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High Skilled Migration, Innovation and Regional Diversification in Europe

Abstract

Regions tend to diversify their industries by entering industries that are related to their current industries. This is because new industry formation relies heavily on the knowledge present in the region. Regions can acquire new knowledge via extra-regional linkages, one of which is through high skilled migration. This paper aims to analyze the effects of high skilled migration as an extra-regional knowledge source on regional innovation and regional diversification. Regional diversification paths of 242 European regions are analyzed using a patent dataset containing information on nationality and region of residence of inventors. Total innovative output of regions increases because of an influx of foreign inventors, and the patents by foreign inventors contribute to regional diversification. In regions with below average patenting activity, the contribution of foreign inventors allows those regions to diversify into more unrelated industries.

Keywords: Innovation, Regional Diversification, Relatedness, High Skilled Migration

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Introduction

Sustaining growth in a changing competitive landscape requires regions to diversify into new activities (Jacobs, 1969). And to do so, when European economies are increasingly knowledge based, attracting high skilled migrants is of paramount importance (Burmann, Pérez, Hoffmann, Rhode, & Schworm, 2018). However, the relationship between high skilled migration and regional diversification is understudied. Furthermore, most studies linking high skilled migration and innovation are US centric. European evidence is sparse. Current literature on regional diversification has focused on the concept of relatedness, concluding that regions diversify into new technologies more often when those technologies are related to the current structure of the region (e.g. Hidalgo *et al.*, 2007; Boschma, Balland and Kogler, 2015).

Entering unrelated technologies, however, also yields benefits (Castaldi, Frenken, & Los, 2015; Pinheiro, Alshamsi, Hartmann, Boschma, & Hidalgo, 2018). By creating access to external knowledge, regions can access unrelated knowledge. High skilled migration is one of the channels through which regions can access such external knowledge (Martin, Aslesen, Grillitsch, & Herstad, 2018; Miguélez & Moreno, 2013). In this article, I investigate how high skilled migration affects regional diversification, by asking the following questions: does high skilled migration affect innovation in European regions? Does high skilled migration lead to regional diversification and if it does, does it reinforce or broaden the current technological structure of a region?

To answer these questions, I use a patent dataset containing both the nationality and NUTS 2 region of residence of inventors to identify migrant and native inventors (Miguélez & Fink, 2013). This allows for the construction of variables counting the number of migrant and native patents per region, as well as constructing a variable measuring the inflow of foreign knowledge into a region (Akcigit, Grigsby, & Nicholas, 2017; Morrison, Petralia, & Diodato, 2018). It also enables the construction of a variable measuring if a technology enters a regional portfolio (entry). After running several two-way fixed effects models, I find that high skilled migration positively influences innovation in Europe, that it increases the chance of entry of technologies into a region, and thus affects regional diversification, and that in regions with below average innovative activity, it allows for diversification in relatively unrelated industries. High skilled migration in Europe thus leads to regional diversification of regions, and can broaden the technological structure of a region.

Theory: Migration & Innovation

The freedom of movement of workers is one of the four pillars of integration in the European Union (EU). In recent years, the movement of workers in Europe has increased (Holland, Fic, Rincon-Aznar, Stokes, & Paluchowski, 2011). Therefore, there is a need to understand the role of migration of skilled workers in knowledge production, or innovation, and regional path development. A classical theory in the literature on innovation is that innovation is dependent on the size of the labor force in the research sector and the available stock of knowledge (Aghion & Howitt, 1990; Grossman & Helpman, 1994). Migration of high skilled labor increases the size of the labor force, thereby increasing innovation. These effects of high skilled migration are well observed in the US. An increase in visa admissions led to more patent applications (W. R. Kerr & Lincoln, 2010) and immigrants with a STEM (Science, Technology, Engineering, Mathematics) background are granted relatively more patents than US natives (Hunt & Gauthier-Loiselle, 2010). Studies with an European perspective find that ethnic diversity (Niebuhr, 2010; Ozgen, Nijkamp, & Poot, 2011) and having a large pool of skilled migrants have a positive effect on innovative output (Bosetti, Cattaneo, & Verdolini, 2015).

This contrasts with the theory that skilled migration displaces local talent out of the labor market. An increase in the supply of labor would lead to a decrease in the wages, therefore an influx of migrant labor would displace native workers. So far results are inconclusive. A 10 percentage point increase in the supply of labor reduces the wages with 3% to 4% (Borjas, 2003), native mathematicians became less productive after migration of mathematicians from the Soviet Union to the US (Borjas & Doran, 2012) and in the age of mass migration to the US, a 1 percentage point increase in the share of foreign born population decreased low-skill wages with 1.5 percentage point (Goldin, 1994). Other studies find positive effects of immigration on native productivity, such as a 31% increase in native patenting because of Jewish immigrants entering the US (Moser, Voena, & Waldinger, 2014), an increase in productivity of natives after immigration of Soviet scientists (Ganguli, 2015) and an crowding-in effect of natives occurring in the age of mass migration in the US (Morrison et al., 2018). In Europe, the effects tend to cluster around zero (S. P. Kerr & Kerr, 2011).

