SPECIALIZATION

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
UPS (lagged)	0.02367***	0.02322***	0.02304***	0.02269***	0.01985***
	(0.00316)	(0.00314)	(0.00314)	(0.00312)	(0.00402)
C1UPS (lagged)				0.00476***	
				(0.00074)	
C1RPS (lagged)					0.00137***
					(0.00012)
RTS (lagged)	0.23580***	0.23567***	0.23562***	0.23527***	0.22502***
	(0.00292)	(0.00292)	(0.00292)	(0.00292)	(0.00297)
Population (lagged)		0.00007***	0.00006***	0.00006***	0.00006***
		(0.00001)	(0.00001)	(0.00001)	(0.00001)
GVA (lagged)			0.00095***	0.00096***	0.00074***
			(0.00016)	(0.00016)	(0.00016)
Constant	0.04093***	0.00598	-0.00938*	-0.00942*	-0.00818
	(0.00025)	(0.00440)	(0.00533)	(0.00533)	(0.00538)
Province	Yes	Yes	Yes	Yes	Yes
Technology sub-class	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.1634	0.1635	0.1635	0.1638	0.1700
Number of clusters	69,850	69,850	69,850	69,850	69,850

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces respectively. Standard errors are reported in parentheses, they have been adjusted for 69,850 clusters obtained by combining the 110 spatial controls (i.e., provinces) with the 635 technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

The second test further controls that our empirical results are not being driven by omitted-variable bias. We generated 1,500 samples with a randomized version of UPS for placebo regressions (further details in the Appendix, Section A.3). We compared all the simulated results with the corresponding realizations in the baseline models under the null hypothesis of no treatment effect. The coefficient for the randomized UPS in all the placebo regressions is significantly smaller than the corresponding ones in the baseline models. This finding, again, indicates the absence of significant omitted variable issues.

To further address the potential endogeneity issue between UPS and RTS, we implemented a set of model specifications relying on instrumental variable (IV) regressions and with multiple fixed effects, coherently with the previous approach[22]. Table X shows the results when different instruments are applied to the potentially endogenous variable: the previous lags of UPS in Models (1) and (2), the university stock of patent family members (UFM) in Models (3) and (4), and the average number of university patent family members (AFM) in Models (5) and (6), respectively. A single invention can be protected in multiple jurisdictions (i.e., countries) with several patents, all belonging to the same family. The count of family members provides a measure of the geographical scope, which is a proxy for the quality of the patented invention (Caviggioli, 2016). This time-variant regressor is computed for the universities at the level of province-technology.

[22] We used the Stata command `ivreghdfe` which combines the possibility of high-dimensional fixed effects (Correia, 2016) and the introduction of instrumental variables (Baum et al., 2023).

Quantity and quality of intellectual output are correlated dimensions, although the average quality of a portfolio is not statistically related to its size (Caviggioli and Forthmann, 2022; Simonton, 2010). In our context, employed patent quality indicators of the university output are expected to be unrelated to the measure of industrial specialization because the latter is based on the relative diffusion of a technology calculated via the number of patents. Thus, quality is not directly taken into account when operationalizing specialization. UFM is computed as the cumulated stock of patent family members (with time depreciation) whereas AFM is the yearly average of the patent family size of the new inventions in each examined year.

With the IV approach, we controlled for potential endogeneity and obtained more reliable estimates of the statistical relationship between the outcome variable and the regressors. All the diagnostics indicate that the models have valid and relevant instruments: the p-value of the overidentification test (Hansen J statistic) does not reject the null hypothesis of the instruments being uncorrelated with the error term whereas the p-value of the underidentification test (Kleibergen-Paap rank Lagrange Multiplier statistic) indicates that the model is identified, and the instruments are not weak.

Concerning the endogeneity test of the variable of interest (UPS), the p-values are different across the models. Model (2) does not reject the null hypothesis that UPS is exogenous, while all the other models suggest that UPS is endogenous (the p-value for Model (1) is not far from the 90% threshold and, thus, it indicates caution in rejecting the null).

The IV results confirm the previous findings obtained in the baseline models. This further reinforces the econometric validity of our approach and underscores the stability of the estimated relationship between university patent stock and industrial specialization.

TABLE X

MODELS WITH INSTRUMENTAL VARIABLES, HIGH-DIMENSIONAL FIXED EFFECTS AND CLUSTERED STANDARD ERRORS

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Excluded instruments	UPS lagged 2 and 3 years	UPS lagged 2 and 3 years	UFS lagged 2 and 3 years	UFS lagged 2 and 3 years	AUF lagged 2 and 3 years	AUF lagged 2 and 3 years
UPS (lagged)	0.03007***	0.02304***	0.03481***	0.02666***	0.04809***	0.03703***
	(0.00854)	(0.00662)	(0.00880)	(0.00684)	(0.00991)	(0.00786)
C1UPS (lagged)	0.00635***	0.00476***	0.00630***	0.00472***	0.00614***	0.00460**
	(0.00233)	(0.00175)	(0.00232)	(0.00175)	(0.00233)	(0.00176)
RTS (lagged)		0.23525***		0.23507***		0.23455***
		(0.00784)		(0.00785)		(0.00786)
Population (lagged)	0.00008*	0.00006*	0.00008*	0.00006*	0.00007	0.00005
	(0.00004)	(0.00003)	(0.00004)	(0.00003)	(0.00004)	(0.00003)
GVA (lagged)	0.00133***	0.00096***	0.00128***	0.00091***	0.00112**	0.00079**
	(0.00043)	(0.00031)	(0.00044)	(0.00032)	(0.00051)	(0.00037)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Technology sub-class dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.0022	0.0567	0.0022	0.0567	0.0017	0.0564
F statistic	7.6970	234.0738	7.3523	231.1795	8.8882	235.8562
P-value of overidentification test (Hansen)	0.7067	0.5759	0.8957	0.6533	0.8866	0.9511
P-value of underidentification test (Kleibergen-Paap)	0.0004	0.0004	0.0160	0.0157	0.0361	0.0356
P-value of exogeneity test	0.0898	0.2149	0.0513	0.0655	0.0260	0.0233

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. C1UPS is the stock of patents filed by academic institutions that are in first-degree contiguous provinces. Standard errors are reported in parentheses, they have been adjusted for intra-cluster correlations. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Finally, in the Appendix we report the results of the models with a different dependent variable: the count of industrial patents in a technology for every province and year. The results for the university patent stock are consistent with those with the specialization as dependent variable. The stock of patent families developed by universities in contiguous provinces is not statistically significant (i.e., the IRR is close to one). We argue that, in terms of quantitative output, the physical distance moderates the knowledge spillovers from the neighboring academies to companies in the adjacent provinces and leads to a statistically non-significant relationship. Our previous results indicated that the stock of inventions developed by contiguous universities plays a small role in favoring the industrial specialization of the local province. This small effect might be related to the technology specificities that lead to specialization and vanish when considering the mere number of inventions.

