Technological Forecasting & Social Change 154 (2020) 119951

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

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

Highly skilled migrants and technological diversification in the US and Europe

Federico Caviggioli[a,*], Paul Jensen[b], Giuseppe Scellato[c,d,e]

[a] Department of Management and Production Engineering, Politecnico di Torino, C.so Duca degli Abruzzi 24 10129, Torino, Italy
[b] Faculty of Business and Economics, University of Melbourne, VIC 3010, Australia
[c] Department of Management and Production Engineering, Politecnico di Torino, C.so Duca degli Abruzzi 24 10129, Torino, Italy
[d] BRICK Collegio Carlo Alberto, Torino, Italy
[e] Future Urban Legacy Lab - Politecnico di Torino, Torino, Italy

ARTICLE INFO

Keywords:
International mobility
Technological diversification
Highly skilled migrants
Inventors
Regional studies

ABSTRACT

We have investigated the impact of highly skilled migrants on the evolution of the technological portfolios of European and US sub-regional geographical areas. The specific contribution of the international mobility of inventors on the technological diversification of the innovation output, a driver of regional economic growth and of the emergence of new industries, has been neglected in previous literature. Migrant inventors have been identified by comparing their nationalities with the residence addresses reported in the patent documents. The diversification of the local technological portfolio has been measured as the number of fields of specialization, which were identified from a comparison with the aggregate portfolio of all the analyzed geographical areas. The measure has been calculated using the Hidalgo–Hausman method of reflections on patent data. The applied econometric models show a negative relationship between migration and diversification of technological specializations, thereby supporting the presence of a specialty matching mechanism associated with migration. We have also computed indicators of the relative rarity of a technological field across regions. Rarity results to be positively correlated with the local incidence of migrant inventors, thus suggesting that destination regions are more likely to enter specialization fields of higher complexity.

1. Introduction

The last few decades have been characterized by extraordinary migration flows, and a significant number of highly skilled individuals have been involved (Arslan et al., 2014). High-skilled migration and its impact on both the origin and the destination countries has increasingly attracted the attention of scholars (Borjas and Doran 2015; Kerr 2010). Researchers have studied the implications of emigration and "brain drain" (i.e. the loss of highly educated workers from the perspective of the country of origin), immigration and "brain gain" (i.e. the acquisition of talents in the country of destination), and of diaspora for the innovation potential of economic systems (Miguelez and Fink, 2013; Breschi et al., 2014; Breschi et al., 2017; Meyer, 2001; Stojcic et al., 2016; Bosetti et al., 2015). Most of the results suggest that the migration of highly skilled individuals has a positive effect on the innovation production function of the destination countries (e.g. Hunt and Gauthier-Loiselle, 2010; Stuen et al., 2012, Franzoni et al., 2012; Miguelez and Moreno, 2013; Aldieri and Vinci, 2016 Bettin et al., 2019). However, some scholars (Zhan et al., 2015; Zheng and Ejermo, 2015) did not find a clear positive relationship due to the complexity of the phenomenon: this suggests that the topic requires further exploration, in an attempt to go beyond the limitations in data availability and in the identification of migrants, and the necessity of examining the relationship between migration and innovation from different perspectives.

In this paper, we investigate the impact of highly skilled migrants on the composition of the regional technological portfolio of 417 geographical areas, located in Europe and in the U.S. The geographical level of analysis is what is referred to in the Nomenclature of Territorial Units for Statistics (NUTS) as the third level (e.g.: Kreis in Germany; Departments in France; Upper tier authorities, groups of unitary authorities and districts in the U.K.; Provinces in Italy). We extend previous studies that have focused on the relationship between migration and innovation by specifically addressing the role of foreign-born inventors, over several dimensions. We focus the analyses on the level of small geographical areas rather than countries or larger regions:

* Corresponding author.
E-mail address: federico.caviggioli@polito.it (F. Caviggioli).

https://doi.org/10.1016/j.techfore.2020.119951
Received 24 April 2019; Received in revised form 8 January 2020; Accepted 31 January 2020

localized technological portfolios are a better representation of the inventive activity of a country than highly aggregated technology portfolios, where different clusters are merged and cross-sectional differences are reduced. In several cases, the employed geographical unit of analysis overlaps metropolitan areas (or a part of the urban territory for larger agglomerates). In fact, cities are being considered more and more important, not only because of the increasing number of inhabitants, but also as relevant *loci* of innovation (Bettencourt et al., 2007). Small regions and metropolitan areas are characterized by elements of persistence and cumulativeness (Boschma et al., 2014) that are correlated with the level of technological specialization, which eventually impacts innovation and growth. Furthermore, the agglomeration of activities at such a geographical unit of analysis is considered conducive for the attraction of talent and highly skilled migrants (Lissoni, 2018; Kerr et al., 2017).

Our study contributes to the literature by going beyond the focus on the effects of migration from a quantitative perspective, and by attempting to identify a correlation between some of the characteristics of the innovation output and the presence of migrants. This work has introduced the perspective of the composition of the local technological portfolio and found that migration is positively related to the local specialization of innovative activities, a result that is in line with the literature on technological relatedness (e.g.: Boschma and Iammarino, 2009; Boschma et al., 2014; Rigby, 2015). We argue that this result confirms a specialty matching mechanism, according to which companies search for and attract specialized and highly skilled workers from the global labor market, reinforcing the technological specialization. At the same time, the attraction of foreign inventors, with their different sets of competences, does not imply the emergence of a new technological specialization but introduces elements of diversity that increase the likelihood of new innovations fitting into less common technological areas, that is, of niche fields of specialization. From a methodological point of view, we adopted the Hidalgo and Hausman (2008) method for patent portfolios, in a similar way to the applications in Boschma et al. (2014) and Antonelli et al. (2017), with the aim of qualifying the local technological specialization patterns.

2. Research framework

2.1. Migration and innovation

Our study builds on the grounds of different streams of literature dealing with migration and technological specialization. In this section, we will address the main findings of each stream and link them in order to advance our hypotheses.

Several authors have studied the relationship between skilled labor mobility and knowledge diffusion, either international (Agrawal et al., 2008; Oettl and Agrawal, 2008; Breschi et al., 2017) or domestic (Song et al., 2003), with special attention to urbanization (Moon et al., 2010; Shang et al., 2018). Scholars that investigated the relationship between innovation and migration identified a positive impact on the innovation production function of the destination countries, in terms of quantity and likelihood of breakthrough inventions (Kerr and Lincoln, 2010; Hornung, 2014; Moser et al., 2014; Fassio et al., 2019). Their results are in line with the evidence that the diffusion of knowledge, especially tacit knowledge, involves direct human interactions (Pavitt, 1998): knowledge exchange between highly skilled professionals is favored by the proximity and agglomeration of activities (Ò Huallacháin and Lee, 2011). These results are consistent, irrespective of whether the analyzed movers are graduate/PhD students (Hunt and Gauthier-Loiselle, 2010; Stuen et al., 2012; Bosetti et al., 2015), scientists (Franzoni et al., 2012, 2014), entrepreneurs (Bettin et al., 2019), or inventors (Miguelez and Moreno, 2013; Bosetti et al., 2015; Stojcic et al., 2016; Aldieri and Vinci, 2016; D'Ambrosio et al., 2019). Previous literature motivated such an increase as being related to the presence of knowledge spillovers (Miguelez and Moreno, 2013; Aldieri and Vinci, 2016; Kang, 2016) and as a result of a selection process, where movers are more productive than non-movers (Docquier and Rapoport, 2009; Gagliardi, 2015). However, the results of some studies suggest that the relationship between migration and innovation is complex. Zhan et al. (2015) found that when distinguishing between ethnic and cultural diversity, the relationships with innovation are negative and positive, respectively. Zheng and Ejermo (2015) analyzed a sample of Swedish residents between 1985 and 2007, and found that the immigrants are generally less likely to patent than the Swedish-born.

With respect to the direction of the knowledge and innovation flows and their geographical extension, Lissoni (2018) identified four main areas of research in the literature dealing with migration: origin-to-destination, destination-to-origin, cross-destination and at destination. Our study fits into the latter research area, as it attempts to contribute by improving the understanding of the impact of migration on local innovative activities. The literature in this stream focused mainly on the importance of ethnic ties in the diffusion patterns (Breschi et al., 2017) and in sector specialization (Kerr and Mandorff, 2015).

2.2. Agglomeration, technological diversity and innovation

If migration has an impact on local innovative activities, it can also contribute to regional growth. Although there is consensus on the positive role of innovation and the stock of human capital on regional growth, the mechanisms that can play key roles are related to two different perspectives: local specialization and the diversification of knowledge and technological activities. As far as the positive impact of the specialization of activities is concerned, previous results (Li, 2015; Huggins and Thompson, 2017) support the definition of externality, as in the case of the Marshall–Arrow–Romer type, with knowledge spillovers mainly occurring within industries. The second group of studies supports the so-called Jacobs externalities (Jacobs, 1969): the presence of heterogenous activities clustering in a geographic space exerts a positive effect on innovation and economic growth. This is in line with the definition of innovation as the recombination of heterogeneous ideas (Fleming, 2001; Curran, 2013; Caviggioli, 2016). Feldman and Audretsch (1999) showed that the specialization of economic activities in specific industries and locations is less conducive of innovation than diversification. However, at the industry level, some authors (Archibugi and Pianta, 1992; Pianta and Meliciani, 1996) found that the variety of the knowledge base and the advance of countries follow a 'U'-shaped pattern.

At the regional level, diversification, qualified in terms of product and technological relatedness, plays a positive role in favoring the emergence of new industries (Boschma and Iammarino, 2009; Boschma et al., 2013). The recombination of different technological paths leads to more radical innovative fields than the incremental advances that are derived from regional branching and specialization fostering (Frenken et al., 2012; Montresor and Quatraro, 2017). In other words, both related and unrelated varieties favor innovations: diversification of the former type supports general innovation, while more radical innovations are more frequent when the diversification is in unrelated technologies (Miguelez and Moreno, 2018). Focusing on a narrower geographical unit, Glaeser et al. (1992) showed that the heterogeneity of activities is one of the main determinants of the growth of metropolitan areas. Such a development is influenced by the technological relatedness of the new, emerging technologies (Boschma et al., 2014). The positive relationship between cities and innovation has been acknowledged by several scholars (Ottaviano and Peri, 2005; Audretsch et al., 2010; Niebuhr, 2010; Nathan, 2014; Lee, 2014). In fact, small geographical areas, like cities, provide grounds for 'matching', 'sharing' and 'learning' economies (Duranton and Puga 2004) and favor the generation, circulation and modification of ideas across firms and sectors (van der Wouden and Rigby, 2017). These agglomeration forces are able to attract highly

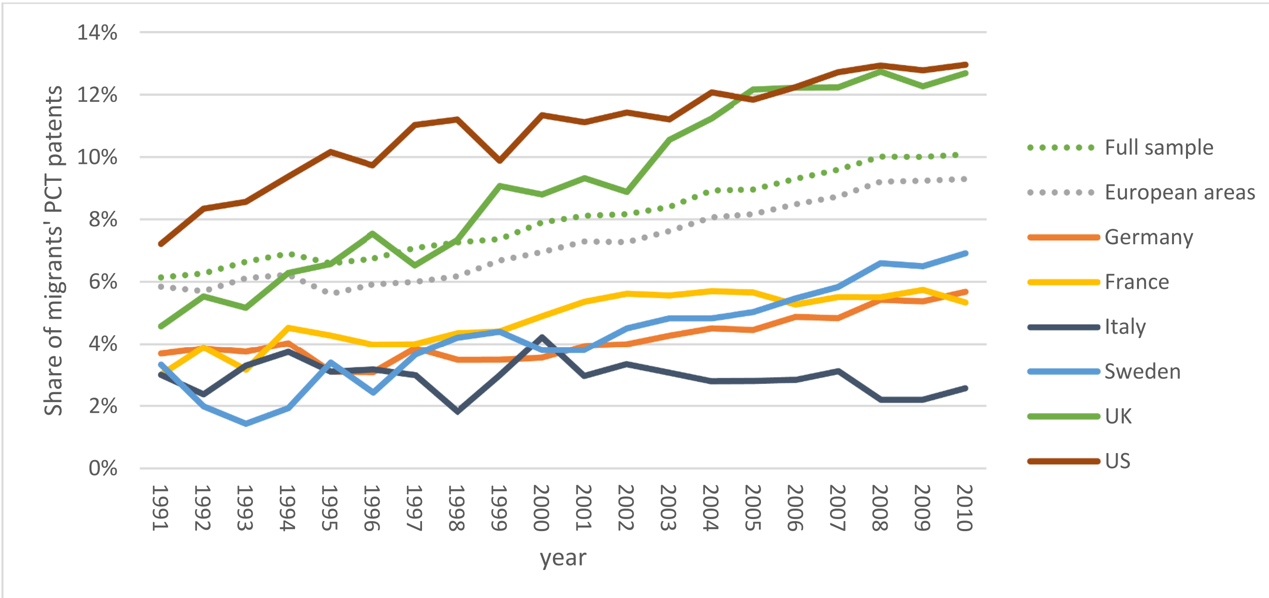

Fig. 1. Share of PCT patents from migrant inventors. Average values for the full sample (dotted green line), European countries (dotted gray line), the US (dark red) and a selection of European countries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

