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RESEARCH ARTICLE

Knowledge spillovers through high-skilled migration network: evidence from OECD countries

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ABSTRACT

We investigate the role of international high-skilled migrants in diffusing innovation from origin to destination countries by assessing their impact on the production of knowledge in host countries. Since better innovation performances can be mechanically correlated with a larger presence of high-skilled immigrants, we propose a new identification strategy to account for migrants' self-selection into the migration network and sort out potential endogeneity bias. Our results, tested on a panel of 20 OECD countries (1987–2016), show that i) high-skilled migration magnifies the effect of internal knowledge in improving national innovation performances (while middle- or low-skilled migration flows have no statistically significant effect); ii) knowledge spillovers are stronger if origin and destination countries assign similar share of their public R&D budget across the same technological fields; iii) the contribution of high-skilled migrants is most valuable when host countries are relatively lagging behind in active research and innovation policies.

KEYWORDS

Innovation; international migration; knowledge diffusion; network; research policy

JEL CLASSIFICATION

O15; O33; O38; F22

1. Introduction

High-skilled immigrants bring 'upper-tail' human capital to host countries and can significantly contribute to their innovation and technological progress (Akcigit, Grigsby, and Nicholas 2017; Squicciarini and Voigtländer 2015). Prominent examples of the role played by foreign-born expertise in this context are largely discussed in the literature (Becker et al., 2024; P. Moser, Voena, and Waldinger 2014; Waldinger 2016). Starting from these anecdotes, this paper provides a systematic inquiry on the contribution of high-skilled immigrants in pushing the national frontier knowledge of their host country. National innovation is driven by both internal and external knowledge, differently combined according to the specific features and structure of the domestic economic system. Given a certain degree of internal technological capabilities, literature has mostly focused on the role played by external knowledge conveyed by means of technological distance (Jaffe 1986), trade agreements and flows (Coe and Helpman 1995) and foreign

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direct investments (Keller 2001). In this paper, we build on an emergent strand of research highlighting the role of international migration as a channel of diffusion of external knowledge to receiving countries (Breschi et al. 2020; Lissoni 2018; Ozgen 2021).[1] Previous empirical studies in this line of research already provided evidence that migrants contribute to the innovation performances of a country by increasing patent applications (Fassio, Montobbio, and Venturini 2019; Kerr and Lincoln 2010; Perez-Silva, Partridge, and Foster 2019) and inventions (P. Moser, Voena, and Waldinger 2014), improving the productivity of scientists (Borjas and Doran 2012; Bosetti, Cattaneo, and Verdolini 2015) and firms (Doran, Gelber, and Isen 2022), providing skilled workforce (Kerr 2017), favouring cultural diversity and creativity (Alesina, Harnoss, and Rapoport 2016; Ferrucci and Lissoni 2019), and diffusing knowledge (Hunt and Gauthier-Loiselle 2010).

The set of interpersonal ties that connect migrants in origin and destination areas generates a network where each node indicates a place, and one edge connecting two nodes registers the number of people moving from one place to another. Motivated by this, research approached the study of migration-driven diffusion of innovation exploiting a gravity-based framework, facilitated by the increasing availability of dyadic migration data (Cappelli and Montobbio 2016; Kerr 2008; MacGarvie 2005; Peri 2005). In this paper, we build on previous studies to investigate the role of the migration network as a mean for facilitating the diffusion of innovation. In doing so, we are motivated by the recent literature on gravity models of international migration (e.g. Beine, Bertoli, and Fernàndez-Huertas Moraga 2016), giving relevance not only to the costs of moving from one country to the other, the so-called bilateral resistance to migration (i.e. the one exclusively related to the characteristics of country i and country j involved in the bilateral migration flow), but also and primarily to the implicit cost of potential alternative destinations, the so-called multilateral resistance to migration (Bertoli and Moraga 2013).

More specifically, we propose a model where the innovation performance of a country is determined by both its domestic efforts to advance the internal knowledge (mainly represented by the domestic public R&D expenditures) and the external knowledge conveyed by high-skilled immigrants (i.e. the skills and competences they learned at home). In a recursive fashion, the performance of the origin countries of high-skilled immigrants is also determined by their internal efforts, and the external knowledge conveyed by their high- skilled immigrants. The benefit of this modelling approach is that it allows to formalise the spillover effects stemming from the innovation advances of a country, diffused to other countries through the international network of high-skilled immigrants, and absorbed through the internal knowledge base of the host country (i.e. national absorptive capacity). This approach also allows to test whether the effect of the internal knowledge in a country on its innovation performance is magnified by the innovation performance of network-connected foreign countries. Conveniently, this model can be expressed as a spatially auto-regressive system of equations, where the innovation outcome of a country depends on its expenditures on R&D, additional

[1]A related field of research also looks at the reverse diffusion of innovation from the destination to origin country (e.g. the implications for the migration-sending countries, risk of brain drain, or reverse knowledge flows) but this is outside the scope of the present work. See, for example, Miguelez and Temgoua (2020).

national characteristics and its (Katz-Bonacich) centrality in the network of high-skilled migrants.

Disentangling the effect of immigration on the innovation performance of a country is not an easy task. Migrants self-select into countries providing them with better opportunities in terms of work and living conditions (Borjas 1987, 1991). For high-skilled migrants, these countries correspond to those featuring relatively higher innovation performances. It follows that a better innovation performance in one country can be mechanically correlated with a higher presence of high-skill immigrants but not necessarily be determined by it. This problem of endogeneity is well-known in the literature on migration (Borjas 2014), and numerous identification strategies have been proposed over the years to overcome this issue (Batista, McIndoe-Calder, and Vicente 2017; McKenzie, Stillman, and Gibson 2010; P. Moser and Parsa 2020; P. Moser, Voena, and Waldinger 2014; Parey et al. 2017). In this paper, we propose a new identification strategy based on a control function approach specifically suited to deal with network data.

