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The role of education in innovation–migration nexus in Europe

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Abstract

Using panel data between 2012 and 2020, this research examines the relationship between the flows of low-skilled immigrants and innovation in the EU-15 group of nations and Switzerland. The empirical component is generated from a theoretical model that we construct. After addressing the potential endogeneity of the share of immigrants in the population, we find that regions with a relatively high immigrant population have a favorable impact on the generation of patent applications, whereas low-skilled immigrants have the reverse effects on innovation. Hence, the results are in line with the proposition in the theoretical section that lower-educated immigrants determine social decreasing returns in the economy.

Keywords Migration · Innovation · Education

JEL Classification J15 · O33

1 Introduction

The channels through which immigration affects innovation concern the increase in the size and density of the population, in its share of immigrants, the skill composition of immigrants and their cultural diversity (Ozgen et al. 2012).

As to the effects on the population of receiving societies, it can stimulate higher levels and diversity of local production besides imports (Mazzolari and

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Neumark 2012) and, in the long run, product and process innovation, firm growth leading to further innovation (Freeman and Soete 1997). Increased population density by immigrants through agglomeration stimulates the exchange of ideas and spillovers of knowledge (for an overview, see Carlino and Kerr 2015).

As Borjas (1999) highlights, there is a process of self-selection guiding migration in terms of age, size and skill composition and out-selection or external selection on the base of specific characteristics of immigrants (Bertoli and Rapoport 2013). As to self-selection, skilled immigrants tend to be younger, more entrepreneurial and less risk averse, which also determine their higher mobility (Kloosterman and Rath 2003; Poot 2008). When changing their residence, they bring with them new ideas, knowledge and work practices with a spillover effect in host countries (Ozgen et al. 2012). Self-selection can also be driven by the effect of migration networks, as immigrants clustered in close geographic areas tend to develop social networks, which provide support also in terms of information and knowledge to newly arrived immigrants who transform them into tangible resources (Massey 1999). In this respect, large networks by reducing the moving costs tend to increase the flow of low-educated migrants (Beine et al. 2011), whereas with small networks the level of immigrants' education raises (McKenzie and Rapoport 2010).

Out-selection of skilled (and unskilled) immigrants is determined by external factors like entry regulation based on observable characteristics like education, age and ability and integration policy (Bertoli et al. 2012 and Macaluso 2022, for an overview).

Cultural diversity (e.g., language, ethnicity, religion) may foster innovation and the creation of new knowledge mostly relying on talents and skills from a wider variety of cultural backgrounds (Alesina and La Ferrara 2005; Berliant and Fujita 2004). This influence depends on the production complementarity between different types of population (Alesina and La Ferrara 2005; Niebhur 2006). Complementarity is hampered by transaction costs due to high cultural distance caused by ethnic, linguistic and religious diversity, all features shaping the integration process and immigrants' sense of belonging to host societies (Ozgen et al. 2012; Niebhur 2006). In fact, cultural diversity and polarization can cause difficult communication, less trust and potential conflicts among employees and eventually hamper innovation (Ozgen et al. 2013).

Overall, extant empirical research has found that skilled immigrants count for innovation in receiving countries. For instance, Hunt and Gauthier-Loiselle (2010) show a positive impact of the share of immigrant college graduates, and of scientists and engineers in the population on patents per capita in the USA. Niebur (2006) highlights that cultural diversity of highly qualified employees positively influences patent applications in Germany. Ozgen et al. (2012) assess the impact of the size, skills and diversity of migrants on the number of patent applications of European Regions (NUTS2 level) in 1991–1995 and 2001–2005. Since no information was available on the skill levels of immigrants, the authors used region-of-origin information as a proxy for the skills and the cultural values that were specific to the country of origin. While the size reveals no conclusive results, a sufficiently high ethnic diversity and average skill level are positively linked to innovation.

From a historical perspective, Hornung (2014) finds that Huguenot diaspora in Prussia led to a transfer of technological and managerial knowledge between the Huguenots and natives in the textile sector, whose effects lasted for nearly the whole eighteenth century. More recently, Akcigit et al. (2017) have demonstrated that in technological areas of the USA, the prevalence of foreign-born expertise raised patents between 1880 and 1940.

Nevertheless, few scholars have analyzed the impact of unskilled immigrants on innovation. Recent research has mainly focused on the causality running from skills and education to technology and to changes in capital-to-labor ratio for the US (Hanson and Slaughter 2002; Lewis 2005) and the Italian provinces (De Arcangelis et al. 2015). It acknowledges that the increase in labor supply driven by low-skilled immigrants leads firms to make production technique more complementary with the characteristics of the labor force, which entails the adoption of labor-intensive technique and the reduction in skill-complementary capital. Lately, some scholars have driven their attention to the influence of low-skilled immigrants on innovation. Ozgen et al. (2013) relying on Dutch micro-data show that when excluding sectors with the highest share of low-skilled foreign born from the sample, the positive influence of ethnic diversity on product innovation is stronger. Bratti and Conti (2018) use province-level data to assess the impact of immigrants on patent applications in Italy, which is a destination country mainly for low-skilled individuals. They address the likely endogeneity of the immigrant share of the population by using immigrant enclaves. The results underline the weak performance of science-based industries and the lower return to immigrants' human capital with respect to natives as factors that attract lower-skilled immigrants in Italy, but they find no evidence of any effects of immigrants on innovation. Pinate et al. (2022) analyze the impact of internal and international migration in Italy at the province level in the period 2003 to 2012 and reveal a negative association between low-skilled migration and innovation.