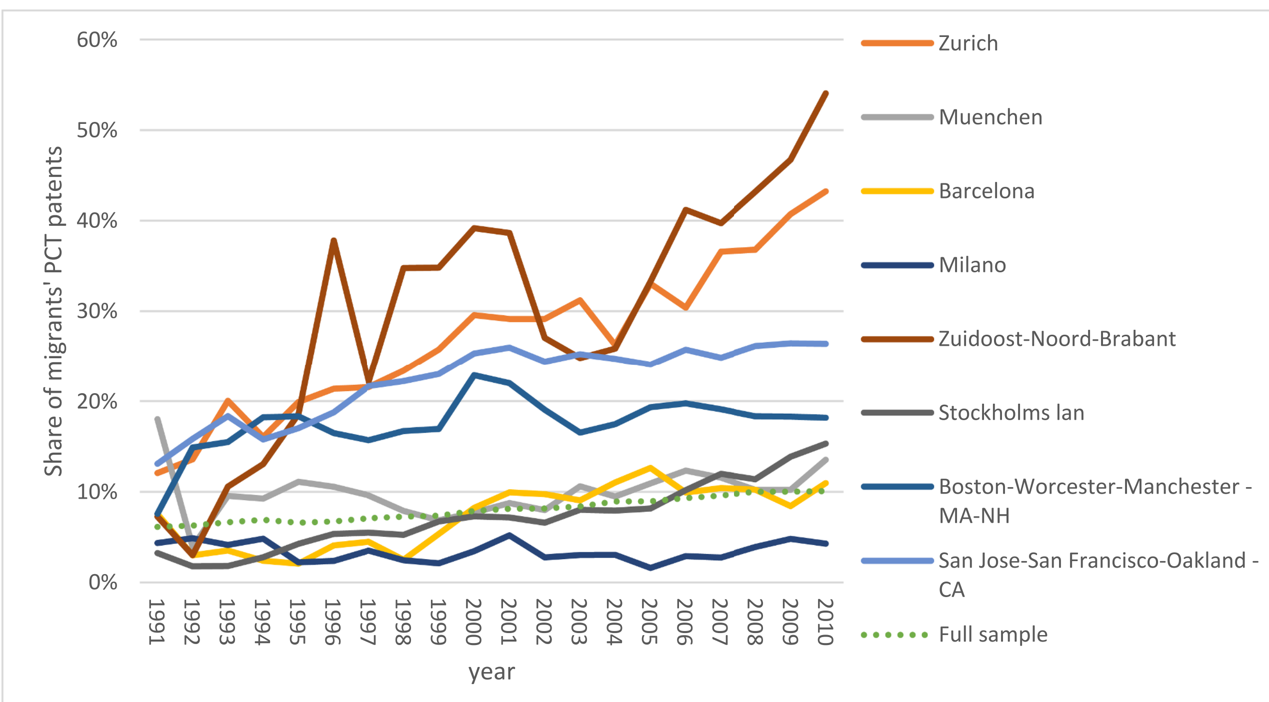

Fig. 2. Share of PCT patents from migrant inventors. Average values for the full sample (dotted green line) and a selection of metropolitan areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

skilled workers (Betz et al., 2016). The peculiarity of small geographical areas is such that specialization and diversification are not competing characteristics of the local technological portfolios, and both instead nurture innovation activities (Ó Huallacháin and Lee, 2011).

2.3. Hypothesis development

In the previous section, we reported evidence of the positive effects of migration on the innovation output. Only recently have scholars started to extend the investigation and consider the relationship not only in terms of magnitude, but also with respect to the composition of the technological portfolio (Kang, 2016; Bahar and Rapoport, 2018; Mihi-ramirez et al., 2016). These seminal results, and the evidence from the analysis of the literature on the geographical proximity and technological diversity described in the previous paragraphs, suggest that the migration phenomenon might be correlated with the local composition of the technological activities. However, the direction of the relationship between migration and technological diversity cannot be clearly formulated because either: (i) the migration of inventors could have a significant impact on the technological composition of a country's innovative output; (ii) the inflow of migrants might be driven by the lack of skilled employees in certain fields; or (iii) a combination of

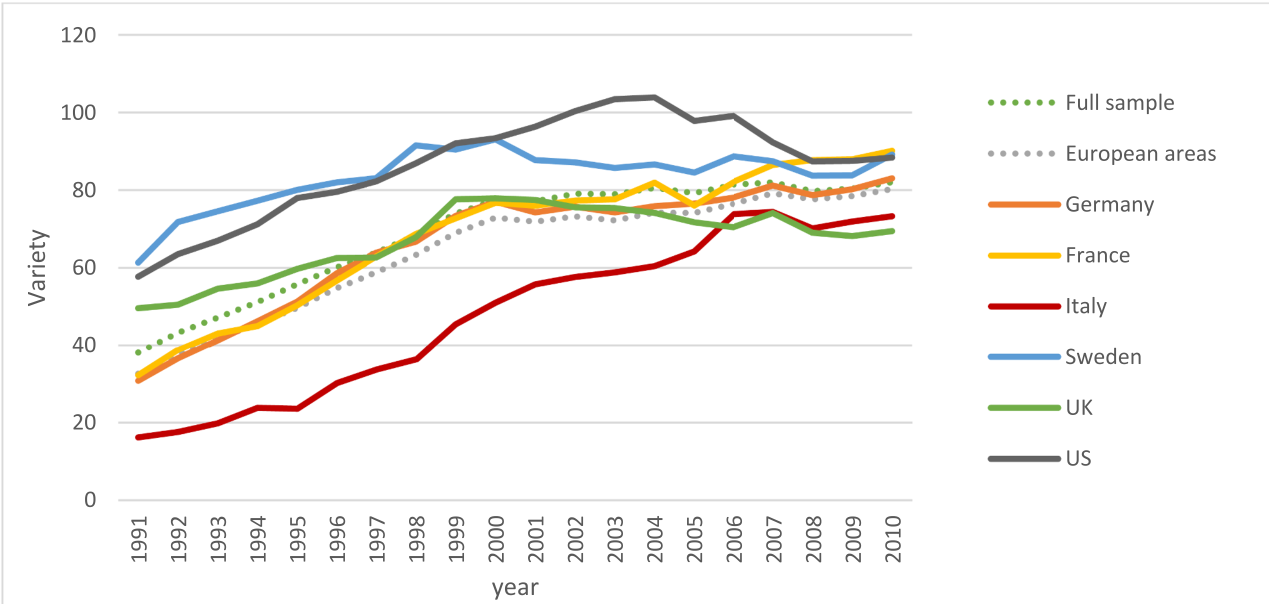

Fig. 3. Trend of variety of technological portfolios. Average values for the full sample (dotted green line), European countries (dotted gray line), the US (dark red) and a selection of European countries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

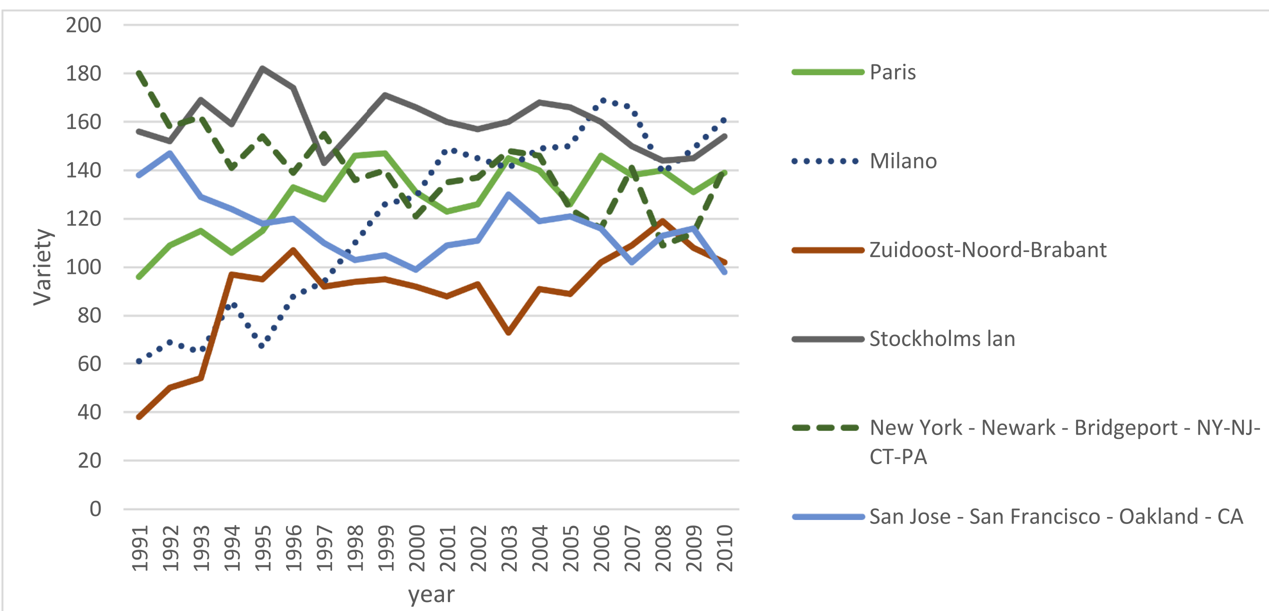

Fig. 4. Trend of variety of technological portfolios. Values for a selection of metropolitan areas.

the two hypotheses occurs.

According to the first perspective, skill portability and knowledge recombination might play significant roles. In fact, blending knowledge from local and distant sources creates opportunities to hybridize ideas and solutions (Dokko and Rosenkopf, 2010; Hargadon and Sutton, 1997; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001; Niebhur, 2010). Specifically, Kang (2016) found that inventors have positive effects on knowledge flows in East Asia, but their effects decrease when the technological portfolios of two countries are similar. Likewise, in a study focusing on the level of exports, Bahar and Rapoport (2018) found a positive correlation with the presence of migrants, considered as a channel of diffusion of productive knowledge. We argue that migrants provide the destination area with a different set of skills and competences from those of the native inhabitants, and this process makes it more likely that the emergence of new ideas and merged technologies are favored. Hence, recombinations might lead to an increase in the variety of specializations. We thus formulate the following hypothesis:

H1a: the skill portability of highly skilled migrants and knowledge recombination lead to an expansion of the local fields of specialization (positive relationship with local technological diversification).

