Migrant Inventors as Agents of Technological Change

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Papers in Evolutionary Economic Geography

21.25

Utrecht University Human Geography and Planning

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Abstract

How do regions enter new and distant technological fields? Who is triggering this process? This work addresses these compelling research questions by investigating the role of migrant inventors in the process of technological diversification. Immigrant inventors can indeed act as carriers of knowledge across borders and influence the direction of technological change. We test these latter propositions by using an original dataset of immigrant inventors in the context of European regions during the period 2003-2011. Our findings show that: immigrant inventors generate positive local knowledge spillovers; they help their host regions to develop new technological specialisations; they trigger a process of unrelated diversification. Their contribution comes via two main mechanisms: immigrant inventors use their own personal knowledge (*knowledge creation*); they import knowledge from their home country to the host region (*knowledge transfer*). Their impact is maximised when their knowledge is not *recombined* with the local one (in mixed teams of inventors), but it is *reused* (in teams made by only migrant inventors). Our work contributes to the existing literature of regional diversification by providing fresh evidence of unrelated diversification for European regions and by identifying important *agents* of structural change. It also contributes to the literature of migration and innovation by adding fresh evidence on European regions and by unveiling some of the mechanisms of immigrants' knowledge transmission.

Keywords: patents, migration, technological diversification, relatedness, Europe

JEL codes: O30, F20, F60

Acknowledgements: *We are indebted to the participants to the 5th Geography of Innovation Conference (Stavanger, January 2020), the XLI Aisre Annual Conference (September 2020), LEREPS Seminar at University of Toulouse on 15th November 2019. Any mistake remains ours. Ernest Miguelez acknowledges financial support from the French National Research Agency (TKC project – reference: ANR-17-CE26-0016) and CNRS-CSIC 2018 IRP ALLIES (LIA). Andrea Morrison acknowledges financial support from H2020-MSCA-IF (GOTaM Cities* *project – Grant agreement ID: 789505).The authors also acknowledge the invaluable data work provided by Jaap Oomen.*

1. Introduction

Technological change tends to follow a path-dependent process (David 1985; Dosi 1988; Ruttan 1997), which implies that countries and regions usually diversify into activities that are related to those they have developed already in the past (Hidalgo et al. 2018). However, in order to avoid lock-in and escape decline, in the long-run regions need to develop new growth paths (Neffke et al. 2011). For that they often require access to new and non-redundant knowledge assets (Breschi and Lenzi 2015; Morrison et al. 2013). But *who* can bring external knowledge and enable such a process of unrelated diversification? These are compelling questions that have not yet found a proper answer in the current literature on *relatedness*. As recently stated by Boschma (2017), there is scant evidence showing how relevant is the process of unrelated diversification and even less is known about who can trigger it.

This paper addresses the above questions by investigating the role of migrant inventors in the process of technological diversification.

Since the seminal work of Saxenian (2006) on the role of new Argonauts in the emergence of technological clusters, till the more recent studies on immigrant inventors in the US (Breschi et al. 2017; S. P. Kerr et al. 2016) and elsewhere (Breschi et al. 2020), a growing bulk of evidence is suggesting that high-skilled migrants can act as carriers of knowledge across borders. In particular, they can transfer across long distances the tacit component of knowledge, which is the one that mostly matters for innovation. What is however less-known is whether they can influence the direction of technological change, and in particular whether they can trigger a process of unrelated diversification. On this latter issue, the literature on regional diversification suggests that external actors can enable this process. For example, Neffke et al. (2018) find that incumbent firms tend to reinforce existing specialization patterns, while start-ups induce structural change, but this is particularly the case if they relocate from outside the region. Likewise, MNCs or FDIs have been acknowledged to playing such transformative role, for example in the context of Hungary, where MNCs favoured a process of unrelated diversification (Elekes et al. 2019). Other recent studies point to the importance of temporary proximity for knowledge diffusion, for example via business trips (Coscia et al. 2020).

We rely on these latter streams of literature to show that immigrant inventors can behave as agents of technological change. We carry out our empirical analysis on European regions during the period 2003-2011. We benefit from an original dataset which is the merge of two novel data sources: the Patent Cooperation Treaty (PCT) patent data assembled by Miguelez and Fink (2017), which provide information on the nationality of PCT inventors; and the disambiguated PCT inventor dataset of Pellegrino et al. (2019), which allows us to track migrant inventors over time and across space.

Our findings show that European regions greatly benefit from the presence of immigrant inventors in a number of ways. First, we show that native inventors already present in the region patent more in the fields of immigrants. Second, immigrant inventors help host regions to enter new technological sectors, and more importantly they contribute to the emergence of technological fields that are unrelated to the current specialization of the region. Moreover, we are able to disentangle between two channels of transmission: first, inventor immigrants contribute to the diversification process with their own specific knowledge (*knowledge creation*); second, they trigger technological change by brokering between the host region and their country of origin (*knowledge transfer*). Finally, we show that immigrant inventors indeed act as agents of technological change, as inferred from the fact that their contribution is larger when their knowledge is not recombined with the local knowledge (in mixed teams of inventors), but it is rather reused (in teams made by only migrant inventors).

Our work contributes to the existing literature on regional diversification in two important ways. First, we provide fresh evidence of unrelated diversification for European regions, which is relatively scant (Boschma 2017) and concerns almost exclusively countries rather than regions (Pinheiro et al. 2018). Second, to the studies that in this tradition have looked at *who* are the agents of structural change (Elekes et al. 2019; Neffke et al. 2018; Whittle et al. 2020), we suggest that also migrant inventors can play this transformative role.

We also contribute to the literature on migration and innovation in a number of ways. We use novel data that allow us to analyse migrant inventors based on nationality, rather than ethnicity. We quantify their contribution to native patenting in the context of European regions, while so far evidence is mainly on the US (S. P. Kerr et al. 2016) or at country level (Bosetti et al. 2015; Fassio et al. 2019). Moreover, we complement previous works showing that immigrant inventors play a brokering role (Bahar et al. 2020; Choudhury and Kim 2019), by adding a regional dimension to this analysis.

The work is structured as follows. In Section 1 we present a concise review of the literature on regional diversification and relatedness. We also briefly review the main findings of the quantitative literature on high-skilled migration and innovation. Section 3 is devoted to lay out a conceptual framework to guide the interpretation of our findings. Section 4 illustrates the main data sources, while section 5 sketches the empirical analysis. In Section 6 results are presented and discussed. We conclude in section 7 with a general discussion of our findings and an attempt to delineate some policy implications.

2. Theoretical background

Among the processes that shape economic and technological development, path dependency is an important one, and suggests that present economic trajectories are bounded to what happened in the past (Dosi 1997). This can be the result of historical events, whereby initial conditions lead to specific choices of techniques (David 1985), which often generates technological lock-in (Capone et al. 2019). More broadly, the concept rests on the evolutionary idea that technological knowledge as well as technological search processes are cumulative by nature: therefore technological development, far from being random, is bound to existing activities (Dosi 1988).

This general law of motion is also telling that the existing capabilities present in an economic system (e.g. social, technological) delimit its growth opportunities and shape the direction of change (Boschma 2017).