We extend the existing contributions in several directions. We build a theoretical model from which the empirical part is derived. The empirical analysis is explicitly centered on the effect of low-skilled immigrants on innovation in the EU-15 group of countries and Switzerland between 2012 and 2020.[1] Low-skilled immigrants are defined as those with lower secondary education to the highest level, as in Bratti and Conti (2018) and Pinate et al. (2022). Formal education is the most used proxy for human capital since it is a signal of skills in the labor market and a comprehensive measure of knowledge, skills and competency needed to participate in society (OECD 2019).

The empirical analysis relies on three datasets. Data on patents registered by firms from the scoreboards have been sourced from the OECD, REGPAT database (August 2022). The shares of migrants and of low-skilled migrants at regional level (NUTS-2) were calculated using the microdata drawn from the European Labour Force Survey (2010–2018).

[1] Our final estimates, however, do not include Germany, Netherlands and Luxemburg because 2001 census data for these countries were not available. To this regard, see also note 8.

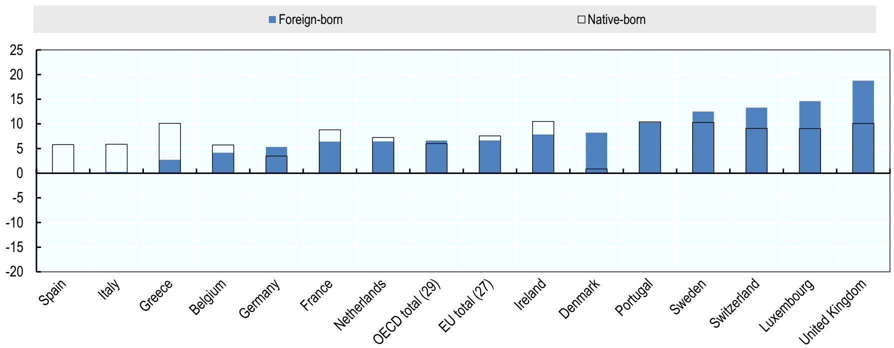

Fig. 1 How shares of the highly educated have evolved—changes in percentage points, 15- to 64-year-olds, 2006–2007 to 2017. *Source*: Indicators of Immigrant Integration 2018: Settling In—© OECD 2018

Finally, when we address the endogeneity of immigrant share in the population, we use as instrumental variables not only immigrant enclaves (Bratti and Conti 2018), but also measures of local attitudes toward immigrants at regional level (NUTS2) drawn from the European Social Survey in 2010 and of integration policies at country level (NUTS0) from the indicators of Migrant Integration Policy Index (MIPEX) (Giacomo and Thomas 2020). How receiving societies perceive immigrants and their policies to integrate migrants in fact are likely to shape out-selection of immigrants as this factor may bring them to move to specific geographical areas, where it can have a fallout in terms of innovation, depending on the skills of immigrants. The outlay of the paper is as follows: Sect. 2 reports some evidence about immigration flows in Europe, Sect. 3 describes our theoretical model, Sects. 4–5 focus on the empirical analysis and main findings, and Sect. 6 contains concluding remarks.

2 Some evidence of immigrants in Europe

To better understand the reason of our interest in low-skilled immigrants, it helps a glance at some evidence in Europe. Around the end of the last decade, in Europe the share of immigrant population with low education was one-third with 39% of non-EU migrants and about 26% of EU-born migrants compared to 23% of the native-born. Poorly educated—over 35% of immigrants—were present especially in Southern Europe, Belgium and France, while highly educated immigrants corresponded to 29% (OECD 2018). Lately, migration flows have been characterized by higher level of education generally throughout Europe (Fig. 1) so that the share of highly educated has become larger.

Immigrants' education characteristics are reflected in their labor market performance though they generally face a penalization in terms of employment against natives. In EU, in 2017 they were mainly concentrated in low-skilled jobs; for instance, 30% of immigrant workers in Southern Europe, except for Portugal, occupied these jobs, three times more than native-born individuals (OECD 2018). As

