HIGHLY SKILLED MIGRATION AND TECHNOLOGICAL DIVERSIFICATION IN METROPOLITAN AREAS

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Abstract

We investigate the impact of highly skilled migrants on the regional technological portfolio of European and US geographical units at the metropolitan level. Previous studies focused on the relationship between migration and innovative performance especially in terms of quantitative output finding a positive correlation. To the best of our knowledge, the effects on the technological diversification of the innovation output, which is found to be a driver of regional economic growth and of the emergence of new industries, have been neglected. Migrants are identified by comparing inventors' nationalities, derived from the WIPO PCT database, with their address of residence, as in OECD REGPAT database. Each geographical area is characterized in terms of migration intensity, dispersion, and technological distance between native and migrant inventors. The variety and average rarity of the fields of specialization of the regional technological portfolios are computed by applying the Hidalgo-Hausman (2008) method of reflections on patent data. Panel data models with fixed effects show a negative relation between migration and variety, supporting the presence of a specialty matching mechanism associated to the migration phenomenon. Rarity is positively correlated suggesting that, although not increasing the variety, the specialization fields are less ubiquitous and thus we argue that technology recombination is more frequent when migration is higher.

Keywords: international mobility, technological diversification, high skilled migrants, inventors, regional studies

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1 Introduction

Extraordinary migration flows have characterized the last few decades, and a significant number of highly skilled individuals were 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 2012; Kerr 2010). Researchers have been studying the implication of "brain drain" (i.e. the loss of highly educated workers from the perspective of the origin country), "brain gain" (i.e. the acquisition of talents in the destination country) and diaspora for the innovation potential of economic systems (Miguelez and Fink, 2013; Breschi et al. 2014; Breschi et al. 2015; 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, in terms of quantity and likelihood of breakthrough inventions. Such findings are consistent when the migrant samples are represented by graduate/PhD students (Hunt and Gauthier-Loiselle, 2010; Stuen et al. 2012), scientists (Franzoni et al., 2012; Scellato et al, 2012) or inventors (Miguelez and Moreno, 2013; Bosetti et al., 2015; Stojcic et al., 2016; Aldieri and Vinci, 2016). Some scholars, however, found mixed evidence (Zhan et al., 2015; Zheng and Ejermo, 2015). Moving from these results, we question whether and under what circumstances the inflow of foreign born inventors has also an effect in reshaping the array of technological competences of a geographical area. This research question is motivated by the fact that the evolution in time of the pattern of technological diversification of a region can heavily influence its capability to further develop complex technological solutions that increasingly require the recombination of different pieces of scientific and technical knowledge.

The degree of variety of the knowledge base is indeed a distinctive property of regional innovation systems: it contributes to the innovative capabilities of local firms (Asheim and Coenen, 2005; Asheim and Gertler, 2005) and supports the aggregated regional economic growth. Knowledge variety plays a positive role in favoring the emergence of new industries (Boschma & Iammarino, 2009; Boschma, Minondo, & Navarro, 2013).

In this paper, we investigate the impact of high skilled migrants on the composition of the regional technological portfolio of 417 geographical areas, located in Europe and in the U.S.. We extend previous studies that have focused mostly on the relationship between migration and innovation by specifically addressing the role of foreign-born inventors, along several dimensions. We focus the analyses at the level of metropolitan areas rather than countries or larger regions: localized technological portfolios are a better representation of the inventive activity than the one at the level of larger regions or countries, where different clusters are merged and cross-sectional differences are reduced. Cities are considered more and more important not only for the increasing number of inhabitants but also as being relevant *loci* of innovation.

Previous literature focused mainly on the effects of immigration from a quantitative perspective while we are interested in evaluating the impact on the composition of the technological portfolio. To do so, we adopt the Hidalgo-Hausman (2008) approach to patent portfolios similarly to what Antonelli et al (2016) have recently applied, but in this case with the aim to qualify the technological specialization patterns of cities.

2 Previous literature

2.1 Relevance of technological diversification

The technological diversification has been found to have a positive effect on innovative activities and regional growth. This result is analyzed in light of the so-called Jacobs externalities (Jacobs, 1969): heterogenous activities clustering in a geographic space exerts positive effects on economic growth. The generation of technological knowledge, in fact, consists in the recombination of heterogeneous and complementary knowledge items in the local knowledge base. When they are available at low absorption costs, Jacobs knowledge externalities exert their positive – pecuniary – effects, reducing the costs of knowledge both as input and output (Antonelli et al., 2016).