A well-grounded evidence has shown indeed that countries (Hidalgo et al. 2007), regions (Neffke et al. 2011) and cities (Boschma et al. 2015) tend to develop new economic and technological activities (i.e. diversification) that are related to those already present. Other streams of literature have shown that proximity matters also at firm level, for example in searching for R&D partners (Angue et al. 2014), in M&A decisions (Ahuja and Katila 2001), for technological alliances (Nooteboom et al. 2007) and inter-organisational projects (Enkel et al. 2018).

The principle of *relatedness* seems to be general enough (Hidalgo et al. 2018), and has proved to work for products (Hidalgo et al. 2007), industries (Neffke et al. 2011) and technological domains (Rigby 2015). This evidence has shown that moving along a process of path related diversification is the norm for the majority of countries and regions, while making big jumps is rather rare (Pinheiro et al. 2018).

Nevertheless, unrelated diversification brings also important benefits. It helps to escape lock-in and build new growth paths (Boschma 2017). In the long-run, higher variety has been associated to more resilient economic systems: increasing the degree of variety in the industrial portfolio of a region works as a shock absorber, by spreading the risk over different economic sectors, and in turn reducing the risk of massive unemployment (Frenken et al. 2007). A region that increases its internal variety is also able to absorb easily those industries becoming redundant over time (Pasinetti and Scazzieri 2016).

Only a few studies however have provided quantitative evidence on how unrelated diversification unfolds and who brings variety into the system. For example, Pinheiro et al. (2018) by looking at the development of new exports by countries, show that only a handful of them were able to jump into distant products. More importantly, they find that those who did it experienced a sharp economic growth, being the Republic of Korea perhaps the most paradigmatic example. Some other works show that unrelated diversification is possible only under certain conditions. For example, Boschma and Capone (2015) find that institutions play an important role in this regard. For the case of Europe, they show that unrelated diversification is more likely in countries adopting more liberal forms of capitalism, as opposed to those with coordinated economic systems. Others have shown that unrelated diversification is triggered by the presence of specific actors. For example, Neffke et al. (2018) found that new economic activities emerged in Swedish regions thanks to newcomers rather than incumbents, and that this was especially true if the new firms relocated from outside the region. Similarly, MNCs have been regarded to be a major driver of unrelated diversification, for example in the context of Eastern European countries (Elekes et al. 2019). More recently, Whittle et al. (2020) look at the diversification process of regions boosted by external collaborative networks (co-inventorship). They show that co-inventor networks compensate for a lack of technological relatedness in a region when collaborations occur within firms' boundaries across geographical locations.

Besides these examples, to the best of our knowledge, evidence about the process of unrelated diversification is scant. In particular, we know little about the role of agency (Boschma 2017). If variety matters, then a compelling question is who can generate it. The literature on external actors and networks in regions can provide some important insights to tackle this question. It shows that regions can acquire new knowledge and non-redundant knowledge via gatekeepers who build extra-regional linkages (Breschi and Lenzi 2015; Morrison et al. 2013). These external connections can operate via different channels (e.g. multinationals, R&D networks, business trips)[1], of which professional communities of knowledge migrants is a prominent one (Saxenian 2006).

[1] It goes beyond the scope of this paper to provide a review of this body of work, some relevant references are: on business trips Coscia et al. (2020), Orazbayev (2017); on MNCs Bahar et al. (2014), Singh (2007); on R&D networks Owen-Smith and Powell (2004).

Indeed, several case studies show that high-skilled immigrants have been catalyst of new ventures both in destination (e.g. Silicon Valley) and origin countries (e.g. Taiwan, India) (Saxenian 2006; Saxenian and Hsu 2001).

A recent literature crossing regional studies, labour economics and innovation studies has produced additional quantitative evidence supporting this view (Breschi et al. 2020; S. P. Kerr et al. 2016). For example, looking at patent applications Kerr and Lincoln (2010) have found that inventors of Indian and Chinese ethnic origins in the US have increased their share of patenting moving from less than 2% to 6% and 9% respectively. Hunt and Gauthier-Loiselle (2010) find that 6.2% of STEM immigrants have been granted a patent relative to 4.9% of US natives. A great deal of attention has been devoted to measure the labour market impact of skilled immigrants. It has been noted that the positive effect of immigration, for example in terms of higher patenting, could be outweighed by the negative impact on natives, so the net effect of immigration would be null or even negative. Empirical evidence is however mixed for the US case. Some studies suggest a positive effect (Bernstein et al. 2018; Doran and Yoon 2019; Hunt and Gauthier-Loiselle 2010; Stephan and Levin 2001), other found limited effects (W. R. Kerr and Lincoln 2010). Borjas and Doran's (2012) work on former soviet mathematicians in the US suggest instead a strong crowding-out effect. Evidence available for Europe, both Europe-wide (Bosetti et al. 2015; Fassio et al. 2019) and on specific countries (Bratti and Conti 2018; Cristelli and Lissoni 2020; Ozgen et al. 2012), though limited, confirm that the inventive activity of immigrants has a positive effect on innovation.

Another stream of literature has paid attention to the role of immigrants as carriers of knowledge (for a review see Lissoni, 2018). For example, Ganguli (2015) shows that former Soviet Union scientists migrating to the US brought with them valuable knowledge, which was used by US natives. Historical studies on the US further indicate that the emergence of new technological fields can be explained by the arrival of immigrant inventors (Diodato et al. 2018; Moser et al. 2014). Likewise, for a large set of countries, Bahar et al. (2020) confirm that immigrant inventors ‘import’ knowledge from their home country. More importantly, evidence shows that this knowledge has shaped the technological evolution at destination, either triggering diversification (Bahar et al. 2020; Diodato et al. 2018; Moser et al. 2014) or in some instances reinforcing existing specialisation (Caviggioli et al. 2020). This latter study is one of the few looking at the influence of migrant inventors on regional diversification, as we do. Interestingly, the authors find that the presence of immigrant inventors correlates negatively with regional diversification, as measured by the number of technologies in which a region is specialized – though they do not directly investigate, as we do, the direction of specialization. Next, some recent evidence shows that unrelated diversification may occur in migrants' home countries too, via return migration (Diodato et al. 2020) or via diaspora networks (Di Iasio and Miguelez 2021). Using the same dataset of migrant inventors we use here, the latter paper shows migrants' origin countries (especially developing ones) diversify into new, unrelated technologies thanks to their diasporas settled in the cities and regions abroad. Finally, for the case of Hungary, Csáfordi et al. (2020) investigate labour flows from foreign-owned firms and subsequent knowledge diffusion, and find that they do matter if multinational companies are significantly more productive, and especially if sending and receiving firms are technologically related.

We build on this latter stream of literature to investigate the impact of immigrant inventors on regional technological diversification. The focus on skilled immigration in regions is not trivial, in fact one striking aspect of skilled immigration is that foreign individuals tend to settle down very unevenly within countries, as shown in several empirical works (see among others, Freeman, 2006; Kerr, 2007; Nathan, 2011). Below we sketch a brief conceptual framework that will guide the empirical analysis.

3. Migrant inventors, knowledge diffusion and technological diversification: a conceptual framework

In this section we lay out a conceptual framework that will help to identify the mechanisms through which migrant inventors contribute to shape the direction of technological change in the host region. We draw mainly on evolutionary economics theories (Nelson and Winder, 1982; Hodgson, 1993), in particular building on the literature of geography of innovation (Asheim and Gertler 2005; Audretsch and Feldman 1996; Boschma and Martin 2010; Radosevic 2002).