Knowledge diffusion

High skilled migration is also seen as a channel for knowledge diffusion. This stems from the difference between explicit (or codified) and tacit knowledge. Explicit knowledge is transferable in formal, systemic language, like operating manuals. Tacit knowledge cannot be transferred in a direct or codified way, it needs direct contact (Polanyi, 1966). This would suggest that codified knowledge is freely available, however many studies find evidence that codified knowledge is also spatially constrained (Howells, 2002). Citations of patents, for example, are disproportionally geographically localized, most often coming from the same city. Over time, patents would get cited from further away locations. This holds for complex and simple knowledge (Jaffe, Trajtenberg, & Henderson, 1993). These geographical constrains of knowledge transfers led to the concept of Local Knowledge Spillovers (LKS).

Knowledge spillovers between and within firms are spatially bounded, thereby suggesting that LKS are R&D externalities bounded in space (Arrow, 1972; Nelson, 1959). However, treating LKS as an externality averts the attention from the underlying mechanisms for knowledge diffusion (Breschi & Lissoni, 2001). Attempts to open up this diffusion process have focused on looking at different type of proximities between actors for information to flow: geographical, social, cognitive, institutional and organizational proximity (R. Boschma, 2005). Without geographical proximity, knowledge flows when it is mediated by one of the other proximities. Social ties, for example, enable knowledge diffusion over large distances (Head, Li, & Minondo, 2018; Miguélez & Moreno, 2013; Singh, 2005; Thompson, 2006).

Regional Diversification

The geographical constraints of knowledge spillovers have important implications for regional diversification. As innovation is often seen as a process of finding and recombining existing technologies (Nelson & Winter, 1982; Schumpeter, 1934), firms innovate by combining newly found knowledge with the technology they already have. Firm diversification thus follows a path-dependent process, depending on the existing technologies within the firm (Danneels, 2002; Maskell & Malmberg, 1999). Regions diversify not out of their own accord, but are a combination of firm diversification within the region (Neffke, Hartog, Boschma, & Henning, 2018). Regional diversification thus follows a similar path-dependent route as firms diversification. In essence, it is an accumulation of all the processes undertaken by the firms within their region. Regions branch out because new activities spin out of activities already present in the region (R. Boschma & Frenken, 2012; Frenken & Boschma, 2007).

Empirical evidence for this path-dependency of regions emerged with the concept of relatedness (Hidalgo et al., 2007). In this paper, the diversification process of countries was examined by looking at the products they exported. Backed by the idea that products that were produced in the same country shared common requirements and were therefore related to each other, the authors created the product space, a network measuring the relatedness between products. They found that the chance of entry of a product in the export basket of a country increased when that product was related to the current export basket. This concept of relatedness spurred research in regional diversification.

The chance of entry of an industry or technology in a region increases when that technology is related to the current capabilities of the region. This was empirically tested with different measures of relatedness. Input-output linkages (Essletzbichler, 2015), co-occurrence of patent classes (R. A. Boschma et al., 2015) and the flow of labor between firms (Neffke & Henning, 2013) all concluded the relatedness between products influenced regional diversification. Even in the case of radically new technology, relatedness is an important predictor of the entry of such technologies in a region (Tanner, 2014). The principle of relatedness is not an egalitarian force. Due to the different technological bases of regions, their diversification process will likely move them further apart, increasing spatial inequality (Hidalgo et al., 2018).

In the product space, the center consists of complex products, while simpler products are found in the periphery of the network. Reaching the center of the network from the periphery is difficult, which is why developing countries face difficulties in developing competitive products (Hidalgo et al., 2007). The process of reaching more complex technologies moves slower for developing countries (Petralia, Balland, & Morrison, 2017). Countries deviate from this path-dependent process in about 7% of the cases, where they enter unrelated activities and experience a small increase in future economic growth (Pinheiro et al., 2018). Understanding how regions enter in more unrelated activities helps to identify possibilities for regions to increase their competitive advantage over other regions.

Related vs Unrelated variety

Regions tend to diversify into related activities, yet the importance of unrelated variety should not remain understated. Unrelated variety can be seen as a portfolio strategy to reduce the risks of a sudden economic shock for a region (Attaran, 1986). Another benefit of unrelated variety lies in the long term economic effect. A region that does not increase the variety of its industrial portfolio will see an increase in unemployment and ultimately stagnate. A region needs to increase its variety to absorb existing sectors becoming redundant over time

(Pasinetti & Scazzieri, 2011). Unrelated variety is necessary to avoid economic lock-in and to ensure future economic growth (Saviotti & Frenken, 2008). And while related variety increases total innovative output of a region, breakthrough innovations occur more often in regions where there is unrelated variety (Castaldi et al., 2015). The success of a region thus relies on a balance between related and unrelated variety.