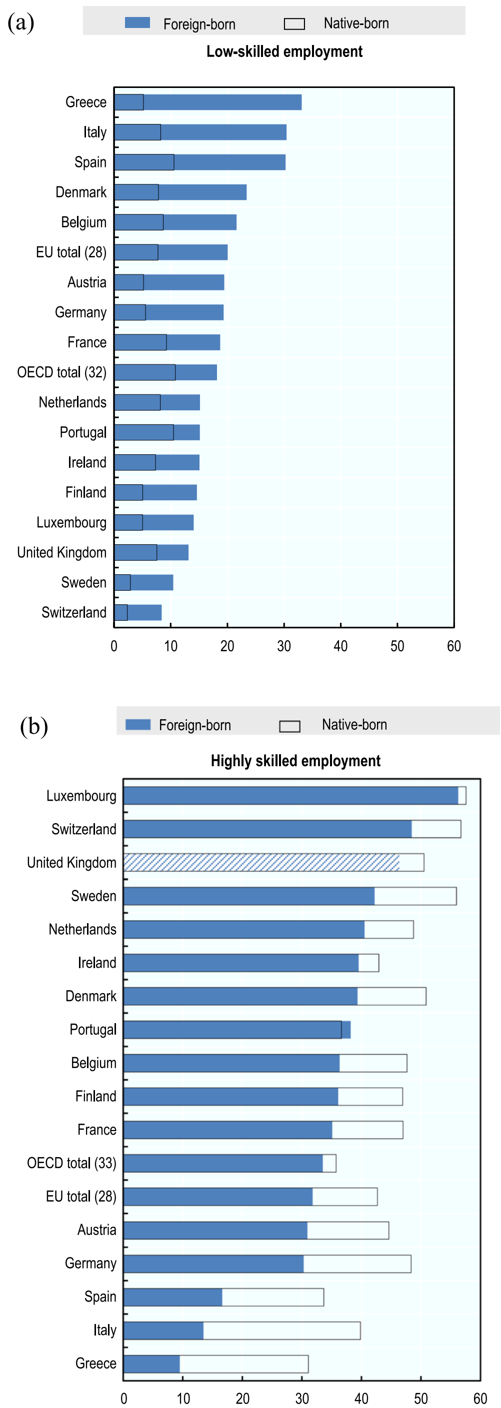

Fig. 2 Low-skilled and highly skilled employment—percentage of 15- to 64-year-olds in employment, 2017. *Source*: Indicators of Immigrant Integration 2018: Settling In—© OECD 2018

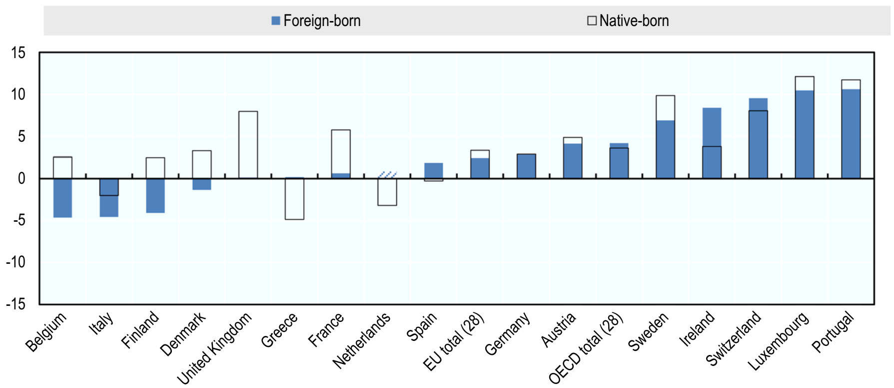

Fig. 3 How shares of workers in highly skilled occupations have evolved—changes in percentage points, 15- to 64-year-olds, 2006–2007 to 2017. *Source*: Indicators of Immigrant Integration 2018: Settling In—© OECD 2018

one can notice in Fig. 2a throughout Europe, the percentage of low-skilled jobs held by immigrants was higher compared to natives, while the opposite occurred for high-skilled jobs (Fig. 2b).

Looking at high-skilled jobs, they were held by one-third of immigrants; this share was lower than the one of natives and even lower for non-EU migrants (OECD 2018). However, in most European countries in the decade from 2006–2007 to 2017, there was an increase in high-skilled jobs occupied by immigrants except for Belgium, Italy, Finland and Denmark (Fig. 3).

The above evidence shows that despite recent changes in immigrants' education and type of employment, low-educated immigrants remain a relevant phenomenon, especially in some European countries. Furthermore, immigrants' employment is concentrated in low-skilled jobs. These features mainly concern non-EU migrants.

Further inspection of immigrants from non-European countries by considering the Human Development Index (HDI) of their country of birth allows to assess immigrants' characteristics that can help the innovation process in destination countries. In fact, the index includes not only life expectancy at birth, but also the mean of years of schooling for adults aged 25 years and more and expected years of schooling for children of school entering age, and standard of living captured by gross national income per capita (UNDP-Human Development Reports Index). One can observe that over the period 2013–2021, when the indicator is available, migrants from countries with a high HDI are mainly in Germany and Spain, followed by France and Italy. Germany, Italy and France are major destinations for migrants from countries with low HDI (Figs. 4 and 5).

In general, the data highlight that the percentage of poorly educated immigrants in Europe is still non-negligible and that the presence of low-skilled immigrants—primarily from non-EU countries—is heterogeneously distributed across countries. This could trigger lower innovation in those areas where low-skilled immigrants are prevailing and ultimately bring down economic growth. For this reason, we focus on low-skilled immigrants defined as those who attained lower secondary education to