Furthermore, at the regional level variety, qualified in terms of product relatedness, plays a positive role in favouring the emergence of new industries (Boschma & Iammarino, 2009; Boschma, Minondo, & Navarro, 2013). Such concept finds corroborating results when the analyses are carried out at the level of technological trajectories and at the micro-level of inventions. At the industry level, previous authors (Archibugi and Pianta (1992) and Pianta and Meliciani (1996) found that the variety of the knowledge base and the advance of countries follows 'U'-shaped pattern. Excess knowledge differentiation is not likely to exert positive effects on the innovative capabilities of local firms (Rigby, 2015).

2.2 Migration and innovation

Scholars that investigated the relation 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. The results are consistent either 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; Scellato et al., 2012), or inventors (Miguelez and Moreno, 2013; Bosetti et al., 2015; Stojcic et al., 2016; Aldieri and Vinci, 2016). Previous literature motivated such increase with 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, some scholars found mixed evidence (Zhan et al., 2015; Zheng and Ejermo, 2015).

Departing from the investigation of the quantitative effects of highly skilled migration on the innovative output, we question whether the inflow of foreign born inventors have an impact in reshaping the technological space of a geographical area. In a recent paper, Kang (2016) found that inventors have positive effects on knowledge flow in East Asia, but their effects decrease when the technological portfolios of two countries are similar. However, it is not clear either the migration of inventors could significantly impact on

the technological composition of a country's innovative output, or the inflow is driven by the lack of skilled employees in certain fields, or a combination of the two hypotheses. In a recent study, Mihi-ramirez et al. (2016) formulated the hypothesis that migrant inventors are attracted to countries where innovative factors (patents and R&D expenditure) are higher; however, their empirical model do not test for causality but only for correlation.

Such considerations suggest the presence of a connection between migration (in terms of intensity and similarity with the destination areas) and the composition of the regional technological portfolio.

2.3 Research hypothesis

The aim of this study is to extend the literature on migration and innovation by integrating it with the evidence scholars found in the analysis of technological diversification, which impacts on regional growth. In particular we want to investigate the relationship between the intensity of high skilled immigration and the capability of a metropolitan area to expand the portfolio of technological specializations and to enter "rarer" technological domains. Such analyses will be carried out considering the role of the diversity of the high-skilled immigrant population in terms of technological competences and concentration of origins in the destination locations.

One of the concepts that explain the migration phenomenon to specific metropolitan areas is the "specialty matching" hypothesis. The presence of a strong specialization is an attractor of foreign born inventors. If this is true, we expect to observe a negative (or not significant) correlation between the intensity of immigration and the degree of technological variety. This hypothesis considers immigration as a reinforcing mechanism of specialization (Jones, 2009; Franzoni et al., 2014).

From the opposite perspective, the concepts of "skill portability and knowledge recombination" might prevail. Migrants provide the destination area with a set of skills and competences different from those of the natives, making it more likely to be recombined and favor the emergence of new ideas and merged technologies (Fleming, 2001; Curran, 2013; Caviggioli, 2016). Blending knowledge from local and distant sources creates opportunities to hybridize ideas and solutions (Dokko et al., 2009; Hargadon and Sutton, 1997; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001). Recombination might lead to an increase in variety of specializations and the new technological field, due to the higher complexity of the merged technology, is likely to be characterized by the entry into niche technologies which are not common.

3 Methodology

3.1 Dataset

The OECD REGPAT database contains information on the address of residence of the inventors. The addresses are associated to the geographical area codes of the Nomenclature of Territorial Units for Statistics (NUTS) in Europe, and of the classification defined by the Bureau of Economic Analysis (BEA) for the U.S., which is comparable to the NUTS classification[1]. The hierarchical structure of NUTS includes countries, regions (NUTS2) and smaller geographical areas (NUTS3).

We decided to limit our analysis to European countries and the U.S.. These geographical areas present more consistent geographical codes through years, rely on innovative activities for growth, and highly skilled migration is not a negligible phenomenon[2].

Since we are interested in the analysis of patent-based metrics, we limited the dataset to a subset of geographical areas with a sufficient number of PCT patents in recent years. We first calculated the total number of PCT patents in each NUTS3 area in the years from 2006 to 2010 by applying a fractional count approach based on the address of residence of the inventors. Then we selected the geographical areas with at least 200 PCT patents: 327 areas in Europe (we considered the 28 European Union members, the European Free Trade Association members, and other countries within the geographical borders[3]) and 90 in the U.S..

The OECD REGPAT database was merged with the WIPO PCT database[4]. With the matching, migrant inventors are identified from the comparison of their country of residence with their nationality. The WIPO PCT data contain information on the nationality of the inventors recorded in the patents that followed the Patent Cooperation Treaty (PCT) procedure from 1978 to 2012 and that subsequently requested an extension at the USPTO. A thorough description of the database and of its limitations is provided by Miguelez and Fink (2013) and Miguélez et al. (2010). It is important for our analyses to remind that PCT patents represent a particular subset of the total innovative

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[1] For further details, please refer to the OECD REGPAT documentation and the official website of the European Commission (http://ec.europa.eu/eurostat/web/nuts , last access in September 2017).