Extra regional linkages

There is a necessity for regions to acquire new knowledge, both related as unrelated to their current knowledge base. There are channels through which knowledge flows between regions. Such channels include R&D collaborations, foreign direct investment, embedded relationships, virtual communities, conferences and international mobility of skilled labor (Martin et al., 2018). These channels act according to the idea of "local buzz, global pipelines", where knowledge in one region, the local buzz, diffused through different channels, or global pipelines, to regions all over the world (Bathelt, Malmberg, & Maskell, 2004; Morrison, Rabellotti, & Zirulia, 2013). However, how regions can ascertain knowledge flows through these pipelines depends on its own regional characteristics (Trippl, Grillitsch, & Isaksen, 2018).

When regions are able to internalize these different knowledge flows, it leads to new path creation. This occurs when the knowledge that arrives in the region is neither too similar nor too different from a regions knowledge base (R. Boschma & Iammarino, 2009). Firm relocations into a region are often more effective for new path creation than start-ups from the region, as they bring new knowledge (Neffke et al., 2018). Firm relocations, however, are uncommon. Individual actors also transfer their expertise and know-how from on region to another via their mobility (Moreno & Miguélez, 2012), thereby acting as a source for path creation (Kapur & McHale, 2007). The rise of the ICT sectors in Asian countries, for instance, has been triggered by returnees from Silicon Valley (Saxenian, 2010). When skilled individuals enter a firm, they take their own knowledge with them, and receive knowledge from their colleagues. This leads to a new combination of ideas (Trippl & Maier, 2011).

Migration and new path creation has not been researched often. One notable exception found that immigrant receiving countries diversify into products originally associated with the country of destination of those immigrants (Bahar & Rapoport, 2018). Other studies look at temporal migration and the effect of return migration. Temporary migrants from Eastern Europe upgrade their skills while in Western Europe, and implement these skills when they move back, thus reducing the technological gap between those regions

(Iara, 2006). Similar effects were observed in India, although it did require assimilation of local firms in India (Kale, Wield, & Chataway, 2008).