5.3. *International orientation of university systems*

We first augment the baseline specifications by including a variable that measures the presence of a highly internationalized local university system through the proportion of foreign graduates. The examined sample thus excludes the provinces with no universities. We test whether the specificities of the local academic institutions, and, particularly, its orientation towards international education moderates the relationship between UPS and the subsequent industrial specialization.

The estimates are presented in Table XI. Models (1) and (3) include only the international orientation dummy whereas Models (3) and (4) contain the interaction between this binary variable and UPS. We find a significantly positive correlation between the international orientation of the university system and the regressand when controlling for the stock of patented inventions developed by those academies located in the first-contiguous provinces, i.e., C1UPS. The interaction term between the UPS variable and the international orientation is negative and significant. The results on the interaction term suggest that the positive relationship between the industrial specialization and the local technology-specific UPS is smaller when the university system is more internationalized. This result supports HP3.

TABLE XI

MODELS ON THE REGIONAL SPECIALIZATION WITH HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS, CLUSTERED STANDARD ERRORS, AND CONTROLLING FOR THE INTERNATIONALIZATION OF THE UNIVERSITY SYSTEM

Model	**(1)**	**(2)**	**(3)**	**(4)**
UPS (lagged)	0.03052***	0.06748***	0.02434***	0.07739***
	(0.00404)	(0.00980)	(0.00570)	(0.00984)
Intl of university system	0.13982***	0.14120***	0.12716***	0.12895***
	(0.00835)	(0.00835)	(0.00837)	(0.00837)
Intl of university system × UPS (lagged)		-0.79767***		-1.14738***
		(0.22025)		(0.23204)
C1UPS (lagged)	0.00700***	0.00689***		
	(0.00140)	(0.00137)		
C1RPS (lagged)			0.00222***	0.00225***
			(0.00027)	(0.00027)
Population (lagged)	0.00004***	0.00004***	0.00004***	0.00004***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	0.03007***	0.02989***	0.02311***	0.02274***
	(0.00100)	(0.00100)	(0.00127)	(0.00127)
Technology sub-class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	777,240	777,240	777,240	777,240
Adjusted R-squared	0.0954	0.0957	0.1094	0.1101
Number of clusters	32,385	32,385	32,385	32,385

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces, respectively. Models (1) and (3) include the university international orientation dummy whereas Models (2) and (4) contain the interaction between this binary variable and UPS. Standard errors are reported in parentheses, they have been adjusted for 32,385 clusters obtained by combining the spatial controls (i.e., provinces) with the technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

5.4. *Northern and Southern provinces*

With the aim of assessing the statistical presence of moderating effects due to regional specificities, we augment the baseline specification by introducing a geographical breakdown indicator variable that equals one if the focal province is located in one of the central and southern regions of Italy or in the two major islands, and zero otherwise.

Table XII reports the corresponding estimates. Models (1) and (3) include only the Southern versus province Northern dummy whereas models (2) and (4) also contain the interaction between such a binary variable and UPS. The geographical breakdown is significantly and negatively correlated with the regressand, indicating that Southern areas are on average less specialized relative to Northern ones. Interestingly, the geographical breakdown of the province is found to positively moderate the statistical relationship between UPS and the dependent variable. This evidence might suggest that the patenting activity of the university system is more likely to generate knowledge spillovers that can be exploited by local firms and induce specialization whenever the focal province is located in the South. This result confirms HP4. Note also that the coefficients of the controls are similar both in sign and magnitude with respect to the baseline results.

TABLE XII

MODELS ON THE REGIONAL SPECIALIZATION WITH HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS, CLUSTERED STANDARD ERRORS, AND CONTROLLING FOR THE GEOGRAPHIC LOCATION OF THE PROVINCES

Model	**(1)**	**(2)**	**(3)**	**(4)**
UPS (lagged)	0.03279***	0.02080***	0.02835***	0.01183***
	(0.00419)	(0.00396)	(0.00550)	(0.00439)
Southern/Northern province	-0.05845***	-0.05909***	-0.04876***	-0.04943***
	(0.00083)	(0.00083)	(0.00102)	(0.00102)
Southern/Northern province × UPS (lagged)		0.04076***		0.05580***
		(0.00731)		(0.00786)
C1UPS (lagged)	0.00823***	0.00826***		
	(0.00099)	(0.00100)		
C1RPS (lagged)			0.00193***	0.00197***
			(0.00015)	(0.00015)
Population (lagged)	0.00005***	0.00005***	0.00005***	0.00005***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	0.05822***	0.05860***	0.04652***	0.04678***
	(0.00082)	(0.00082)	(0.00117)	(0.00117)
Technology sub-class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.0991	0.0997	0.1123	0.1134
Number of clusters	69,850	69,850	69,850	69,850

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces, respectively. Models (1) and (3) include the Northern versus Southern province dummy whereas Models (2) and (4) contain the interaction between this binary geographical breakdown variable and UPS. Standard errors are reported in parentheses, they have been adjusted for 69,850 clusters obtained by combining the spatial controls (i.e., provinces) with the technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

5.5. *High-tech and low-tech patent fields*

Table XIII shows the results of a set of models in which a high-tech versus low-tech patent field dummy has been added to the main econometric specification. It provides indications of whether the idiosyncratic characteristics of the examined technology areas exert any moderating effect on the relationship between UPS and regional specialization. All patent fields (i.e., sub-classes) have been classified in terms of their relative complexity following the taxonomy in Van Looy et al. (2014).

Models (1) and (3) contain only the high-tech versus low-tech dummy whereas Models (2) and (4) also include the interaction between this binary variable and UPS. The high-tech dummy is positively and significantly correlated with the dependent variable, meaning that industrial specialization is on average more likely in the presence of sectors characterized by higher technological sophistication.