Intuitively, our procedure works in three steps. First, we use a dyadic model in a gravity- like fashion to predict the number of immigrants received by one country on the basis of the difference between its characteristics and the characteristics of other countries. Second, we compute the difference between the actual and the predicted number of immigrants in that country. This residual value is considered a measure of everything that we cannot explain about the presence of immigrants in the country: i.e. the unobserved drivers of their choice to relocate there, including those correlated with the economic and the innovative performance of the country. Third, we include this value in our network model, in order to control for migrants' self-selection, sort out endogeneity concerns, and make sure to correctly assess the impact of the migrants' network on the country's performance.[2]

We test our model using a panel of 20 OECD countries from 1987 to 2016,[3] and we assess the extent to which national innovation performance (proxied by each country's number of registered triadic patents) is magnified by the innovation performance of network-connected foreign countries. The main mechanism at work here is that skilled migrants bring with them specific expertise learned at home and transfer these capabilities to the country they migrate to. They contribute to the host country's innovation performance either by directly driving innovation, by fostering origin-host and international collaborations, or by stimulating host innovation through the access of natives to immigrants' origin-specific knowledge (Wigger 2022). However, integrating migrants' skills requires some pre-existing knowledge base available in the host country (Caviggioli, Jensen, and Scellato 2020). Notably, the host country's capacity to absorb knowledge and technologies (i.e. its national absorptive capacity) is shaped by the quality of its labour force and R&D activities (Abramovitz 1986). This capacity also plays a crucial role in facilitating the uptake of international knowledge spillovers generated by labour mobility (Migu´elez and Moreno 2015). Indeed, when the skills of highly skilled migrants are successfully absorbed and combined with existing domestic expertise, we expect

[2]Observe that this control function approach is identified even without exclusion restrictions. Identifica- tion, in this case, exploits non-linearities specific to the network structure of the model adopted in the first stage. In fact, the dyad-specific regressor terms contained in the gravity-like model do not appear in the model adopted in the last stage.

[3]Observe that this sample represents more than half of the OECD countries and about 75% of the total GDP of countries in this group.

a positive knowledge spillover effect, strengthening the host country's national innovation capacity and boosting its overall innovation performance. Accordingly, our first research hypothesis (RH) can be summarised as follows:

RH1: *External knowledge conveyed by high-skilled migrants has a positive effect on the innovation output in the destination country.*

Previous studies have shown that technological similarity facilitates knowledge diffusion, mostly because learning from similar technology is easier (or less costly) and opportunities for innovation spillover are stronger across less distant technological trajectories (Atkinson and Stiglitz 1969; Dosi 1988; Malerba, Mancusi, and Montobbio 2013). This is consistent with the idea that the role of migrants in boosting innovation spillover from the origin and destination countries is stronger if both countries specialise in related technological fields (Bahar, Choudhury, and Rapoport 2020; Miguelez and Temgoua 2020).[4] In such cases, the host country's absorptive capacity provides greater opportunities for high-skilled migrants to create synergies (Drivas et al. 2020). Along these research lines, we investigate if similar priorities pursed by the two countries within their national research and innovation policy framework affect the benefits arising from the absorption and recombination of knowledge spillovers. More specifically, we look at how governments allocate their R&D budget across different socio-economic fields[5] and test if the impact of foreign innovation policies is stronger/weaker depending on how similar the origin and host countries are in allocating their R&D budget to different missions. This leads to our second hypothesis:

RH2: *The indirect positive effect of external R&D expenditures on internal knowledge via high-skilled immigrants is stronger when host and origin countries have a high field-proximity in research and innovation policies.*

Finally, we remove the assumption that all countries benefit equally from the external knowledge conveyed by high-skilled immigrants and test if the innovation spillovers are heterogeneous depending on the host country characteristics. To test our third research hypothesis, we examine whether absorptive capacity has a non-linear influence on the relationship between high-skilled migration and innovation. Indeed, diffusing, absorbing and translating knowledge into innovations becomes more difficult as the complexity of the embedded knowledge increases, and the scope for learning from other countries may decrease at high level of absorptive capacity (Filippetti, Frenz, and Ietto-Gillies 2017). As Criscuolo and Narula (2008) high- light, countries approaching the technological frontier experience a decline in their ability to absorb foreign knowledge if compared to the more rapid technological accumulation experienced in catching-up phases. Similarly, Mancusi (2008) shows that greater absorptive capacity enhances the responsiveness of lagging countries' innovation productivity to international spillovers, while its marginal effect is negligible for countries at the technological frontier.

Since innovation is expensive to produce but cheap to reproduce (NBER 1993), this evidence suggests that the processes of learning from others' knowledge, facilitated by the

[4]For example, Bahar, Choudhury, and Rapoport (2020) (p. 14) find that 'a twofold increase in the number of inventor immigrants can explain an increase of 25–60% in the likelihood of gaining technological advantage in the same technology in which the inventors' home countries specialise.'

[5]Public research and innovation policy fields here considered are: Environment, Space, Defence, Energy, TTI (Transport, Telecommunications and other Infrastructures), IPT (Industrial Production and Tech- nology), General Advancement of Knowledge from General University Funds, General Advancement of Knowledge from other sources.

skills and competencies provided by external drivers, such as high-skilled immigrants, can significantly benefit countries with larger space for learning. Conversely, these benefits are subject to diminishing marginal returns as the absorptive capacity of national innovation systems reaches its limits. While we cannot determine why migrants should move to such countries (as the drivers of migrant relocation are modelled as an omitted variable in our analytical framework), we can assess how their presence influences the national innovation system when they are found there, also accounting for host countries' absorptive capacity. Accordingly, we argue that:

RH3: *The external knowledge conveyed by high-skilled migrants provide a stronger contribution in host countries lagging behind in active research and innovation policies.*

The rest of the paper is developed as follows: Section 2 introduces the network methodology implemented in the econometric estimation[6]; Section 3 describes the data and variables considered in the econometric estimation; Section 4 describes the empirical results; Section 5 concludes.