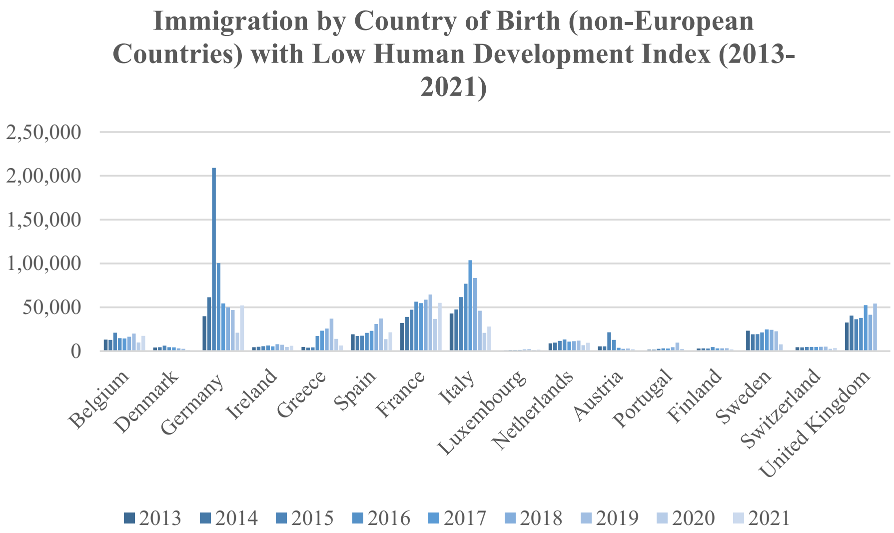

Fig. 4 Immigration by country of birth (non-European countries) with low human development index (2013–2021)

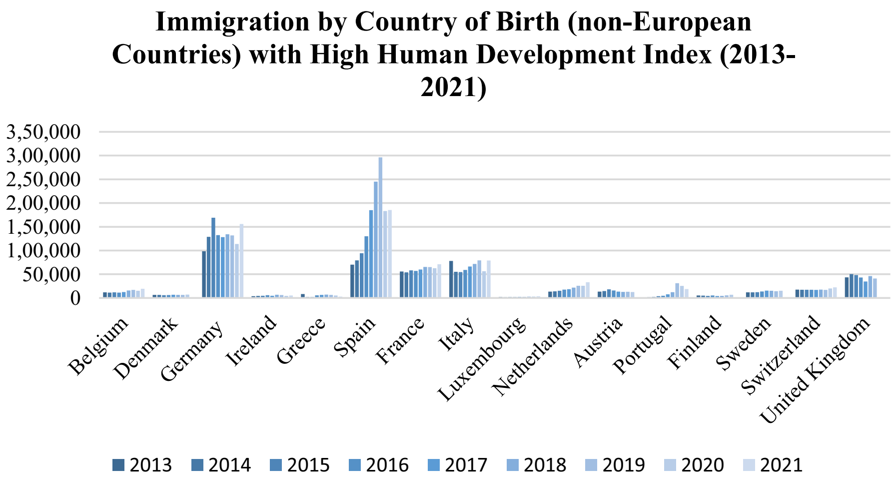

Fig. 5 Immigration by country of birth (non-European countries) with high human development index (2013–2021)

the highest level. We chose lower secondary education as cutoff point as it covers a more significant group of low educated individuals who left education after compulsory school. In all European countries, the full-time compulsory education/training period includes primary and lower secondary education (European Education and Culture Executive Agency, European Commission 2022). Importantly, we know that formal education does not entirely capture individual skills meant as "*the ability or* *capacity of an agent to act appropriately in a given situation*" involving the ability to use text-based information including mathematical information. This ability depends on understanding and elaborating such information (OECD 2013).[2]

The following section will explain how low-skilled migrants can affect innovation and growth.

3 A basic theoretical framework

In this section, we presume the existence of two countries: the destination and the origin one. As our focus is on the impact of immigration on knowledge exchange in the exercise of the diffusion of agents' ideas during the innovation process in the destination economy, we will investigate more extensively the latter. The analysis of the source economy will be constrained to workers' migration choice. In line with Acemoglu (1996), we consider a simple non-overlapping generation model where in both the economies each generation consists of a continuum of entrepreneurs and workers normalized to unity. All agents live for two periods and are assumed to be risk neutral with an intertemporal preference rate equal to zero. In the first period, entrepreneurs and workers of the host economy determine their investments in physical and human capital, respectively, while workers of the source country must opt for migration or not. In the second period, patents' production arises in the form of a partnership of one firm and one worker, and then, consumption from the patent's benefits occurs. Finally, all agents die leaving no bequests. Different costs of acquiring human capital are assumed in the two economies so here is why in the host country there are two types of workers—natives and immigrants—with different levels of human capital. In the host economy, the production of patents is assumed to have constant returns to scale and takes the following functional form:

$$P_{i,j,t} = Ah_{i,t}^{\alpha}K_{j,t}^{(1-\alpha)} \quad \text{with} \quad 0 < \alpha < 1 \tag{1}$$

where $P_{i,j,t}$ represents patents of the host country, $h_{i,t}$ is the human capital of the ith worker while $K_{j,t}$ the physical capital of the jth entrepreneur. A captures technological and geographical proximity effects.

We assume that in host and source economies labor markets are characterized by the presence of a costly search activity and a matching technology function assumed to be constant return to scale in its arguments: job vacancies and unemployed workers. The randomness of the matching technology function will imply that:

- Entrepreneurs have the same probability of meeting each worker, irrespective of both human capital and home country, and once a partnership has formed, it is too expensive for all of agents to break it up to engage in a new one.

[2] However, the data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) do not cover the period and the countries we evaluate.

