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Co-evolution patterns of university patenting and technological specialization in European regions

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

Keywords Technological co-evolution processes · Regional specialization · Technological distance · University patents · Innovation activities

JEL Classification O31 · O33 · O34 · R10 · R12

1 Introduction

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

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

In this paper, we contribute to the literature on regional technological specialization in three main respects. First, we provide new evidence on the co-evolution patterns of the technological specialization of innovation activities of firms and academic institutions located in the same European region, defined at the NUTS3 level, during the years from 2003 to 2014. More specifically, the work aims at exploring to what extent and under what conditions there have been in place convergent or divergent processes in the relative specialization of the innovation activities carried out by co-located firms and universities. Our focus is on the patenting activities of universities, rather than their scientific publications, because patents can be assumed as a more precise proxy for more applied knowledge developed locally, as well as a more technology-transfer oriented activity. Second, we exploit an original and unique dataset that has been built by merging data from four different sources: (1) the European Commission CORDIS dataset reporting EU funded R&D projects under FP7, (2) the ETER database reporting information on Higher Education Institutions (HEIs) in Europe, (3) the PATSTAT database containing worldwide patent information, and (4) the Eurostat database reporting economic region-level data. The dataset allows us to map the full patent portfolios of about 500 European universities and those of all firms in their region with additional region-level and university-level controls. Third, we apply the conceptual framework for the identification of alternative co-evolution patterns developed by Colombelli et al. (2020). This taxonomy and its operationalization offer interesting evidence and call for the investigation of the location-specific factors that might have influenced the emergence of diverse patterns of technological evolution. The literature has indeed emphasized that many factors, at different levels of analysis, may affect the effectiveness of knowledge transfer from universities to firms (Bruneel et al., 2010; Muscio & Vallanti, 2014). Thus, we provide an empirical test of the four possible models of university-region technological evolution processes illustrated in the taxonomy, linking such patterns to both region-specific and university-specific structural characteristics.

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

the further development of applied research in the region. Regression analyses show that the overall innovation performance of a region is associated with a divergence pattern in the co-evolution of industry and academic technological portfolios, while a dynamic of convergence in the specialization patterns of industry and academia is revealed when local universities are large and have a STEM orientation. The paper elaborates on such empirical findings and suggests implications for the design of policy approaches in line with the so-called Smart Specialization Strategies (S3).

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

2 Universities and the local technological system

2.1 Technological specialization in regional innovation systems

The recent economic geography literature on regional branching and technological specialization shows that regions stay close to their existing capabilities when diversifying into new products and technologies (Boschma & Frenken, 2011; Frenken & Boschma, 2007). These dynamics are engendered by the cumulative nature of innovation processes, the existence of learning economies in knowledge generation, and the localized nature of knowledge spillovers (Antonelli, 1995; Jaffe & Trajtenberg, 1999; Jaffe et al., 1993). Such a thesis has been confirmed in different geographical contexts (e.g., Boschma et al., 2013; Colombelli et al., 2014; Neffke et al., 2011). This evidence has stimulated the debate, in both policy and academic circles, about the role of technological specialization on regional performance and has contributed to the adoption of *Smart Specialization Strategies* (S3) in the latest wave of regional policies (Boschma, 2014). These policies are aimed at identifying strategic areas of intervention to sustain regional innovation activities by building on cumulated knowledge, collective intelligence, and distinctive assets of the territory (Foray, 2014). However, the debate on regional diversification patterns has started questioning the desirability of these strategies because of path dependence and lock-in effects. Understanding the factors that help regions sustain their competitive advantage through technological specialization dynamics becomes of paramount importance. Universities may exert a crucial role in this process, as they are key sources of knowledge for the local ecosystem. Yet, the literature on regional branching has neglected the role of universities so far.