2. Empirical model

We propose a model of national innovation, where the innovation performance of country i at time t ($y_{i,t}$), proxied by its number of registered triadic patents, is determined by its national efforts to advance internal knowledge here measured in terms of Government R&D budget ($KNint_{i,t}$) and its external knowledge. This latter factor is obtained as a weighted sum of the innovation performance produced by i 's network-connected countries, with weights measuring the percentage of immigrants received by i from each of these countries ($g_{i,j}$).

Formally, the model takes the form[7]

$$ln\left(y_{i,t}\right) = \beta ln\left(KNint_{i,t}\right) + \phi_{j=i}^{I} g_{i,j,t} ln\left(y_{j,t}\right) \tag{1}$$

where ϕ is the measure of the effect of i's external knowledge on its innovation performance: i.e. the spillover effects stemming from the innovation advances of i's network-connected countries and conveyed by immigrants.

Identification strategy. A problem with the identification of the effect of the external knowledge of country i (ϕ) on that country's performance ($y_{i,t}$) is that migrants self-select into i for many reasons: e.g. because their origin country and i share similar technological similarities. If we neglect to consider these reasons, the estimation of ϕ becomes problematic, because if we find a positive and statistically significant correlation (i.e. $\phi > 0$) between i) the presence of migrants from j in i, and ii) the performance of i, we cannot claim that this is (at least in part) due to the presence of these migrants. The high performance of i can be what is causing the presence of migrants from j, and not vice-versa.

In order to deal with this issue, we use an empirical strategy which allows us to assess the impact of knowledge spillovers generated by migrants on a national innovation

[6]See Section A.1 in Appendix for the full description of the model.

[7]For the sake of simplicity, we omit other terms included in the model specification that we adopt in our empirical analysis. These are: a factor common to all countries (δ), time-varying country-specific characteristics ($X_{i,t}$), unobserved time-invariant factors controlled using country (η_i) and time (ι_t) fixed effects, and an idiosyncratic factor ($u_{i,j}$).

system regardless of the reasons why they are found there. Specifically, these reasons are modelled as an omitted variable of our analysis, and dealt with an ad hoc strategy building on a standard control function approach a l`a Heckman. While we relegate to the Appendix the technicalities of this empirical strategy, we offer here the intuition behind it.

Suppose that we observe (or can measure with data) some but not all the reasons why migrants move to i, and define with Z the set of observed and measurable reasons for migrants to move, and with W the set of reasons that are unobserved or for which data is lacking. Now consider the following model, a standard gravity model where the probability for migrants to move from origin j to i, i.e. $g_{i,j}$, is a function of the many reasons why migrants decide to relocate in one place, such as the difference/similarity in characteristics between their origin country and the destination. Some of these characteristics are observable and can be operationalised with available data, thus they are denoted with Z. Other characteristics, instead, are not available, and they are denoted with W. The probability for migrants to move from j to i thus takes the form:

$$g_{i,j,t} = Z + W + u_{i,j,t} \tag{2}$$

where $u_{i,j}$ is all that we cannot explain about the migration choices from j to i.[8]

Now, because W is unobserved, Equation 1 cannot be estimated. What we can estimate instead is:

$$g_{i,j,t} = Z + \varepsilon_{i,j,t} \tag{3}$$

where $\epsilon_{i,j,t} = W + u_{i,j,t}$.

If we repeat this operation for all the j countries from which migrants can potentially reach i, we can calculate:

$$\xi_{i,t} = \overset{I}{\underset{j=i}{}}\varepsilon_{i,j,t}$$

where $\xi_{i,t}$ is a measure of all the reasons why migrants from the j^{th} country choose i as a destination that are unobserved (falling either in the set W or $u_{i,j}$).[9]

When we include $\xi_{i,t}$ into the specification of our model of national innovation Equation 1, we are thus able to control for the mechanical correlation that exists between i) the presence of migrants from j at destination i, and ii) the performance of destination i. This is for instance the case when highly skilled migrants are present at destination i because both i and j have an advanced technological profile, and they both have a high performance.[10]

Put differently, $\xi_{i,t}$ works as a measure of self-selection bias, and when included in the model of national innovation, it allows us to assess the effect of the external knowledge of

[8]Observe that this model is affected by an omitted variable problem, because W is unobserved. It follows that estimates from this equation from cannot be used to correctly study the drivers of migration. However, as we will explain the following, this does not represent a threat to our identification strategy.

[9]This interpretation of ξ_i is possible under a number of assumptions, which we omit here, but they are detailed in the appendix.

[10]It should be clear by now that Equation 2 only serves the purpose to estimate ξ_i, in order to correctly conduct inference in the national innovation model. It follows that Equation 1 is identified whether or not Equation 2 suffers from an omitted variable problem. In a robustness check however, we augment the model specification in Equation 2 with additional control variables (the amount of inward FDI and total trade flows between the two countries). As expected, all our results are qualitatively unchanged.

i on its outcome above and beyond the mechanical reasons why migrants from j are located in i. Since this solution offers us the opportunity to correctly assess the effect of the external knowledge in the national innovation of a country, we augment Equation 1 in the following way:

$$ln(y_{i,t}) = \delta + \beta ln(KNint_{i,t}) + \phi^{I}_{j=1} g_{i,j,t} ln(y_{j,t}) + \psi \xi_{i,t} \tag{4}$$

where ξ is the measure of migrants' self selection bias.

Estimation and interpretation of the model. Equation 4 represents the structural form of our model of national innovation. In order to estimate it, we rearrange the terms to obtain its reduced form, that is[11]

$$ln(y_t) = (I - \phi G)^{-1}(\beta ln(KNint_t) + \psi \xi_t) \tag{5}$$

where G is a matrix where the generic i, j^{th} cell registers the migration flows $g_{i,j}$ connecting country j to country i (in year t) in the high skilled migration network.