- Anonymity of contracts in the sense that each worker has no idea of the entrepreneur he/she is going to meet and so takes decisions based on the total distribution of physical capital across all entrepreneurs.

The randomness of the matching function will imply anonymity of contracts as each worker does not discern the characteristics of firms they are going to meet. Therefore, their choices will be contingent on the total distribution of physical capital across all entrepreneurs.

3.1 Native workers

The utility functions of the ith native worker may be written as:

$$U_{i,t} = P^{e}_{i,j,t} - \frac{\theta_i h_{i,t}^{(1+\gamma)}}{(1+\gamma)} \tag{2}$$

θ_i is a positive taste parameter measuring disutility from catching human capital to acquire patents. Equation 2 may be written as follows:

$$U_{i,t} = A h_{i,t}^{\alpha} \int K_{j,t}^{(1-\alpha)} \mathrm{d}j - \frac{\theta_i h_{i,t}^{(1+\gamma)}}{(1+\gamma)} \tag{3}$$

From the maximization process' *f.o.c.* we may easily derive:

$$h_{i,t} = \left\{ \frac{A\alpha \int K_{j,t}^{(1-\alpha)} \mathrm{d}j}{\theta_i} \right\}^{\frac{1}{\gamma+1-\alpha}} \tag{4}$$

3.2 Foreign workers

As to foreign workers' behavior, the human capital investment choice is related to the decision of migrating by comparing the optimal utility levels derived from moving or otherwise. Utility functions of foreign workers are assumed to be written as:

$$U^{f}_{i,t} = P^{e}_{i_f,j,t} - \frac{\delta_{i_f} h_{i,t}^{f(1+\gamma)}}{(1+\gamma)} \tag{5}$$

$$U^{o}_{i,t} = \left\{ P^{oe}_{i_o,j,t} - \frac{\delta_{i_o} h_{i_o,t}^{o(1+\gamma)}}{(1+\gamma)} \right\} \phi_{i_o} \tag{6}$$

where f and o refer to foreign and origin countries, ϕ_{i_o} is a positive taste parameter capturing the preference for home country lifestyle and is assumed greater than unity, different among workers, and distributed according to a uniform cumulative distribution function $F(\phi)$ with parameter b.[3] From *f.o.c.* for Eqs. 5 and 6 maximization, we obtain:

$$h^f_{i_f,t} = \left\{ \frac{A(1-\alpha)\int K^\alpha_{i,t}\mathrm{d}i}{\delta_{i_f}} \right\}^{\frac{1}{\gamma+\alpha}} \tag{7}$$

$$h^o_{i_o,t} = \left\{ \frac{A^o(1-\alpha)\int K^\alpha_{i_o,t}\mathrm{d}i}{\delta_{i_o}} \right\}^{\frac{1}{\gamma+\alpha}} \tag{8}$$

The decision whether migrate or not derives from the comparison of the two maximum utility levels:U^{f*}, U^{o*}. A worker will move to the host country if and only if:

$$U^{f*} > U^{o*} \tag{9}$$

The above migration condition decision (9) can be reshaped as:

$$\phi_{j_o} < \overline{\phi} \text{ where } \overline{\phi} = \frac{P^e_{i_f,j,t} - \frac{\delta_{i_f} h^{*f(1+\gamma)}}{(1+\gamma)}}{P^{oe}_{i_o,j,t} - \frac{\delta_{i_o} h^{*o(1+\gamma)}}{(1+\gamma)}} \tag{10}$$

From inspection of (10), it appears clear as the number of migrants depends on the distribution function across population of taste parameter ϕ_{j_o} and on the parameters of threshold value $\overline{\phi}$ related to origin and host countries' economic conditions.

The share of migrant workers will be:

$$\chi = \int_0^{\overline{\phi}} \frac{1}{b} d\phi_{i_o} = \frac{\overline{\phi}}{b} \tag{11}$$

The total population of native and foreign workers will be P: $(1+\chi)$.[4] Normalizing to unity the above and defining with β the native workers' share, the quota of immigrants in the host economy will be given by: $(1-\beta) = \frac{\chi}{1+\chi} = \frac{\overline{\phi}}{b+\overline{\phi}}$.

3.3 Entrepreneurs

In the host economy, each entrepreneur invests in physical capital to maximize his/her utility function:

[3] Following Aldieri and Vinci (2016), and Carillo et al. (1999).

[4] In a context of no unmatched agent, an equal increase in entrepreneurs in the host economy may be assumed.

$$U_{j,t} = P^e_{i,j,t} - \frac{\lambda_j K_{j,t}^{(1+\gamma)}}{(1+\gamma)} \tag{12}$$

with parameter λ_j capturing disutility for investment in physical capital. Considering that there are two types of workers, natives and non-natives, the above utility function may be written as:

$$U_{j,t} = AK_{j,t}^{(1-\alpha)}\left[\beta \int h^{\alpha}_{i,t} di + (1-\beta)\int h^{\alpha}_{i_f,t} di\right] - \frac{\lambda_j K_{j,t}^{(1+\gamma)}}{(1+\gamma)} \tag{13}$$

from which we may derive:

$$K_{j,t}^{RD} = \left\{\frac{A(1-\alpha)\left[\beta \int h^{\alpha}_{i,t} di + (1-\beta)\int h^{\alpha}_{i_f,t} di\right]\int K^{\alpha}_{i,t} di}{\lambda_j}\right\}^{\frac{1}{\gamma+\alpha}} \tag{14}$$

From the above, we may state what follows.