As discussed above, we know that variety (e.g. technological variety) is an important driver of economic dynamism (Dosi and Nelson 1994). We are also aware that variety can decline over time because of path dependency. In particular, this happens in regions that keep reinforcing their existing specialization (Martin and Sunley 2006). In the long-run, they run the risk to lock-in into outdated technologies or industries (Boschma 2017). Inventor migrants can represent an important channel to help these regions to unlock. In fact, migrant inventors are (or build) external networks that allow regional economies to tap into new and complementary knowledge assets. This non-redundant knowledge constitutes an important source of variation for regional economies (Morrison et al. 2013), which contributes to develop new technological trajectories and growth paths.

The beneficial effects of migrant inventors come via different mechanisms. First of all, they emerge directly from the interaction between immigrants and natives, for example in inventor teams, as cultural diversity correlates with creativity (Ferrucci and Lissoni 2019). Natives benefit also indirectly, via localized knowledge spillovers generated by immigrant activity, as shown by a well-grounded literature (S. P. Kerr et al. 2016).

Second, ideas travel across borders embodied in migrants' brains. The importance of migration as channel for knowledge diffusion rests on the idea that knowledge is largely tacit, personal and idiosyncratic (Cowan et al. 2000; Polanyi 1958), therefore it travels across large distances when embodied in the individuals who contributed to its production. This logic explains why mobility of inventors is claimed to be a relevant channel for knowledge transfer (Breschi and Lissoni 2009). Migrant inventors carry with them the tacit component of knowledge, which is not yet available in the place of destination. In a way, we can argue that they *import* knowledge from the country of origin to the country of destination (Bahar et al. 2020; Diodato et al. 2018). Migrants bring with them own specific knowledge, as well as a more general corporate or scientific culture and routines (we can call the latter *foreign expertise*). To the extent these two types of knowledge complement the one of natives, they will benefit from it.

When migrants start applying and/or sharing their own tacit knowledge in the host region, they will give rise to knowledge recombination which are not only new, but also unrelated to the existing knowledge in that region. Therefore, migrant inventors will potentially trigger technological diversification in new specializations that are unrelated to the existing ones.

Third, by building on Choudhury and Kim (2019), we explore the mechanisms through which unrelated diversification unfolds in regions. The process of recombination initiated by migrant inventors occurs at the organization level, in teams. In these contexts, migrants and natives share and socialize their own knowledge. The new knowledge they produce will incorporate both a non-redundant component of knowledge brought by the immigrants, which is new to the region, as well as the knowledge of the natives, which is largely grounded in the organization (and the region). This process of *recombination* will generate novelty, but it is most likely related to the existing regional specialization. On the other side, recombination can also take the form of *reuse* (see Carnabuci and Operti, 2013, as cited in Choudhury and Kim, 2019). If migrants use their own knowledge without recombining it with the one of natives, the process of reuse will generate again novelty, but this time it will be more unrelated to the existing regional specialization than the one shared in teams with natives.

4. Data

Our analysis relies on a set of patent applications that were filed under the Patent Cooperation Treaty (henceforth PCT), at the World Intellectual Property Organization (WIPO). The PCT started in 1978, it currently includes 153 states and received, only in 2019, around 266,000 applications. Neither

WIPO nor the PCT are able to granting intellectual property protection to patent applicants. They only facilitate patent protection in more than one office simultaneously, which is a great advantage for patent applicants. In fact, the applications via the PCT system have been growing constantly over the years, currently reaching 56.9% of all internationally-oriented patents (WIPO 2020).

Our source of PCT applications is not directly WIPO's PCT unit record data, but three different re-processed datasets, which we describe in turn.

First, we exploit the regionalized dataset of Maraut et al. (2008) (OECD, REGPAT database), which provides detailed regional information of all OECD and EU28 countries – plus a few other selected economies – for both EPO and PCT applicants and inventors. For Europe, for which we run the present analysis, the data are available at the NUTS3 and NUTS2 levels of regional aggregation. Using this source of data, we assign patents to regions corresponding to the share of the inventors living in that region (inventors' address, fractional counting). From REGPAT we also extract information on technological classes. In particular, we exploit the first 4 digits of the International patent classification (IPC) codes the applicants and examiners include in the front page of the application. We limit our analysis to cover the years 2003 to 2011[2] (for reasons sketched below), and a sample of EU countries and their NUTS2 regions (excluding regions where patenting activity is small). All in all, we end up working with around 500,000 patents with at least 1 inventor residing in our sample of 200 European NUTS2 regions (in 26 countries) and 539 technologies (4-digit IPC codes) for a period of 9 years (2003-2011).

The second source of data refers to the information of nationality (or citizenship) of inventors listed in PCT applications (Miguelez and Fink 2017). To the best of our knowledge, PCT patents are the only international source recording systematically this type of information. This has to do with the

[2] Our data goes actually from 2002 to 2011. Since we use lagged variables in our analysis, our findings refer only to the period 2003-2011.

requirement under the PCT that only nationals or residents of a PCT contracting state can file PCT applications. To verify that applicants meet at least one of the two eligibility criteria, the PCT application form requests both nationality and residence information. Unfortunately, after 2011 this requirement was suppressed, and therefore the coverage of this information went from 90-100% during the 2000s to minimum numbers after 2011.[3]

We believe that the use of PCT data for high-skilled migration analysis is highly appropriate, for two main reasons. First, inventors are a more homogeneous group of skilled workers compared to tertiary educated ones (census data for migration analysis is covered in Arslan et al., 2016), and the data are released way more frequently than census records (annually versus every 10 years). Second, different from other approaches to inventor migration (Agrawal et al. 2011; Breschi et al. 2017; Kerr 2008), our approach does not rely on name analysis to infer likely migratory backgrounds of inventors, which are a quite imperfect measure of the inventor migrant stocks in regions. We have to acknowledge some potential limitations or sources of bias of PCT patents. Since they include international oriented patents, they might mainly refer to more valuable ones. Moreover, the relatively short time span might limit the interpretation of results, especially when it goes to policy prescriptions.

Finally, we fish from a recent publicly available dataset by Pellegrino et al. (2019). These authors also exploit WIPO's PCT unit record data and information listed in applications to disambiguate inventors' names. Inventor disambiguation refers to the identification of unique inventors that are listed in multiple patents without a pre-existing identifier. This is of utmost importance given the presence of homonymy (two different inventors with the same name and surname) and spelling variations (the same inventor is spelled differently, for many potential reasons – such as spelling mistakes, in

[3] Unfortunately, and differently to EPO applications available in REGPAT, there is no unique identifier linking the PCT applicants and inventors in REGPAT records with those in WIPO's PCT unit record data, which contain nationality information. As such, PCT records in both sources can only be linked through their applications numbers leaving the direct link between inventors' information on each source – namely region and nationality – to be established at through their names.

different patent documents belonging to him/her) in inventor records. In essence, the authors applied machine learning techniques and the rich information contained in patent documents to infer who is who among inventors in PCT applications. This dataset allows us to track migrant inventors over time and across space. As immigrant inventors tend to be more productive than natives (Bernstein et al. 2018; Hunt 2015; Hunt and Gauthier-Loiselle 2010; Pellegrino et al. 2019), name disambiguation can deliver important differences in immigrant stocks across regions with respect to simply counting the number of patents these migrants produce.