The reduced form of the national innovation model (Equation 5) provides an important intuition on the mechanism through which the external knowledge conveyed by migrants contributes to the national innovation of migrants host countries. To understand this, consider the term $(I - \phi G)^{-1}$. The literature refers to the term $(I - \phi G)^{-1}q$ (with q being a generic vector) as to Katz-Bonacich centrality (Bonacich 1972, 1987; Katz 1953), because it approximates the number of all countries that can be reached by country i through a direct or indirect path in the network, penalising through the parameter ϕ the contributions of distant countries.[12]

In other words, in our model of national innovation, the impact of external knowledge on i's national innovation depends on the degree of exposure of i to the spillover effects flowing in the international high-skilled migration, or, put more simply, its centrality in the network. Specifically, the literature refers to the term $(I - \phi G)^{-1}q$ as to Katz-Bonacich centrality (Bonacich 1972, 1987; Katz 1953).

From a theoretical standpoint then, our model predicts that the national innovation performance of a country is a weighted measure of its Katz-Bonacich centrality in the international high-skilled migration network, with weights given by its characteristics, i.e. its internal knowledge. The intuition behind this model is that the national innovation of a country depends on both its internal knowledge and its position in the network, and the extent to which a country benefits from its position in the network is determined by the term ϕ, that is the measure of the exposure to the external knowledge conveyed by immigrants (i.e. the spillover effects).

Importantly, we stress that in this formulation of the national innovation model, the traditional linear regression model is nested. In fact, if spillover effects are not at play (i.e. external knowledge conveyed by migrants has no statistically significant impact on the national performance of a country), then $\phi = 0$, and the model becomes $ln\ (y_{i,t}) = \beta\ ln(KNint_{i,t})$, where the innovation performance of the country is only determined by its internal knowledge.[13]

[11]Obtaining this reduced form from Equation 4 requires a number of assumptions that are discussed in the appendix.:
[12]Additional details on this interpretation of the term $(I - \phi G)^{-1}$ are provided in the appendix
[13]For more details about the reason why the linear model is nested in Equation 5 see the appendix.

Disentangling the effect of internal and external knowledge. Estimated coefficients from Equation 4 cannot be directly interpreted as in the case of a traditional linear regression. The reason is that they represent a combination of the impact of the advances in the internal and external knowledge of a country on its innovation performance. In other words, the estimated coefficient of the generic variable k is a combination of: i) the direct impact of an increase of k by i on its outcome, and ii) the indirect impact of an increase of k by countries other than i on i's outcome. Formally, the estimated effect of k is:

$$\overline{M}_{tot}^{k} = \frac{\widehat{\beta_k}}{1-\widehat{\phi}}$$

where $\beta\hat{}_k$ and $\hat{\phi}$ are the estimated coefficient associated to, respectively, k and the spillover effects obtained from the estimation of Equation 4.

In order to single out the direct impact of an increase of k by i on its outcome, i.e. the effect of an advance in the internal knowledge of a country on its innovation performance, one needs to compute the average marginal direct effects of k on Y, that is:

$$\overline{M}_{dir}^{k} = n^{-1}tr[\frac{I\widehat{\beta_k}}{I-\widehat{\phi}}]$$

Finally, the indirect impact of an increase of k by countries other than i on i's outcome, that is the impact of the external knowledge advance determined by k on i is simply:

$$\overline{M}_{\text{ind}}^{k} = \overline{M}_{tot}^{k} - \overline{M}_{dir}^{k}$$

which formally indicates the average marginal indirect effects of k on Y.

Modelling heterogeneous spillover effects. In Equation 4, we implicitly assume that the impact of the external knowledge on a country's performance is equal regardless of the characteristics of the country: i.e. all countries benefit in the same way from the innovative performance of other countries conveyed by high-skilled immigrants. However, it is plausible to expect that some countries may benefit more than others from the presence (and competences) of high-skilled immigrants, that can be modelled in empirical terms with the parameter ϕ being not homogeneous for all countries.

In order to test the effect of a country's characteristic on its ability to benefit from the external knowledge conveyed by migrants, and consequently to test **RH3**, it is possible to expand our model in the following way:

$$lnY = (I - \theta\Lambda G)^{-1} \times \left(\delta + \beta_1 lnKNint + \beta_2 lnX + \psi\xi + u\right) \tag{6}$$

where Λ is a n x n identity matrix and $\theta = \phi_{baseline} + \phi_{host} \times z$.

Here, the term ϕ_{baseline} registers spillover effects common to all countries, i.e. the baseline effect, while ϕ_{host} quantifies the extent to which a country benefit more (or less) from spillover effects given characteristic z, i.e. the heterogeneous spillover effects that depend from the characteristic of the country.

Table 1. Data sources of variables and networks.

Variables	Indicators	Sources
Dependent Variable	Total patents TRIADIC per million population	OECD Patstat
Independent Variables	Government Budget Allocation for R&D (GBARD) stock over GDP GDP per capita High-skilled employment share over population	OECD Science, Technology and Patents OECD National Accounts ILOSTAT
Interaction Variables	Business Expenditure in R&D (BERD) stock over GDP General Expenditures in R&D (GERD) stock over GDP Dummy median GERD Total Economy Researchers over population	OECD Science, Technology and Patents OECD Science, Technology and Patents OECD Science, Technology and Patents OECD Science, Technology and Patents
Network (G)	High-skilled migrants flow Medium-skilled migrants flow Low-skilled migrants flow High-skilled migrants flow weighted with GBARD proximity Medium-skilled migrants flow weighted with GBARD proximity Low-skilled migrants flow weighted with GBARD proximity	Institute for Employment Research (IAB) Institute for Employment Research (IAB) Institute for Employment Research (IAB) IAB and OECD Science, Technology and Patents IAB and OECD Science, Technology and Patents IAB and OECD Science, Technology and Patents

3. Data and variables description

We test our model in an empirical exercise based on a panel database of 20 OECD countries, in the time span from 1987 to 2016.[14] In what follows, we describe in detail the variables and migration networks introduced in our empirical analysis. We report in Table 1 at the end of this section, the summary of variables, networks and data sources, and in Table A1 in the Appendix of summary statistics.