On a parallel ground, the regional economics literature has instead provided a great deal of evidence on the crucial role of universities in the creation and development of local ecosystems for innovation. Different frameworks like *Regional Innovation Systems* (Braczyk et al., 1998; Cooke et al., 1997), Triple Helix (Etzkowitz & Leydesdorff, 1995, 2000), industrial district (Becattini, 1990; Marshall, 1920), clusters (Porter, 1998), entrepreneurial ecosystems (Isenberg, 2010; Spigel, 2017) and innovation ecosystems (Granstrand &

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

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

However, only a few scholarly works have empirically tested the impact of academic research on the technological trajectories of geographical areas and vice versa (Acosta et al., 2009; Braunerhjelm, 2008; Calderini & Scellato, 2005; Coronado et al., 2017). Overall, these contributions have provided mixed results concerning the existence, the direction, and the causal relationship between academic research and industrial specialization. Moreover, these studies have adopted different empirical models and implemented different variables to compute the technical specialization of regions and universities (e.g., scientific publications, patents, employees, and researchers). Calderini and Scellato (2005) studied the wireless sector and found a causal effect of academic research specialization on the patenting activity of local firms. Braunerhjelm (2008) found a positive impact of the research specialization of a university on the industrial specialization of the region where

the academic institution was located, with this impact depending upon the commercial environment in which the university was embedded. Acosta et al. (2009) showed a strong correlation between university and industry specialization only in a few regions and no significant result emerging at the sector level. This evidence was explained referring to two possible reasons: i) universities tend to satisfy only a fraction of the demand for technological knowledge; ii) academic research is more focused on internal objectives (i.e., scientific publications) and therefore does not consider the external demand for knowledge. Finally, Coronado et al. (2017) studied the effects of reverse spillovers in high-tech sectors and found that the productive specialization of a region has a significant effect on the patenting activity of universities located in the same area. Overall, these contributions provide mixed results concerning the existence, the direction, and the causal relationship between academic research specialization and industrial one. More recently, Colombelli et al. (2020), to obtain a better understanding of the role played by universities in the technological development and specialization of the territories in which they are located, have developed an original taxonomy composed of four models of university-region technological evolution processes.

2.2 Co-evolution patterns of industry and academic innovation activities

Our analysis aims at gathering novel evidence on the relative dynamics of the specialization of innovation activities carried out by firms and universities, which are co-localized in the same region. In this regard, we use the composition over time of their patent portfolios as a proxy for the specialization of the innovation activities within a region. Patent technological classifications allow mapping on a sufficiently fine scale the set of competencies and the innovative knowledge available in a specific local area. In order to analyze the determinants (at the university, firm, and ecosystem levels) of university-region technological evolution processes, we adopt the taxonomy adopted in the work by Colombelli et al. (2020). It is based on two dimensions: (1) the direction of the technological evolution process that allows divergent processes to be distinguished from convergent ones and (2) the leading role of local universities versus firms in the entry of a new technology, that allows region-pull versus university-push processes to be identified. In divergent processes, the technological specialization of universities and local firms follows different trajectories (Acosta et al., 2009), while convergent processes are characterized by increasing technological proximity over time between local firms and universities. In the case of region-pull processes, local firms exert the leading role and guide the evolution of the local technological specialization (Coronado et al., 2017), while in university-push processes, regional technological trajectories are driven by local universities through their entry into new technological fields (Braunerhjelm, 2008; Calderini & Scellato, 2005).

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

Quadrant A in Table 1 refers to a context in which universities enter into new technological fields, and that is characterized by a loose innovation ecosystem and firms with a low absorptive capacity. This configuration leads to divergent technological evolution

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

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

Source: Colombelli et al. (2020)

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

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

3 Data and methods

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

The first step of the process was identifying a set of European universities that were involved in substantial research activities and with a significant performance in obtaining EU funds on competitive projects. The use of data about EU funding is motivated by the purpose of identifying those academic institutions that are not only active in research but have a good performance on collaborative (and mostly applied) projects, often involving collaboration with firms. Hence, we collected data on the largest recipients of FP7 funds among European universities. We disambiguated the names of the universities available in the CORDIS database.[1] We sorted universities according to the number of the awarded EU projects and selected those accounting cumulatively for 90% of the total funding to universities. We ended up with a sample of 528 largest universities. The universities were then geolocalized in the corresponding regions at the third level of the NUTS system[2] on the basis of the information provided in the ETER dataset.[3]

For each university and the corresponding geographical area, we collected all patents filed and identified the aggregate portfolio in the years between 1992 and 2014. The university patents were searched with queries that exploited the assignee field in PATSTAT,[4] as well as the standardized names available in OECD HAN.[5] We collected all patent filings (domestic and international) and then consolidated them into patent families to avoid double counting. Since we are attributing patents to universities based on the patent applicant name, we had to exclude from the sample Finland, Sweden, and Norway, as such countries had in force during the examined years the so-called *professor's privilege*[6] (see Lissoni et al., 2008, 2013).