However, the interaction term is not significantly different from zero, meaning that the statistical association between UPS and the regressand is not affected by the technological complexity of the filed patents. This finding supports HP5.

Two previous scientific articles addressed the characteristic of high-tech or low-tech, but the comparison is not immediate. The empirical setting in Coronado et al. (2017) cannot be directly paralleled to ours since they considered a measure of specialization based on the local employment and aggregated several sectors in two indicators: one for high-tech and the other for low-tech fields. The authors found a causal relationship from regional specialization to university output for high-tech sectors. We tested our IV models also including the high/low-tech dummy (see Table VI in the Appendix): they confirm our causal direction from UPS to industrial specialization and the results on the high-tech dummy. Our findings are in line with those in Caviggioli et al. (2023), where, instead of UPS, university activities are measured through the first patent in a technology field.

TABLE XIII

MODELS ON THE REGIONAL SPECIALIZATION WITH HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS, CLUSTERED STANDARD ERRORS, AND CONTROLLING FOR THE TECHNOLOGICAL COMPLEXITY OF THE PATENT FIELDS

Model	**(1)**	**(2)**	**(3)**	**(4)**
UPS (lagged)	0.04163***	0.05813***	0.02830***	0.04783***
	(0.00518)	(0.01320)	(0.00674)	(0.01260)
High-tech/Low-tech sector dummy	0.00281***	0.00299***	0.00147*	0.00169*
	(0.00097)	(0.00096)	(0.00089)	(0.00089)
High-tech/Low-tech sector dummy × UPS (lagged)		-0.01803		-0.02133
		(0.01416)		(0.01421)
C1UPS (lagged)	0.01808***	0.01813***		
	(0.00111)	(0.00111)		
C1RPS (lagged)			0.00267***	0.00268***
			(0.00020)	(0.00020)
Population (lagged)	0.00006***	0.00006***	0.00006***	0.00006***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
GVA (lagged)	0.00113***	0.00112***	0.00073***	0.00071***
	(0.00021)	(0.00021)	(0.00021)	(0.00021)
Constant	-0.00737	-0.00668	-0.00717	-0.00635
	(0.00714)	(0.00716)	(0.00714)	(0.00711)
Province dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.0644	0.0645	0.0939	0.0939
Number of clusters	67,100	67,100	67,100	67,100

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces, respectively. Models (1) and (3) include the high-tech versus low-tech dummy whereas Models (2) and (4) contain the interaction between this binary technological complexity variable and UPS. Standard errors are reported in parentheses, they have been adjusted for 67,100 clusters obtained by combining the spatial controls (i.e., provinces) with the technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

6. CONCLUSION

This study contributes to the literature on regional technological specialization as a path-dependent process (Boschma et al., 2013; Neffke et al., 2011) and investigates the role of universities further. Although the previous literature has found evidence of a positive role played by academic institutions in spurring innovation activities of co-localized firms (Agrawal and Cockburn, 2003; Tötterman and Sten, 2005), only a few empirical studies analyzed the relationship between industrial specialization and prior university research output (Acosta et al., 2009; Braunerhjelm, 2008; Calderini and Scellato, 2005; Caviggioli et al., 2023; Coronado et al., 2017). Our work combines several elements of all the previous empirical approaches which were not considered jointly and introduces novel factors in the econometric approach.

The empirical setting considers the patenting activities of Italian universities and firms at the third level of NUTS system in the years from 1995 to 2018. The empirical analyses confirm our hypothesis that, in general, there is a positive statistical relationship between the stock of patented knowledge of universities in a specific field and the specialization of the co-located innovation systems in the same technological domain. Several model specifications supported the robustness of the result, including multiple fixed effects that account for unobserved characteristics of geographical areas, time trends, and technology fields. Instrumental variable regressions were also used to control for potential endogeneity issues: the results indicate a causal relationship between the patent stock accumulated by universities in a technology and the subsequent industrial specialization.

Our econometric analyses also considered the spatial dimension of knowledge through the stocks of patented inventions accumulated by neighboring universities and firms (i.e., those located in the contiguous provinces). Both stocks are positively and significantly related to specialization in all the examined models, confirming our second hypothesis. Differences in the size of the coefficients can be explained by the heterogeneous dimensions of patent portfolios, but if the standard deviations are also considered, there is evidence of a diminishing effect of geographical distance on knowledge spillovers, especially for neighboring universities. On the contrary, the knowledge accumulated by neighboring firms seems to have a larger impact on industrial specialization than the local university stock. These findings indicate that NUTS regions are a suitable unit of analysis to identify ecosystems of innovation when measuring technological specialization: the universities play the role of anchor tenant and the neighboring ecosystems are sufficiently distant to determine a smaller inter-provinces relationship. This is also in line with the available evidence that geographical proximity increases the probability of collaboration between academies and companies (Laursen et al., 2011): the academic knowledge of universities operating in contiguous provinces is not easily absorbed by companies located in the focal one. The influence of the industrial knowledge developed in neighboring areas is even smaller. This might be due to the different goals and collaborative approaches of academies and companies. University inventions are characterized by a lower technology readiness level (i.e., more basic) than industrial ones and thus might find subsequent applications outside the local innovation ecosystem, with the inter-provincial collaboration between academic institutions and firms more likely to occur than among competitors.

To improve the characterization of empirical results with respect to regional and technological specificities, we included three sets of models that examine the internationalization of graduates as measure of local orientation of the university, differences between Southern and Northern regions, and between high-tech and low-tech sectors[23]. All models confirm the positive relationship of both local (larger) and contiguous (smaller) university patent stock with the industrial specialization.

The international orientation of academies is significantly and positively related to specialization, suggesting that universities can act as intermediate actors in bringing technological knowledge and favor the realization of absorption capabilities that support specialization. However, the patenting activity of more internationally oriented university institutions is found to be less advantageous for industrial specialization than the stock

[23] The accompanying plots of marginal effects are reported in the Appendix, Section A.4.

of patents accumulated by less internationalized academic systems. We argue that such a penalty is due to the outward circulation of technological knowledge which reduces the chances to observe a specialization in a single technology. In other words, there is a trade-off, since an innovation developed by a university within an open context is more likely to be shared in some aspects of its technical development outside regional boundaries and, thus, it is relatively less likely that neat specialization will emerge locally.