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

[3] Andorra, Albania, Bosnia and Herzegovina, Serbia, Montenegro, FYROM, San Marino, Città del Vaticano.

[4] The process of merging the datasets accounted for an additional work since the NUTS codes available in the two data sources are not completely overlapping. In fact, different releases of the NUTS codes are available and includes events like changes in recoding, borders, merges and splits of geographical areas. The WIPO PCT data are available on request from the WIPO.

production. Due to their expected higher maintenance fees due to the on average wider geographical coverage, this type of patent can be considered as of higher value with respect to the average national patent.

Once migrant inventors are identified, it is possible to calculate several metrics to describe the phenomenon at the geographical level. Through a fractional count of PCT patents, the intensity of the presence of migrant inventors in each geographical area is computed as the share of migrants' patents.

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

Figure 1 shows the average values in time for the total sample of 417 areas, the U.S., the European areas, and for a selection of some European countries. Figure 2 shows the trend for a selection of metropolitan areas. Although there is a general increase (from 6% in 1991 to 10% in 2010), the local patterns are heterogeneous, with areas like Milano almost not affected by any change, and areas like Zurich showing a steep increase up to more than 50% of migrant inventors.

Figure 1 Share of PCT patents from migrant inventors. Average values for the full sample (dotted green line), European countries (dotted grey line), the US (dark red) and a selection of European countries.

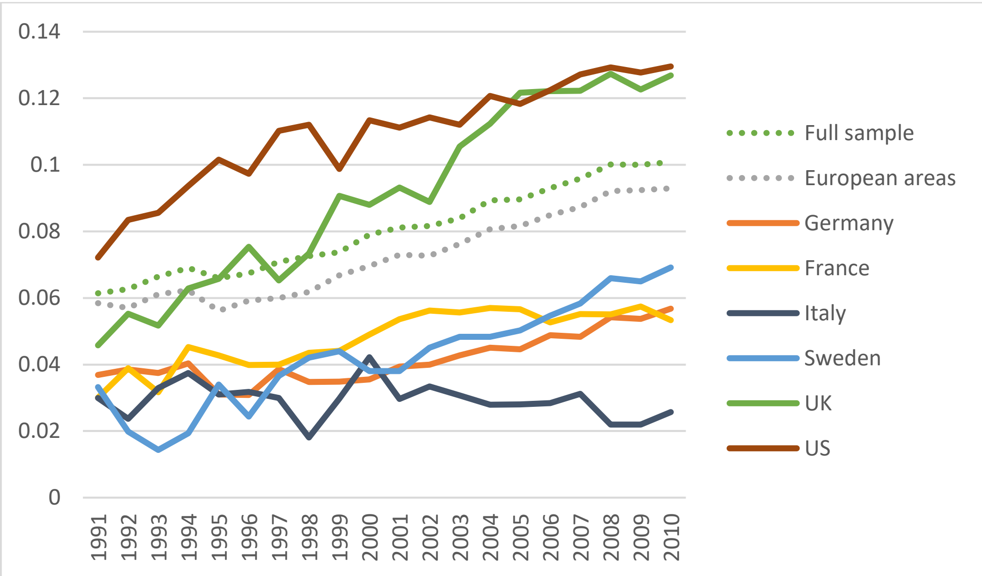
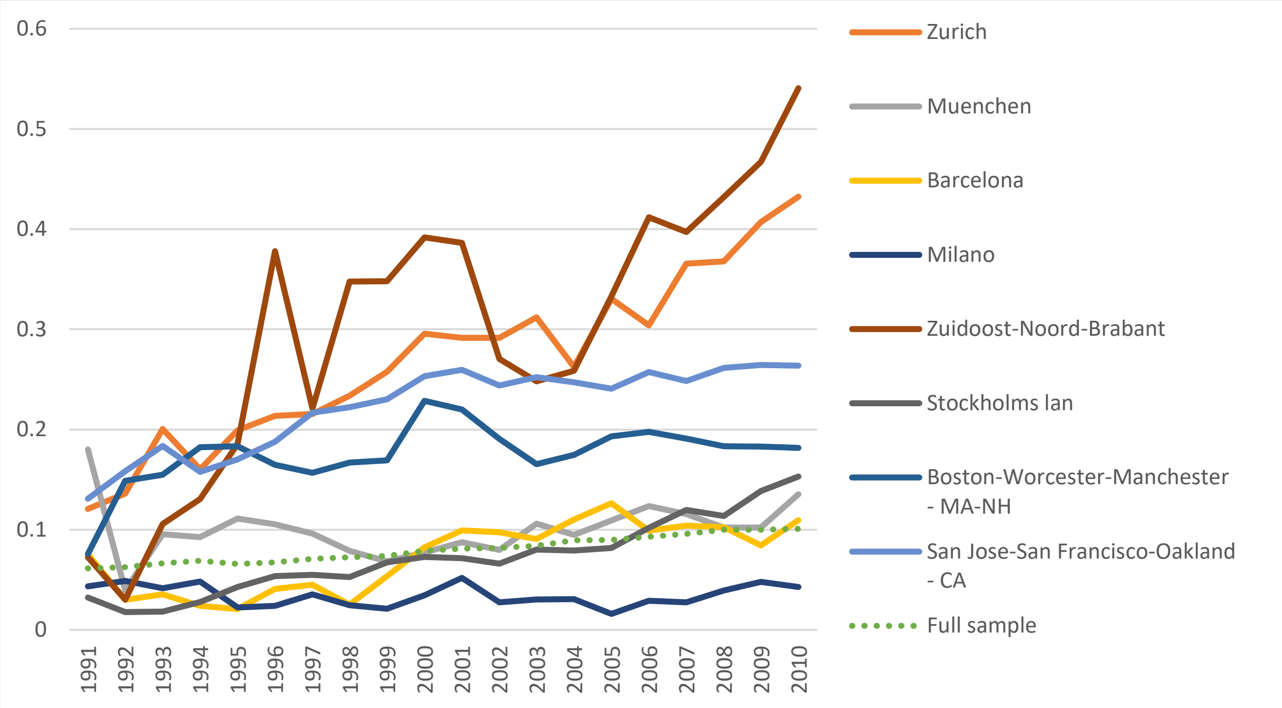