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

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

[2] The Nomenclature of Territorial Units for Statistics (NUTS) is a hierarchical and harmonized classification that partitions the economic territory of European member countries into smaller geographical units for statistical purposes. It is composed of three sub-national levels based on existing administrative divisions and target population thresholds.

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

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

[5] A database maintained by the Organization for Economic Co-operation and Development (OECD) that harmonizes patent applicant names. For each university, we searched different spelling variations, integrated the patent filings managed by TTOs or ad-hoc companies (e.g., Oxford University Innovation), and controlled for false-positive results to refine the final identification strategy.

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

Note that we excluded from the final sample the NUTS3 regions and the universities with very small patent portfolios to avoid problems in the computation of specialization indexes.[7] After such a filtering process, we obtained a final sample composed of 428 universities that are located in 263 geographical NUTS3 areas. The patent-level dataset associated with this sample includes 827,627 patent families (Table 8). These data have been processed to derive specialization indicators according to the methods presented in Sect. 4.1.

We also collected and matched additional data to characterize the universities and the regions. The selected universities were matched with the records available in the ETER database to collect information on types, presence of STEM courses, size, and other structural variables. The geographical areas were characterized by the economic indicators available in the Eurostat Regio Database.[8] We also collected data about the Regional Innovation Scoreboard (RIS)[9] to gather information on the regional innovation systems.

A single NUTS3 region included in the dataset can host more than one university. In these cases, we added up the patent portfolios of the different academic institutions within a specific region since we are interested in mapping the evolution of the relative specialization of industry and the co-localized academic research system.[10] We aggregated in a similar fashion the other quantitative measures relating to universities.

3.1 Methodology for assessing the evolution of specialization patterns

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

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

3.1.1 Evolution of the technological distance: the convergence-divergence process

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

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

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

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

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

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

Variable	Definition	Objective
Evolution of the technological distance	Variation of the Euclidean distance between the patent portfolios of the region and the local universities (consolidated into patent families)	Measuring the process of technological convergence or divergence over time
Entry ratio	Number of technologies in which the entry was led by the university divided by number of technologies in which the entry was led by the industry (the cases in which those two events occur simultaneously were considered both in the numerator and the denominator of the ratio)	Measuring the prevalence of university-push or region-pull dynamics in the change of the local knowledge base

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

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

3.1.2 Entry ratio: measuring entry into a new technological field

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

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

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

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

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

The entry of region i in technology j is defined as the first year in which the vector of its *NRTA* becomes greater than zero for the specific IPC sub-class j, thus indicating that region i is over-specialized for technological domain j. Given the limited number of patent applications filed by universities, we used the count of patents rather than the values of the

[11] We compute it by dividing the technological distance D_t^{RU} by its maximum value, which is $\sqrt{2}$.

NRTA index for local academic institutions. Hence, the entry of a university in field j was defined as the first year in which it filed a new patent application associated with the specific IPC sub-class j. By comparing the timing of entry of the region and the university, we can assess, for each technological class, whether the entry was led by the local university or by the co-localized firms.

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

4 Analyzing the patterns of university-industry specializations in European regions

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

Table 3 illustrates the distribution of NUTS3 regions by the count of local university patent families. About 27.0% of NUTS3 regions total between 100 and 200 patent families, 24.3% more than 200 patent families, and 23.6% between 16 and 50 patent families. The aggregate number of patent families in the analyzed NUTS3 regions (excluding the corresponding university patent families) is increasing from 35,284 to 41,352 in the considered years, namely from 2003 to 2014 (see Table 9). During the same period, the share of university patent families almost doubled, from 6.0 to 11.5%, confirming the growing relevance of academic patenting activities in these economic systems. There is considerable variation across regions in the size of the patent portfolios attributed to the local universities.

Figure 2 illustrates the incidence in the sample of regions showing, alternatively, a convergent or divergent co-specialization process between local universities and co-localized firms. The x-axis reports the values of the Euclidean distance computed between the technological portfolio of the university system and the other patent families associated with the same NUTS3 region for the years from 2003 to 2008. The y-axis indicates the values of the same variable but for the subsequent time frame (from 2009 to 2013). The dots in the scatterplot represent pairs of university systems and regions. The NUTS3 regions positioned below the bisector (i.e., dots colored in blue) are characterized by a decrease in the technological distance between the university system and the local firms: their portfolios of technologies are converging (45.6% of the sample). For the universities and the corresponding regions located above the bisector (i.e., dots colored in orange), the technological distance is increasing over time and indicates the presence of a diverging process of technological co-evolution (54.4% of the sample). The university-region pairs closer to the origin are those with more similar technological portfolios in both intervals. We also highlight that the dispersion of the points around the diagonal of the quadrant gets larger as the technological distance between the specializations of the region and those of the local university increases.