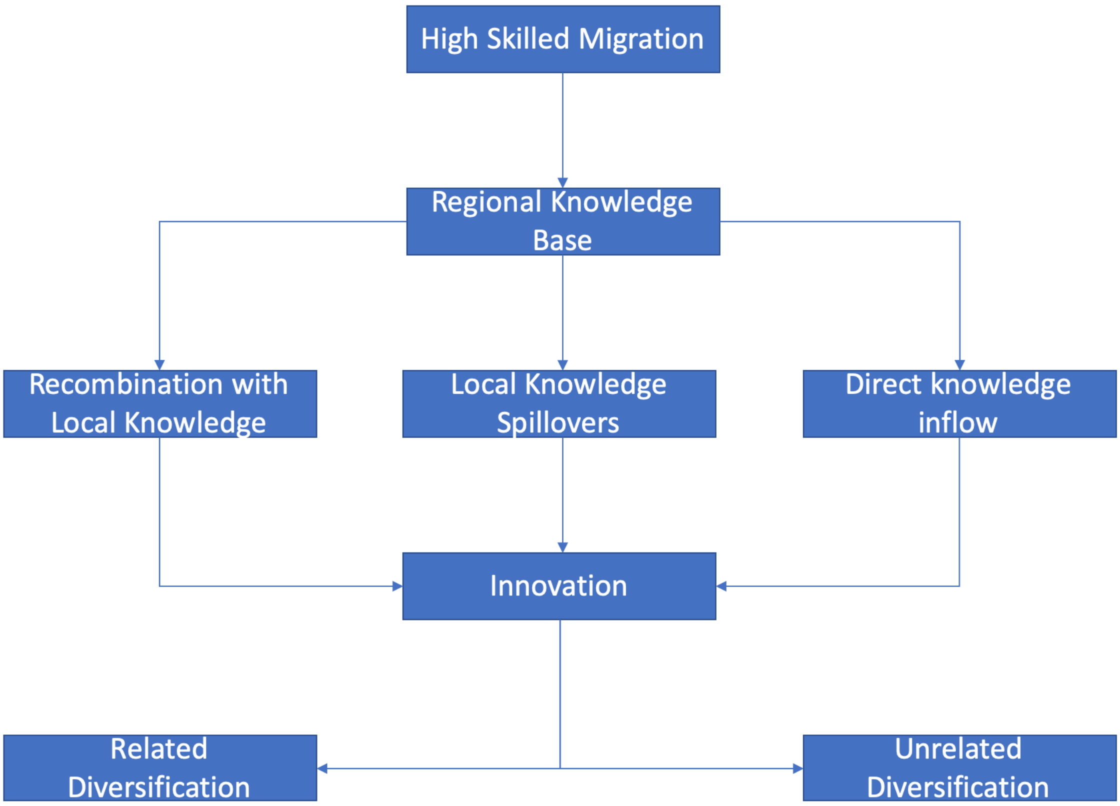
Conceptual Framework

The different theories in the literature described above are summarized in figure 1. High skilled migration affects the regional knowledge base of the host region, leading to increased innovation in a region through the direct inflow of knowledge, new local spillovers and recombination with local knowledge. If those innovations affect regional diversification, they can either reinforce (related diversification) or broaden (unrelated diversification) the current knowledge structure. The aim of this paper is to identify whether high skilled migration has an impact on the regional knowledge base and innovation in a region and if this impact leads to related or unrelated diversification.

Important to note is that I only look at the regional diversification process by measuring patents, and high skilled migration is measured by patents by migrant inventors. The data comes from patents filed under the Patent Cooperation Treaty (PCT), kindly provided by Miguelez & Fink (2013). The main benefit of using patents filed through this treaty is the inclusion of both the address as the nationality of inventors, which enables differentiation between migrant and native inventors without name disambiguation. Patents filed under the PCT follow an advantageous route for seeking international intellectual property protection. In 2010, 54% of patents seeking international protection went through the PCT system (WIPO, 2012). Clearly, not all patents are filed through this system, yet several studies have shown that the patents filed under the PCT are among the most valuable patents (Guellec & Van Pottelsberghe de la Potterie, 2002; van Zeebroeck & van Pottelsberghe de la Potterie, 2011). Without name disambiguation, it is impossible to track inventors over time, therefore the assumption is made that inventors acquire their knowledge in their country of origin.

Research into diversification of regions in the US often uses commuting zones, while research in Europe tends to focus on NUTS 2 regions (Asheim, 2019). This is because of the spatial constraints of knowledge diffusion. These areas are generally larger than cities, but smaller than provinces or states. There are currently 310 NUTS 2 regions in Europe, of which 242 are included in this study. Just as important as the geographical unit of observation is the technological classification. To see the effect of immigrant inventors it is important to differentiate between the types of knowledge of immigrant and native inventors. Patents are classified into several levels of categories, which gives multiple for this differentiation. This research will focus on IPC subclasses. There are currently 645 subclasses, of which 571 are present in this study. Using patent data comes with some limitations. Firstly, patents do not represent every part of knowledge production in an economy (Pavitt, 1985). Secondly, inventors represent a small part of all high skilled labor. Despite these limitations, the use of patent data is justified because it enables the use of a large scope, investigating most European regions through a prolonged period of time.

Figure 1: Conceptual Model



Data & Methodology

The full dataset contains patents issued between 1978 and 2012, however, I only include patents filed between 2001 and 2012 because of unstable use of the PCT system and coverage of nationality. In this period, 462,524 patents were filed in Europe under the PCT system. As there are 242 regions and 571 subclasses, there are 138,182 region-class combinations. Most patents have multiple inventors, sometimes living in multiple regions. The patents are assigned to regions corresponding to the share of the inventors living in that region. An example case is presented in table 1, displaying information for patent number

WO2008077364. WO indicates the patent is seeking protection over all the countries following the PCT treaty. The first 4 digits, 2008, indicate the year the patent is filed, the 6 following digits are the unique identifier for the patent.

This particular patent has two different inventors. Each of their inventor shares is therefore 0.5. These two inventors reside in different regions, region DE71 (Darmstadt) and region DEA1 (Düsseldorf). The patent is classified into two different IPC subclasses, C21D and B23K. Hence the region share for each unit of observation, Region-IPC, is 0.25. The region share thus counts the knowledge that is present in the region, proportional to the total patent.

Table 1: Example patent

PCT NUMBER	INVENTOR NAME	REGION CODE	REGION SHARE	INVENTOR SHARE	IPC
WO2008077364	TOMZIG, Michael	DE71	0.25	0.5	C21D
WO2008077364	TOMZIG, Michael	DE71	0.25	0.5	B23K
WO2008077364	KÜMMEL, Lutz	DEA1	0.25	0.5	C21D
WO2008077364	KÜMMEL, Lutz	DEA1	0.25	0.5	B23K

Additional variables, such as GDP and population per region, were extracted from the Eursotat database. Technology control variables, such as technology size and technology growth rate, were constructed from the patent data. Technology size counts the number of patents per IPC subclass in each year. With these yearly sizes, the technology growth rate is constructed.

Summary Statistics

Table 2 displays the ten NUTS 2 regions that produced the most patents and the share of those patents produced by migrant inventors. Out of the top ten regions, North-Brabant stands out as the only region where nearly half of the patents are produced by migrant inventors. It is also noteworthy that the number one region produced almost 2.5 as many patents as the number 10 region. Most of the top 10 patenting regions are highly urbanized regions. In this period, the IPC code with most patents is A61K, which corresponds to Preparations For Medical, Dental, or Toilet Purposes. The region with the most patents in this category is FR10 (Île de France). Summary statistics on the dataset are presented in table 3.