Proposition[5]: *Assuming* $\theta_i = \theta, \lambda_j = \lambda$: *From Eqs.* (7), (8) *and* (14), *there will be a unique equilibrium and there are social increasing returns in the sense that a small increase in the investments of all agents will make everyone better off, and when a small group of workers (entrepreneurs) invests more in human (physical) capital, other agents will respond, and the equilibrium rate of return of all subjects will improve. Moreover, we may differentiate two different cases*:

a) If migrant workers are more educated than the native ones, there are social increasing returns, and the immigration policies may be careful as a source of investment.
b) In case of immigrants with a lower level of human capital, increasing social returns may be reversed.

To test the theoretical proposition concerning the impact of migrants' educational level on local economic growth, the subsequent section develops an empirical analysis where increasing returns for the economy are measured by the number of patents.

5 Analytical proofs may be postponed to Aldieri and Vinci (2016).

4 Empirical analysis

We estimate the impact of migration flows (*m)* on innovation in the EU-15 nations[6] and in Switzerland between 2012 and 2020 through the following regression model, in which innovation is proxied by the number of patents (*p*):

$$lnp_{it} = \alpha_0 + \alpha_1 lnm_{it-2} + \alpha_2 lnmlow_{it-2} + \alpha_3 x_{i2011} + \beta_t + \gamma_c + \varepsilon_{it} \tag{15}$$

where *i, c* and *t* are regions (NUTS2), countries and time subscripts, respectively, and ε_{it} is the error term. The share of immigrants in the population (*m*) is lagged two periods to make it predetermined with respect to the dependent variable; the analysis focuses on the association between the percentage of low-skilled immigrants (*mlow*) and innovation.

The vector X includes working-age population (*pop)* and people with tertiary education (*tertiary)* as measured by the 2011 census. These variables have been added in a year preceding the estimation period because they could be affected by the emigration flows in the years 2012–2020 (see also Bratti and Conti 2018).

We rely on a parsimonious specification of the model, excluding potentially endogenous controls as local industrial sectors and level of R&D effort.[7] However, country fixed effects are added to the regressors to control for national institutional and socio-economic factors.

Data on patents registered by firms from the scoreboards have been sourced from the OECD, REGPAT database (August 2022). REGPAT collects data on patents registered with PATSTAT (the EU patent office) and allocated to each country.

Using sample weights, the share of immigrants in the population at regional level (NUTS2),[8] as well as the percentage of low-skilled immigrants, is computed using data from the Labor Force Survey (2010–2018). As already specified, low-skilled immigrants correspond to individuals who attained a lower secondary education to the highest level.

Taking into account that the same socioeconomic factors at regional level could both attract immigrants and increase local innovation, we investigate potential endogeneity issues. We propose several instruments to test for endogeneity of the local share of immigrants.

Firstly, we propose an instrument, largely used in previous studies,[9] that relies on the tendency for immigrants to migrate to areas where communities of immigrants from the same country of origin have already settled. Previous findings also highlight that networks favor less-skilled more than skilled immigrants (Beine and Salomone 2013; Bratti and Conti 2018).

6 Overall, we consider 152 European regions (NUTS2). In the Netherlands and Luxemburg, the analysis is at national level.

7 Bratti and Conti (2018) included variables accounting for R&D, but they did not find significant evidence.

8 In the UK, the share of immigrants in the population is at NUTS1 level.

9 Card (2001), Cortes and Pan (2015), Barone et al. (2016), Bratti and Conti (2017), Caselli et al. (2020)

Therefore, the distribution among regions of immigrants according to their origins in the past should provide the required exogenous source of variation in the local share of immigrants.

Formally, the instrumental variable "immigrant enclaves" can be written as follows:

$$\text{Imm. enclaves} = \sum_{a=1}^{N} \frac{\text{immigrants}_{ai,2001}}{\text{immigrants}_{ac,2001}} * \frac{\text{immigrants}_{ac2001-i}}{\text{immigrants}_{ae,2001}} \tag{16}$$

where "i" denotes the NUTS2 region (in the EU country "c") and "a" denotes immigrants' geographical area of origin;[10] hence, the first term represents the share of immigrants from "a" living in region i in 2001, whereas $\text{immigrants}_{ac2001-i}$ denotes the total number of immigrants coming from "a" to the European country "c" in 2001 minus the contribution of region i to this total, and $i\text{mmigrants}_{ae2001}$ denotes the total number of immigrants coming from "a" to Europe in 2001.

The identifying assumption is that local factors that attracted migrants by different nationalities in the past (2001) are uncorrelated with the state of innovation in the years 2012–2020, controlling for the correlates included in the final specification of the model (e.g., population in working age, people with tertiary education, year and country dummies accounting for unobserved socioeconomic conditions). Indeed, 10 years seems like enough time for the assumption to be considered fair. To test the validity of the chosen IV (by the Sargan test), we also rely on additional instruments, namely natives' concern about immigration at a regional level (NUTS2) and an indicator of migration policies in receiving societies.