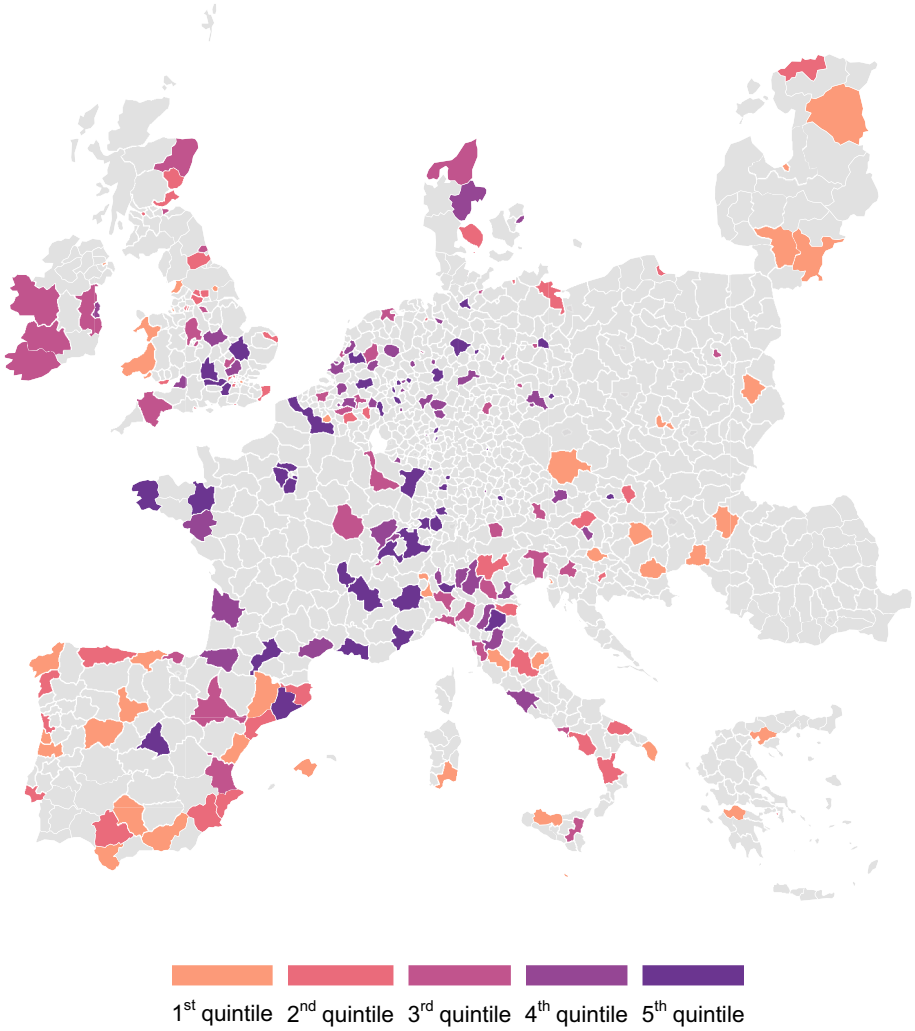


Fig. 1 Distribution of the count of patent families by NUTS3 region

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

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

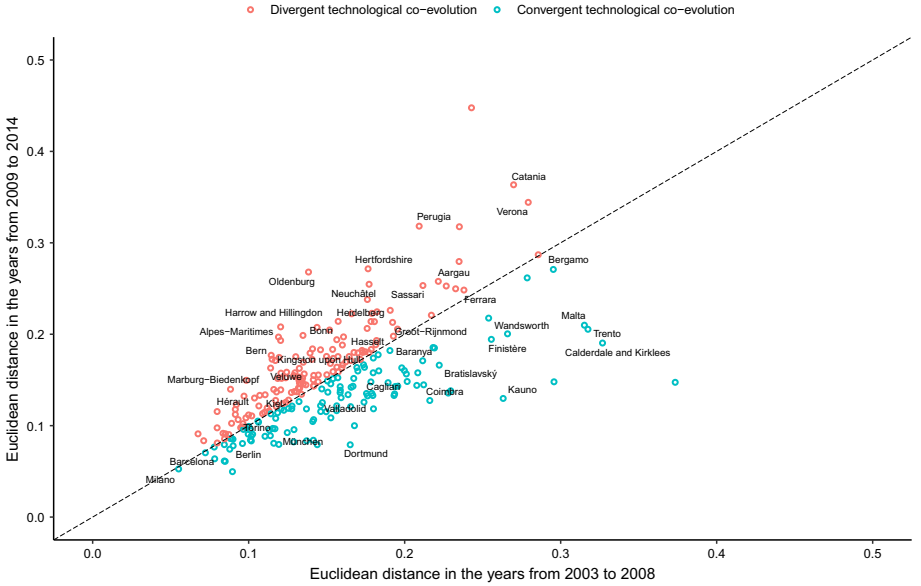


Fig. 2 Evolution of the technological distance by NUTS3 region between the two considered time frames (2009–2014 and 2003–2008)

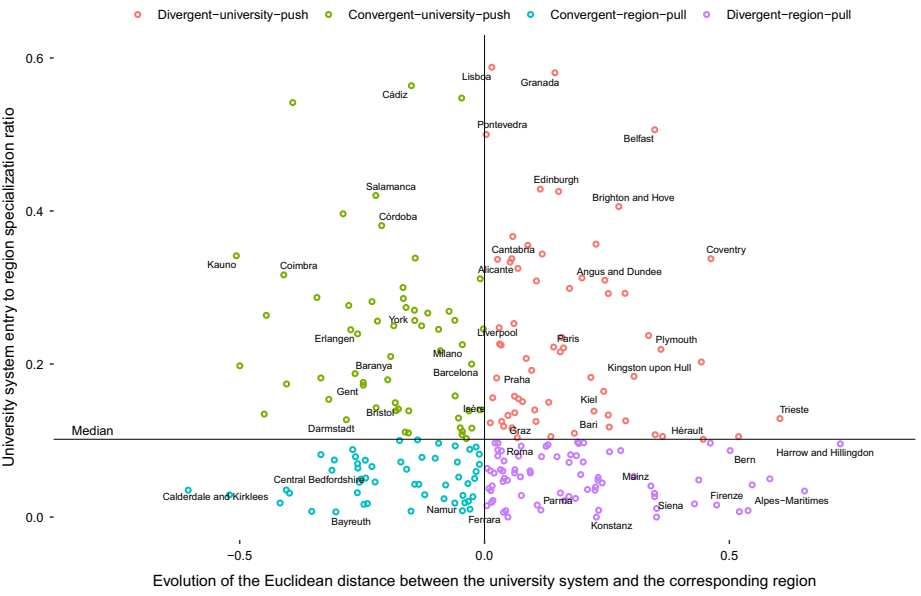


Fig. 3 Taxonomy of university entry versus NUTS3 region specialization processes

Figure 3 provides the empirical distribution of the examined geographical areas according to the taxonomy proposed in the previous section. The horizontal axis measures the ongoing convergence (divergence) process between the university technological portfolio

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

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

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

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

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

4.1 Factors affecting the co-evolution of specialization patterns

Starting from the proposed taxonomy, we evaluated the significance of the impact of several variables on the distribution of the identified universities and regions across the four illustrated categories. First, we present the results of *t*-tests to understand the presence of differences in university-level and regional-level characteristics when converging or diverging patterns are in place. Then, we introduce two sets of multivariate analyses, based on OLS regressions and Tobit models with technological distance and entry ratio as dependent variables, respectively.