Table 2: Top 10 most patenting regions

Region	*Total patents*	*Share of immigrant patents*
Île de France	41289	0.12
North-Brabant	30959	0.46
Oberbayern	30902	0.10
Stuttgart	28975	0.07
Darmstadt	20308	0.14
Rhône-Alpes	19605	0.11
Köln	18525	0.12
Düsseldorf	18101	0.11
Karlsruhe	17629	0.13
Helsinki-Uusimaa	16933	0.15

Table *3*: Summary Statistics *Patents*

	Mean	*SD*	*Min*	*Max*
Patents per region	4233.32	5968.401	88	41289.2
Native patents per region	3633.0	5038.968	64.8	36197.6
Migrant patents per region	600.29	1281.675	9.8	14098.6
Patents per class	1876.7	3591.636	70	44639
Native patents per class	1607.8	2930.888	61	36831
Migrant patents per class	268.893	686.1713	4	7808
Patents per year	80432	3008.961	72569	84674
Native patents per year	69143	5840.345	62325	74161
Migrant patents per year	11289	3008.961	9344	16605
Number of regions				242
Number of classes				571
Number of years				10

The distribution of migrant patents through Europe between 2002 and 2011 is presented in figure 2. Most of the regions with many patents by migrants are located in highly populated areas in Western Europe and Scandinavia, while most of the regions with few patents by migrants are populated in rural areas and in Eastern Europe.