Figure 1 depicts the share of patents, over time, produced by PCT migrant inventors, and compares Europe as a whole with an arbitrary selection of countries. As can be seen, migrants' contribution to innovation in PCT patents has been growing steadily over the years. However, Anglo-Saxon countries, such as the US or Australia, attract way more migrant inventors than Europe as a whole. On the other side of the spectrum, large patenting countries like Japan or R. of Korea do not see their innovative activity being strongly influenced by foreign talents.

[Insert Figure 1 here]

Yet, even within Europe large differences emerge with respect to attracting foreign talent. Figure 2 shows the share of migrant patenting during our period of analysis (2003-2011) for the countries analysed in this paper, plus other highly innovative ones for comparison purposes. As can be seen, small, highly innovative European economies manage to attract larger shares of foreign inventors than the US. However, other large innovative countries such as Germany, France or Italy, lag behind. This is also reflected when looking at the share of foreign inventors across NUTS2 regions. Again, large variation exists across regions, though Figure 3 shows only the top-30 NUTS2 regions of our sample.

[Insert Figures 2 and 3 here]

In what follows we set up our methodology and describe the way in which the variables for the regression analysis are built.

5. Methods and variable construction

As discussed above, we aim to understand the role of migrant inventors in shaping the technological path of European regions, for the 2003-2011 period. To this aim, we test first of all whether migrant inventors influence natives' patenting, and therefore can trigger the development of certain technologies in host regions. The following model will be estimated:

$$NativePatents_{irt} = \beta_1 MigrantInv_{irt-1} + \beta_2 ForeignExpertise_{irt-1} + \gamma_{rt} + \varphi_{it} + \varepsilon_{irt}$$

where the dependent variable is the number of PCT patents produced by native inventors in region r, technology i and time t. We apply to this variable the Inverse Hyperbolic Sine (IHS) transformation (Burbidge et al. 1988), which allows the log transformation of variables including zeros. The explanatory variables are the number of migrant inventors ($MigrantInv_{i,r,t-1}$) in a given region and technology (IHS transformed) and the inflow of foreign expertise ($ForeignExpertise_{i,r,t-1}$). The former is built simply counting the number of active inventors with foreign nationality in a given region, technology and year (the inventor is *active* in that region-technology pair in all years between her first and last patent in that region-technology pair). This migrant inventor variable captures the direct effect of migrants on co-located natives, via local spillovers and diversity. *Foreign Expertise* aims at capturing the effect of knowledge diffusion between the country of origin and the host region, and it is computed in two alternative ways: first, following

Akcigit et al. (2017) and Diodato et al. (2018) *Foreign Expertise (FE) Origin Country* is given by the following formula:

$$FE\ OriginCountry_{i,r,t} = \sum_c \frac{P_{c,i,t}}{P_{c,t}} \times M_{c,r,t}$$

where $P_{c,i,t}$ is the number of patents of country c in technology i and time t, $P_{c,t}$ is the total number of patents produced in country c and year t, and $M_{c,r,t}$ is the number of migrants from country c residing in region r in time t. It measures the sum of the share of patents that a country *c* has in a given technological class multiplied by the number of migrants originated from country *c* that settled in a given region *r* ($M_{c,r}$). That is, it accounts for the potential experience of current migrants in their country of origin, by imputing them their country of origin technological portfolio. We acknowledge that this is a strong assumption, given how recruitment of foreign talent by local firms currently works – differently from the historical contexts analysed in Akcigit et al. (2017) and Diodato et al. (2018). For instance, many foreign inventors may have acquired their skills in a country different from their declared citizenship, or even may have migrated for studying to acquire their skills in their host region.

As an alternative, we also compute the variable *FE Migrant inv.*, which essentially counts the number of active inventors in a given region-year, who have foreign nationality, and have previous experience abroad in the focal technology *i*, but irrespectively on the technology class they are *currently* patenting in the host region. Thus, with this alternative measure we aim to account for the actual previous experience of foreign inventors, by looking at their own personal patent portfolio before they settled in the current region. Yet, this alternative measure is not fully satisfactorily either, as the inventors that are able to have PCT patents in more than one country are really the tip of the iceberg, and therefore they are likely to not fully reflect the average behaviour of all migrant inventors[4].

Next, all explanatory variables are lagged one year, in order to lessen endogeneity concerns. Finally, all models introduce region-time (γ_{rt}) and technology-time (φ_{it}) fixed effects, in order to account for region-variant and technology-variant heterogeneity. That is, all potential regional characteristics, such as R&D investments, agglomeration economies, or human capital stocks, as well as all technology-specific shocks, are absorbed by our fixed effects.

In order to test the influence of migrant inventors on the direction of regional technological diversification, we rely on models that analyse the probability that a region develops a new RTA in a given technology (Boschma et al. 2015; Rigby 2015), and therefore develops regional diversification in a given technology *i*, as follows:

$$\begin{aligned} Entry_{irt} = {} & \beta_1 MigrantInv_{irt-1} + \beta_2 ForeignExpertise_{irt-1} \\ & + \beta_3 RelatednessDensity_{irt-1} + \beta_4 PatentingActivity_{irt-1} + \gamma_{rt} \\ & + \varphi_{it} + \varepsilon_{irt} \end{aligned}$$

where $Entry_{i,r,t}$ reflects regional diversification into a new technological domain, and is analysed by looking at changes in the technological portfolio of regions. The regional technological portfolio is defined as all technologies wherein a region has a Relative Technological Advantage (RTA) compared to the entire dataset. RTA is calculated as follows:

[4] In addition, we compute also another measure of foreign expertise, which complements *FE Migrant inv.* as it includes inventor migrants that had expertise in the focal technology in the home country, but are patenting in other classes in the host region. This variable behaves like *FE Migrant inv.* in our regressions, however it is populated with large share of zeros. We thank an anonymous referee for this suggestion.

$$RTA_{irt} = \frac{P_{irt} / \sum_i P_{rt}}{\sum_{ir} P_t \,/\, \sum_{irt} P}$$

where $P_{irt} / \sum_i P_{rt}$ is the share of patents of technology i, at time t, in region r. $\sum_{ir} P_t \,/\, \sum_{irt} P$ is the share of patents of technology i, at time t, in the entire dataset. If the RTA of a region-technology combination is higher than 1, that technology belongs to the regional technological portfolio. $Entry_{i,r,t}$ is then coded 1 if the region moves from having an RTA=<1 in period t-1, to have an RTA>1 in period t, 0 otherwise. If the region was already in RTA>1 in period t-1, and therefore *Entry* cannot occur, then that observation is set to missing.

As before, the main predictors of *Entry* are the number of migrant inventors (*MigrantInv*) in a given region and technology (IHS-transformed) and foreign expertise ($ForeignExpertise_{i,r,t-1}$), measured in the two alternative ways commented above. The inclusion of the number of migrant inventors in the *Entry* regressions aims to account for the fact that they may contribute by themselves to the process of diversification, via knowledge creation. Adding *Foreign Expertise* accounts for the fact that migrants trigger technological change by brokering between the host region and their country of origin (knowledge transfer).