Focusing on the sub-samples of Northern and Southern provinces, the former are more frequently associated with technological specialization. However, the increase in university patent stock seems more effective in leading to a specialization when it happens in a province in the South of Italy. This result is in line with those in Cowan and Zinovyeva (2013) where areas with low income per capita benefit more from knowledge spillovers generated by universities. Additionally, universities in the South could be more rooted in their local territories and the co-located firms particularly able to capture their academic results and leverage them to become specialized.

With respect to the distinction between low-tech and high-tech sectors, the specialization is more frequently associated with high-tech areas, where edge innovations can provide competitive advantage. However, our analysis indicates that the positive effect of the university patent stock is similar both in high-tech and low-tech fields, with no clear prevalence.

Our findings contribute to the extant literature under many respects. The results can lead to a better understanding of the role of local academic institutions in influencing the branching process that leads to the technological specialization of regions (Boschma and Frenken, 2012; Frenken and Boschma, 2007). There is a growing awareness that regional performance is intrinsically related to a set of localized capabilities and regionally embedded knowledge (Maskell and Malmberg, 1999). Policy prescriptions have progressively endorsed the idea of regional technological specialization based on regional branching arguments and around the concepts of heterogeneity and path-dependence in regional know-how bases, variety, and specialization strategies (Boschma, 2014; Frenken and Boschma, 2007). This is important when considering that a regional specialization occurring in fields unrelated to the usual ones provides with enduring economic growth (Essletzbichler, 2015; Frenken et al., 2007; Neffke et al., 2018). In this perspective, all the policies that aim at developing technological competences in fields unrelated to the existing regional portfolio could favor investments in those areas by leveraging the university labs: their output could represent the knowledge base and the new assets to drive the subsequent industrial specialization. This could overcome the problem of effectively operationalizing the theoretical framework into policies (Foray et al., 2011).

Our work is not exempt from limitations and future research can extend the analyses by considering multiple countries, additional economic characteristics of the geographical areas to improve their qualification, and controls for the level of university-industry collaboration both in research projects and patenting activities. Finally, by addressing the potential endogeneity concern through instrumental variable techniques, our study provides valuable insights into the causal relationship between these variables, although future research might improve the analysis with the identification of province-and-technology level exogenous shocks.

APPENDIX

A.1. *Additional descriptive statistics*

In Table I, we report both the number and share of technological specializations by group of years. The last period has only four years. The proportion of specialized patent domains (i.e., sub-classes) is growing slightly over time, from about 4.2% in the years from 1995 to 1999 to about 5.9% in the years between 2015 and 2018. Interestingly, the average number of specialized technologies by region is also increasing over time, from 26.7 patent fields in the first period to about 37.3 areas in the latter one.

TABLE I

COUNT AND SHARE OF TECHNOLOGICAL SPECIALIZATIONS BY GROUP OF YEARS

Reference period	Number of specializations	%	Number of provinces with at least one specialization	Average number of tech specializations by province
From 1995 to 1999	14,703	4.2%	88.5%	26.7
From 2000 to 2004	18,704	5.4%	93.1%	34.0
From 2005 to 2009	20,066	5.7%	94.5%	36.5
From 2010 to 2014	20,409	5.8%	94.2%	37.1
From 2015 to 2018	16,394	5.9%	93.2%	37.3
Total	**90,276**	**5.4%**	**92.7%**	**34.2**

A.2. *Robustness test with the number of industrial patent families as dependent variable*

In this section, we provide a set of additional tests on the robustness of the baseline models by considering a different regressand. Instead of specialization, we focus on one of its main components, i.e., the number of patent families associated with a specific technological class. The econometric specification thus is the following:

$$RP_{ijt} = \alpha + \beta \cdot UPS_{ijt-1} + \Gamma \cdot C_{it-1} + \delta_t + \eta_j + \vartheta_i + \varepsilon_{ijt}$$

where RP_{ijt} is the number of industrial patent families that are associated with region i, technology j (identified by the four-digit IPC sub-classes), in year t. The use of this dependent variable focuses the analyses on the industrial output with no direct comparison with the global patenting activities in a certain specific technology field.

Table II reports summary statistics for this alternative outcome variable whereas Table III shows the results of all the specifications employing RP as regressand. The count dependent variable requires the use of Poisson pseudo-maximum likelihood regressions with multi-way fixed effects. Incidence rate ratios (IRR) are provided, i.e., above (below) one for positive (negative) signs. The partial correlation between RP and UPS is positive and significant whereas the coefficient of C1UPS is not significantly different from zero.

TABLE II

DESCRIPTIVE STATISTICS OF THE ALTERNATIVE DEPENDENT VARIABLE

Variable name	Count	Mean	Q1	Median	Q3	SD	Min	Max
RP	1,676,400	0.125	0.000	0.000	0.000	0.916	0.000	122.000

TABLE III

MODELS ON THE COUNT OF REGIONAL PATENT FAMILIES WITH HIGH-DIMENSIONAL FIXED EFFECTS POISSON PSEUDO-MAXIMUM LIKELIHOOD ESTIMATORS, CLUSTERED STANDARD ERRORS, AND YEAR, PROVINCE, AND SECTION DUMMIES

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
UPS (lagged)	1.02580***	1.02304**	1.03637***	1.03330***	1.03477***	1.03042***
	(0.00762)	(0.00978)	(0.00743)	(0.00974)	(0.00532)	(0.00710)
C1UPS (lagged)	0.99207		0.99505		0.99391	
	(0.00560)		(0.00602)		(0.00474)	
C1RPS (lagged)		1.00213***		1.00218***		1.00245***
		(0.00035)		(0.00035)		(0.00027)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Technology sub-class dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year × Province dummies			Yes	Yes		
Year × Section × Province dummies					Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400
Log-likelihood	-435,189.5	-433,052.7	-427,869.3	-425,668.6	-390,013.2	-388,120.6
Chi-squared	23.6	44.4	32.4	54.5	54.3	120.0
Pseudo R-squared	0.4511	0.4538	0.4533	0.4561	0.4655	0.4681
Number of clusters	69,850	69,850	69,850	69,850	69,850	69,850

Notes: RP is the dependent count variable indicating the number of patent families developed by local firms in each patent sub-class and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces, respectively. All the regressors are lagged one period. Incidence rate ratios are shown. Standard errors are reported in parentheses, they have been adjusted for 69,850 clusters obtained by combining the spatial controls (i.e., provinces) with the technology sectors (i.e., patent sub-classes). Incidence rate ratios are reported for each regressor. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

A.3. *Placebo regressions*

This section describes the results of placebo regression tests, which provide support that the results of parametric models are not affected by omitted variable bias. First, we employed the `ritest` command (Hess, 2017) to iteratively resample (i.e., randomly permute) the values of the UPS variable, collect its estimated placebo regression coefficient for each draw and compare the simulated distribution of its values with the corresponding realization in the baseline models (i.e., the marginal effect of UPS computed with the original data) under the null hypothesis of no treatment effect. Two-sided and one-sided (i.e., right-tailed) tests based on 1,500 draws are performed. Results are provided in Table IV.