The second perspective builds on the "specialty matching" concept to explain the relationship between migration and the composition of the local technological activities. In general terms, migrant inventors seem to be attracted by countries where the intensity of innovative factors (patents and R&D expenditure) is higher (Mihi-ramirez et al., 2016). From this perspective, immigration can be considered as a reinforcing mechanism of specialization (Jones, 2011; Franzoni et al., 2014). For example, the case of Silicon Valley suggests that the area attracts inventors specialized in those ICT fields where businesses operate. The specific demand for such edge technologies preserves the focus of the innovation output, and also shows externalities of the

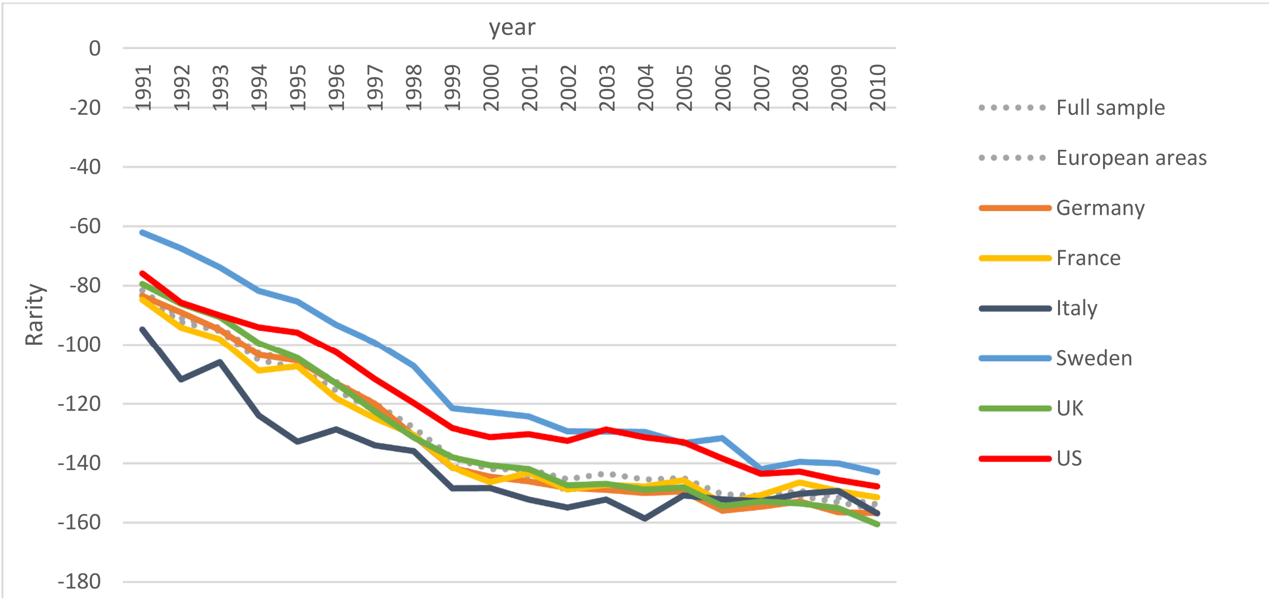

Fig. 5. Trend of average rarity of technological portfolios. Average values for the full sample (dotted green line), European countries (dotted gray line), the US (dark red) and a selection of European countries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

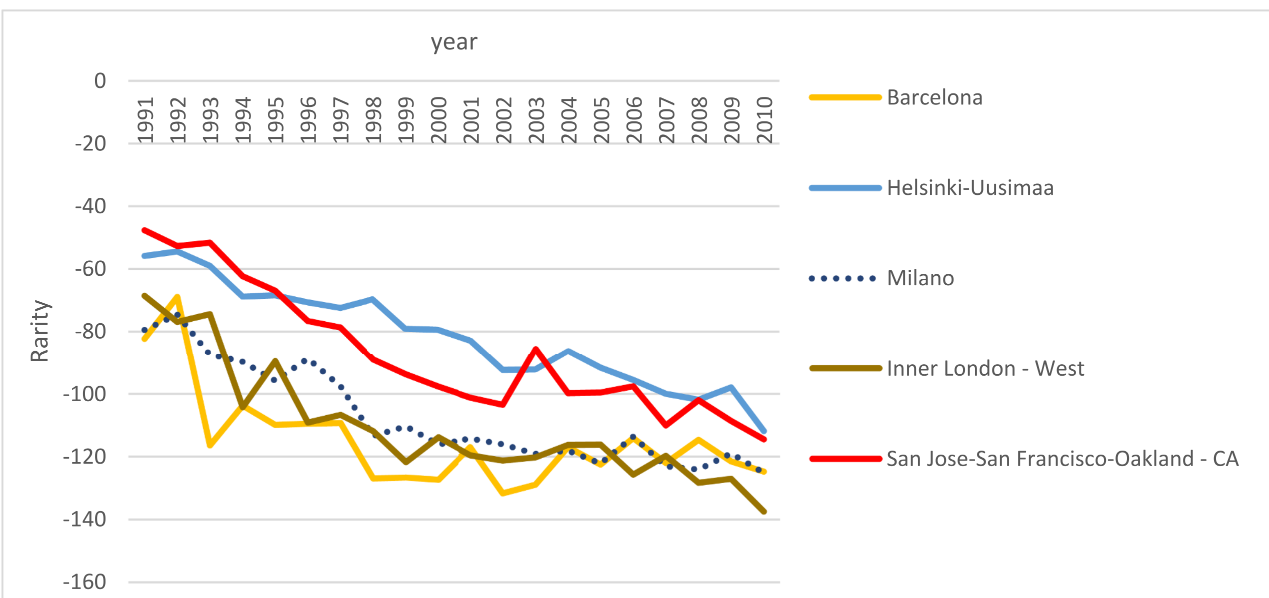

Fig. 6. Trend of average rarity of technological portfolios. Values for a selection of metropolitan areas.

Marshall–Arrow–Romer type. From this perspective, demand-driven high-skilled migration is expected to respond to the lack of local inventors in a technological field, with no substitution effect on the local workforce, and to increase the specialization level in such a sector. The presence of a strong specialization can thus be an attractor of foreign-born inventors. If this is true, we can expect to observe no correlation or a negative one between the intensity of immigration and the degree of technological diversification. With respect to the relationship between migration and diversification of the local technological activities, we formulate an additional hypothesis:

H1b: highly skilled migrants are attracted to areas where their competences are required the most ("specialty matching"), thus the local technological activities focus on a smaller number of specialization fields.

As mentioned above, the competences of migrant inventors can impact the composition of the local technological portfolio. The focus of the portfolio can shift to areas which can be more or less complex and thus more or less widespread with respect to the global innovation activities. Under the lens of the recombination of migrant and native inventors' competences, the local portfolio of technological activities can be reshaped toward more complex fields of specialization, which are associated with a rarer diffusion, i.e. niches. The same effect can be expected also when adopting the perspective of the specialty matching mechanism: the attraction of highly specialized talents from the global market is expected to be associated to further vertical technological development and higher complexity. These characteristics that push the local technological portfolio to less widespread fields.

Hence, both the ideas of "skill portability and knowledge recombination" and "specialty matching" support the formulation of the second hypothesis pertaining to the average ubiquity of the local technological activities:

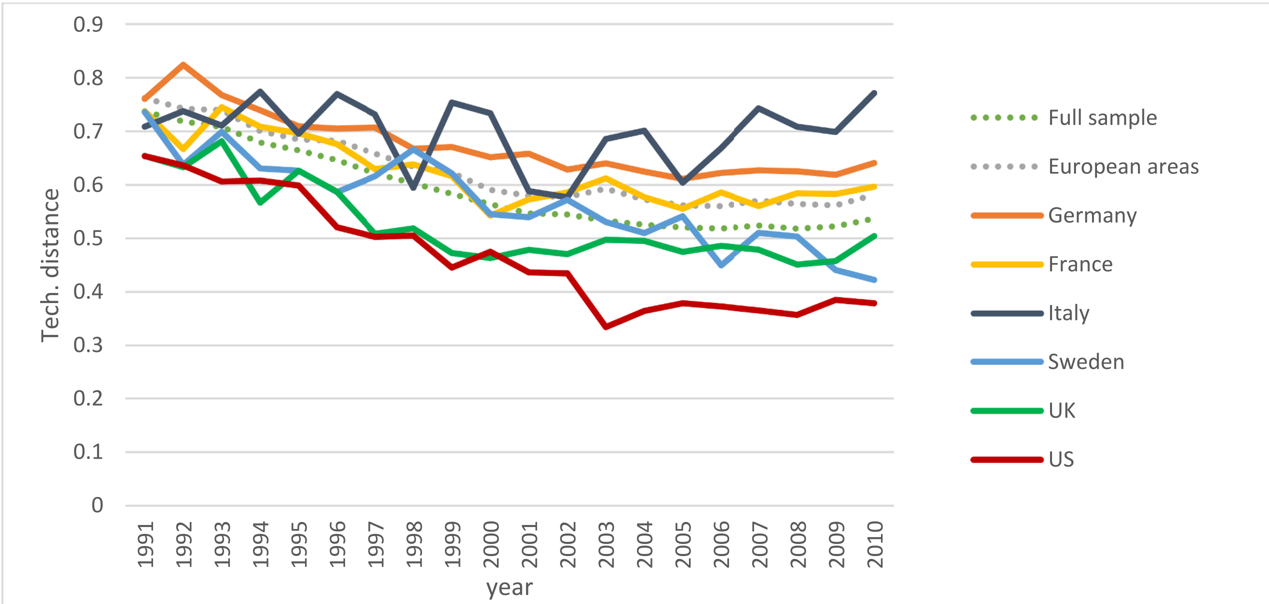

Fig. 7. Technological distance between migrant and inventors. Average values for the full sample (dotted green line), European countries (dotted gray line), the US (dark red) and a selection of European countries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

H2: the migration of highly skilled individuals is positively related to an increase in the average rarity of the local technological portfolio.

3. Method and data

3.1. Dataset

Our study has merged several data sources to compute the variables that proxy technological specialization and the migration of inventors at the NUTS3 level of a geographical unit. The OECD REGPAT database contains information on the residence address of inventors. The addresses are associated with the geographical area codes of the NUTS in Europe, and with the classification defined by the Bureau of Economic Analysis (BEA) for the U.S., which is comparable with the NUTS classification.[1] The investigation was limited to Europe and the U.S., since the associated geographical area codes are more consistent over the years, and the migration of highly skilled workers is not a negligible phenomenon.[2] The inclusion of two geographical areas is useful to investigate the potential presence of common patterns in regions with different characteristics in terms of specialization (Mendonça amd Heitor, 2016).

The measure of migration was built with reference to the WIPO PCT database,[3] which contains information on the nationality of the inventors of those patents that followed the Patent Cooperation Treaty (PCT) procedure from 1978 to 2012 and who subsequently requested an extension at the USPTO. A detailed description of the database and of its limitations was provided by Miguelez and Fink (2013) and Miguélez et al. (2010) .[4] Migrant inventors were identified from a comparison of their country of residence and their nationality. It is important, for our analyses, to recall that PCT patents represent a particular subset of the total innovative production: the protected inventions can be considered of higher value than the average national patent, since they are expected to incur higher maintenance fees due to their on average wider geographical coverage.

The matching process between the OECD REGPAT and the WIPO PCT database was integrated by imposing a minimum threshold of 200 PCT patents in the years from 2006 to 2010 to assure the presence of sufficient data points. The final sample was thus made of 327 areas in Europe[5] and 90 in the U.S.. According to the definition available in the OECD STAN database, the identified geographical units can be distinguished as “urban” and “rural/intermediate” areas: our sample included 197 urban areas (47%). It is worth to note that although defined as “rural”, those areas satisfy the criterion about the minimum number of PCT patents, hence they were likely to host innovative companies with R&D facilities and should not be considered as low-innovation agricultural rural regions. Further details on the geographical coverage of the selected sample are included in the Appendix (Table 6).

3.2. Technological diversification of the regional knowledge base

We generated the technological portfolios of the analyzed geographical areas as vectors, where each element represents the share of patents in a specific field, defined according to the International Patent Classification (IPC). We focused on the 4-digit IPC codes or subclasses, which, among the diverse aggregation levels, provides an appropriate

[1] The hierarchical structure of NUTS includes countries, regions (NUTS2) and smaller geographical areas (NUTS3). For further details, please refer to the OECD REGPAT documentation and the official website of the European Commission (https://ec.europa.eu/eurostat/web/nuts/background, last access in October 2019).

[2] For instance, the presence of migrant inventors is very limited in several Asian countries. Similar findings are reported in Miguelez and Fink (2013).

[3] The process of merging the datasets involved additional work, since the NUTS codes available in the two data sources do not overlap completely. In fact, different releases of the NUTS codes are available and they include such events as changes in recoding, borders, merges and splits of geographical areas. The WIPO PCT data are available on request from WIPO.