FIGURE 2 SHARE OF PCT PATENTS FROM MIGRANT INVENTORS. AVERAGE VALUES FOR THE FULL SAMPLE (DOTTED GREEN LINE) AND A SELECTION OF METROPOLITAN AREAS.



We compute a measure of the concentration of different nationalities in a destination area to take into consideration whether a certain metropolitan area is subject to migration flows from a single origin country or from multiple locations. We employed the Herfindhal index to measure the concentration (in the economic literature), that corresponds to the Simpson Index (in ecology literature):

$$concentration_r = \sum_e {s_{re}}^2$$

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

3.2 Measuring technological diversification of the regional knowledge base

We have 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 measure due to sufficient

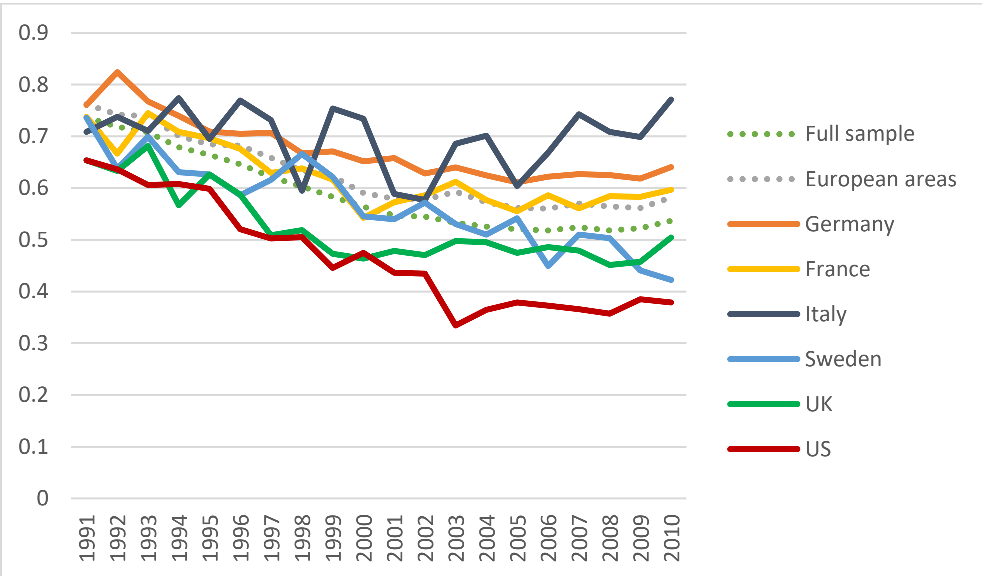
characterization of the technologies across a reasonable and treatable number of categories (van Zeebroeck et al.,2006; Caviggioli, 2016). The distinct technological portfolios of migrant and native inventors are transposed in the two corresponding vectors and then compared to calculate a measure of similarity (or distance). We applied the method described in Jaffe (1986) that 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 is 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, respectively for native (n) and migrant (m) inventors. TP ranges from 0 to 1, hence we can compute technological distance (TD) as:

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

FIGURE 3 TECHNOLOGICAL DISTANCE BETWEEN MIGRANT AND INVENTORS. AVERAGE VALUES FOR THE FULL SAMPLE (DOTTED GREEN LINE), EUROPEAN COUNTRIES (DOTTED GREY LINE), THE US (DARK RED) AND A SELECTION OF EUROPEAN COUNTRIES.