Next, following the literature (Boschma et al. 2015; Hidalgo et al. 2007), *Entry* models include the variable *Relatedness Density* among the r.h.s. variables. It is defined as the number of existing neighbouring technologies a given technology i has in region r and time t-1. Neighbouring technologies are defined using the concept of relatedness in knowledge space, which is a measure of technological proximity between pairs of technologies. In a nutshell, we count the number of technology co-occurrences listed in PCT patents in a given period (i and j technologies), and standardize the count by the absolute number of patents listing technology i and j (separately), so relatedness measures the probability of a given pair of technologies to appear together in patents. All in all, we consider a probabilistic measure of co-occurrence between any pair technologies i and j (ϕ_{ij}):

$$\phi_{ij} = \frac{mc_{ij}}{s_i s_j}$$

where c_{ij} denotes the number of times technologies i and j occur together in the same patent, s_i and s_j are the total number of times technologies i and j appear, and m is the total number of patents. When $\phi_{ij} > 1$, technologies i and j are said to be related. We then can build a matrix for each time period of dimension JxJ, where each element $\eta_{ij} = 1$ if $\phi_{ij} > 1$, and zero otherwise, with J being the total number of technologies in the dataset.

Neighbouring technologies of i exist in a region r if that region is specialized in those technologies ($RTA_{irt} > 1$). Thus, relatedness density of technology i in region r is computed as:

$$\omega_{i,r} = \frac{\sum_j \eta_{i,j} \times RTA_{jr}}{\sum_j \eta_{i,j}}$$

The former formula essentially counts the set of technologies j that are related to technology i that are present in region r, divided by the sum of the proximities between technology i and all other technologies. A high density indicates that many of the technologies that are similar to technology i are present in the region (Hidalgo et al. 2007).

Finally, our *Entry* model also includes the number of patents produced in that technology and region ($PatentingActivity_{i,r,t-1}$), as well as region-time (γ_{rt}) and technology-time (φ_{it}) fixed effects.

A second objective of our analysis is to qualify the type of influence exerted by migrant inventors on the process of technological diversification. In particular, we want to see whether migrant inventors are more prone to help in the process of related or unrelated diversification. To assess their specific role, we are going to estimate the following equation:

$$\begin{aligned} Entry_{irt} = {} & \beta_1 MigrantInv_{irt-1} + \beta_2 ForeignExpertise_{irt-1} \\ & + \beta_3 RelatednessDensity_{irt-1} + \beta_4 PatentingActivity_{irt-1} \\ & + \beta_5 MigrantInv_{irt-1} * Relatedness_{irt-1} \\ & + \beta_6 ForeignExpertise_{irt-1} * Relatedness_{irt-1} + \gamma_{rt} + \varphi_{it} + \varepsilon_{irt} \end{aligned}$$

where we add interaction terms between our focal variables and *Relatedness Density.* We expect β_5 and β_6 to be negative and significant, which we would interpret as evidence of migrant inventors kicking in especially when *Relatedness Density* is in low levels. In essence, that would mean that migrant inventors do not only help regions to diversify into new technologies, but they favour entry in technologies that are less related (or unrelated) to the current knowledge base of the region.

Finally, we aim unveiling some of the mechanisms through which diversification unfolds in regions. To this aim we look at the teams formed by migrants in their host regions. In particular, we test whether unrelated diversification occurs via knowledge *recombination*, which we assume it is more likely to happen in native-migrant mixed teams, or via migrants' own-knowledge *reuse*, which we assume it is more likely to happen in teams composed of only migrants. To do so, we build two additional indicators and incorporate them to our *Entry* regressions. In particular, we build the ratio mixed teams to only-native teams (*Ratio mixed/native*) and the ratio only-migrant teams to only-native teams (*Ratio migrant/native*), and interact both of them with the variable *Relatedness Density*, in order to gauge the direction of diversification in each of the cases, as follows (with X accounting for all variables explained above):

$$\begin{aligned} Entry_{irt} = {} & \beta_n X_n + \beta_3 RelatednessDensity_{irt-1} + \beta_7 RatioMixed/Local_{irt-1} \\ & + \beta_8 RatioMigrant/Local_{irt-1} + \beta_9 RatioMixed/Local_{irt-1} \\ & * Relatedness_{irt-1} + \beta_{10} RatioMigrant/Local_{irt-1} \\ & * Relatedness_{irt-1} + \gamma_{rt} + \varphi_{it} + \varepsilon_{irt} \end{aligned}$$

Table 1 depicts the summary statistics of the variables used in our analysis, while Table 2 shows the correlation matrix.

[Insert Tables 1 and 2 here]

6. Results

In this section we present the findings of the empirical analysis. We first discuss the results concerning the impact of migrant inventors on natives patenting (Section 6.1). It follows the discussion of results on technological diversification (Section 6.2), and on the role of recombination in the direction of diversification (Section 6.3).

6.1 Natives' patenting

Table 3 reports our first set of results. The models presented in columns 1-5 test the impact of our two main variables of interest (i.e. *Migrant inventors*, *Foreign expertise*) on the patenting of natives. All models include region-time and technology-time fixed effects. Columns 1 to 3 report the results of models with one explanatory variable at a time, respectively *migrant inventor, FE Country Origin* and *FE Migrant inv.*. Columns 4 and 5 present the full models, where we include the two variables of knowledge transfer in two separate models (i.e. *FE Country Origin*, column 4, and *FE Migrant inv., column 5*). The first important finding is that the coefficient of *migrant inventors* is positive and significant across all specifications. This finding aligns well with the existing evidence on migration and innovation (S. P. Kerr et al. 2016), and confirms for European regions what has been found for the US, i.e. migrant inventors generate positive localized knowledge spillovers. The positive sign of *FE Origin Country* captures the role of immigrants as knowledge brokers, which is confirmed when we replace it with *FE Migrant inv.*. The latter findings suggest that immigrant inventors bring knowledge from their home countries, as natives' patenting increases in fields in which the countries of origin of the inventors are also specialized. This finding is in line with previous works testing similar effects (Akcigit et al. 2017; Bahar et al. 2020; Diodato et al. 2018).

[Insert Table 3 here]

6.2 Technological diversification

In Table 4, we present the main findings of our baseline model. We first test the impact of immigrant inventors (i.e. *migrant inventors*) on technological diversification (Column 1). Second, we test the impact of the two alternative measures of foreign expertise (i.e. *FE Origin Country, FE Migrant inv.*) on technological diversification (Columns 3 and 4). Finally, we present the full model when both immigrant inventors and foreign expertise are included (Columns 3 and 4). In all models we also control for the overall patenting activity and for relatedness density[5].

The first set of findings show that migrant inventors positively influence the process of technological diversification. The coefficient estimate of *migrant inventors* is positive and significant in 2 out of 3 specifications (Columns 1 and 4). Migrant inventors help the host region to enter new specializations. This effect mainly captures the inventive activity migrants develop in the host region (i.e. knowledge creation). The effect is robust to the introduction of the overall number of patents produced in the region-technology

The brokering role of immigrants has also a positive impact on technological diversification (only when measured with *FE Migrant inv.*). Immigrants bring knowledge from their country of origin, which helps the host region to diversify towards that technology (Columns 3 and 5). The host regions move to technologies similar to the patent portfolio of their newly arrived immigrant inventors – that is, to the patents they made in their home country, before they moved to the host region. When *Foreign Expertise* is

[5] In order to avoid potential multicollinearity with fixed effects, we also run an alternative model without *patenting activity*. Results seem not to be affected.

instead measured with the *FE Origin Country* variable, the coefficient estimates are negative and significant. If we trust this variable, we can argue that the more immigrants bring knowledge resembling the specialization of their country of origin, the less the host region will diversify towards that technology (Columns 2 and 4). The diverging results reflect the differences in the two measures of knowledge diffusion: while *FE Migrant inv.* captures the experience of the incoming inventors, *FE Origin Country* captures instead the bridging role of immigrants between host region and home country. This latter variable accounts for the knowledge structure of the country of origin – which may not fully coincide with the individual's one. Our findings possibly suggest that foreign knowledge brought by immigrants does help regional diversification, but they do not act as knowledge bridges and do not favour technological convergence between origin and destination. Note also that the bridging role may need more time to become effective, while we have limited our analysis to the very short run only, for data constraints. An assessment of the medium- and long-run effects of *Foreign Expertise* may well deliver different results.