TABLE IV

RESULTS OF THE RANDOMIZATION INFERENCE ON THE UNIVERSITY PATENT STOCK VARIABLE

Hypothesis test	**Two-tailed**	**Right-tailed**
Realization of the test statistic in the original data	0.03006	0.03006
Overall count of resamplings (i.e., random permutations of the values taken by UPS)	1,500	1,500
Count of draws with an extreme realization of the test statistic in the resampled data	0	0
Estimated fraction of extreme realizations (i.e., randomization inference p-value)	0.000	0.000

The implied randomization inference p-value is zero, meaning that the marginal effect of UPS from the baseline models is located in the rejection interval at any conventional significance level, (i.e., this implies that it is an extremely improbable value to obtain if we posit that the treatment has zero effect on all the units). Namely, the randomized samples lead to an estimated coefficient of UPS that is significantly lower than the one found in our models.

Second, we manually checked the results of 150 random samples and looked at the regression results. Five of these models are in Table V. The randomly permuted UPS (i.e., RUPS) is not significantly correlated with the regressand (i.e., RTS) in about 90% of the instances[24].

[24] When found significant, the RUPS variable has a magnitude 10 times smaller than the coefficient of

TABLE V

BASELINE MODELS ON THE REGIONAL SPECIALIZATION WITH RANDOMLY PERMUTED UNIVERSITY PATENT STOCK, HIGH-DIMENSIONAL FIXED EFFECTS LINEAR REGRESSION ESTIMATORS, AND CLUSTERED STANDARD ERRORS

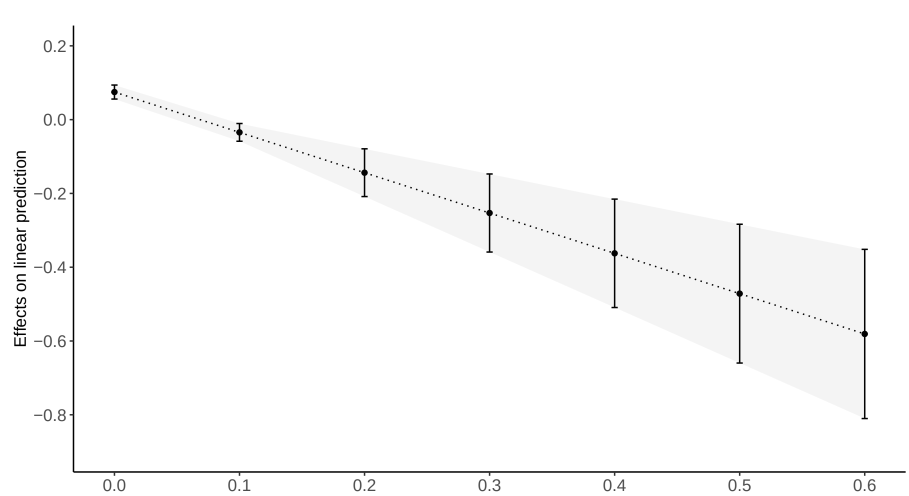
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
RUPS (randomly permuted UPS)	-0.00050	-0.00039	0.00026	-0.00028	-0.00106
	(0.00087)	(0.00092)	(0.00144)	(0.00066)	(0.00102)
Population (lagged)	0.00010***	0.00010***	0.00010***	0.00010***	0.00010***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
GVA (lagged)	0.00168***	0.00168***	0.00168***	0.00168***	0.00168***
	(0.00020)	(0.00020)	(0.00020)	(0.00020)	(0.00020)
Constant	-0.03082***	-0.03083***	-0.03084***	-0.03082***	-0.03083***
	(0.00661)	(0.00661)	(0.00661)	(0.00661)	(0.00661)
Province dummies	Yes	Yes	Yes	Yes	Yes
Technology sub-class dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,676,400	1,676,400	1,676,400	1,676,400	1,676,400
Adjusted R-squared	0.1137	0.1137	0.1137	0.1137	0.1137
Number of clusters	69,850	69,850	69,850	69,850	69,850

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent sub-class and year. RUPS is a randomly permuted version of UPS, a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS and C1RPS variables are the stocks of patents filed by academic institutions and firms that are in first-degree contiguous provinces, respectively. Standard errors are reported in parentheses, they have been adjusted for 69,850 clusters obtained by combining the 110 spatial controls (i.e., provinces) with the 635 technology sectors (i.e., patent sub-classes). Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

A.4. *Marginal effects of the university patent stock for different moderating factors*

In this section, we plot the average marginal effects of the UPS variable and the related confidence intervals computed at different values of three moderating factors: the international orientation of the university (Figure 1), the geographic location of the spatial unit (Figure 2), and the technological complexity of the patent domains (Figure 3).

Figure 1: marginal effects of UPS at different values of university international orientation



UPS in our baseline models.