3.1. Dependent variable

We follow a standard approach in economics of innovation, and largely used also in innovation- migration studies, and use patent statistics to measure countries' innovation performances (Bahar, Choudhury, and Rapoport 2020; Kerr 2008; Kerr and Lincoln 2010; P. Moser, Voena, and Waldinger 2014; Nagaoka, Motohashi, and Goto 2010). More specifically, we use triadic patents applications (classified by priority year and inventor's countries of residence), which include all inventions filed at the three major patent offices: the European Patent Office (EPO), the Japan Patent Office (JPO) and the United States Patent and Trademark Office (USPTO).

Several reasons make triadic patents peculiar. First, patents grant the monopoly rights and legal protection for the invention only in the country in which the patent has been filed. Hence, to acquire the right to exploiting the invention in additional countries, patent must be filed at each patent office, at additional costs. The fact that a triadic patent has been filed at the three major patent offices at the world level reflects the higher quality of the innovation and its greater potential economic value, i.e. higher commercial use (Kortum 1997), higher citation impact than ordinary patents (Ferrucci and Lissoni 2019;

[14]The 20 countries included in the analysis are: Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and USA. The selection of countries is primarily driven by the availability of bilateral high-skilled migration data.

Sternitzke 2009). For these reasons, triadic patents are referred to as inventions of higher technical value, better technological performances (Walsh, Lee, and Jung 2016) and wider international market perspectives (De Rassenfosse et al. 2013). As a result, they can be used as a general quantification of the profitable outcome of investments in innovation-related activities (Baudry and Dumont 2006). Second, patent filed to an individual patent office is usually subject to a 'home advantage' effect (Criscuolo 2006), e.g. innovations are almost always filed at the patent office of the inventors' home country. Conversely, triadic patent statistics are better suited for international comparison of innovation performances and to evaluate national relative technology competitiveness (De Rassenfosse and de la Potterie 2009). As a standard procedure, we express our dependent variable in terms of number of patents per capita (per million population) to control for the different sizes of each country. In so doing, we are able to assess the role of high-skilled migrants and their relative characteristics explained by their countries of origins in the same vein of the recent empirical studies on the interplay between patent-based innovation performance evaluation and migration routes and qualifications (Fassio, Montobbio, and Venturini 2019; Pinate et al. 2023).

3.2. Explanatory variables

The inputs of a knowledge production function typically include the amount of resources devoted to R&D activities. In our country-level analysis, we look at the role of public innovation policies and focus on the Government Budget Allocation for R&D (GBARD) statistics provided by the OECD. GBARD measures all R&D activities financed by the public budgets and performed in government establishments, business enterprises, private non-profits and higher education sectors.[15]

GBARD is distributed according to the mission of the specific activities, following a classification of socio-economic objectives (SEOs), which represents cross-cutting technology fields driven by political priorities. In our data, the GBARD statistics distinguishes eight SEOs: Environment; Space; Defence; Energy; Transport, Telecommunications and other Infrastructures (TTI); Industrial Production and Technology (IPT); General Advancement of Knowledge from General University Funds; General Advancement of Knowledge from other sources. Our primary measure for testing **RH1** includes the overall amount of GBARD, but we further exploit the differences in SEOs budget allocation across countries for testing **RH2**. We assume knowledge to cumulate with an obsolescence rate represented by the discount procedure according to the Perpetual Inventory Method (PIM) suggested by OECD (2009), taking an average discount rate d of 15% applied to GBARD expenditures for computing a stock measure of the public innovative efforts, rescaled for GDP to control for the different economic size of each country (Marrocu, Paci, and Usai 2013). Accordingly, the final formulation for our main regressor of interest for country i at time t is given by:

$$GBARDstock_{i,t} = \frac{L_{t_{s=0}}\left(GBARD_{i,s} \times e^{-d(t-s)}\right)}{GDP_{i,t}} \tag{7}$$

[15]According to Mowery (2009), GBARD can be considered a proxy for public innovation policies mainly focusing on breakthrough technologies, e.g. mission-oriented innovation policies (Ergas 1987).

In addition to the R&D input, we include further explanatory variables as proxy of internal knowledge (i.e. $X_{i,t}$ in Equation 4). First, in line with Furman, Porter, and Stern (2002), we introduce GDP per capita to capture the capability of a country to convert its internal knowledge stock into an accomplished state of economic development, also interpreted as a measure of a country's technological sophistication.[16] Second, we control for the ratio between high-skilled employment and population, as a proxy for the endowment of domestic human capital and the country's absorptive capacity to learn and imitate foreign advanced technologies (Verspagen 1991). We acknowledge that the use of country-based data strongly reduces the possibility to exploit more fine-grained labour market databases, as those used to assess the role played by the evolution of skills into the job market to explain the capacity of workers to reorient in the direction of high-value job placement (Consoli et al. 2021, 2023). Nonetheless, the empirical method here developed could be further enriched by the use of subnational labour market statistics in future research work.

3.3. Migration network

To analyse the knowledge spillovers due to skilled workers' mobility, we account for measures of bilateral international migration provided by the *Institute for Employment Research* (IAB) *brain-drain dataset* (Brücker, Capuano, and Marfouk 2013).