Table 4 reports descriptive statistics for the variables used in the empirical analysis. Variables refer to university-level and regional-level characteristics. Universities are characterized by their STEM orientation, the research intensity (proxied by the share of Ph.D. students), their size (measured in terms of total students), the propensity to rely on funding (i.e., the relative amount of awarded FP7 projects), and to collaborate with firms (i.e., the share of FP7 projects with industrial partners). The regional characteristics are determined using the openness or collaborativeness of the local companies proxied by the share of co-assigned patent families and the urbanization level (measured

Table 4 Descriptive statistics of the regressors

Variable	Description	Count	Mean	Median	SD	Min	Max
STEM orientation	Share of STEM graduates on total graduates	258	0.228	0.217	0.145	0.000	0.969
Ph.D. intensity	Share of Ph.D. students on total undergraduate students	256	0.062	0.046	0.052	0.004	0.429
University size	Total graduates ISCED 5–7 (ISCED-5 are diplomas with a duration of fewer than three years, ISCED-6 are bachelor diplomas or equivalent levels, ISCED-7 are master diplomas or equivalent levels in the pre-Bologna system)	258	8.035	5.374	7.627	0.338	53.579
University funding propensity	Ratio of financed costs for total FP7 projects over professors	252	1.678	0.887	2.244	0.077	18.801
University collaborativeness	Ratio of financed costs for FP7 projects with firms over professors	252	0.940	0.502	1.314	0.035	9.049
R&D expenditure of the business sector	Value at the NUTS2 level from the RIS (2019)	259	0.888	0.840	0.333	0.169	1.693
Innovation index	Value at the NUTS2 level from the RIS (2019)	259	0.993	1.040	0.255	0.431	1.601
Technological openness of the region	Share of co-assigned patents developed by each NUTS3 area (university patents are excluded)	263	0.126	0.120	0.058	0.033	0.381
Population	Thousand inhabitants, value at the NUTS3 level (2019)	241	0.721	0.542	0.705	0.064	5.702
Population density	Thousand inhabitants per square kilometer, value at the NUTS3 level (2019)	241	1.395	0.503	2.318	0.023	20.476

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

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

Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively

through the population density). Additionally, we derived from the Regional Innovation Scoreboard (RIS) two NUTS1 and NUTS2 level variables and matched them to the examined NUTS3: the R&D investment of the business sector and the RIS innovation index. This latter index identifies innovation leaders, strong innovators, moderate, and modest innovators by combining various regional innovation metrics.

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

Table 6 reports OLS regressions where factors affecting divergence patterns are investigated. Results show that a higher presence of STEM students and a greater university size are negatively and significantly associated with a divergence pattern of

Table 6 Factors affecting divergence patterns, OLS models with clustered standard errors

Model	(1)	(2)	(3)	(4)	(5)	(6)
Technological distance in the years from 2003 to 2008				0.359***	0.363***	0.349***
				(0.052)	(0.051)	(0.051)
STEM orientation	−0.347***	−0.363***	−0.353***	−0.243***	−0.250***	−0.248***
	(0.058)	(0.055)	(0.057)	(0.049)	(0.048)	(0.050)
Ph.D. intensity	0.043	0.010	0.027	0.080	0.068	0.075
	(0.190)	(0.182)	(0.179)	(0.147)	(0.138)	(0.136)
University size	−0.007***	−0.005***	−0.007***	−0.004***	−0.003**	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
University funding propensity	−0.007	−0.008	−0.011	−0.005	−0.007	−0.009
	(0.011)	(0.012)	(0.011)	(0.009)	(0.010)	(0.010)
University collaborativeness	0.000	0.004	0.006	0.009	0.013	0.014
	(0.019)	(0.020)	(0.019)	(0.017)	(0.017)	(0.016)
R&D expenditure of the business sector	0.048			0.038		
	(0.029)			(0.025)		
Innovation index		0.205***	0.188***		0.139**	0.133**
		(0.066)	(0.064)		(0.057)	(0.055)
Technological openness of the region	−0.102	−0.123	−0.118	−0.120	−0.136	−0.131
	(0.170)	(0.163)	(0.165)	(0.138)	(0.134)	(0.135)
Population	0.009	−0.005		0.009	0.001	
	(0.014)	(0.017)		(0.014)	(0.015)	
Population density	0.012***		0.010***	0.007**		0.005*
	(0.003)		(0.003)	(0.003)		(0.003)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	226	226	226	226	226	226
Adjusted R-squared	0.409	0.406	0.430	0.559	0.562	0.568

The dependent variable is the Euclidean technological distance computed in the years from 2009 to 2014. Coefficient estimates for both country dummies and the constant are not shown in the table although they have been included in the models. Standard errors are clustered at the region level and reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively

Table 7 Factors affecting university-push patterns, Tobit models with clustered standard errors

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

The dependent variable is the ratio between the number of technological entries of the universities and the number of technological specializations of the corresponding region. Coefficient estimates for both country dummies and the constant are not shown in the table although they have been included in the models. Standard errors are clustered at the region level and reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively

technological portfolios. The greater the RIS innovation index is, the larger the variation of the Euclidean distance between the patent portfolio of the region and that of the local universities, confirming a diverging trend.