[4] In particular, we should recall that the nationalities of some of the inventors are not reported (especially before 2004 and after 2010) and it is not possible to keep trace of the changes in nationality when an individual becomes eligible and obtains her/his second nationality in the host country.

[5] Our definition of Europe includes the 28 European Union members, the European Free Trade Association members, and other countries within the broadest geographical borders (Andorra, Albania, Bosnia and Herzegovina, Serbia, Montenegro, FYROM, San Marino, Città del Vaticano). However, only 31 European countries satisfied the inclusion criteria: further details in the Appendix.

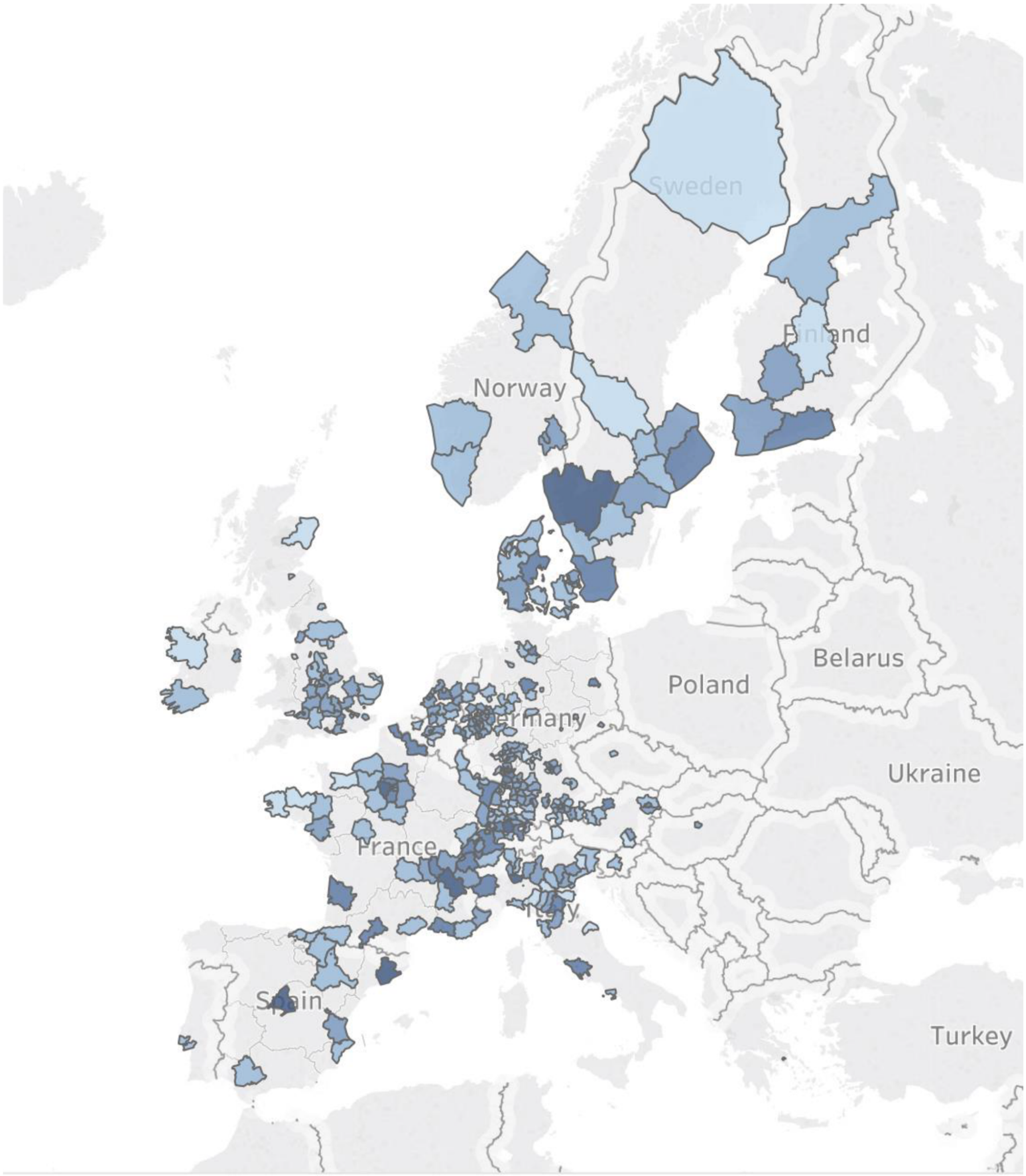

Fig. 8. Map of variety of technological specialization in Europe. Geographical areas with higher levels of variety (in darker color) have a patent portfolio with specializations in multiple technological fields. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

measure, due to a sufficient characterization of the technologies across a reasonable and treatable number of categories (van Zeebroeck et al.,2006; Caviggioli, 2016).

With the aim of capturing the relative complexity of the regional knowledge base, we adapted the method proposed by Hidalgo and Hausmann (2008 and 2009; HH hereafter) to qualify the knowledge composition of the economic system. The HH method is based on the measure proposed by Soete (1987) to compute the revealed comparative advantage of export levels. The technique characterizes the specialization patterns of the knowledge base in a specific economic system by taking into consideration the relative diffusion in other economic systems. From an empirical perspective, the first applications of the method relied on data on country-level exports of final products, and it is argued that these are linked to the competences their production requires. In this paper, we used the operationalization presented in previous works, such as those of Boschma et al. (2014) and Antonelli et al. (2017), and directly measure the technological capabilities in different regional economic systems by looking at the information contained in patent documents.

The HH method does not make use of the ex-ante technological distances to measure the diversification of the knowledge bases. Such distances are commonly computed on large samples of patents and are, by definition, generated irrespectively of the geographic distribution of the patents. On the contrary, the HH method implicitly derives such patterns from the empirical observation of the distribution of patenting activities across regions. Hence, the method can be regarded as a

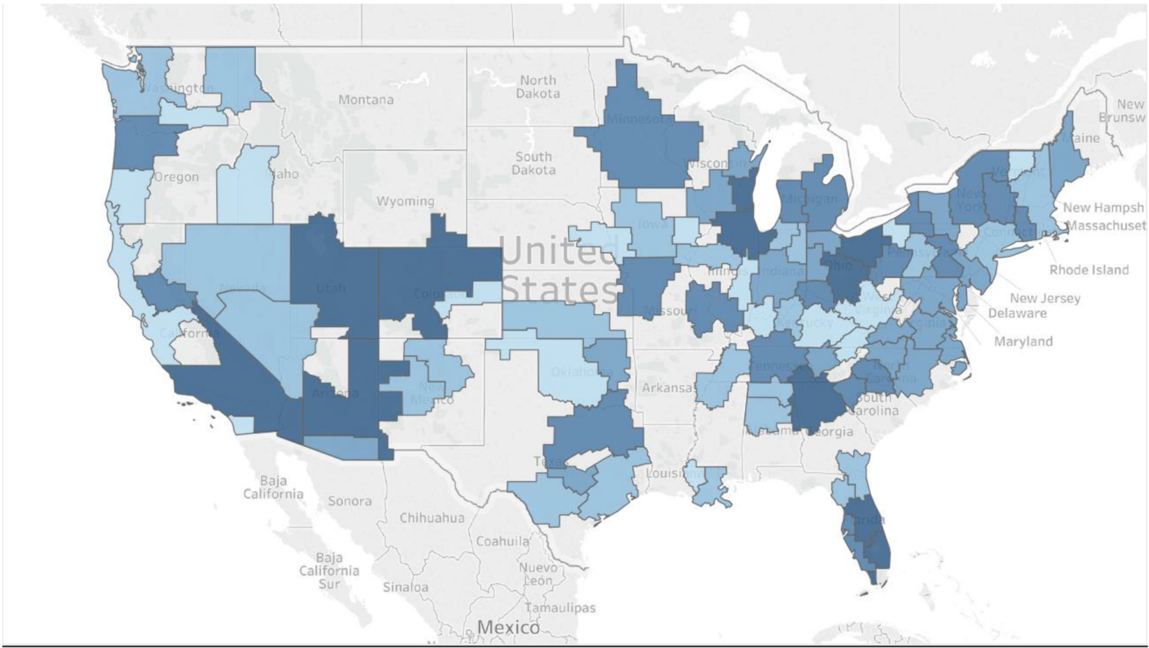

Fig. 9. map of variety of technological specialization in U.S. Geographical areas with higher levels of variety (in darker color) have a patent portfolio with specializations in multiple technological fields. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

bottom-up approach in which the observed evolution of the specializations of innovation systems implies actual complementarities among the technological domain, rather than a top-down approach in which the structure of interdependency (or relatedness) between technologies is pre-defined on pure technological (patent-based) evidence (Antonelli et al., 2017).

We adopted the HH method and computed a Revealed Technological Advantage index (RTA), which is defined as:

$$RTA_{rj} = \frac{P_{rj}/\sum_{j=1}^{J} P_{rj}}{\sum_{r=1}^{R} P_{rj}/\sum_{r,j} P_{rj}} = \frac{S_{rj}}{S_j}$$

where P_{rj} is the number of patents of geographical area r in patent subclass j, R is the number of areas and J is the number of technological fields. Basically, RTA is the share of patents in technology j of region r normalized by the average share across all technologies. When $RTA_{rj} = 1$, region r has a share of technology j that is equal to the average share of all the other regions. Thus, it follows that $RTA_{rj} = 1$ represents a threshold of specialization: when $RTA_{rj} > 1$, region r is considered to be specialized in technology j. The next step was to define a "specialization matrix", M, as a binary-valued matrix, in which the rows represent regions and the columns represent technologies, whose generic element (r, j) is equal to 1 if region r is specialized in technology j.

$$M(r, j) = \left| \begin{array}{l} 1 if\, RTArj > 1 \\ 0 if\, RTArj < =1 \end{array} \right.$$

Following the work of Antonelli et al. (2017), we computed two vectors from matrix M that measure, respectively, *technological diversification*, i.e., the number of technologies in which region r is specialized and the *ubiquity* of a specific technology, i.e., the number of regions specialized in technology j. From ubiquity, it is possible to calculate, for each geographical area, the average value of ubiquity (AvgUbiq) of the technologies the region is specialized in:

$$AvgUbiq_j = \frac{\sum_{j=1}^{J} m_{rj} {*} ubiq_j}{variety_r}$$

where m_{rj} is the j-th element of row r in matrix M. The average ubiquity shows whether the region is specialized in technologies that are frequently fields of specialization in other geographical areas. The same concept can be explained from the opposite perspective, that is, in terms of "*rarity*". A geographical area can be specialized in several technological fields which, however, are niche technologies. We measured the average rarity as the inverse of the average ubiquity

$$AvgRarity_j = -AvgUbiq_j$$

The following Figs. (from 3 to 6) show the trends of variety and rarity of the total sample for a selection of countries (as averages) and of NUTS3 geographical units. The maps of the European and U.S. geographical areas are reported in the Appendix (Figs. from 8 to 11) with visualization of the computed measures of technological diversification and rarity in technological specialization.

3.3. Migration characteristics at the geographical and technological levels

Once the migrant inventors had been identified, it was possible to calculate several metrics to improve the characterization of the phenomenon at the geographical level.

3.3.1. Local presence of migrants

The intensity of the presence of migrant inventors in each geographical area was computed as the share of migrants' patents through a fractional count of the PCT patents, according to the following formula (r is the geographical unit of analysis):

$$S_r = \frac{fractional\ \ count\ \ of\ \ migrants'\ \ patents_r}{fractional\ \ count\ \ of\ \ patents_r}$$

Fig. 1 shows the yearly average values of S_r for the total sample of 417 areas, for the U.S., the European areas and for a selection of some European countries. Fig. 2 shows the trend of a selection of geographical areas. Although there is a general increase (from 6% in 1991 to 10% in 2010), the local patterns are heterogeneous, with areas like "Milano" being almost unaffected by any change, and areas like "Zurich" showing a steep increase of up to more than 50% of migrant inventors.