Figure 2: marginal effects of UPS at different values of the Southern/Northern province dummy

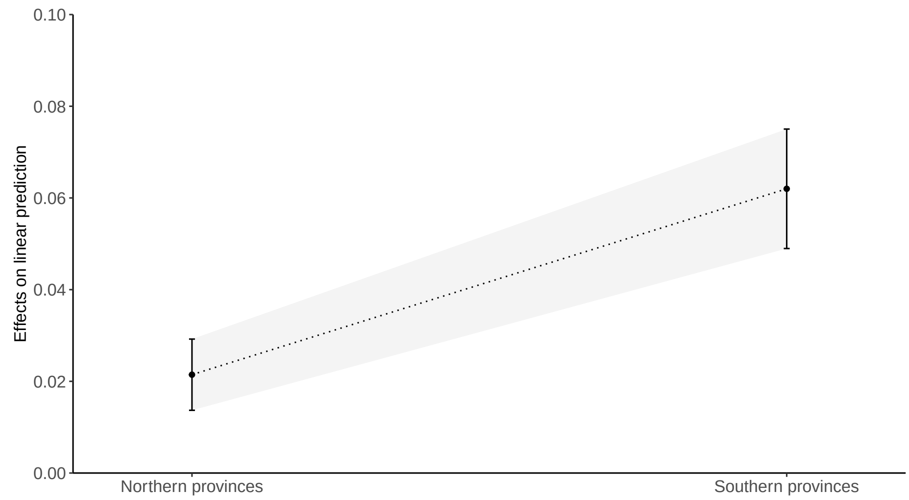
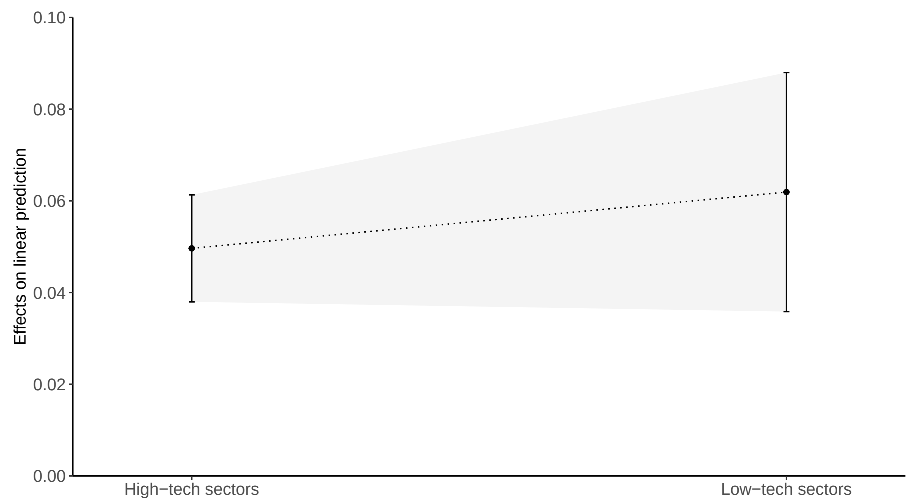


Figure 3: marginal effects of UPS at different values of the high/low-tech sector dummy



A.5. *Instrumental variable regressions with the high-tech/low-tech sector dummy*

TABLE VI

MODELS WITH INSTRUMENTAL VARIABLES AND HIGH-TECH/LOW-TECH SECTOR DUMMY

Model	**(1)**
Excluded instruments	UPS lagged 2 and 3 years
UPS (lagged)	0.04188***
	(0.00988)
C1UPS (lagged)	0.01806***
	(0.00182)
High-tech/Low-tech sector dummy	0.00280**
	(0.00127)
Population (lagged)	0.00006
	(0.00004)
GVA (lagged)	0.00113**
	(0.00049)
Province dummies	Yes
Year dummies	Yes
Observations	1,676,400
Adjusted R-squared	0.0094
F statistic	30.6678

Notes: RTS is the dependent binary variable (based on the RTA index) capturing the technological specialization of local firms in each patent subclass and year. UPS is a continuous variable that measures the stock of patents filed by local universities in the same technological field and year. The C1UPS is the stocks of patents filed by academic institutions that are in first-degree contiguous provinces. Standard errors are reported in parentheses, they have been adjusted for intra-cluster correlations. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

REFERENCES

G. Abramo, C. A. D'Angelo, and F. Rosati. The North-South divide in the Italian higher education system. *Scientometrics*, 109(3):2093–2117, 2016.

M. Acosta, D. Coronado, M. D. León, and M. A. Martínez. Production of university technological knowledge in European regions: evidence from patent data. *Regional Studies*, 43(9):1167–1181, 2009.

Z. Acs, D. Audretsch, and M. Feldman. R&D spillovers and recipient firm size. *The Review of Economics and Statistics*, 76(2):336–340, 1994.

A. Agrawal and I. Cockburn. The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems. *International Journal of Industrial Organization*, 21(9):1227–1253, 2003.

A. Y. Aksoy, D. Pulizzotto, and C. Beaudry. University-industry partnerships in the smart specialisation era. *Technological Forecasting and Social Change*, 176(C):121438, 2022.

C. Antonelli. Technological districts localized spillovers and productivity growth. The Italian evidence on technological externalities in the core regions. *International Review of Applied Economics*, 8(1):18–30, 1994.

R. Apa, V. De Marchi, R. Grandinetti, and S. R. Sedita. University-SME collaboration and innovation performance: the role of informal relationships and absorptive capacity. *The Journal of Technology Transfer*, 46(4):961–988, 2021.

C. Baum, M. Schaffer, and S. Stillman. Stata module for extended instrumental variables 2SLS and GMM estimation. Technical report, Boston College, 2023.

C. Beaudry and A. Schiffauerova. Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy*, 38(2):318–337, 2009.

G. Becattini. The marshallian industrial district as a socio-economic notion. *Revue d'Économie Industrielle*, 157(1):13–32, 2017.

G. Becattini, F. Pyke, and W. Sengenberger. *Industrial districts and inter-firm co-operation in Italy*. International Institute for Labour Studies, 1990.

M. Bigoni, S. Bortolotti, M. Casari, and D. Gambetta. At the root of the North-South cooperation gap in Italy: preferences or beliefs? *The Economic Journal*, 129(619):1139–1152, 2019.

R. Boschma. Proximity and innovation: a critical assessment. *Regional Studies*, 39(1):61–74, 2005.

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

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

R. Boschma and K. Frenken. Technological relatedness and regional branching. In *Beyond territory: dynamic geographies of knowledge creation, diffusion and innovation*. Routledge, 2012.

R. Boschma and C. Gianelle. Regional branching and smart specialization policy. Technical Report No. 6, European Commission, 2014.

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

R. Boschma, P. A. Balland, and D. F. Kogler. Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, 24(1):223–250, 2015.

D. Bragoli, F. Cortelezzi, and M. Rigon. Firms' innovation and university cooperation: new evidence from a survey of Italian firms. *Oxford Economic Papers*, 76(1):136–161, 2024.

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

M. Calderini and G. Scellato. Academic research, technological specialization and the innovation performance in European regions: an empirical analysis in the wireless sector. *Industrial and Corporate Change*, 14(2):279–305, 2005.