The trends in Figure 3 show that in general the average portfolio of migrants is getting similar to natives'. However, in recent years it seems to have stabilized. The average values at the country level are heterogeneous. For instance, in the U.S. and in the U.K. the technological portfolio of migrants is more similar to the local knowledge base, with respect to Italy, Germany and France, where the difference is more prominent.

Previous authors (Archibugi and Pianta, 1992; Pianta and Meliciani 1996) found that the variety of the knowledge base and the innovation performance follows a non-monotonic function. An

excessive knowledge differentiation is not necessarily linked to positive effects on the innovative capabilities of local firms (Rigby, 2015; Noteboom, 2000). For such reasons, we will include the technological distance with a quadratic form in our empirical specification.

With the aim of capturing the relative complexity of the regional knowledge base, we have implemented a more sophisticated method proposed by Hidalgo and Hausmann (2008 and 2009; HH hereafter) for qualifying the knowledge composition of the economic system. Such technique characterizes the specialization patterns of the knowledge base in a specific economic system by taking into consideration the relative diffusion among other economic systems. From an empirical perspective, HH used data on country-level export of final products, considering that these are linked to the competences their production requires. In this paper, we use the operationalization of the HH model presented in Antonelli et al. (2017) and directly measure technological capabilities in different regional economic systems by looking at the information contained in patent documents. The HH method makes no use of ex-ante technological distances for measuring 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 bottom-up approach in which the observed evolution of the specializations of innovation systems provides hints on the actual complementarities among technological domain, rather than a top-down approach in which the structure of interdependency (or relatedness) between technologies are pre-defined on pure technological (patent-based) evidence (Antonelli et al. 2017).

We followed HH 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 is 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*.

$$M(r, j) = \begin{cases} 1 \text{ if } RTA_{rj} > 1 \\ 0 \text{ if } RTA_{rj} <= 1 \end{cases}$$

From the matrix M we computed two vectors that measure respectively *variety*, i.e., the number of technologies in which region *r* is specialized and *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 which 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 the row r in matrix M. The average ubiquity shows whether the region is specialized in technologies that are frequently fields of specialization for other geographical areas. The same concept can be explained from the opposite perspective in terms of “rarity”. A metropolitan area can be specialized in several technological fields that however are niche technologies. We measure the average rarity as the opposite of the average ubiquity

$$AvgRarity_j = -AvgUbiq_j$$

The following charts show the trends of variety and rarity of the total sample and for a selection of countries (as averages) and of metropolitan areas.

FIGURE 4 TREND OF VARIETY OF TECHNOLOGICAL PORTFOLIOS. AVERAGE VALUES FOR THE FULL SAMPLE (DOTTED GREEN LINE), EUROPEAN COUNTRIES (DOTTED GREY LINE), THE US (DARK RED) AND A SELECTION OF EUROPEAN COUNTRIES.

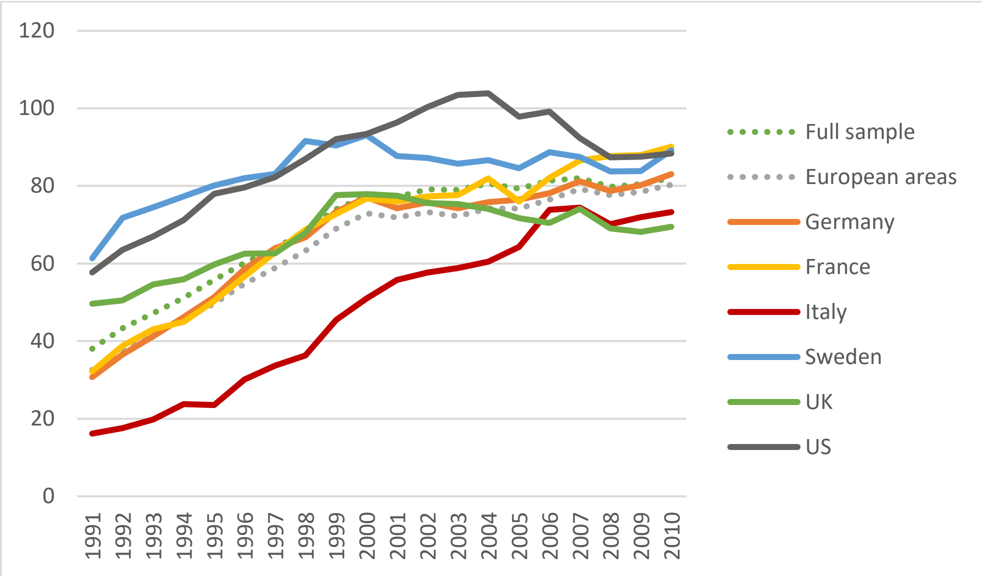


FIGURE 5 TREND OF VARIETY OF TECHNOLOGICAL PORTFOLIOS. VALUES FOR A SELECTION OF METROPOLITAN AREAS.