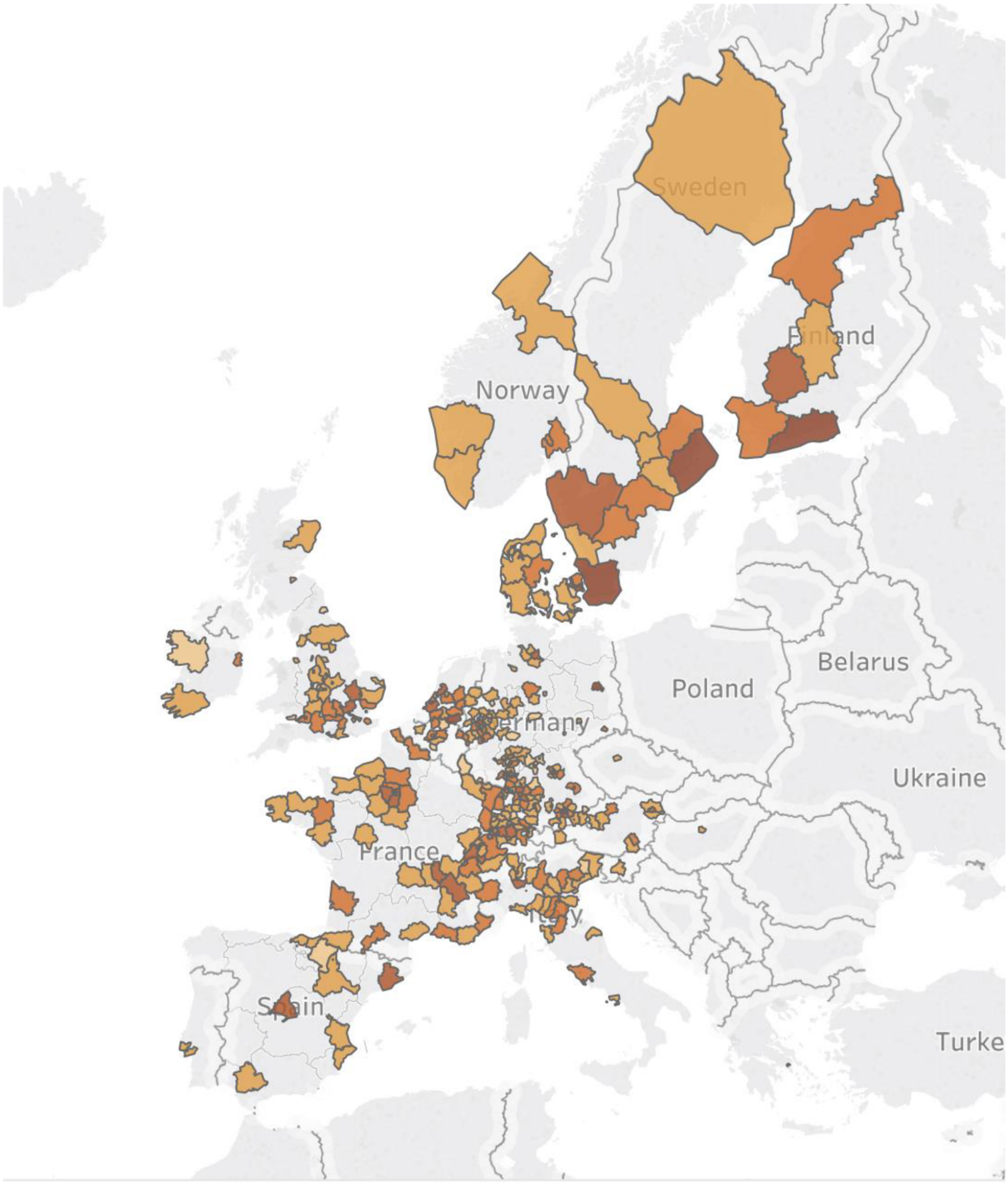

Fig. 10. Map of average rarity of technological specialization in Europe. Geographical areas with higher levels of rarity (in darker color) have a patent portfolio with specializations in rarer technological fields. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3.2. Technological distance

As discussed above, blending different competences might favor the innovation production outcome (Fleming, 2001; Caviggioli, 2016) and the positive impact would be more pronounced when the competences and skills of migrant and native inventors are different. However, the diversification of the knowledge base and the innovation performance follows a non-monotonic function (Archibugi and Pianta, 1992; Pianta and Meliciani, 1996). In fact, excessive knowledge differentiation is not necessarily linked to positive effects on the innovative capabilities of local firms (Rigby, 2015). We included the technological distance between the two groups of migrant and native inventors to control for this issue.

In order to assess the difference between the technological portfolios of native and migrant inventors, they were described in terms of 4-digit IPC codes and transposed into the two corresponding vectors. The two vectors were then compared to calculate a measure of distance. We applied the method described in Jaffe (Jaffe, 1986) to calculate the angle distance of vectors as technological proximity (TP):

$$TP_{nm}\frac{v_n * v'_m}{\sqrt{(v_n * v'_n)(v_m * v'_m)}}$$

The indicator was calculated for each geographical area, where v_n and v_m are the vectors whose elements represent the portfolio share of each technological field identified through IPC subclasses for native (n) and migrant (m) inventors, respectively. TP ranges from 0 to 1, hence we computed technological distance (TD) as:

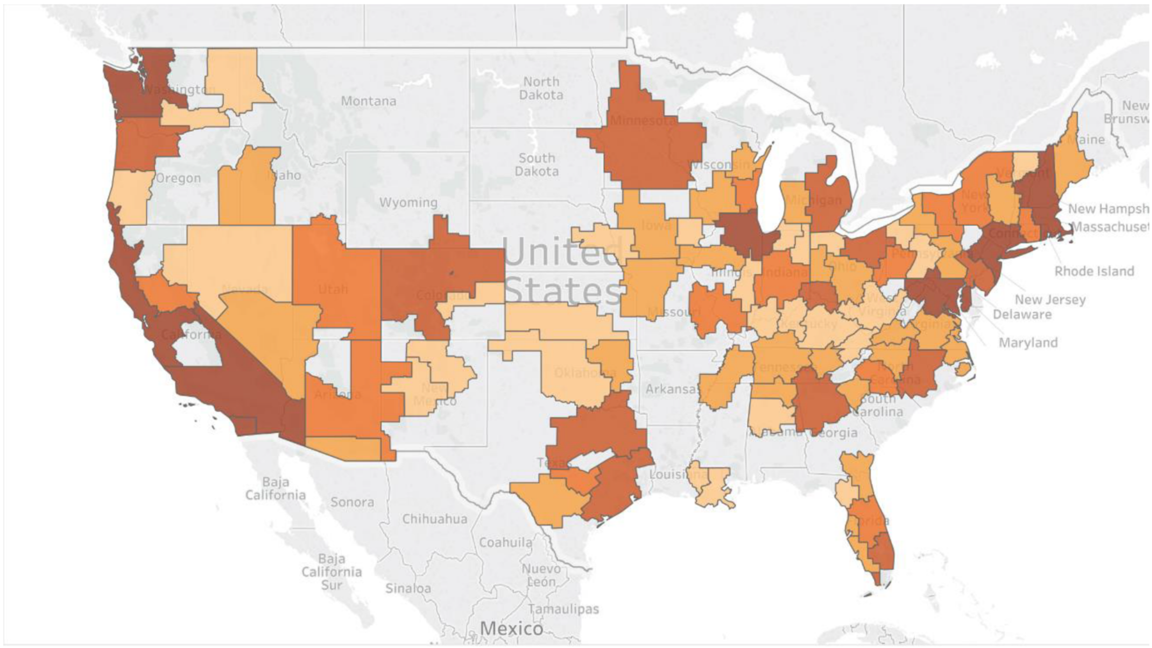

Fig. 11. Map of average rarity of technological specialization in US. Geographical areas with higher levels of rarity (in darker color) have a patent portfolio with specializations in rarer technological fields. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary statistics of the analyzed variables.

Variable	Label	Obs	Mean	Std. Dev.	Min	Median	Max
Number of technological fields of specialization in the regional portfolio	Tech_Diversif	8336	69.013	34.863	1.000	64.000	228.000
Average rarity of the technological fields of specialization in the regional portfolio. Rarity is calculated with respect to the frequency of specializations of a certain field across all the regions	Rarity	8336	−129.664	30.976	−256.000	−133.650	−24.000
Share of PCT patents from migrant inventors on total PCT patents	Migr_Intensity	8336	0.080	0.091	0.000	0.053	1.000
Technological distance between migrants and local inventors, as angle distance of the corresponding patent portfolios	Tech_Dist	7095	0.579	0.283	0.011	0.601	1.000
Diversification of migrants' nationalities calculated as HH index	Nat_Dispersion	7095	0.413	0.301	0.040	0.310	1.000
Share of patents with at least one migrant and one local inventor on the total number of PCT patents	Integration	7095	0.406	0.297	0.000	0.410	1.000
Total number of PCT patents	Portf_size	8336	3.936	1.160	0.000	3.927	8.693
Population density	Pop_dens	8336	702.549	1510.489	2.4	230.95	21,369.8

Table 2
Results of panel data models with geographical areas fixed effects. Dependent variable: Technological diversification as number of specialization fields.

Variables	Model (1)	(2)	(3)
$(\text{Migr\_intensity})_{t\text{-}1}$	−17.080***	−14.633***	−17.806***
	(2.645)	(2.665)	(2.737)
$(\text{Tech\_dist})_{t\text{-}1}$		28.619***	26.535***
		(2.797)	(2.825)
$(\text{Tech\_dist}\ \hat{}\ 2)_{t\text{-}1}$		−24.697***	−22.697***
		(2.299)	(2.380)
$(\text{Nat\_dispersion})_{t\text{-}1}$			3.994***
			(0.758)
$(\text{Integration})_{t\text{-}1}$			−1.073*
			(0.599)
$(\text{Pop\_dens})_{t\text{-}1}$	0.004*	0.005**	0.006***
	(0.002)	(0.002)	(0.002)
$(\text{Portf\_size})_{t\text{-}1}$	2.041***	2.449***	2.266***
	(0.416)	(0.427)	(0.430)
Year dummies	Yes	Yes	Yes
Constant	72.266***	62.690***	63.487***
	(2.808)	(3.078)	(3.085)
Observations	6687	6687	6687
Number of geographical areas	417	417	417
R-squared	0.519	0.528	0.530
adjusted R2	0.486	0.495	0.497

$$TD_{nm} = 1 - TP_{nm}$$

The trends in Fig. 7 show that the average portfolio of migrants is in general becoming more similar to that of the natives. However, in recent years, it seems that the technological distance between the two groups has become stabilized. The average values at the country level are heterogeneous. For instance, the technological portfolio of migrants in the U.S. and in the U.K. is similar to the local knowledge base, while the difference is far more prominent in Italy, Germany and France. To account for the non-monotonic relationship between technological distance and innovation outcome (Archibugi and Pianta, 1992), we included the technological distance with a quadratic form in our empirical specification.

3.3.3. *Dispersion of migrants' origins*

The migration phenomenon can involve a wider or a narrower variety of nationalities, as a result of the proximity of borders and historical flows. Previous works (Niebhur, 2010; Nathan and Lee, 2013; Zhan et al., 2015) suggested the presence of a positive impact of cultural diversity on innovation. The presence of communities "on the move" facilitates integration and fosters the generation of innovations (Parrilli et al., 2019). Hence, in those destination areas where migrants have origin from multiple countries, it might be more likely to identify

Table 3
Results of panel data models with geographical areas fixed effects. Dependent variable: Technological diversification as number of specialization fields. Tests on the subsamples of: (i) urban and rural areas; (ii) US and European geographical zones; (iii) geographical areas belonging to regions identified as "Innovation Leaders" according to the European Regional Innovation Scoreboard.