M. Carree, A. Della Malva, and E. Santarelli. The contribution of universities to growth: empirical evidence for Italy. *The Journal of Technology Transfer*, 39(3):393–414, 2014.

F. Caviggioli. Technology fusion: identification and analysis of the drivers of technology convergence using patent data. *Technovation*, 55–56(C):22–32, 2016.

F. Caviggioli and B. Forthmann. Reach for the stars: disentangling quantity and quality of inventors' productivity in a multifaceted latent variable model. *Scientometrics*, 127(12):7015–7040, 2022.

F. Caviggioli, A. Colombelli, A. De Marco, G. Scellato, and E. Ughetto. Co-evolution patterns of university patenting and technological specialization in European regions. *The Journal of Technology Transfer*, 48 (1):216–239, 2022.

F. Caviggioli, A. Colombelli, A. De Marco, G. Scellato, and E. Ughetto. The impact of university patenting on the technological specialization of european regions: a technology-level analysis. *Technological Forecasting and Social Change*, 188:122216, 2023.

G. Cicerone, A. Faggian, S. Montresor, and F. Rentocchini. Regional artificial intelligence and the geography of environmental technologies: does local AI knowledge help regional green-tech specialization? *Regional Studies*, 57(2):330–343, 2023.

A. Civera, D. Donina, M. Meoli, and S. Vismara. Fostering the creation of academic spinoffs: does the international mobility of the academic leader matter? *International Entrepreneurship and Management Journal*, 16(2):439–465, 2020.

W. Cohen, R. Nelson, and J. Walsh. Links and impacts: the influence of public research on industrial R&D. *Management Science*, 48(1):1–23, 2002.

A. Colombelli, J. Krafft, and F. Quatraro. The emergence of new technology-based sectors in European regions: a proximity-based analysis of nanotechnology. *Research Policy*, 43(10):1681–1696, 2014.

A. Colombelli, E. Paolucci, and E. Ughetto. Hierarchical and relational governance and the life cycle of entrepreneurial ecosystems. *Small Business Economics*, 52(2):505–521, 2019.

L. Compagnucci and F. Spigarelli. The third mission of the university: a systematic literature review on potentials and constraints. *Technological Forecasting and Social Change*, 161:120284, 2020.

D. Coronado, E. Flores, and M. A. Martínez. The role of regional economic specialization in the production of university-owned patents. *The Annals of Regional Science*, 59(2):513–533, 2017.

S. Correia. A feasible estimator for linear models with multi-way fixed effects. Working paper, Duke University, 2016.

S. Correia, P. GuimarÃ£es, and T. Zylkin. Fast poisson estimation with high-dimensional fixed effects. *The Stata Journal*, 20(1):95–115, 2020.

R. Cowan and N. Zinovyeva. University effects on regional innovation. *Research Policy*, 42(3):788–800, 2013.

G. De Santis, M. Maltagliati, and A. Petrucci. So close, so far: the cultural distance of foreigners in Italy. *Social Indicators Research*, 158(1):81–106, 2021.

L. A. De Vasconcelos Gomes, A. L. F. Facin, M. S. Salerno, and R. K. Ikenami. Unpacking the innovation ecosystem construct: evolution, gaps and trends. *Technological Forecasting and Social Change*, 136(C): 30–48, 2018.

P. D'Este and P. Patel. University-industry linkages in the UK: what are the factors underlying the variety of interactions with industry? *Research Policy*, 36(9):1295–1313, 2007.

V. Di Giacinto, M. Gomellini, G. Micucci, and M. Pagnini. Mapping local productivity advantages in Italy: industrial districts, cities or both? *Journal of Economic Geography*, 14(2):365–394, 2014.

A. Di Liberto, F. Pigliaru, and R. Mura. How to measure the unobservable: a panel technique for the analysis of TFP convergence. *Oxford Economic Papers*, 60(2):343–368, 2008.

T. Dias Sant'Ana, P. H. de Souza Bermejo, M. F. Moreira, and W. V. B. de Souza. The structure of an innovation ecosystem: foundations for future research. *Management Decision*, 58(12):2725–2742, 2020.

G. Dosi. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, 22(2):102–103, 1993.

EC. Regional innovation scoreboard. Technical report, Directorate-General for Research and Innovation of the European Commission, 2023.

J. Essletzbichler. Relatedness, industrial branching and technological cohesion in US metropolitan areas. *Regional Studies*, 49(5):752–766, 2015.

H. Etzkowitz and L. Leydesdorff. The dynamics of innovation: from national systems and mode two to a triple helix of university-industry-government relations. *Research Policy*, 29(2):109–123, 2000.

E. Felice. The socio-institutional divide: explaining Italy's long-term regional differences. *Journal of Interdisciplinary History*, 49(1):43–70, 2018.

O. Figueiredo, P. GuimarÃ£es, and D. Woodward. Industry localization, distance decay, and knowledge spillovers: following the patent paper trail. *Journal of Urban Economics*, 89(C):21–31, 2015.

L. Fleming. Recombinant uncertainty in technological search. *Management Science*, 47(1):117–132, 2001.

L. Fleming and O. Sorenson. Science as a map in technological search. *Strategic Management Journal*, 25 (8–9):909–928, 2004.

D. Foray. *Smart specialisation: opportunities and challenges for regional innovation policy*. Routledge, 2014.

D. Foray, P. A. David, and B. H. Hall. Smart specialisation from academic idea to political instrument, the surprising career of a concept and the difficulties involved in its implementation. Technical report, École Polytechnique Fédérale de Lausanne, 2011.

C. Forliano, P. De Bernardi, and D. Yahiaoui. Entrepreneurial universities: a bibliometric analysis within the business and management domains. *Technological Forecasting and Social Change*, 165(C):120522, 2021.

K. Frenken and R. Boschma. A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. *Journal of Economic Geography*, 7(5):635–649, 2007.

K. Frenken, F. Van Oort, and T. Verburg. Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41(5):685–697, 2007.

M. Fritsch and V. Slavtchev. Universities and innovation in space. *Industry and innovation*, 14(2):201–218, 2007.

M. García-Vega and O. Vicente Chirivella. Do university technology transfers increase firms' innovation? *European Economic Review*, 123:103388, 2020.