The *IAB brain-drain data* contains information on the total number of foreign-born individuals aged 25 years and older living in each host country. The dataset covers international migration related to 20 OECD countries for the years 1980–2010 with 5-years intervals.[17]

Foreign-born individuals are divided by gender, country of origin and education level. Crucial to our analysis is that the educational level is distinguished among low, medium and high: low-skilled migration includes migrants with lower secondary, primary education and no schooling; medium-skilled includes migrants with high-school certificate or equivalent; and high-skilled migration includes migrants with a certificate higher than the high-school. It follows that in our study, high-skilled migrants are individuals who have obtained a certificate from an institution that is higher than high school in their home country, and then move to a different (foreign) country. This implies that our data on high-skill migrants do not comprise the number of migrants moving for tertiary education (to develop their skills and knowledge in the destination country rather than the origin country). By focusing on this specific subset of migrants, we aim to capture individuals who have already acquired advanced competences learned in their home country before migrating.[18]

[16]GDP per capita and all other economic aggregates are expressed in US$ at constant 2015 prices and constant PPP.
[17]Missing data for few specific years and countries have been handled with a multiple imputation technique according to Honaker and King (2010).
[18]Of course, we recognise the diversity within this migrants' population, which may as well include those who may move for further training or education in the destination country (e.g. PhD students), but of course we do not expect them to represent a significant portion of this population. In general, we expect migrants in search of receiving further training to be those migrants with high-school certificate or equivalent, which are registered by a different data source used in our analysis: that relative to medium-skilled migrants. Importantly, our evidence indicates no statistically significant effects associated to this group of migrants (who includes those moving for education or further training). Of course, this corroborates the fact that our analysis primarily captures the contributions of migrants with already acquired skills and knowledge.

Accordingly, we use the *IAB brain-drain data* to operationalise our matrix G_t recording the bilateral high-skilled migration network. We assume that the number of migrants moving across countries is homogeneously distributed within each 5-years period and, following the approach by Beine, Bertoli, and Fern´andez-Huertas Moraga (2016), we express the connections in matrix G_t in terms of flows, i.e. the number of high-skilled migrants which move from the origin country j to the host country i at time t. Furthermore, the matrix G_t is normalised such that the generic connection $g_{ij,t}$ represents the percentage of high-skilled migrants moving from the origin country j to the host country i at time t, with respect to the overall number of high-skilled migrants which reach country i from all other origin places.[19]

We assume that the flow of knowledge embedded in skilled migrants is the channel which can magnify the stock of internal knowledge in host countries, leading to an increase of their national innovation performances. Conversely, we should expect that the flows of medium- and low-skill migrants do not affect host countries' innovation performances. Hence, our primary focus is on high-skill migration data, but we also compute the medium and low- skilled migration networks. Indeed, by exploiting the full set of information available in the *IAB brain-drain data* we can conduct a placebo test on **RH1**.

Moreover, in **RH2,** we test whether the contribution of external knowledge to the national innovation performance is affected by the similarity between migrants' origin and host countries in terms of the technological and socio-economic priorities pursed through their innovation agenda. The main explanation behind this mechanism is that the similar (internal) knowledge in countries i and j facilitates knowledge recombination into the host country i. In other words, since high-skilled immigrants bring with them specific skills and competences, we test whether the recombination of these skills with those available in the host countries is affected by the similarity between the two countries in the way the public R&D budget is allocated across different socio-economic objectives.

To this aim, we construct a pairwise indicator to measure how similar/distant two countries are in allocating their public R&D budget across the eight socio-economic objectives. We follow the approach of Marrocu, Paci, and Usai (2013) and build a proxy for technological distance based on the Herfindahl – Hirschman index and applied to the GBARD indicator. In analytical terms:

$$GBARDproximity_{i,j,t} = 1 - \frac{1^{k=8}}{2_{k=1}} \left| GBADsh_{i,k,t} - GBARDsh_{j,k,t} \right|^{!} \tag{8}$$

[19]When working with spatial autoregressive models such as Equation 4, the normalisation of the matrix has the desirable property to ensure the feasibility of the model estimation. In addition, the normalisation adopted here is convenient because the exposure of a country to the external knowledge of another country is expressed in relative terms, making it easier to model situations when a country is expected to provide the same (relative) contribution to the internal knowledge of different countries: e.g. if high- skilled migrants from country *i* represent 50% of the high-skilled migrant population in country *j* and *k*, the relative contribution of *i* to *j* and *k* is the same. The drawback of this approach is that one cannot account for the absolute impact that a country exerts on the internal knowledge of other countries: e.g. even if the percentage of high-skilled migrants received by *j* and *k* from *i* is the same, their number can be different, and this may result in a different contribution that *i* will provide to *j* and *k*. Clearly, the easiest solution to this problem is to include a control for the total number of high-skilled immigrants within a country into our model specification. In footnote (21), we discuss how our results are robust to the inclusion of this variable.

where $GBARD\ sh_{i,k,t}$ ($GBARD\ sh_{j,k,t}$) is the share of R&D devoted to the specific socio-economic objective k in country i (j) at time t. The index varies between 0 and 1, and higher values signal that the two countries are more similar in their GBARD distribution across objectives.

We then use the *GBARD proximity* between each country pair to weight the international migration flow network, thus accounting for the similarity among the public expenditures specialisation across socio-economic objectives and technologies. If compared to the original matrix G, in this network the connection between a pair of countries is stronger than that registered in the original high-skilled network if the two countries pursue similar goals in the definition of their innovation policies. Conversely, their connection is weaker if the two countries prioritise different goals in the definition of the government R&D budget. By doing so, we implicitly assume that high-skilled migrants may play a stronger role in the innovation performance of the host country if their home and host countries have similar innovation policies.

3.4. Drivers of heterogeneous spillover effects

To test **RH3** and verify whether the magnitude of the spillover effects is heterogeneous depending on the characteristics of the country i hosting the high-skilled migrants, we collect additional indicators measuring the (private, public and relative) strength of i's national innovation system.

First, we introduce Total Business Expenditures in R&D (BERD) to account for the role of the private sector in the design of the technological trajectory of the national system. Second, to account for the total expenditures in R&D of a country, we replace the GBARD variable with the General Domestic Expenditures on R&D (GERD), which aggregates government, business enterprises, higher education and private non-profit R&D expenditures. For both GERD and BERD, we follow the same approach described for the variable GBARD: we take the R&D stock as in Equation A.6 rescaled for the country's GDP. In addition to the overall amount of GERD, we also introduce a variable capturing the (relative) countries' commitment to invest in innovative activities. This is operationalised by comparing the share of GDP that each country devotes to GERD with respect to the other countries in the sample. In analytical terms, we compute a dummy variable which is formulated as follows:

$$Dummy\ median\ GERD \begin{matrix} GERD_{i,t} > median\ GERD_t, x = 1 \\ GERD_{i,t} < median\ GERD_t, x = 0 \end{matrix} \tag{9}$$

where if a country i at time t features a value higher than the median in the sample, we assign 1 and 0 otherwise. Finally, the last variable we include is the ratio between the number of researchers over the total population, as an additional proxy of domestic human capital and high-skilled workers in contributing to the system of innovation (Wang 2010).