Variables	Group I Sample: Urban	Group II Sample: Rural	Group III Sample: US	Sample: Europe	Sample: European Innovation Leaders	Sample: Other European regions
$(Migr\_intensity)_{t-1}$	−20.998***	−17.246***	−22.594***	−12.828***	−12.912***	−4.749
	(4.019)	(3.742)	(5.695)	(2.901)	(3.526)	(6.075)
$(Tech\_dist)_{t-1}$	29.400***	23.974***	23.221***	25.373***	30.083***	15.275**
	(4.272)	(3.710)	(5.960)	(2.996)	(3.707)	(6.098)
$(Tech\_dist \hat{} 2)_{t-1}$	−24.473***	−21.003***	−25.378***	−19.705***	−24.088***	−10.499**
	(3.650)	(3.090)	(5.312)	(2.492)	(3.163)	(4.863)
$(Nat\_dispersion)_{t-1}$	4.938***	3.021***	6.446***	1.375*	1.355	0.284
	(1.168)	(0.986)	(2.004)	(0.759)	(1.005)	(1.377)
$(Integration)_{t-1}$	−1.345	−0.607	−3.114**	0.008	−0.926	1.094
	(0.946)	(0.761)	(1.558)	(0.598)	(0.833)	(1.012)
$(Pop\_dens)_{t-1}$	0.005**	0.140***	−0.123**	0.002	0.001	0.009
	(0.002)	(0.026)	(0.056)	(0.002)	(0.002)	(0.006)
$(Portf\_size)_{t-1}$	4.369***	0.830	−0.634	9.377***	7.736***	13.172***
	(0.663)	(0.569)	(1.057)	(0.539)	(0.696)	(0.998)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	58.418***	41.312***	101.224***	32.427***	44.455***	4.712
	(5.188)	(5.810)	(7.974)	(3.511)	(4.606)	(7.092)
Observations	3367	3320	1532	5155	2934	1664
Number of geogr. areas	197	220	90	327	174	117
R-squared	0.534	0.541	0.484	0.614	0.625	0.594
adjusted R2	0.502	0.504	0.443	0.586	0.598	0.556

Table 4
Results of panel data models with geographical areas fixed effects. Dependent variable: rarity of technological specializations.

Variables	Model (1)	(2)	(3)
$(Migr\_intensity)_{t-1}$	7.332***	6.030**	6.034**
	(2.578)	(2.618)	(2.695)
$(Tech\_dist)_{t-1}$		−11.721***	−11.679***
		(2.747)	(2.782)
$(Tech\_dist \hat{} 2)_{t-1}$		9.524***	9.457***
		(2.259)	(2.343)
$(Nat\_dispersion)_{t-1}$			−0.062
			(0.747)
$(Integration)_{t-1}$			−0.039
			(0.590)
$(Pop\_dens)_{t-1}$	0.006***	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
$(Portf\_size)_{t-1}$	5.298***	5.054***	5.060***
	(0.406)	(0.419)	(0.423)
Year dummies	Yes	Yes	Yes
Constant	−178.99***	−174.49***	−178.358***
	(2.737)	(3.023)	(3.038)
Observations	6687	6687	6687
Number of geographical areas	417	417	417
R-squared	0.759	0.760	0.760
adjusted R2	0.743	0.743	0.743

a relationship with the composition of the local portfolio of technological activities.

The diversification of the nationalities of migrant inventors is expected to proxy their heterogeneity in a specific geographical zone. We computed a measure of the dispersion of migrants' nationalities in a destination area to distinguish areas subject to migration flows from a single origin country or from multiple locations. We employed the Herfindhal–Hirschman index to measure the concentration and subtracted it from 1 to obtain the dispersion:

$$Nat\_Dispersion_r = 1 - \sum_e s_{re}^2$$

where s_{re} represents the share of patents in geographical area r associated with inventors with nationality *e*.

3.3.4. Integration in inventor teams

An additional factor that might impact our analysis framework is the presence of firm-level characteristics that could have the potential to introduce heterogeneity into the local approaches to innovation. Diversity in research personnel fosters innovation activities (Lee, 2014) and firms might apply policies to favor collaboration. Although the proposed framework focuses on a larger unit of analysis than a single firm, we tried to control for this issue by considering the relative average presence of mixed teams of inventors, i.e. when migrants and native workers collaborate. To partially cope with this issue, we introduced a measure of the level of *integration* of migrants in inventor teams. This variable captures the level of absorption of migrants in local teams and their ability to co-develop new inventions. It is computed by considering the number of patents where a migrant inventor is part of a team in which at least one member is a domestic inventor.

4. Empirical analysis and results

The examined sample consists of 417 geographical areas and covers the years from 1991 to 2010, for a total of 8336 observations, excluding missing data points. The variables introduced in the previous section are described in Table 1, which also shows the main statistics.

Our empirical analysis employed two sets of panel models with geographical area fixed effects and time dummies. We aimed to evaluate the presence of significant correlations between the diversification of the local technological portfolio and the past incidence of foreign inventors, by controlling for several context factors. The two sets of models are based on the following formula:

$$yi,\ t = (Migr\_Intensity)i,\ t-1 + (Tech\_Dist)i,\ t-1 + (Tech\_Dist)2i,\ t-1 + (Nat\_Dispersion)i,\ t-1 + (Integration)i,\ t-1 + (Portf\_Size)i,\ t-1 + (Pop\_Dens)i,\ t-1 + ai + ei,\ t$$

where i represents the geographical unit and t the time unit (year); the dependent variable y stands for *Technological Diversification* in the first set of models and average rarity in the second set; "*Migr_Intensity*" is the share of migrant inventors; "*Tech_Dist*" is the angle distance between the vector portfolios from the contributions of native and migrant inventors. "*Nat_Dispersion*" is a measure of the geographical variety of the nationalities of the highly skilled migrants; "*Portf_Size*" is the total

Table 5
Results of panel data models with geographical areas fixed effects. Dependent variable: rarity of technological specializations. Tests on the subsamples of: (i) urban and rural areas; (ii) US and European geographical zones; (iii) geographical areas belonging to regions identified as "Innovation Leaders" according to the European Regional Innovation Scoreboard.

Variables	Group I Sample: Urban	Group II Sample: Rural	Group III Sample: US	Sample: Europe	Sample: European Innovation Leaders	Sample: Other European regions
$(Migr\_intensity)_{t-1}$	11.676***	−1.959	8.293*	5.673*	7.701**	10.340
	(3.610)	(4.065)	(4.832)	(3.166)	(3.682)	(6.939)
$(Tech\_dist)_{t-1}$	−8.935**	−14.011***	−10.909**	−10.640***	−12.760***	−6.167
	(3.837)	(4.030)	(5.058)	(3.271)	(3.871)	(6.965)
$(Tech\_dist\ \hat{}\ 2)_{t-1}$	8.080**	10.675***	9.735**	8.363***	9.449***	6.685
	(3.278)	(3.357)	(4.507)	(2.721)	(3.303)	(5.554)
$(Nat\_dispersion)_{t-1}$	0.031	0.265	−5.684***	0.420	1.474	−0.353
	(1.049)	(1.071)	(1.700)	(0.829)	(1.050)	(1.573)
$(Integration)_{t-1}$	0.493	−0.434	0.898	−0.068	−1.705*	1.623
	(0.850)	(0.827)	(1.322)	(0.653)	(0.870)	(1.156)
$(Pop\_dens)_{t-1}$	0.004*	0.063**	0.092*	0.004*	0.007***	−0.002
	(0.002)	(0.028)	(0.047)	(0.002)	(0.002)	(0.006)
$(Portf\_size)_{t-1}$	6.170***	4.497***	4.359***	7.034***	6.394***	7.117***
	(0.596)	(0.618)	(0.897)	(0.588)	(0.726)	(1.140)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−184.905***	−183.438***	−171.525***	−188.852***	−187.926***	−186.888***
	(4.660)	(6.311)	(6.766)	(3.832)	(4.810)	(8.100)
Observations	3367	3320	1532	5155	2934	1664
Number of geogr. areas	197	220	90	327	174	117
R-squared	0.790	0.732	0.780	0.765	0.803	0.720
adjusted R2	0.775	0.711	0.763	0.748	0.789	0.694

Table 6
Details on the geographical coverage of the selected sample as a result of the matching process between the OECD REGPAT and the WIPO PCT database and of the application of the minimum number of PCT patents in the years 2006–2010. Regions coded as "Not classified" (Eg. ATZZZ, BEZZZ, etc.) were excluded.

Country	Fractional sum of PCT patents according to inventors' address	Matchedgeographicalareas	Matched geogr.areas with >200 PCT patents	Share of PCT patents inmatched areas above the threshold / country total
US	231,349.38	179	90	97%
Germany	88,757.75	402	125	75%
France	34,302.20	103	39	89%
UK	29,412.30	139	38	75%
Netherlands	16,732.24	40	16	88%
Italy	16,019.49	109	25	73%
Sweden	14,626.02	21	11	92%
Switzerland	11,373.23	27	17	95%
Spain	8131.68	57	9	75%
Finland	7784.23	19	5	87%
Austria	6483.38	35	10	71%
Denmark	6005.08	11	10	100%
Belgium	5701.78	44	8	64%
Norway	3434.85	19	5	69%
Ireland	1750.89	8	3	68%
Hungary	1129.89	20	1	50%
Poland	1020.77	66	0	0%
Czech Republic	895.06	14	1	27%
Slovenia	622.43	12	1	49%
Portugal	621.62	24	1	35%
Greece	504.41	36	1	63%
Hungary	262.05	20	0	0%
Luxembourg	250.59	1	1	100%
Estonia	222.65	5	0	0%
Slovakia	209.94	8	0	0%
Romania	182.49	31	0	0%
Iceland	149.80	6	0	0%
Bulgary	143.94	20	0	0%
Latvia	114.52	6	0	0%
Lithuania	72.45	4	0	0%
Cyprus	42.54	1	0	0%
Malta	20.70	2	0	0%
Total	488,330.34	1489	417	88%

number of patents, that is, a measure of the size of the innovative output of the geographical unit; "*Pop_Dens*" is the population density of the region. "a_I" is the intercept for each geographical unit and "$+e_{it}$" is the error term.

We introduced the variables through a stepwise approach and provided robustness checks by replicating the regression analyses on three subsamples to check for specific characteristics of the regions.

The results shown in Table 2 suggest the presence of a negative correlation between the share of foreign inventors and the technological diversification of the geographical area, thus confirming the validity of the hypothesis H1b. The evidence is robust across the models and supports the specialty matching hypothesis: on average, the presence of highly skilled migrants is not associated to an increase in the number of specialization fields in the technological portfolio of the destination area. The effect seems to be mitigated by the technological distance, for which we can observe an inverse U-shaped pattern. The further the technological portfolio of the migrants is from that of the native inventors, the higher is the likelihood of observing an increase in diversification of specializations. However, when the two portfolios are extremely different, the effect on technological diversification is reversed: the new set of competences of migrants is not integrated with the local one and does not lead to specializations in new fields. The dispersion of migrants' nationalities is positively related to the variety of the technological portfolio: where migrants are more dispersed, in terms of countries of origin, an increase in the technological diversification of specializations can be observed. No significant effect is found for the level of integration of migrant inventors with local inventors, in terms of joint participation in inventor teams. The results obtained when controlling for portfolio size and population density are robust.

Further robustness checks are reported in Table 3. The first test focuses on the subsamples of urban and rural geographical areas, according to the definition available in the OECD STAN database.[6] The second analysis splits the initial sample between the U.S. and European geographical areas. The results of the first and second robustness analyses are coherent with those of the main model. The third group of tests is limited to European regions and introduces the categories defined in the European Regional Innovation Scoreboard (RIS)[7]: relying on several innovation metrics, RIS computed a single index that proxies the regional innovativeness at the NUTS1 and NUTS2 level and uses it as a reference to split the regions in four categories: "Innovation Leaders", "Strong Innovators", "Moderate Innovators", and "Modest Innovators". The same categories have been associated to the NUTS3 areas in our sample, by deriving them from the upper hierarchical level. For 11% of the 327 European areas in our sample it was not possible to identify a RIS category. Among the identified, 60% are "Innovation Leaders", 29% "Strong Innovators" and 12% "Moderate innovators" (the lowest category is not represented, coherently with the inclusion criterion of the minimum number of PCT patents). The models show that for the "Innovation Leaders" the results are very similar to the specification tested on the full sample. However, the results for the areas identified as less innovative than the "Leaders" show a negative but not significant correlation between the presence of migrant inventors and the technological diversification of specializations.

The second group of econometric analyses was focused on technological rarity. It should be recalled that rarity captures the presence of particular niches in the local technological portfolio: high values of rarity are associated with local technological portfolios with specializations in fields that are not frequently found across the panel of examined geographical areas. The results are shown in Table 4.