A. Geuna and A. Muscio. The governance of university knowledge transfer: a critical review of the literature. *Minerva*, 47(1):93–114, 2009.

H. Goldstein and C. Renault. Contributions of universities to regional economic development: a quasi-experimental approach. *Regional Studies*, 38(7):733–746, 2004.

Z. Griliches. Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 10(1):92–116, 1979.

M. R. Guevara, D. Hartmann, M. AristarÃ¡n, M. Mendoza, and C. Hidalgo. The research space: using career paths to predict the evolution of the research output of individuals, institutions, and nations. *Scientometrics*, 109(3):1695–1709, 2016.

C. Gunasekara. The generative and developmental roles of universities in regional innovation systems. *Science and Public Policy*, 33(2):137–150, 2006.

B. H. Hall, A. Jaffe, and M. Trajtenberg. Market value and patent citations. *The RAND Journal of Economics*, 36(1):16–38, 2005.

M. Hansen. The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, 44(1):82–111, 1999.

G. Heimeriks and P. A. Balland. How smart is specialisation? An analysis of specialisation patterns in knowledge production. *Science and Public Policy*, 43(4):562–574, 2016.

S. Hess. Randomization inference with Stata: a guide and software. *The Stata Journal*, 17(3):630–651, 2017.

C. Hidalgo and R. Hausmann. The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26):10570–10575, 2009.

D. Iacobucci and F. Perugini. Innovation performance in traditional industries: does proximity to universities matter. *Technological Forecasting and Social Change*, 189:122340, 2023.

A. Jaffe, M. Trajtenberg, and R. Henderson. Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3):577–598, 1993.

J. Kim, S. Lee, and G. R. Marschke. The influence of university research on industrial innovation. Working Paper No. 11447, National Bureau of Economic Research, 2005.

K. Laursen, T. Reichstein, and A. Salter. Exploring the effect of geographical proximity and university quality on university-industry collaboration in the United Kingdom. *Regional Studies*, 45(4):507–523, 2011.

B. Leten, P. Landoni, and B. Van Looy. Science or graduates: how do firms benefit from the proximity of universities? *Research Policy*, 43(8):1398–1412, 2014.

A. N. Link and M. van Hasselt. On the transfer of technology from universities: the impact of the Bayh-Dole Act of 1980 on the institutionalization of university research. *European Economic Review*, 119(C): 472–481, 2019.

F. Lissoni, M. Pezzoni, B. Potì, and S. Romagnosi. University autonomy, the professor privilege and academic patenting. *Industry and Innovation*, 20(5):399–421, 2013.

K. Lyytinen, N. Nahar, and N. Huda. IT supported complex technology transfer in high-tech sector. In *Proceedings of the Portland International Conference on Management of Engineering and Technology*. Institute of Electrical and Electronics Engineers, 2001.

E. Mansfield. Academic research and industrial innovation. *Research Policy*, 20(1):1–12, 1991.

E. Mansfield and J. Y. Lee. The modern university: contributor to industrial innovation and recipient of industrial R&D support. *Research Policy*, 25(7):1047–1058, 1996.

P. Maskell and A. Malmberg. The competitiveness of firms and regions: ubiquitification and the importance of localized learning. *European Urban and Regional Studies*, 6(1):9–25, 1999.

C. Mason and Y. Pierrakis. Venture capital, the regions and public policy: the United Kingdom since the post-2000 technology crash. *Regional Studies*, 47(7):1156–1171, 2013.

P. McCann and R. Ortega-Argilés. Smart specialization, regional growth and applications to European Union cohesion policy. *Regional Studies*, 49(8):1291–1302, 2015.

G. Medda, C. Piga, and D. Siegel. University R&D and firm productivity: evidence from Italy. *The Journal of Technology Transfer*, 30(1):199–205, 2004.

S. Montresor and F. Quatraro. Regional branching and key enabling technologies: evidence from European patent data. *Economic Geography*, 93(4):367–396, 2017.

R. Moreno, R. Paci, and S. Usai. Spatial spillovers and innovation activity in European regions. *Environment and Planning A: Economy and Space*, 37(10):1793–1812, 2005.

F. Neffke, M. Henning, and R. Boschma. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3):237–265, 2011.

F. Neffke, M. Hartog, R. Boschma, and M. Henning. Agents of structural change: the role of firms and entrepreneurs in regional diversification. *Economic Geography*, 94(1):23–48, 2018.

OECD. Patent statistics manual. Technical report, Organisation for Economic Co-operation and Development, 2009.

OECD. University-industry collaboration: new evidence and policy options. Technical report, Organisation for Economic Co-operation and Development, 2019.

R. Paci, E. Marrocu, and S. Usai. The complementary effects of proximity dimensions on knowledge spillovers. *Spatial Economic Analysis*, 9(1):9–30, 2014.

J. M. Piqué, J. Berbegal-Mirabent, and H. Etzkowitz. The role of universities in shaping the evolution of Silicon Valley's ecosystem of innovation. *Triple Helix*, 7(2–3):277–321, 2020.

R. Ponds, F. v. Oort, and K. Frenken. Innovation, spillovers and university-industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, 10(2):231–255, 2009.

D. Rigby. Technological relatedness and knowledge space: entry and exit of US cities from patent classes. *Regional Studies*, 49(11):1922–1937, 2015.

D. K. Simonton. Creative thought as blind-variation and selective-retention: combinatorial models of exceptional creativity. *Physics of Life Reviews*, 7(2):156–179, 2010.

L. Soete. The impact of technological innovation on international trade patterns: the evidence reconsidered. *Research Policy*, 16(2–4):101–130, 1987.

S. L. Sun, V. Z. Chen, S. A. Sunny, and J. Chen. Venture capital as an innovation ecosystem engineer in an emerging market. *International Business Review*, 28:101485, 2019.

H. Tötterman and J. Sten. Start-ups: business incubation and social capital. *International Small Business Journal*, 23(5):487–511, 2005.

E. Uyarra. Conceptualizing the regional roles of universities, implications and contradictions. *European Planning Studies*, 18(8):1227–1246, 2010.

M. Van Den Berge and A. Weterings. Relatedness in eco-technological development in European regions. Working Paper No. 13, Utrecht University, 2014.

A. Van Looy, M. De Backer, and G. Poels. A conceptual framework and classification of capability areas for business process maturity. *Enterprise Information Systems*, 8(2):188–224, 2014.