Figure 2: Migrant Patents in European NUTS *2* Regions, 2002 – 2011

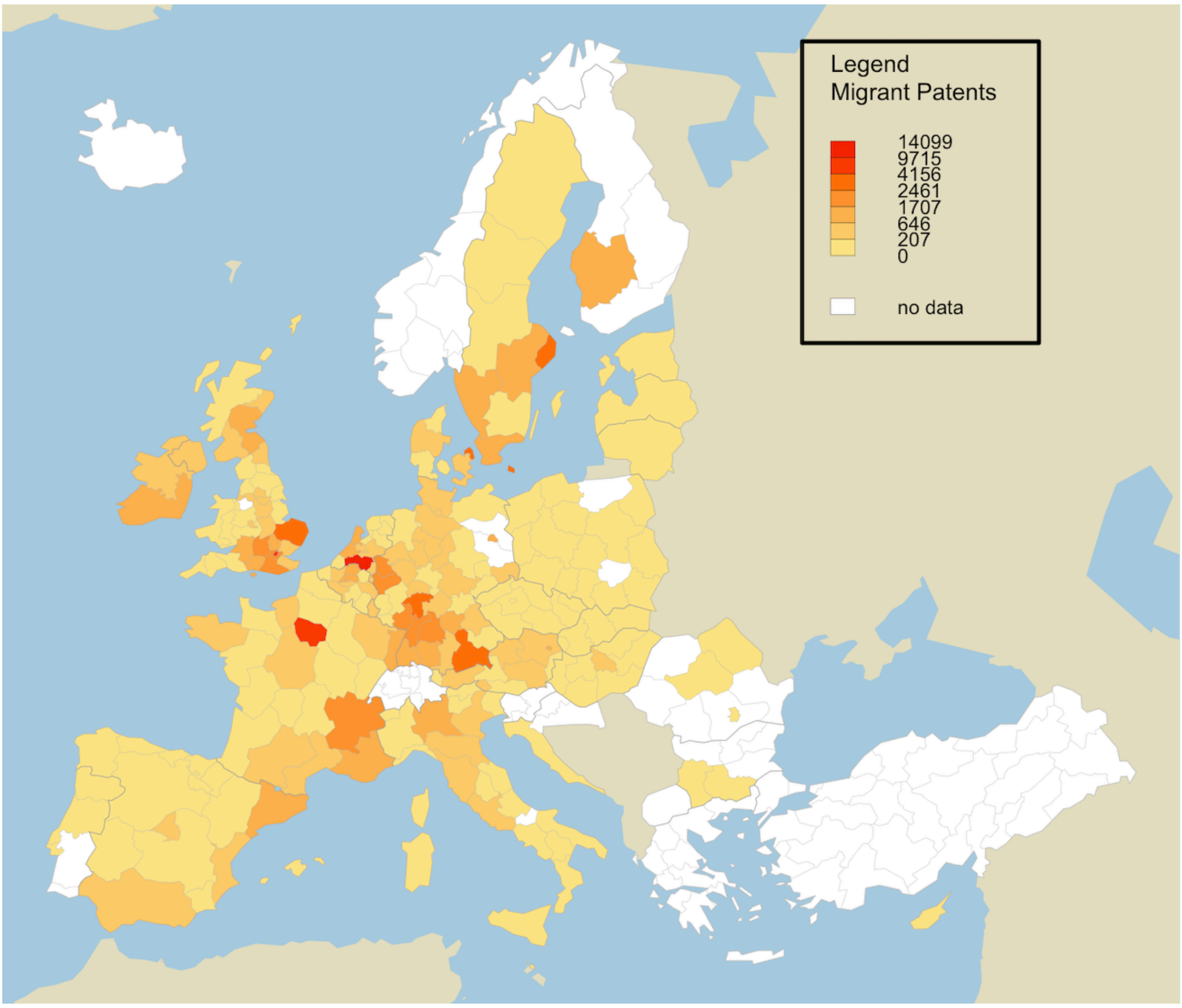


Table 4: Summary Statistics of constructed variables

	Mean	*SD*	*Min*	*Max*
Migrant Patents	0.05	0.67	0	209
Total Patents	0.34	2.23	0	278
Expertise Inflow	0.045	0.35	0	84.89
Relative Density	0.22	1.17	-7.645	42.28
Entry	0.07	0.26	0	1
Population	1896062	1514911	119353	11852851
GDP Millions	45633	43867	2610	352857
Technology Size	138.4	310	1	5002
Technology Growth Rate	0.12	1.31	-0.93	86

Variable construction

Regional diversification is analyzed 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:

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

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. Analyzing whether an entry reinforces or broadens the current technological structure is done by assessing the relative density of the technology that enters. The relative density is constructed by first assessing the proximity between two technologies. Proximity is defined as the minimum pairwise probability two technological classes occur in the same region:

$$\phi_{i,j} = \min\{\, P(RTA_{r_i} RTA_{r_j}), P(RTA_{r_j} | RTA_{r_i}) \,\}$$

A proximity of 0.2 between technological classes *i* and *j* indicates that given that a region has a RTA in technology *i,* there is a 20% chance it has a RTA in technology *j* as well (Hidalgo et al., 2007). With proximity, the density between a technology and a regions technological portfolio is calculated:

$$\omega_{i,r} = \frac{\sum_i \phi_{i,j} \ \times \ RTA_{ir}}{\sum_i \phi_{i,j}}$$

The density between technology *i* and region r is the sum of the proximities between technology *i* and the technologies in the technological portfolio of the region 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). With density, relative density is constructed. The relative density compares the density of a technology not present in the region with the density of a regions option set (OS). The option set of a region consists of all the technologies not yet present in the region. Relative density is computed as follows:

$$\widetilde{\omega_{i,r}} = \frac{\omega_{i,r} - mean(\omega_{i,r,OS})}{\sigma(\omega_{i,r,OS})}$$

So the relative density is calculated by taking the density between a technology and a region, subtracting the mean density of all technologies in the option set, and then dividing it by the standard deviation of the density of the technologies in the option set (Pinheiro et al., 2018). The relative density of a technology centers around 0, where negative values indicate unrelated technologies. As a final step, the relative density is multiplied with entry, indicating how related or unrelated an entry of a technology is compared to the current regional technological portfolio.

The influence of high skilled migration is measured with two variables, firstly the number of patents by migrants in a certain region-technology combination. Secondly, to capture the effect of knowledge diffusion between the country of origin and the host region, the inflow of foreign expertise (Akcigit et al., 2017; Morrison et al., 2018) is calculated with the following formula:

$$Exp_{irt} = \sum_{c=1}^{c} \frac{P_{ci}}{P_c} \times M_{cr}$$

Where P_{ci} is the number of patents of country c in industry I, P_c is the total number of patents and M_{cr} is the number of migrants from country c in region r. It is thus measured as the sum of the share of patents that country *c* has in a given technological class multiplied by the number of migrants from country *c* (M_{cr}) that moved to a given region. Table 4 displays the summary statistics of the constructed variables.

Empirical model

To assess whether high skilled migration has an broadening or reinforcing impact on regional diversification I first test whether it has an effect on innovation in European regions. Therefor, the following model will be estimated:

$$P_{total,irt} = \beta_1 P_{mig,ir,t-1} + \beta_2 Exp_{ir,t-1} + \beta_3 Pop_{rt} + \beta_4 GDP_{rt} + \beta_5 TS_{it} + \beta_6 TGR_{it} + \gamma_t + \varphi_{ir} + \varepsilon_{irt}$$

The dependent variable is the number of patents (in log) in region *r* and industry *i.* The explanatory variables are the number of patents (in log) by migrant inventors ($P_{mig,ir,t-1}$) and the inflow of foreign expertise ($Exp_{\,ir,t-1}$). Both these variables are lagged by one year. The model is controlled by relative density ($\widetilde{\omega_{irt}}$), population (in log) (Pop_{rt}), GDP in millions (in log) (GDP_{rt}), technology size (TS_{it}) and technology growth rate (TGR_{it}). A region-technology (φ_{ir}) and a time fixed effect (γ_t) are included to filter out unobserved regional, technological and time effects.