A large body of literature has been written about the correlation between migration flows and local population attitudes toward immigrants (Fetzer 2000; Dustmann and Preston 2007; Sobczak 2007; Jolly and DiGiusto 2014; Nese 2022). Immigrants may choose to live in regions where residents are less averse to foreigners; at the same time, the share of foreigners at regional level may increase hostility toward ethnic minorities, in particular, for economic reasons. The instrumental variable "ethnic threat" was developed at a regional level (NUTS-2) based on the following three questions included in the European Social Survey: (i) "Immigration is good or bad for the country's economy," (ii) "the country's cultural life is undermined or enriched by immigrants," and (iii) "immigrants make the country a worse or better place to live." The answers were coded on a scale of 0 to 10 (lower values indicate lower propensity to accept immigration).[11] To make the instrumental variable exogenous with respect to the estimation period, we measure "ethnic threat" using the European Social Survey carried out in 2010.

[10] We considered the following geographical areas: EU-15 nations, Central and Eastern Europe, Other European countries, Northern Africa, other African countries, North America, other American countries, Near and Middle Asia, Other Asian countries, Oceania. Hence, in (2) N = 15.

[11] The scores are highly correlated (Cronbach's reliability coefficient alpha was measured as 0.89), and the mean for the three items is nearly the same (about 5). This suggests that nothing is lost by using the total index which covers all aspects of immigrant evaluation.

Table 1 Descriptive statistics

Variables	Mean (std. dev.)
p	724.18 (0.044)
m	0.136 (0.002)
mlow	0.342 (0.003)
pop	719.08 (26.58)
tertiary	211.124 (9.05)
Number of observations	1308

Table 2 OLS regressions

Variables	Coefficients (std errs) (1)	Coefficients (std errs) (2)
pop	1.027***(0.107)	1.05***(0.104)
tertiary	0.336***(0.095)	0.29***(0.095)
m	0.573***(0.066)	0.578***(0.064)
mlow		−0.74***(0.098)
No. of observations	1308	1308
R-squared	0.74	0.75
F test	161.49	162.89

Country and year dummies included. ***Significant at 1% level. Robust standard errors

The last instrument, **Permanent Residence** is another aspect of reception context at country level (NUTS0). It measures whether temporary legal residents have facilitated access to a long-term residence permit (e.g., like UE nationals) on a scale 0–100.[12]

Table 1 reports the descriptive statistics of the variables used in the empirical model. We observe that migrants are about 14% of the population, and about 34% of them are low skilled.

5 Results and discussion

Firstly, Eq. (15) is estimated by OLS considering *m* and *mlow* as a exogenous variables (Table 2).

The findings in column 1 indicate a positive correlation between migration flows (m) and innovation. Moreover, we get a positive correlation between people with tertiary education and the number of patents, as well as a positive correlation between active people and innovation.

[12] Range 80–100 corresponds to favorable, 60–79 to slightly favorable, 41–59 to halfway favorable, 21–40 to slightly unfavorable, 1–20 to unfavorable, 0 to critically unfavorable.

Table 3 Endogeneity tests

	Statistics	*P* value
Instruments: Imm. enclaves, ethnic threat, ethnic threat squared		
Wu–Hausman	F(2,1282) = 7.1	(0.0009)
Durbin–Wu–Hausman	χ^2 (2) = 14.33	(0.0008)
Instruments: Imm. enclaves, ethnic threat, ethnic threat squared, permanent residence		
Wu–Hausman	F(2,1282) = 8.49	(0.0009)
Durbin–Wu–Hausman	χ^2 (2) = 17.10	(0.0008)

Table 4 F-test of excluded instruments

	Statistics	*P* value
Instruments: Imm. enclaves, ethnic threat, ethnic threat squared		
m	F (3, 1283) = 195.12	(0.00000)
mlow	F(3, 1283) = 31.63	(0.00000)
Instruments: Imm. enclaves, ethnic threat, ethnic threat squared, permanent Residence		
m	F (3, 1283) = 102.49	(0.00000)
mlow	F(3, 1283) = 13.69	(0.00000)

Table 5 Validity test

	Statistics	P-value
Instruments: Imm. enclaves, ethnic threat, ethnic threat squared		
Sargan test	χ^2 (1) = 3.11	(0.08)
Instruments: Imm. enclaves, ethnic threat, ethnic threat squared, permanent residence		
Sargan test	χ^2 (1) = 0.011	(0.91)

Consistently with our argumentations, when the share of low immigrants (*mlow)* is added to the regressors (column 2), we report a negative association with innovation.[13]

One must be cautious in interpreting as causal the coefficients on the migration flows (*m, mlow*) because of likely endogeneity issues. To test for endogeneity, we carry out Hausman specification tests (Wu–Hausman and Durbin–Wu–Hausman, or DWH), relying on the instruments "Imm. enclaves," "ethnic threat," "ethnic threat squared." Considering that public opinion about immigration can be influenced by integration policies, we add further 2SLS estimates interacting the instruments "ethnic threat," "ethnic threat squared" with the variable "permanent residence."

[13] The correlation between the variables **m** and **mlow** is − 0.09.