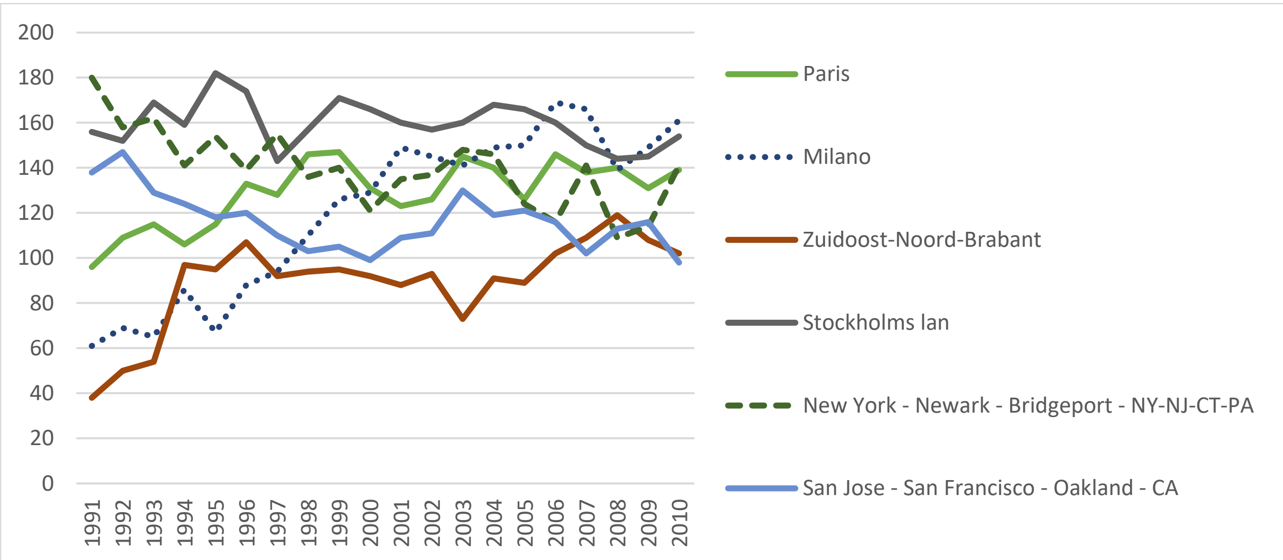


FIGURE 6 TREND OF AVERAGE RARITY OF TECHNOLOGICAL PORTFOLIOS. AVERAGE VALUES FOR THE FULL SAMPLE (DOTTED GREEN LINE), EUROPEAN COUNTRIES (DOTTED GREY LINE), THE US (DARK RED) AND A SELECTION OF EUROPEAN COUNTRIES.