[Insert Table 4 here]

Second, we test whether our main explanatory factors help host regions to enter distant technological activities (Table 5). The second set of findings include an interaction term of our variables of interest (i.e. *migrant inventors*; *foreign expertise*) with the relatedness density variable. A negative sign of the coefficient indicates that entry is stronger in technological fields with lower degree of relatedness. Our results report a negative and significant coefficient for all the variables of interest when they are included one by one (Columns 1 to 3) or together (Columns 4 and 5). Therefore, both immigrant inventors and their foreign expertise are sources of unrelated diversification for the host region. Based on these findings, we can argue that the role of immigrants in pushing the region towards new technologies is more preponderant when other possibilities, such as related technological activities in the region, are small or absent.

Overall, these results align well with the literature on migration and knowledge diffusion in the US. These studies in fact find that high-skilled immigrants (e.g. inventors, scientists) brought knowledge that helped the US to enter new technological or scientific domains.

[Insert Table 5 here]

6.3 Knowledge recombination and reuse

Table 6 finally shows the results on unrelated diversification of mixed teams versus only-migrant teams. To do so, we build indicators of local reliance on mixed teams (*Ratio mixed/native teams*) and local reliance on only-migrant teams (*Ratio migrant/native teams*). The logic behind our approach is that when only migrant teams dominate, there is a relatively higher *reuse* of external knowledge, while if mixed teams with natives dominate, *recombination* between external (of immigrants) and local (of natives) knowledge is more prevalent (Choudhury and Kim 2019). Our findings indicate a strong and robust positive association between only-migrant teams and unrelated diversification in all specifications (see Columns 1, 3 and 4). Instead this evidence is weaker (Column 2) or insignificant (Columns 3 and 4) for mixed teams. Our findings seem to support the idea that immigrants behave as agents of technological change mainly when they reuse the external knowledge they bring from home, rather than recombining it with the one of natives.

[Insert Table 6 here]

7. Conclusions

Regional economies strive to renew their repertoire of competences and technologies. A large bulk of evidence shows that this process follows well-established trajectories, which are strongly path-dependent (i.e. related diversification). Instead, very little is known on how regions deviate from the existing paths and enter completely new specialisations (i.e. unrelated diversification). Even less is known about *who* can trigger this change.

In this paper, we address the above questions by investigating the role of high-skilled migrants – proxied by inventors – in triggering unrelated diversification in European regions. Our main point is that migrant inventors can affect innovation (i.e. patenting) and technological diversification in the host regions via two main channels: knowledge creation, which is produced by migrant inventors when moving to and working in the host region (including localized knowledge spillovers); knowledge transfer, which occurs when migrant inventors broker knowledge between the country of origin and the region of destination. We show that one of these two mechanisms (knowledge creation) affect the productivity of native inventors and trigger processes of unrelated diversification. The other one (knowledge transfer) makes an impact only under certain conditions. Finally, we test to what extent migrant inventors behave as agents of structural change by comparing the effect of patenting in mixed-teams vs only-migrant teams. We show that unrelated diversification is mainly affected by the work made by only-migrant teams. This latter finding suggests that external knowledge has a greater impact when *reused* rather than *recombined* with local one.

The global race of talents has spurred a plethora of policies around the world in order to attract the best and brightest talents. Our work does not provide an assessment of these interventions, nevertheless our findings can be highly informative for policy makers, in particular as far as Europe is concerned. Three main implications are in order.

First, our work shows that the circulation and attraction of migrant inventors is crucial for the renewal of regional innovation systems. However, skills and talents do not have a central stage in European regional innovation schemes, like the place-based Smart Specialisation Strategy of the European Commission.

Second, immigration policies are the realm of national states, with little or no say from regions and the EU. However, labour markets are mainly local. Our findings show that the attraction of talents has a clear regional dimension, which can be incorporated more explicitly in national immigration policies (for examples, see OECD, 2019).

Third, besides immigration policies, regions can have a more active role in talent attraction by developing explicit strategies and targets. Although there are already examples of such regional interventions (e.g. expat centres), talent attraction is not yet given central stage in regional industrial strategies.

Overall, the main policy implication to draw is that regional innovation policies and national/European immigration policies should be better aligned. A greater coordination and integration among these policies, which nowadays work independently one another, could make them more effective and in turn increase the innovative potential of regions in Europe.

Our work has provided new insights into the role of migrant inventor as agents of technological change. Nevertheless, more can be done to unveil the mechanisms driving this process and overcome potential limitations of our study. First, our analysis relies on PCT patent data, and covers a relatively short time period. Besides the usual limitations of PCT already mentioned above, the short time span of our analysis might weaken the relevance of our findings, in particular for policy. To lessen these concerns, it can be added that PCT applications made by foreign inventors follow a trend which is not dissimilar to the one observed for ethnic inventors in EPO and USPTO patent applications, and it has been growing in recent years (Lissoni and Miguelez 2021). Second, additional research is needed in order to identify the winners and losers (e.g. core vs peripheral regions) in the race for talents in Europe. Fourth, the role of diversity (e.g. in teams of inventors) for technological diversification can be further explored (e.g., Ferrucci and Lissoni, 2019). Third, better data on the educational background and mobility patterns of inventor migrants could help to disentangle the true effect of migration from other factors (i.e. intrinsic talent, education, etc). Finally, a number of policies schemes have been recently implemented in different European countries (OECD 2019). An empirical assessment of these schemes will provide useful insights to policy makers and scholars working on innovation and migration topics.