These four indicators are entered one by one in the model described in Section 2 and correspond to the characteristics z upon which we test whether the impact of the external knowledge made available by high-skilled immigrants is heterogeneous across countries. We observed that, given the structure of the empirical model, when estimating Equation A.6 the role of the generic characteristic z will be captured by two terms: the estimated coefficient (similarly to any other explanatory variable) and the sign and magnitude of ϕ_{host}.

4. Empirical results

In this section, we present our main results obtained from the estimation of Equation 4. To sort out the reverse causality issues, all control variables and the network G are entered in the model with a lag of 1 year. Estimates presented in Table 2 allow us to discuss our first research hypothesis (**RH1**) about the role played by high-skilled migrants in enhancing national innovation performances.

In Column (1), we estimate our main model specification, where changes in the internal knowledge of a country are measured by the stock of public expenditures in R&D ('GBARD stock') and GDP per capita. Our results indicate that the estimated coefficient associated with these variables are both positive and statistically significant: e.g. an increase in public R&D expenditures and in GDP per capita corresponds to an increase in the number of triadic patents in one country. Importantly, we find that the effect of these variables is magnified by the external knowledge conveyed by high-skilled immigrants.[20] In fact, the spillover effect ϕ is positive and statistically significant, indicating that being more central (i.e. having a higher Katz-Bonacich centrality) in the high-skilled migration network has the effect to improve national innovative performances, fully confirming **RH1**.[21] Moreover, we note that the correction term used to sort out the selection bias in our model, ξ, indicated with the term *Unobservables*, is also statistically significant. This implies that if estimates are obtained neglecting this term they would be affected by an endogeneity problem, and the correct identification of the spillover effects would be at risk.[22]

In Column (2), we extend our model specification by including a variable measuring the percentage of high-skilled employment in the country's population. This is a proxy of human capital used to control for the country's ability to imitate and absorb foreign technologies. We find that our results are qualitatively unchanged, reinforcing our findings on **RH1** confirmation. We also observe that, in line with theory, the variable

[20]Since many of the countries included in our sample belong to the Schengen area, one might fear that our results are simply explained by the mechanic correlation that exists between movement of migrants in this area, and its large innovation performance. If this is the case, then by including a Schengen area fixed effect into our model specification, this should be collinear with the parameter of the model registering the effect of the migration network (ϕ). As a result, this latter effect should become not statistically significant, or at least be significantly reduced. In a robustness check, we test this hypothesis. Reassuringly, when accounting for the Schengen fixed effect all our previous results are confirmed. In particular, the coefficient associated to the spillover effects is positive and large in magnitude. This is suggestive evidence that our results are not driven by the composition of our sample. Results are available upon request.

[21]As anticipated in footnote (19), one may question whether our results may be biased by the fact that exposure to external knowledge is modelled in relative and not in absolute terms in matrix G. As indicated there, the solution to this issue is to include a control for the total number of high-skilled immigrants within a country into our model specification. Unfortunately, this exercise bears a number of difficulties. First, the total number of high-skilled migrants in a country is strongly correlated with the variable 'High-skilled employment/Population'. Second, this variable is endogenous in our model, because it is mechanically correlated with the number of 'Total Patents per capita' in a country, i.e. the dependent variable. Nevertheless, we tested the robustness of our results to the inclusion of this variable into our model specification. Reassuringly, all our results remain qualitatively the same. However, since this variable falls into the category of 'bad controls', we prefer not to use it into our preferred model specification, and results are made available upon request.

[22]The model specification adopted to compute the term ξ (see Eq (A.6) in Appendix) and included in the models presented in Table 2 are reported in Table A2 of the Appendix. This table is reported in the Appendix only for completeness. This is because we are not interested in the results returned from Eq (A.6) in explaining the drivers of migration, but only to the residuals obtained from it to compute the term ξ. As we stressed in Section 2, in fact, our method is only useful to assess the presence of spillover effects stemming from migration (i.e. to estimate Equation 4), not to model the drivers of migration. Importantly, spillover effects are correctly identified even when the model specification of Eq (A.6) is not (because the term ξ captures all variables potentially omitted in this equation).

Table 2. Baseline results for **RH1** and placebo test.

	Dep. var: Total Patents per capita					
Lagged network migration by skills	High-skilled		Medium-skilled		Low-skilled	
Lagged variables	(1)	(2)	(3)	(4)	(5)	(6)
ϕ	0.0592***	0.0448**	0.0045	0.0037	−0.0053	−0.0076
	(0.0105)	(0.0095)	(0.0057	(0.0053)	(0.0059)	(0.0042)
GBARD stock	0.6123***	0.5665***	0.5523***	0.5024***	0.5026***	0.4561***
	(0.0687)	(0.0691)	(0.0678)	(0.068)	(0.0662)	(0.0663)
GDP per capita	0.5006***	0.4445**	0.5266***	0.4279**	0.3728*	0.2657
	(0.1444)	(0.1492)	(0.1450)	(0.1490)	(0.1615)	(0.1628)
High-skilled employment/Population		0.1293*		0.1920**		0.2071**
		(0.064)		(0.0627)		(0.0647)
Unobservables	−0.1702***	−0.1292**	−0.0141	−0.01274	0.0216	0.0285
	(0.0214)	(0.0459)	(0.0166)	(0.0152)	(0.0141)	(0.0098)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	560	560	560	560	560	560
AIC	4.03	2.44	17.34	10.14	11.5	4.12