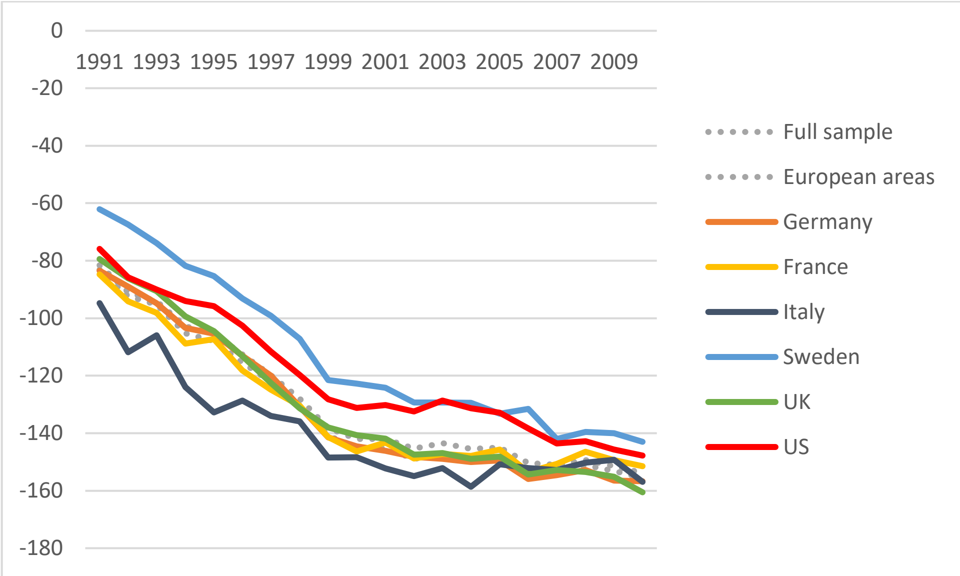
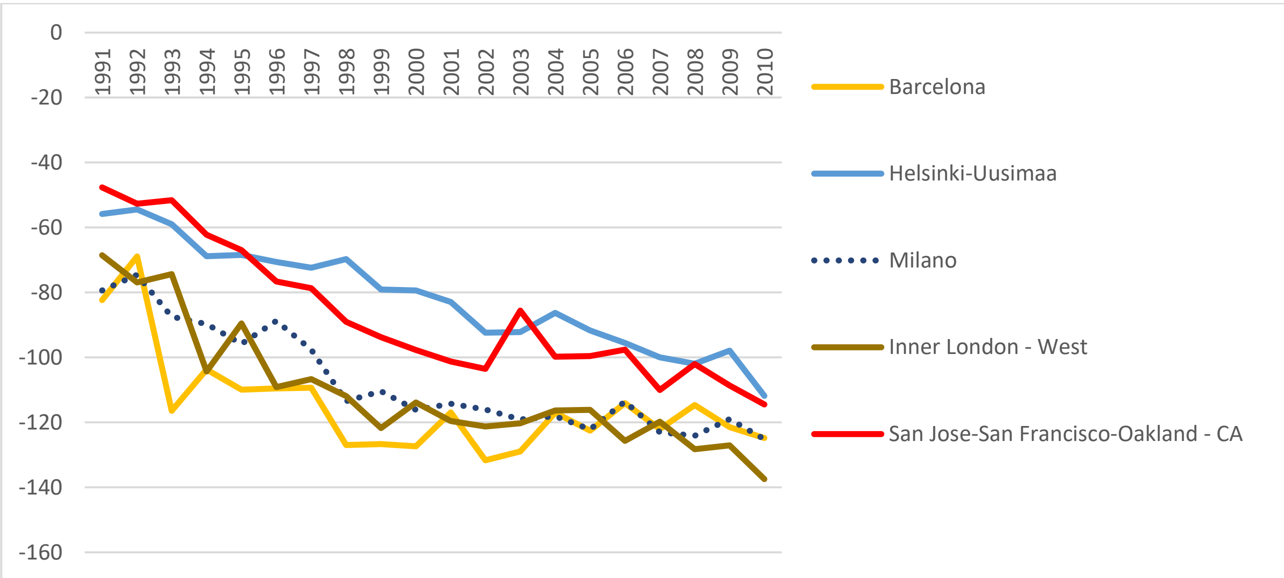


FIGURE 7 TREND OF AVERAGE RARITY OF TECHNOLOGICAL PORTFOLIOS. VALUES FOR A SELECTION OF METROPOLITAN AREAS.



The following table shows the main descriptive statistics of the analyzed variables.

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Variety	8340	69.013	34.863	1.000	64.000	228.000
Rarity	8340	-129.664	30.976	-256.000	-133.650	-24.000
Intensity (share of patents from immigrants)	8340	0.080	0.091	0.000	0.053	1.000
Tech Distance	7095	0.579	0.283	0.011	0.602	1.000
Concentration (of migrants' nationalities)	7095	0.413	0.301	0.040	0.310	1.000
Total PCT patents	8340	3.936	1.160	0.000	3.927	8.693

4 Empirical approach and preliminary results

Our preliminary empirical analysis employs two sets of panel models with metropolitan area fixed effects and time dummies. We aim to evaluate the presence of significant correlations between the technological diversification, measured in terms of variety and average rarity of the local technological portfolio, and the past incidence of foreign inventors by controlling for several context factors. The two set of models are based on the following formula:

$$y_{i,t} = (Intensity)_{i,t-1} + (Tech\_Dist)_{i,t-1} + (Tech\_Dist)^2_{i,t-1} + (Concentration)_{i,t-1} + (Portf\_size)_{i,t-1} + (Pop\_dens)_{i,t-1} + e_{i,t}$$

where i represents the geographical unit and t the time unit (year); the dependent variable y is variety in the first set of models and average rarity in the second set; "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. "Concentration" is a measure of the geographical concentration of highly skilled migrants (a measure of variety of the nationalities); "Portf_Size" is the total number of patents, a measure of size of the innovative output of the geographical unit; "pop_dens" is the population density of the region.

We introduce the variable with a stepwise approach and provide a robustness check by replicating the regression analyses on two subsamples of urban and rural geographical areas, according to the definition available in OECD STAN database[5].