Figures and Tables

Figure 1: Share immigrant inventors, 1990-2011

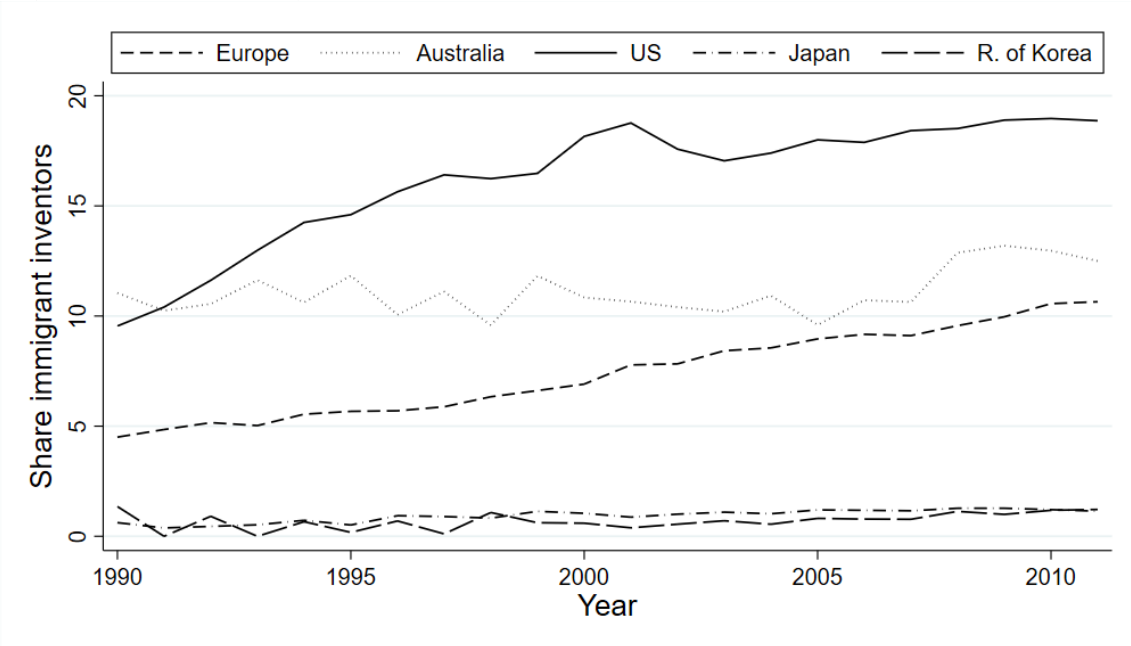
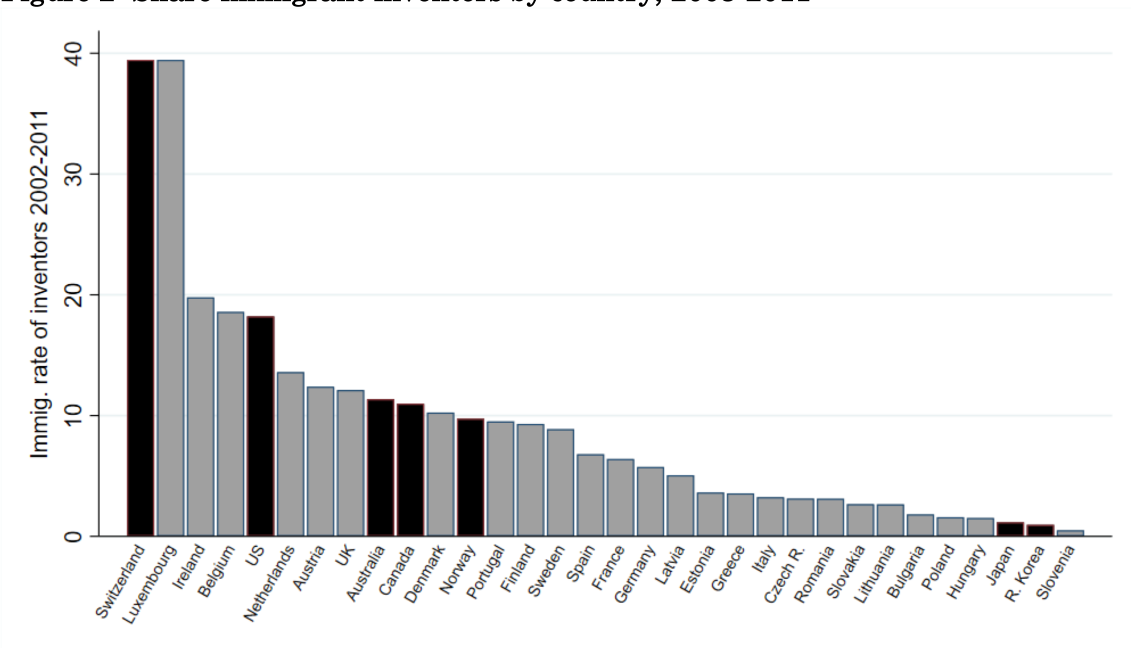
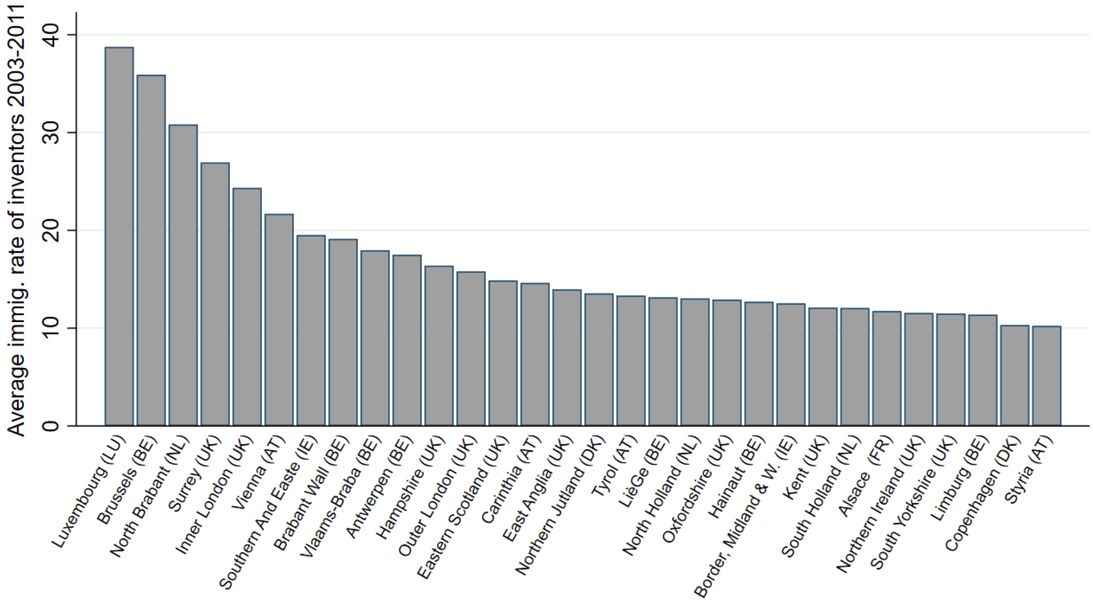


Figure 2: Share immigrant inventors by country, 2003-2011



Note: Countries included in our analysis are grey coloured.