A second model will be estimated to see if high skilled migration has an effect on regional diversification:

$$
\begin{aligned}
Entry_{irt} = \; & \beta_1 P_{mig,ir,t-1} + \beta_2 Exp_{\,ir,t-1} + \beta_3 \widetilde{\omega_{irt}} + \beta_4 P_{mig,ir,t-1} * \widetilde{\omega_{irt}} + \\
& \beta_5 GDP_{rt} + \beta_6 Pop_{rt} + \beta_7 TS_{it} + \beta_8 TGR_{it} + \gamma_t + \varphi_{ir} + \varepsilon_{irt}
\end{aligned}
$$

The dependent variable is the entry of a technological class in a region. The main explanatory variables are the number of patents (in log) by migrant inventors and the inflow of foreign expertise. Besides the control variables present in the previous model, the relative density between a technology and the current technological portfolio is added ($\widetilde{\omega_{irt}}$). Furthermore, an interaction term between the number of patents of migrants and relative density is added. Again, region-technology and time fixed effects are included.

Results

This section discusses the results of the two models. The effects of high skilled migration on innovation are displayed in table 5 and the effects on regional diversification in table 6. In each of these tables, the first column focusses on migrant patenting, the second column on the inflow of foreign expertise and the third column on the combined effect. The final column in table 6 also includes the interaction term between migration and relative density. As expected, high skilled migration has a positive influence on innovation and a positive influence on the chance of entry of a technological class in a regional technological portfolio.

Migration and innovation

There are significant positive effects for both patents by migrants and expertise inflow on the total number of patents produced. A 10% increase in the number of patents by migrants corresponds roughly to a 0.2% increase in the number of total patents in the next period. A one unit increase of the expertise inflow corresponds roughly to a 4% increase in the total number of patents in the next period. In the final column the combined effect of expertise and migrant patenting on the total patenting output is displayed. Both variables have a significant positive effect on the total number of patents.

Table 5: High skilled migration and total innovative output

	Total Patents (log)		
	(1)	(2)	(3)
Migrants (log)	0.020***		0.020***
	(0.002)		(0.002)
Expertise Inflow		0.039**	0.038**
		(0.016)	(0.016)
Population (log)	0.036	0.036	0.035
	(0.025)	(0.025)	(0.025)
GDP (log)	0.083***	0.085***	0.084***
	(0.013)	(0.013)	(0.013)
Tech Size	0.001***	0.001***	0.001***
	(0.00002)	(0.00002)	(0.00002)
Tech Growth Rate	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)
Observations	946,917	946,917	946,917
R^2	0.636	0.636	0.636
Adjusted R^2	0.590	0.590	0.590
Residual Std. Error	1.150 (df = 839556)	1.150 (df = 839556)	1.150 (df = 839555)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Results Innovative Output. Heteroskedastic robust standard errors in brackets. Patents (total and by migrants), GDP and Population have been log transformed

All the control variables behave as expected. With a higher regional income, patent output increases. Larger population sizes see increasing patenting output. Similarly, when the size of a technology is large or growing, the number of patents increase. Considering that each region has an average of 600 patents of foreign inventors, a 10% increase in the number of foreign inventors corresponds roughly to a 2.3% (0.038 * 60) increase in the total number of patents of that region if the number of patents by migrants remains the same.

Entry

The number of patents by migrants (in log) in the previous period has a positive effect on the chance a certain technology will enter the technological portfolio. The inflow of foreign expertise does not have an effect on the chance of entry. The control variables have the expected effects. If the relative density between a technological class and the region is higher, the chance of entry increases, which is in line with previous research into regional diversification. The size of a technology and the growth rate also have a positive effect on the chance of entry, while the population of a region has a negative effect. All in all, migrant patenting contributes to regional diversification.

Table 6: High skilled migration and regional diversification

	Entry			
	(1)	(2)	(3)	(4)
Migrants (Log)	0.002***		0.002***	0.003***
	(0.001)		(0.001)	(0.001)
Expertise Inflow		-0.007	-0.007	-0.007
		(0.005)	(0.005)	(0.005)
Relative Density	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Migrants*Density				-0.002
				(0.004)
GDP Millions (log)	0.027***	0.027***	0.027***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)
Population (log)	-0.029***	-0.029***	-0.029***	-0.029***
	(0.006)	(0.006)	(0.006)	(0.006)
Tech Size	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Tech Growth Rate	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	828,103	828,103	828,103	828,103
R^2	0.306	0.306	0.306	0.306
Adjusted R^2	0.203	0.203	0.203	0.203
Residual Std. Error	0.247 (df = 721926)	0.247 (df = 721926)	0.247 (df = 721925)	0.247 (df = 721924)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Results regional diversification. Heteroskedastic robust standard errors in brackets. Migrant Patents, GDP Millions and Population have been log transformed