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

TABLE 1 RESULTS OF PANEL DATA MODELS WITH GEOGRAPHICAL AREAS FIXED EFFECTS. DEPENDENT VARIABLE: VARIETY.

VARIABLES	Model (1)	(2)	(3)	URBAN	NOT_URBAN
$(Intensity)_{t-1}$	-17.080***	-14.633***	-16.941***	-19.999***	-16.725***
	(2.645)	(2.665)	(2.695)	(3.957)	(3.684)
$(Tech\_Dist)_{t-1}$		28.619***	26.340***	29.189***	23.853***
		(2.797)	(2.823)	(4.270)	(3.706)
$(Tech\_Dist ^ 2)_{t-1}$		-24.697***	-22.015***	-23.667***	-20.599***
		(2.299)	(2.350)	(3.606)	(3.048)
$(Concentration)_{t-1}$			-4.018***	-4.981***	-3.027***
			(0.758)	(1.168)	(0.986)
$(Pop\_dens)_{t-1}$	0.004*	0.005**	0.006**	0.005**	0.141***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.026)
$(Portf\_size)_{t-1}$	2.041***	2.449***	2.202***	4.273***	0.803
	(0.416)	(0.427)	(0.428)	(0.660)	(0.568)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	72.266***	62.690***	64.993***	60.345***	42.559***
	(2.808)	(3.078)	(3.102)	(5.151)	(5.826)
Observations	6,687	6,687	6,687	3,367	3,320
Number of nuts3	417	417	417	197	220
R-squared	0.519	0.528	0.530	0.534	0.541
adjusted R2	0.486	0.495	0.497	0.501	0.504

VARIABLES	Model (1)	(2)	(3)	URBAN	NOT_URBAN
$(Intensity)_{t-1}$	7.332***	6.030**	6.065**	11.310***	-1.586
	(2.578)	(2.618)	(2.653)	(3.554)	(4.002)
$(Tech\_Dist)_{t-1}$		-11.721***	-11.686***	-8.857**	-14.098***
		(2.747)	(2.779)	(3.835)	(4.026)
$(Tech\_Dist ^ 2)_{t-1}$		9.524***	9.482***	7.784**	10.964***
		(2.259)	(2.313)	(3.238)	(3.311)
$(Concentration)_{t-1}$			0.062	-0.015	-0.269
			(0.746)	(1.049)	(1.070)
$(Pop\_dens)_{t-1}$	0.006***	0.005**	0.005**	0.004*	0.064**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.028)
$(Portf\_size)_{t-1}$	5.298***	5.054***	5.058***	6.206***	4.477***
	(0.406)	(0.419)	(0.422)	(0.592)	(0.617)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	-178.998***	-174.491***	-174.526***	-181.119***	-179.314***
	(2.737)	(3.023)	(3.054)	(4.626)	(6.328)
Observations	6,687	6,687	6,687	3,367	3,320
Number of nuts3	417	417	417	197	220
R-squared	0.759	0.760	0.760	0.790	0.732
adjusted R2	0.743	0.743	0.743	0.776	0.711

Preliminary results suggest the presence of a negative correlation between the share of foreign inventors and the technological variety of the geographical area. The evidence is robust across the

models and supports the specialty matching hypothesis: on average migrants do not increase the number of specialization fields in the technological portfolio of the destination area. The effect seems to be mitigated by technological distance for which we observe an inverse U-shaped pattern. The further the technological portfolio of migrants from the one of native inventors is, the higher is the likelihood to observe an increase in diversification. However, when the two portfolios are particularly different the effect on variety is reversed: the new set of competences of migrants does not integrate with the local one and does not lead to specializations in new fields. The concentration of migrants' nationalities is negatively related to the variety of the technological portfolio: where migrants are more dispersed in terms of origin countries, we observe an increase in the technological variety.

Considering the average technological rarity of the regional portfolio of patents, we observe a robust positive correlation in time with the intensity of foreign born inventors. The evidence supports the presence of an effect of the skill portability and knowledge recombination hypothesis. Interestingly, migration of more "technologically distant" inventors has a robust positive effects on the capability of a city to enter rarer technological fields, showing a U-shaped relation. In this case there is no significant effect of the concentration of migrants.

The results are robust controlling for portfolio size and population density. We also included a specific analysis distinguishing between urban and rural geographical areas, with limited differences to the main models.

Although we are aware of the complexity of the mechanism that includes an interplay between the demand and the supply of skilled workers, we believe that our analyses can contribute to improve the understanding of the dynamics of inventors' mobility. Furthermore, the results will provide arguments for the definition of policies dealing with the migration of highly skilled workers especially with respect to the geographical specialization of a metropolitan area.

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