Figure 3: Share immigrant inventors, top-30 regions, 2003-2011



Note: Only regions with an average number of inventors of 90 through the whole period are considered

Table 1: Summary statistics

	Obs	Mean	SD	Min	Max
Entry	868,951	0.069	0.253	0.000	1.000
Native patents	970,200	0.190	0.508	0.000	6.039
Native patents>0	213,164	0.864	0.771	0.004	6.039
Patenting activity	970,200	0.137	0.444	0.000	6.064
Patenting activity>0	146,547	0.907	0.777	0.011	6.065
Migrant inventors	970,200	0.051	0.311	0.000	6.697
Migrant inventors>0	32,868	1.499	0.826	0.881	6.697
FE Origin Country	970,200	0.024	0.197	0.000	44.79
FE Migrant inv.	970,200	0.171	0.504	0.000	5.561
Relatedness density	868,951	10.016	8.323	-1.000	99.000
Ratio migrant/native teams	868,951	0.004	0.079	0.000	14.500
Ratio mixed/native teams	868,951	0.001	0.031	0.000	4.000

Note: We apply the Inverse Hyperbolic Sine (IHS) transformation to the variables Patenting activity, Migrant inventors, Pat. only natives, and Migrant inv. foreign expertise

Table 2: Correlation table

	1	2	3	4	5	6	7
1) Patenting activity	1						
2) Migrant inventors	0.608	1					
3) FE Origin Country	0.323	0.356	1				
4) FE Migrant inv.	0.438	0.403	0.322	1			
5) Relatedness density	0.290	0.155	0.127	0.320	1		
6) Ratio migrant/native teams	0.302	0.537	0.142	0.131	0.084	1	
7) Ratio mixed/native teams	0.211	0.327	0.132	0.105	0.056	0.140	1

Note: We apply the Inverse Hyperbolic Sine (IHS) transformation to the variables Patenting activity, Migrant inventors, Pat. only natives, and Migrant inv. foreign expertise

Table 3: Effect of migration and foreign expertise on native patenting

	(1)	(2)	(3)	(4)	(5)
	Dep. Var.: Native patents				
Migrant inventors	0.492***			0.461***	0.369***
	(0.00718)			(0.0102)	(0.00631)
FE Origin Country		0.382***		0.199***	
		(0.0956)		(0.0545)	
FE Migrant inv.			0.424***		0.287***
			(0.00640)		(0.00448)
Constant	0.165***	0.181***	0.117***	0.162***	0.122***
	(0.000836)	(0.00234)	(0.00118)	(0.00119)	(0.00103)
Observations	970,200	970,200	970,200	970,200	970,200
R-squared	0.441	0.385	0.430	0.445	0.465
IPC * Year FE	YES	YES	YES	YES	YES
Region * Year FE	YES	YES	YES	YES	YES

Notes: * p<0.05, ** p<0.01, *** p<0.001. Region-tech clustered standard errors. All explanatory variables are lagged 1 year. We apply the Inverse Hyperbolic Sine (IHS) transformation to the variables Native Patents, Migrant inventors and Migrant inv. foreign expertise.

Table 4: Effect of migration and foreign expertise on technological diversification

	(1)	(2)	(3)	(4)	(5)
			Diversification (Entry)		
Patenting activity	0.00724**	0.0194***	-0.0117***	0.0128***	-0.0107***
	(0.00344)	(0.00354)	(0.00321)	(0.00373)	(0.00352)
Relatedness density	0.0164***	0.0163***	0.0158***	0.0163***	0.0158***
	(0.000216)	(0.000216)	(0.000215)	(0.000216)	(0.000215)
Migrant inventors	0.0102***			0.0147***	-0.00216
	(0.00365)			(0.00372)	(0.00366)
FE Origin Country		-0.0267***		-0.0284***	
		(0.00758)		(0.00802)	
FE Migrant inv.			0.0530***		0.0532***
			(0.00209)		(0.00210)
Constant	-0.106***	-0.105***	-0.105***	-0.104***	-0.105***
	(0.00222)	(0.00223)	(0.00221)	(0.00223)	(0.00221)
Observations	868,951	868,951	868,951	868,951	868,951
R-squared	0.083	0.083	0.085	0.083	0.085
IPC * Year FE	YES	YES	YES	YES	YES
Region * Year FE	YES	YES	YES	YES	YES

Notes: * p<0.05, ** p<0.01, *** p<0.001. Region-tech clustered standard errors. All explanatory variables are lagged 1 year. We apply the Inverse Hyperbolic Sine (IHS) transformation to the variables Patenting activity, Migrant inventors and Migrant inv. foreign expertise.

Table 5: Effect of migration and foreign expertise on technological diversification: related and unrelated diversification

	(1)	(2)	(3)	(4)	(5)
	Diversification (Entry)				
Patenting activity	0.0105***	0.0245***	0.00401	0.0186***	0.00424
	(0.00346)	(0.00375)	(0.00325)	(0.00383)	(0.00359)
Relatedness density	0.0164***	0.0164***	0.0164***	0.0164***	0.0164***
	(0.000216)	(0.000216)	(0.000219)	(0.000216)	(0.000218)
Migrant inventors	0.0699***			0.0560***	0.0308**
	(0.0121)			(0.0125)	(0.0122)
Migrant inventors # Relatedness	-0.00254***			-0.00169***	-0.00125**
	(0.000506)			(0.000528)	(0.000511)
FE Origin Country		0.0365***		0.0241***	
		(0.00823)		(0.00842)	
FE Origin Country # Relatedness		-0.00312***		-0.00261***	
		(0.000569)		(0.000566)	
FE Migrant inv.			0.111***		0.108***
			(0.00428)		(0.00430)
FE Migrant inv. # Relatedness			-0.00305***		-0.00292***
			(0.000214)		(0.000216)
Constant	-0.106***	-0.105***	-0.113***	-0.105***	-0.113***
	(0.00222)	(0.00222)	(0.00225)	(0.00222)	(0.00225)
Observations	868,951	868,951	868,951	868,951	868,951
R-squared	0.083	0.083	0.086	0.083	0.086
IPC * Year FE	YES	YES	YES	YES	YES
Region * Year FE	YES	YES	YES	YES	YES

Notes: * p<0.05, ** p<0.01, *** p<0.001. Region-tech clustered standard errors. All explanatory variables are lagged 1 year. We apply the Inverse Hyperbolic Sine (IHS) transformation to the variables Patenting activity, Migrant inventors and Migrant inv. foreign expertise.

Table 6: Effect of mixed-teams vs solo-migrant teams on technological diversification

	(1)	(2)	(3)	(4)
	Diversification (Entry)			
Patenting activity	0.0133***	0.0131***	0.0134***	0.0119***
	(0.00374)	(0.00374)	(0.00374)	(0.00321)
Relatedness density	0.0163***	0.0163***	0.0163***	0.0164***
	(0.000216)	(0.000216)	(0.000216)	(0.000216)
Migrant inventors	0.0162***	0.0155***	0.0172***	
	(0.00418)	(0.00380)	(0.00427)	
FE Origin Country	-0.0288***	-0.0285***	-0.0289***	
	(0.00811)	(0.00803)	(0.00812)	
Ratio migrant/native teams	0.0792***		0.0750***	0.0723***
	(0.0249)		(0.0249)	(0.0250)
Migrant/native # Relatedness	-0.00364***		-0.00349***	-0.00283***
	(0.00108)		(0.00108)	(0.00107)
Ratio mixed/native teams		0.107*	0.0817	0.0750
		(0.0592)	(0.0589)	(0.0588)
Mixed/native # Relatedness		-0.00505**	-0.00405	-0.00330
		(0.00251)	(0.00250)	(0.00250)
Constant	-0.105***	-0.105***	-0.105***	-0.106***
	(0.00223)	(0.00223)	(0.00223)	(0.00222)
Observations	868,951	868,951	868,951	868,951
R-squared	0.083	0.083	0.083	0.083
IPC * Year FE	YES	YES	YES	YES
Region * Year FE	YES	YES	YES	YES

Notes: * p<0.05, ** p<0.01, *** p<0.001. Region-tech clustered standard errors. All explanatory variables are lagged 1 year. We apply the Inverse Hyperbolic Sine (IHS) transformation to the variables Patenting activity, Migrant inventors and Migrant inv. foreign expertise.

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