When considering the impact on the average rarity of the technological portfolios, the models show a positive and significant effect for the intensity of migrants: it confirms the validity of the hypothesis H2. However, the presence of more "technologically distant" migrant inventors has a negative effect on the capability to enter rarer technological fields, and shows a U-shaped relation. The results obtained after controlling for portfolio size and population density are robust.

The results obtained for the variable *rarity* were then tested on the same subsamples that were examined for the technological diversification. Table 5 shows the results for the subsamples of: (i) urban and rural geographical areas, (ii) the U.S. and European geographical areas, (iii) "Innovation Leaders" and the less innovative European NUTS3 areas. The results are similar to the main model with the exception of the rural and the European less innovative areas, for which the relation between the intensity of highly skilled migrants and rarity of local specializations is not statistically significant.

5. Conclusion

This study has analyzed the relationship between the migration of highly skilled researchers and the changes in the technological specialization of NUTS3-level geographical areas, in terms of portfolio composition. Our work is an attempt to connect the previous streams of research on the effects of migration on innovation trajectories in the destination geographical areas and on regional growth and technological specialization.

The investigation has been based on the analysis of a database that merges different sources, where the nationality of PCT patent inventors is linked to their residence address, in order to identify migrants in specific geographical areas in Europe and in the U.S. The technological portfolio of each region has been built from the IPC codes of the geolocalized patents between the years 1991 and 2010. Technological diversification measures the variety of specializations across technical fields and it was computed following the procedure described in Hidalgo–Hausman (2008), Boschma et al. (2014) and Antonelli et al. (2017).

The econometric models show that the relationship between the intensity of high-skilled immigration and the capability of a geographical area to expand its portfolio of technological specializations (more variety) is negative. This result supports the "specialty matching" hypothesis, according to which the presence of a remarkable specialization is an attractor of foreign-born inventors, which reinforces the specialization in that field (Jones, 2011; Franzoni et al., 2014). This evidence is in line with previous findings on technological relatedness in the development of the portfolio of regions and cities (Boschma et al., 2014; Rigby, 2015). From this perspective, the agglomeration of highly skilled workers contributes to the process of technological specialization, as theorized by Marshall–Arrow–Romer's externalities.

The second set of analyses made use of a more sophisticated indicator that captured not only the number of different specialization fields in local portfolios but also qualified the technological areas, in terms of their diffusion among all the examined geographical units, and hence defined its degree of rarity. We claim that the technological fields that are rarer are those that are characterized by higher technological complexity and which show higher entry barriers. In this case, the results indicate a positive relationship between the intensity of migration and the capability to enter "rarer" technological domains. This finding supports the concepts of "skill portability and knowledge recombination", according to which migrants provide the destination area with a set of novel skills and competences that are more likely to be recombined, and favor the emergence of new ideas and merged technologies (Fleming, 2001; Curran, 2013; Caviggioli, 2016). The recombination is associated with greater complexity and seems to foster specialization in new technological fields which are not common.

Hence, migration seems to be positively associated with an increase in specialization in more complex and less ubiquitous technological fields, or, in other words, migration improves the regional capabilities and favors the local development of emerging novel technologies.

These effects are moderated by the technological distance of the competences between migrant and native inventors. The evolution of the technological diversification of regions is positively associated with the distance between the technological skills of migrants and natives, and it follows an inverted U-shaped relation. This might reflect the fact that is harder to integrate migrants' competences when there is an insufficient pre-existing knowledge base in that field at a local level.

The results are robust to several tests on different subsamples. However, the analysis carried out on the sample of European less

[6] Rural areas include both those categorized as being strictly "Rural" in the OECD STAN database and those defined as "Intermediate".

[7] More information available here: https://ec.europa.eu/growth/industry/innovation/facts-figures/regional_en (last access in October 2019).

innovative areas did not provide statistically significant results between migration intensity and the two characteristics of the technological portfolio, i.e. diversification and rarity. It suggests that other region-specific factors in these areas might moderate the impact of migration on the local technological portfolio. Future research could try to explore further the issue by introducing additional variables to characterize the economic and industrial geographical context.

The overall results raise a set of relevant policy implications. The increasing globalization of science and R&D, linked to the increasing mobility of a highly skilled workforce, has an impact on destination areas, not only in terms of innovation output volumes but also in terms of composition. The global competition for scientific and technological talent appears to be driven mostly by strong agglomeration forces that lead to local specialization. This suggests the importance of setting up policies to support brain gain and build on the characteristics of the local knowledge base (or of the future development goals).

At the same time, international openness of the local innovation ecosystems appears to be a key factor to improve the capability of further developing more "complex" technologies that could benefit from the recombination of different knowledge components.

Furthermore, skills are portable, as witnessed by the presence of a non-negligible distance between the domestic and migrant inventors' portfolios. We have identified that such a distance and the diversity of origins of highly skilled migrants are associated with the presence of more complex technologies at a local level. Even if skills portability does not seem to be associated with an increase in technological diversification, it does seem to be associated with an increase in the complexity of the fields of specialization. These results suggest that the definition of policies that favor mobility and employment of foreign talent would help the local industrial context to cover the lack of specific competences. The positive effect may not necessarily lead to an increase of the diversification of innovation activities in the destination regions, a finding quite different from the conclusion of Bahar and Rapoport (2018) that identified a positive correlation between migrants and the number of products exported by a country. However, this kind of policies could contribute to add depth to the specialization of the local technological portfolio and impact positively on the implementation of approaches like the so-called Smart Specialization, developed in the EU in the last decade and spread globally (Foray, 2013; McCann et al., 2015; Krammer, 2017; Piirainen et al., 2017; Prieto et al., 2019). Coherently with the goals of the Smart Specialization approach, policies that foster high-skilled mobility would support regions to shape the development of the technological portfolio according to the unique socio economic local conditions.

Our analysis suffers from some limitations concerning the examined data. First, the identification of migrant inventors is not exempt from the drawbacks of the WIPO dataset on inventors' nationalities, as accurately described in Miguelez and Fink (2013). In addition, future research can try to clearly identify individuals through the application of disambiguation algorithms on the inventors' names provided in the WIPO PCT database. This would make it possible to compute a measure of migration intensity based on the count of the inventors' heads and exclude the confounding effect given by the potential presence of the most productive migrants in the regions where the migration phenomenon is larger. Second, focusing on PCT patents limits the scope of the investigation to a subset of patents potentially more relevant than the average ones. Third, the employed variables only partially address the firm level effect as they consider the level of collaboration of migrants with local inventors. We are well aware of the complexity of the mechanism that includes an interplay between the demand and the supply of skilled workers. Our empirical setting cannot disentangle those cases when a single company starts hiring a large number of employees, most of them from abroad (e.g. the opening of a new subsidiary), therefore influencing both specialization and migration. However, a firm's choice of location for a new subsidiary is not a completely random decision and considers the local knowledge specializations as a positive element (Tallman and Chacar, 2011; Hervas-Oliver and Boix-Domenech, 2013): hence, our model is expected to be robust to such types of events. Nonetheless, further research could investigate the potential firm level effects in more detail, following the evidence presented in the work of Lee (2014). Finally, alternative measures of diversification based on the identification of patents in technological fields that are new to the geographical area could be explored and integrated in a specific methodological setting.

CRediT authorship contribution statement

Federico Caviggioli: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Paul Jensen:** Conceptualization, Writing - review & editing, Supervision. **Giuseppe Scellato:** Conceptualization, Methodology, Writing - review & editing, Supervision.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2020.119951.

References

Agrawal, A., Kapur, D., McHale, J., 2008. How do spatial and social proximity influence knowledge flows? Evidence from patent data. J. Urban Econ. 64 (2), 258–269.

Aldieri, L., Vinci, C.P., 2016. Knowledge migration: a cross-national analysis. Economist (Netherlands) 164 (2), 109–123.

Antonelli, C., Crespi, F., Mongeau Ospina, C.A., Scellato, G., 2017. Knowledge composition, Jacobs externalities and innovation performance in European regions. Reg. Stud. 51 (11), 1708–1720.

Archibugi, D., Pianta, M., 1992. Specialization and size of technological activities in industrial countries: The analysis of patent data. Research Policy 21 (1), 79–93.

Arslan, C., et al., 2014. A new profile of migrants in the aftermath of the recent economic crisis", OECD social. Employment and Migration Working Papers. OECD Publishing.

Audretsch, D., Dohse, D., Niebuhr, A., 2010. Cultural diversity and entrepreneurship: a regional analysis for Germany. Ann. Reg. Sci. 45, 55–85.

Bahar, D., Rapoport, H., 2018. Migration, knowledge diffusion and the comparative advantage of nations. Econ J. 128 (612), F273–F305.

Bettencourt, L., Lobo, J., Strumky, D., 2007. Invention in the city: increasing returns to patenting as a scaling function of metropolitan size. Res. Policy 36, 107–120.

Bettin, G., Bianchi, P., Nicolli, F., Ramaciotti, L., Rizzo, U., 2019. Migration, ethnic concentration and firm entry: evidence from Italian regions. Reg. Stud. 53 (1), 55–66.

Betz, M.R., Partridge, M.D., Fallah, B., 2016. Smart cities and attracting knowledge workers: which cities attract highly-educated workers in the 21st century? Pap. Reg. Sci. 95 (4), 819–841.

Borjas, G.J., Doran, K.B., 2015. Cognitive mobility: labor market responses to supply shocks in the space of ideas. J. Labor Econ. 33 (S1), S109–S145.

Boschma, R., Iammarino, S., 2009. Related variety, trade linkages, and regional growth in Italy. Econ. Geogr. 85 (3), 289–311. https://doi.org/10.1111/j.1944-8287.2009.01034.x.

Boschma, R., Balland, P.A., Kogler, D.F., 2014. Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. Ind. Corp. Chang. 24 (1), 223–250.

Boschma, R., Minondo, A., Navarro, M., 2013. The emergence of new industries at the regional level in Spain: a proximity approach based on product relatedness. Econ. Geogr. 89, 29–51. https://doi.org/10.1111/j.1944-8287.2012.01170.x.

Bosetti, V., Cattaneo, C., Verdolini, E., 2015. Migration of skilled workers and innovation: a European perspective. J. Int. Econ. 96 (2), 311–322 July 2015.

Breschi, S., Lissoni, F., Miguelez, E., 2017. Foreign-origin inventors in the USA: testing for diaspora and brain gain effects. J. Econ. Geogr. 17 (5), 1009–1038.

Breschi, S., Lissoni, F., Tarasconi, G., 2014. Inventor data for research on migration and innovation: a survey and a pilot. WIPO Econ. Stat. Ser.(17).

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

Curran, C.S., 2013. The Anticipation of Converging Industries. Springer. London.

D'Ambrosio, A., Montresor, S., Parrilli, M.D., Quatraro, F., 2019. Migration, communities on the move and international innovation networks: an empirical analysis of Spanish regions. Reg. Stud. 53 (1), 6–16.

Docquier, F., Rapoport, H., 2009. Documenting the brain drain of "La Creme de la Creme. J. Econ. Stat. 229, 679–705.

Dokko, G., Rosenkopf, L., 2010. Social capital for hire? Mobility of technical professionals and firm influence in wireless standards committees. Organ. Sci. 21 (3), 677–695.

Duranton, G., Puga, D., 2004. Micro-foundations of urban agglomeration economies. Handbook of Regional and Urban Economics 4. Elsevier, pp. 2063–2117.

Fassio, C., Montobbio, F., Venturini, A., 2019. Skilled migration and innovation in European industries. Res. Policy 48 (3), 706–718.