Table 6 T-SLS regressions

Variables	I[a] Coefficients (std. errors)	II[b] Coefficients (std. errors)
pop	1.097*** (0.069)	1.109***(0.072)
tertiary	0.189***(0.068)	1.166**(0.072)
predicted m	0.832***(0.139)	0.836***(0.161)
predicted mlow	− 1.43***(0.42)	− 1.801***(0.669)
No. of observations	1308	1308
Wald test	3680.78	3478.65
R-squared	0.74	0.73

[a]Instruments; Imm. enclaves, ethnic threat, ethnic threat squared; [b] Instruments: Imm. Enclaves, ethnic threat, ethnic threat squared and permanent residence. ***Significant at 1 percent level. **Significant at 5 percent level. Robust standard errors. Country and year dummies included

As we may observe in Table 3, the endogeneity tests are rejected at 5 percent level, suggesting that we may treat '*m*' and "*mlow*" variables as endogenous. To evaluate whether our potential instruments are weak, opportune test is employed. Indeed, the relevance of the instrument is assessed by evaluating the *F*-test for the joint significance of the instruments in the first-stage regression. The first-stage regression is reduced-form regression of the endogenous variable on the instrument and other exogenous regressors. A rule of thumb states that an *F*-statistic below ten is indicative of a weak instrument problem (Staiger and Stock 1997; Stock et al. 2002). Table 4 clearly shows that we have an *F*-statistic largely above the threshold value of ten.

The validity of our instruments is confirmed by Sargan Test of over-identification in Table 5.

Since the instruments are relevant and valid, we rely on T-SLS estimation in Table 6.

The IV estimation highlights (i) a positive effect of migration flows and (ii) a negative effect of low-educated migrants on innovation, proxied by the number of patents. OLS coefficients on *m* and *mlow* are biased downwards,[14] suggesting that same institutional and socioeconomic factors at regional level could both attract immigrants and promote local innovation.

Our findings display an increase of 0.83% in patenting as the result of raising the overall immigrants' share in the population by 1 percentage point. The result is much lower than the estimates (12–15%) reported by Hunt and Gauthier-Louiselle (2010) though for college immigrants in the USA. This finding is different from the one of Ozgen et al. (2012), who show that in European regions the share of immigrants does not conclusively influence innovation.

An increase in the share of low-educated immigrants by 1% determines a 1.4–1.8% decrease in patents applications. This evidence is consistent with the

[14] Similarly, Ozgen et al. (2011) found that OLS estimates were biased downwards.

result of Ozgen et al. (2013) from Dutch micro-data, which points to a reduction in the positive influence of ethnic diversity on product innovation due to a larger share of low-skilled immigrants. It seems to indirectly confirm that the increase in labor supply driven by low-skilled immigrants induces firms to adopt labor-intensive technique and to reduce skill-complementary capital (Hanson and Slaughter 2002; Lewis 2005; De Arcangelis et al. 2015). A major implication is scarce innovation. It is non-negligible the fact that low-educated immigrants may also face significant barriers to participating in the innovation process, such as language barriers, discrimination and lack of access to education and training (Ozgen et al. 2013).

Overall, while cultural diversity may contribute to innovation, the results reinforce the arguments that low-educated immigrants may hamper it. Hence, it is important to consider the complexities of this issue when designing policies allowing both high- and low-skilled immigrants to fully participate in the innovation process.

6 Concluding remarks

This paper focuses on the effects of overall and low-educated immigrants on innovation in most Western European regions (NUTS2). This issue is particularly important in Europe, where at the end of the last decade, the share of immigrant population with low education was one-third with 39% of non-EU migrants and about 26% of EU-born migrants compared to 23% of the native-born.

The important findings of our analysis are as follows: Firstly, the regions with relatively many immigrants have a positive impact on the production of patent applications; secondly, low-skilled immigrants have opposite effects on innovation. We addressed the potential endogeneity of migration flows with valid instruments, nominally immigrant enclaves, local attitudes toward immigrants and an indicator of migration policy.

Therefore, our empirical findings support the proposition in the theoretical section that lower-educated immigrants determine social decreasing returns in the economy. It is likely that the growth in labor supply due to low-skilled immigrants leads firms to make changes in the production techniques by making them more adapt to the education characteristics of labor force. The consequent adoption of labor-intensive techniques hampers innovation. This has considerable implications for Europe. As recent evidence shows, poorly educated immigrants are heterogeneously distributed across European countries and concentrated, especially in Southern Europe, Belgium and France. Hence, in these areas there could be innovation and growth at a slower rate. It may occur a certain disparity among countries with a higher level of human capital triggering a virtuous circle with social increasing returns and countries with low human capital with the opposite situation. In fact, low-educated immigrants tend to move where the demand for lower skilled jobs is higher, which is likely to further the shift toward labor-intensive techniques. On the other hand, immigrants may be trapped in low-skilled jobs with poor earnings and social mobility. In this respect, given that political instability and warfare are likely to feed growing waves of young and low-educated immigrants (Bratti et al. 2018), an in-depth understanding of the relationship among human capital formation, labor markets and migration in receiving countries would help. In general, integration programs providing support and training to new arrivals should aim to balance the needs of immigrants with the development needs of different European geographical areas.

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Data availability Data are available upon request.

Declarations

Conflict of interest We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all the authors. We declare that there is no conflict of interest.

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