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

5 Conclusion

This paper contributes to the literature on the evolution of the technological specialization at the regional scale and on the role played by academic institutions by empirically operationalizing and testing the taxonomy proposed by Colombelli et al. (2020) on a larger

sample of EU geographical areas. Our findings improve the understanding of the university-industry technological evolution processes. We have investigated the co-evolution patterns in the technological specialization of firms and universities located in the same European region during the years from 2003 to 2014. To this aim, we relied on an original dataset including information on patents, EU-funded R&D projects, university-level characteristics, and economic data at the region level. We have offered insights into the role played by universities and local firms in the evolution of regional specialization, disentangling between convergent versus divergent processes and university-push versus region-pull dynamics to identify alternative co-evolution patterns. We have also explored the factors (at the region and university levels) that might have influenced the emergence of such diverse patterns of technological specialization. Our approach complements the existing studies on the effectiveness of knowledge transfer from universities to firms (e.g., Bruneel et al., 2010; Muscio & Vallanti, 2014) and provides further characterization to the central role of universities (e.g., Agrawal & Cockburn, 2003; d'Este & Patel, 2007; Etzkowitz & Leydesdorff, 1995; Granstrand & Holgersson, 2020).

Our evidence shows the presence of different configurations of technological co-evolution processes for industry and academia specializations across the analyzed EU regions. During the years from 2003 to 2014, we observe both diverging and converging specialization patterns between co-localized industrial and academic systems of the sample regions. In more than half of all the region-university pairs, the technological distance is increasing over time, suggesting that the technical knowledge generated by academic institutions and local firms follows different trajectories (Acosta et al., 2009). However, just in a limited number of cases, the specialization into a new technological domain is led by the patenting activity of local universities (Braunerhjelm, 2008; Calderini & Scellato, 2005). Empirical tests reveal that this happens when universities are large and have a STEM orientation. A region-pull configuration is more frequent in the case of pre-existing R&D and innovation activities of private firms, thus indicating that the design of regional specialization policies should support the process of transformation of the knowledge bases within local innovation systems. The cumulative nature of the technological innovation process, the presence of learning and local effects in knowledge generation and diffusion suggests that when regions stay close to their existing innovative capabilities, it is the local industrial ecosystem to lead technological specialization patterns (Coronado et al., 2017). This is in line with the design of policy approaches that emphasize Smart Specialization Strategies (S3) building upon distinctive regional assets and knowledge bases.

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

The paper is not exempt from some limitations which should be acknowledged. Although we controlled for country specificities, local characteristics such as the regulation of universities to incentivize industry collaboration, the policies governing intellectual property rights (IPRs), and the role of technology transfer offices (TTOs) were

not directly considered in our analyses and might not be significantly related to the size of academic institutions, eluding our model specification. Those characteristics favor the exchange of knowledge and technologies between academic institutions and private companies and thus affect the patenting behavior of university scientists (Goel and Göktepe-Hultén, 2013). Another element not tackled in our study that would require a specific data generation process deals with the characteristics of academic inventors: their ties and previous collaborations with the industry sector might also provide heterogenous incentives to file patents (Göktepe-Hultén, 2010; Goel and Göktepe-Hultén, 2018). Future research can provide further evidence by considering the impact of both organizational and administrative characteristics of universities (e.g., TTOs, local policies on IPRs) and reconstructing the careers of academic inventors.

Appendix

See Tables 8 and 9.

Table 8 Count of NUTS3 regions and local universities in the sample by country

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

Table 9 Aggregate count of patent families of the NUTS3 regions and the university systems by priority year

Priority year	Patent families of the regions	Patent families of the university systems	Percentage (%)
2003	35,284	2131	6.0
2004	39,010	2214	5.7
2005	40,702	2531	6.2
2006	43,881	3041	6.9
2007	45,405	3315	7.3
2008	47,445	3641	7.7
2009	45,708	3820	8.4
2010	46,574	4153	8.9
2011	46,178	4702	10.2
2012	47,387	4734	10.0
2013	47,836	4825	10.1
2014	41,352	4756	11.5
Total	**798,676**	**57,077**	**7.1**

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