Feldman, M.P., Audretsch, D.B., 1999. Innovation in cities: science-based diversity, specialization and localized competition. Eur. Econ. Rev. 43 (2), 409–429.
Foray, D., 2013. The economic fundamentals of smart specialisation. Ekonomiaz 83 (2), 83–102.
Fleming, L., 2001. Recombinant uncertainty in technological search. Manag. Sci. 47 (1), 117–132.
Franzoni, C., Scellato, G., Paula, S., 2012. Foreign-born scientists: mobility patterns for 16 countries. Nat. Biotechnol. 30 (12), 1250–1253.
Franzoni, C., Scellato, G., Stephan, P., 2014. The mover's advantage: the superior performance of migrant scientists. Econ. Lett. 122 (1), 879–893.
Frenken, K., Izquierdo, L.R., Zeppini, P., 2012. Branching innovation, recombinant innovation, and endogenous technological transitions. Environ. Innov. Soc. Transit. 4, 25–35.
Gagliardi, L., 2015. Does skilled migration foster innovative performance? Evidence from British local areas. Pap. Reg. Sci. 94, 773–794.
Glaeser, E., Kallal, H., Scheinkman, J., Shleifer, A., 1992. Growth in cities. J. Political Econ. 100 (6), 1126–1152. https://doi.org/10.1086/261856.
Hargadon, A., Sutton, R.I., 1997. Technology brokering and innovation in a product development firm. Adm. Sci. Q. 42 (4), 716–749.
Hervas-Oliver, J.L., Boix-Domenech, R., 2013. The economic geography of the meso-global spaces: integrating multinationals and clusters at the local–global level. Eur. Plan. Stud. 21 (7), 1064–1080.
Hidalgo, C.A., Hausmann, R., 2008. A network view of economic development. Dev. Altern. 12, 5–10.
Hidalgo, C.A., Hausmann, R., 2009. The building block of economic complexity. In: Proceedings of the National Academy of Sciences of the United States of America. 106. pp. 10570–10575.
Hornung, E., 2014. Immigration and the diffusion of technology: the Huguenot diaspora in Prussia. Am. Econ. Rev. 104 (1), 84–122.
Huggins, R., Thompson, P., 2017. Networks and regional economic growth: a spatial analysis of knowledge ties. Environ. Plan. A 49 (6), 1247–1265.
Hunt, J., Gauthier-Loiselle, M., 2010. How much does immigration boost innovation? Am. Econ. J. 2 (2), 31–56.
Jacobs, J., 1969. The Economy of Cities. Jonathan Cape, London.
Jaffe, A.B., 1986. Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. The American Economic Review 984–1001.
Jones, B.F., 2011. The Knowledge trap: Human Capital and Development Reconsidered. NBER Working paper, pp. 14138.
Kang, B., 2016. What best transfers knowledge? capital, goods, and labor in East Asia. Econ. Lett. 139, 69–71.
Katila, R., Ahuja, G., 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. Acad. Manag. J. 45 (6), 1183–1194.
Kerr, S.P., Kerr, W., Özden, Ç., Parsons, C., 2017. High-skilled migration and agglomeration. Annual Review of Economics 9, 201–234.
Kerr, W.R., Lincoln, W.F., 2010. The supply side of innovation: H-1B visa reforms and US ethnic invention. J. Labor Econ. 28 (3), 473–508.
Kerr, W.R., Mandorff, M., 2015. Social networks, ethnicity, and Entrepreneurship. National Bureau of Economic Research.
Kerr, W.R., 2010. Breakthrough inventions and migrating clusters of innovation. J. Urban Econ. 67 (1), 46–60.
Krammer, S.M., 2017. Science, technology, and innovation for economic competitiveness: the role of smart specialization in less-developed countries. Technol. Forecast. Soc. Chang. 123, 95–107.
Lee, N., 2014. Migrant and ethnic diversity, cities and innovation: firm effects or city effects? J. Econ. Geogr. 15 (4), 769–796.
Li, X., 2015. Specialization, institutions and innovation within China's regional innovation systems. Technol. Forecast. Soc. Chang. 100, 130–139.
Lissoni, F., 2018. International migration and innovation diffusion: an eclectic survey. Reg. Stud. 52 (5), 702–714.
McCann, P., Ortega-Argilés, R., 2015. Smart specialization, regional growth and applications to European Union cohesion policy. Reg. Stud. 49 (8), 1291–1302.
Meyer, J.B., 2001. Network approach versus brain drain: lessons from the Diaspora. Int. Migr. 39 (5), 91–110.
Mendonça, J., Heitor, M., 2016. The changing patterns of industrial production: how does it play for the Iberian Peninsula? Technol. Forecast. Soc. Chang. 113, 293–307.
Miguelez, E., Fink, C., 2013. Measuring the International Mobility of Inventors: A New Database. WIPO Economics & Statistics Series.
Miguelez, E., Moreno, R., 2013. Collaborations Foster geographical knowledge diffusion? The case of. Growth Chang. 44 (2), 321–354.
Miguelez, E., Moreno, R., 2018. Relatedness, external linkages and regional innovation in Europe. Reg. Stud. 52 (5), 688–701.
Miguélez, E., Moreno, R., Suriñach, J., 2010. Inventors on the move: tracing inventors' mobility and its spatial distribution. Pap. Reg. Sci. 89 (2), 251–274. https://doi.org/10.1111/j.1435-5957.2010.00280.x.
Mihi-ramirez, A., Garcia-rodriguez, Y., Cuenca, E., 2016. Innovation and international high skilled migration. Inzinerine Ekonomika-Eng. Econ. 27 (4), 452–461.
Montresor, S., Quatraro, F., 2017. Regional branching and key enabling technologies: evidence from European patent data. Econ. Geogr. 93 (4), 367–396.
Moon, J., Park, J., Jung, G.H., Choe, Y.C., 2010. The impact of IT use on migration intentions in rural communities. Technol. Forecast. Soc. Chang. 77 (8), 1401–1411.
Moser, P., Voena, A., Waldinger, F., 2014. German Jewish émigrés and US invention. Am. Econ. Rev. 104 (10), 3222–3255.
Nathan, M., 2014. The wider economic impacts of high-skilled migrants: a survey of the literature for receiving countries. IZA J. Migr. 1 (3), 1–20.
Nathan, M., Lee, N., 2013. Cultural diversity, innovation, and entrepreneurship: firm-level evidence from London. Econ. Geogr. 89 (4), 367–394.
Niebuhr, A., 2010. Migration and innovation: does cultural diversity matter for regional R&D activity? Pap. Reg. Sci. 89 (3), 563–585.
Ó Huallacháin, B., Lee, D.S., 2011. Technological specialization and variety in urban invention. Reg. Stud. 45 (1), 67–88.
Oettl, A., Agrawal, A., 2008. International labor mobility and knowledge flow externalities. J. Int. Bus. Stud. 39 (8), 1242–1260.
Ottaviano, G., Peri, G., 2005. The economic value of cultural diversity: evidence from US cities. J. Econ. Geogr. 6, 9–44.
Parrilli, M.D., Montresor, S., Trippl, M., 2019. A new approach to migrations: communities-on-the-move as assets. Reg. Stud. 53 (1), 1–5.
Pavitt, K., 1998. The social shaping of the national science base. Res. Policy 27 (8), 793–805.
Pianta, M., Meliciani, V., 1996. Technological specialization and economic performance in OECD countries. Technology Analysis & Strategic Management 8 (2), 151–174.
Piirainen, K.A., Tanner, A.N., Alkærsig, L., 2017. Regional foresight and dynamics of smart specialization: a typology of regional diversification patterns. Technol. Forecast. Soc. Chang. 115, 289–300.
Prieto, J.G., Demblans, A., Martinez, M.P., 2019. Smart Specialisation in the world, an EU Policy Approach Helping to Discover Innovation globally: Outcomes, Lessons and Reflections from the First Global Workshop On Smart Specialisation. Joint Research Centre (Seville site).
Rigby, D.L., 2015. Technological relatedness and knowledge space: entry and exit of US cities from patent classes. Reg. Stud. 49 (11), 1922–1937. https://doi.org/10.1080/00343404.2013.854878.
Rosenkopf, L., Nerkar, A., 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. Strategic management journal 22 (4), 287–306..
Shang, J., Li, P., Li, L., Chen, Y., 2018. The relationship between population growth and capital allocation in urbanization. Technol. Forecast. Soc. Chang. 135, 249–256.
Soete, L., 1987. The impact of technological innovation on international trade patterns: the evidence reconsidered. Res. Policy 16 (2–4), 101–130.
Song, J., Almeida, P., Wu, G., 2003. Learning–by–hiring: when is mobility more likely to facilitate interfirm knowledge transfer? Manag. Sci. 49 (4), 351–365.
Stojcic, N., Becic, M., Vojinic, P., 2016. The impact of migration movements on innovation activities in croatian counties. Drustvena Istrazivanja 25 (3), 291–307.
Stuen, E.T., Mobarak, A.M., Maskus, K.E., 2012. Skilled immigration and innovation: evidence from enrolment fluctuations in US doctoral programmes. Econ. J. 122, 1143–1176.
Tallman, S., Chacar, A.S., 2011. Communities, alliances, networks and knowledge in multinational firms: a micro-analytic framework. J. Int. Manag. 17 (3), 201–210.
van der Wouden, F., Rigby, D.L., 2017. Co-inventor networks and knowledge production in specialized and diversified cities. Pap. Reg. Sci.
van Zeebroeck, N., van Pottelsberghe, B., Han, W., 2006. Issues in measuring the degree of technological specialisation with patent data. Scientometrics 66 (3), 481–492.
Zhan, S., Bendapudi, N., Hong, Y., 2015. Re-examining diversity as a double-edged sword for innovation process. J. Organ. Behav. 36, 1026–1049 (2015).
Zheng, Y., Ejermo, O., 2015. How do the foreign-born perform in inventive activity? Evidence from Sweden. J. Popul. Econ. 28 (3), 659–695.

Federico Caviggioli: is Assistant Professor at the Department of Management and Production Engineering of "Politecnico di Torino" (Italy). He completed his PhD in "Economics and Management of Technology" at the University of Bergamo, Italy, in 2011. His-research focuses on Economics of Innovation and, in particular, technology strategy, market for technologies, patent data intelligence, and quality of patent systems. Quantitative analysis and patent data treatment are among his main skills. He published in international journals such as Research Policy, Industry and Innovation, Technovation and Technological Forecasting & Social Change. He contributed to several projects funded by the European Commission (eg. the projects "Universities in the Framework Programmes" and "PatQual"), national institutions (eg. Chamber of Commerce of Turin), and Italian companies (eg. Leonardo-Finmeccanica Spa). He has been a member of the Senate of "Politecnico di Torino" from 2015 to 2017.

Prof. Paul Jensen: is currently Deputy Dean (Faculty) at the Faculty of Business and Economics at The University of Melbourne. He is an industrial economist who specialises in the economics of innovation, science and technology policy. He has published in prestigious international journals (Journal of International Economics, RAND Journal of Economics, Review of Economics and Statistics) and participates regularly in policy debates. He has consulted widely to international organisations (IBM, PricewaterhouseCoopers, the OECD, the European Commission) as well as domestic Australian organisations (Productivity Commission, Victorian Department of Premier & Cabinet, NSW Treasury). He was also an expert panel member on the Australian Federal Government's National Innovation Systems Review and WIPO's Roundtable on "IP and SMEs". He is a Research Fellow of the Oxford Intellectual Property Research center and was part of the scientific committee for the European Policy on Intellectual Property (EPIP) conference held at Oxford in Sept 2016. He is a recipient of numerous competitive grants (Australian Research Council, Swiss Network for International Studies) and has served as a referee for the National Science Foundation, the Flemish Science Foundation and the British Council.

Giuseppe Scellato: holds a Ph.D. in Economics and is Associate Professor at Politecnico di Torino, where he teaches corporate finance and economics and management of innovation. From 2015 to 2018 he has been the Vice Dean of the Faculty of Industrial Engineering and Management. Since 2018 he is the president and CEO of the Innovative Companies Incubator (I3P) of Politecnico di Torino. Since 2017 he is a member of the board of the Future Urban Legacy Lab (FULL) at Politecnico di Torino. Since 2008 he is research affiliate of the Bureau of Research in Innovation Complexity and Knowledge (BRICK) at Collegio Carlo Alberto. His-main research interests are in the areas of economics and management of innovation, industry dynamics, the economic analysis of intellectual property rights, and the economics of science. His-scientific publications have appeared in leading international journals, including Science, Nature, Journal of Management Studies, Journal of Corporate Finance, Research Policy, Journal of Banking and Finance, Journal of Business Research, and Cambridge Journal of Economics. In recent years, he has been the principal investigator of research projects funded by the European Commission, the European Patent Office, the Joint Research Center, the European Investment Bank, the National Bureau of Economic Research. He has been member of expert groups and committees for the evaluation of public policies for research and innovation in different Italian regions. He has managed numerous consulting project with public and private organisations in the areas of intellectual property and innovation.