Table 7: Regional differences: high skilled migration and entry

	Entry			
	Regions > mean migrant patents		*Regions < mean migrant patents*	
Migrants (Log)	0.002*	0.002*	0.003**	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Expertise Inflow	-0.012*	-0.012*	0.027	0.028*
	(0.006)	(0.006)	(0.017)	(0.017)
Relative Density	0.008***	0.008***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Migrants*Density		0.001		-0.022**
		(0.005)		(0.010)
GDP Millions (log)	0.200***	0.200***	0.002	0.002
	(0.011)	(0.011)	(0.003)	(0.003)
Population (log)	0.066***	0.066***	-0.008	-0.008
	(0.012)	(0.012)	(0.008)	(0.008)
Tech Size	-0.0001***	-0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Tech Growth Rate	0.003***	0.003***	0.001***	0.001***
	(0.001)	(0.001)	(0.0002)	(0.0002)
Observations	167,742	167,742	660,361	660,361
R^2	0.304	0.304	0.299	0.299
Adjusted R^2	0.197	0.197	0.197	0.197
Residual Std. Error	0.304 (df = 145487)	0.304 (df = 145486)	0.231 (df = 576423)	0.231 (df = 576422)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Results for entry with different subsets of the regions. The top patenting regions subset consists of 50 regions, the bottom subset consists of 192 regions. Heteroskedastic robust standard errors in brackets. Migrant Patents, GDP and Population have been log transformed

The interaction term in table 6 between migrant patenting and relative density does not have a significant effect and does not change the direction of the relationship between high skilled migration and regional diversification. However, as regional differences might influence how high skilled migration affects regional diversification, the dataset is split into two subsets based on the number of patents by migrants in the region. The first subset contains he regions that have more than the mean number of patents by migrants, the second subset contains the regions with less than the mean number of patents by migrants. The results of the model run on these subsets is displayed in table 7.

The first two columns in table 7 show the results for the model run on the top migrant patenting regions. The results are mostly consistent with the results in table 6. This time however, the inflow of foreign expertise has a slightly significant negative effect on the chance of entry of a technology in the regional portfolio. The interaction term between migrant patenting and density is still insignificant. The last two columns in table 7 display the results for the model run on the bottom migrant patenting regions. Again, the effect of migrant patenting and relative density are positive and significant, indicating an increasing chance of entry of a technology. The interaction term in this subset is significant and negative, indicating that the effect of migrant patenting on regional diversification becomes more important when the density between a technology and the regional portfolio is lower. At the same time, the density between a technology and regional portfolio becomes more important when there are fewer patents by migrants. This indicates that migrant patenting is important for regional diversification when that knowledge is relatively unrelated to the knowledge present in the region.

Conclusion and Discussion

The main question this study is concerned with is threefold: Does high skilled migration affect innovation in Europe, if yes, does high skilled migration lead to regional diversification and if it does, does it lead to related or unrelated diversification in a region? Many studies have found an increase in innovative activity of regions because of high skilled migration, however most of them have a US perspective (e.g. Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Morrison, Petralia and Diodato, 2018). The results above show that this positive relationship is also present in European regions. Furthermore, the number of patents by migrants in a certain technology increase the chance of that technology entering the technological portfolio of a region in the next period. Thus, high skilled migration affects regional diversification. The inflow of foreign expertise, used as a proxy to capture knowledge diffusion as a result of high skilled migration, does not have an effect on the chance of entry of a technology.

To test how the qualitative aspect of regional diversification, i.e. whether it moves into related or unrelated areas, an interaction term between migrant patenting and relative density was added. The results indicate that the patents of migrant inventors are increasing the chance of unrelated entries in a region for regions with relatively few patents by migrants. There was no effect of the interaction term in regions with many patents by migrant inventors, which could indicate that those regions are less reliant on outside knowledge for unrelated diversification than regions with few patents by migrants. Further research into different regional structures and the qualitative aspect of regional diversification can shed more light on the possibilities of regions to diversify their technological portfolio. One interesting avenue might be, for example, to assess how the coherence of a current technological portfolio of a region affects the chance of unrelated and related diversification.

One assumption made in this article is that knowledge transfers between a the country of origin and the region of destination of migrant inventors, because of interaction and knowledge spillovers in the region of destination. To gain a better understanding in the relationship between high skilled migration, innovation and regional diversification, research into these interactions and knowledge flows is important. This assumption could for instance be opened up by looking at the composition of teams of inventors or by tracking individual inventors over time, to better estimate how knowledge is acquired and transferred. Better measurements of knowledge inflow into a region could provide extra understanding of a regions capabilities and diversification. For now, it is clear that high skilled migration affects regional diversification.

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