Note: Results for model in Equation 4 of the paper. NLLS estimated coefficients and (standard errors) are reported. Standard errors are bootstrapped with 500 replications. In Columns (1)–(2), the estimated parameter ϕ is obtained using the high-skilled migration matrix. In Columns (3)–(4), the estimated parameter ϕ is obtained using the medium-skilled migration matrix. In Columns (5)–(6), the estimated parameter ϕ is obtained using the low-skilled migration matrix. A precise definition of control variables can be found in Section 3 of the paper. Summary statistics for these variables are reported in Table A1. *, **, *** indicate statistical significance at the 10, 5 and 1 percent level.

high-skilled employment has a positive and statistically significant effect, and its inclusion in the model improves the Akaike Information Criterion (AIC) with respect to the model specification presented in Column (1): i.e. this variable increases our understanding of the drivers of a country's innovative performance by improving the model's fit to the data.[23]

According to the recent debate in theoretical and empirical literature, high-skilled migrants have the ability to contribute to the national innovation of a country by conveying knowledge spillovers from their home country. On the contrary, medium and low-skilled migrants could have a substantially reduced impact on the national performance of the host country. It follows that if our model is able to correctly formalise the effect of foreign-born expertise in magnifying the effect of the internal knowledge of a country on its production of patents, then by replacing the term G in Equation 4, that is the high-skilled migration network, with a term registering the medium- or low-skilled migration network, we should find that the spillover effects stemming from foreign innovation on a country performance, measured by ϕ, are not statistically significant.

We conduct this placebo test in the remaining columns of Table 2. Columns (3) and (5) present the results obtained when using the same model specification used in Column (1), but replacing the high-skilled network with the medium and low-skilled ones, respectively. Similarly, Columns (4) and (6) implement the model specification adopted in Column (2), but they, respectively, use the medium- and low-skilled network.

[23]As additional robustness, we also control for the amount of inward FDI stock and total trade (import plus export) and results are confirmed. See Tables A3 and A4 in Appendix for, respectively, the first and second stage estimations.

Consistently with expectations, we find that the presence of medium- and low-skilled migrants plays no role in the innovation performance of a country.[24] In fact, an increase in the innovation performance of their home country has no statistically significant impact on the performance of the host country: i.e. $\phi = 0$. Put differently, we find that being central to the medium- and low-skilled migrants network has no statistically significant effect in magnifying the internal knowledge of a country. The only migration network relevant for the advancement of national knowledge is that of high-skilled migrants.

4.1. Proximity in innovation policies

In this section, we estimate our model by using the GBARD proximity-weighted version of the high-skilled migration matrix as in Equation A.6, with weights given by the similarity between the origin and destination countries in the way the government R&D budget is allocated across different socio-economic objectives and technology fields. If compared to the standard formulation, this modified version of the matrix G puts stronger weight on the connections (i.e. migration flows) between countries i and j, since the more similar the two countries are in the allocation of the GBARD resources the stronger the bilateral connection.

The results obtained from this exercise are reported in Table 3. We find that all previous estimates are qualitatively unchanged and we confirm the results obtained with our main model specification (Table 2). Incidentally, the comparison of the spillover effects registered by ϕ in Columns (1) and (2) in Table 3, with respect to the main model specification in Table 2, seems to suggest that the spillover effect may be stronger in the proximity-weighted case.

To answer to our second research hypothesis (**RH2**) and test whether the impact of external R&D policies mediated by high-skilled migration is magnified by higher proximity in innovation policies between origin and destination countries, we need to decompose the overall effect associated with the variable GBARD. To verify whether an increase in the R&D budget by countries other than i affects i's outcome, we need to calculate the indirect impact as discussed in Section 2.

In practice, we conduct our analysis by estimating the average marginal indirect effects of the variable GBARD obtained from the two model specifications (i.e. that adopting the original high-skilled migration network and that adopting the proximity-weighted version). We then compare the effect of the external knowledge returned by the two models. Specifically, we compare the estimated effects obtained from the models in Columns (1) and (2), Table 2, with those returned by from the models in Columns (1) and (2), Table 3. The average value of these effects are reported in Table 4. Under the Column 'Standard', we report the marginal average effects obtained when using the original network (i.e. those from Table 2). Under the Column 'Proximity', we report the marginal average effects obtained when using the network weighted by the cross-country proximity

[24]At least, they don't as long as they do not participate to the upper tail human capital of the host country. Yet, we know from previous research (Ganguli, Shulamit, and Megan 2020) that if they participate to high-education programs in the host country, they will have an effect on national innovation in the future.

Table 3. Homogeneous spillovers network migration – GBARD proximity.

Lagged network migration by skills	Dep. var: Total Patents per capita					
	High-skilled		Medium-skilled		Low-skilled	
Lagged variables	(1)	(2)	(3)	(4)	(5)	(6)
ϕ	0.1138***	0.0987***	0.0074	0.0062	−0.0163	−0.0195
	(0.0253)	(0.0243)	(0.0060)	(0.0058)	(0.0143)	(0.0136)
GBARD stock	0.5823***	0.5475***	0.5543***	0.5050***	0.5087***	0.4601***
	(0.0698)	(0.0723)	(0.0702)	(0.0719)	(0.0729)	(0.0734)
GDP per capita	0.5360***	0.4690**	0.5276***	0.4300**	0.3570**	0.2460
	(0.1488)	(0.1534)	(0.1504)	(0.1532)	(0.1600)	(0.1633)
High-skilled employment/Population		0.1280*		0.1906**		0.2150**
		(0.0684)		(0.0666)		(0.0687)
Unobservables	−0.3134***	−0.2732***	−0.0215	−0.0193	0.0588	0.0690
	(0.0731)	(0.0704)	(0.0138)	(0.0135)	(0.0449)	(0.0690)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	560	560	560	560	560	560
AIC	−4.7620	−7.2912	17.2559	10.2010	10.1346	2.3151

Note: Results for model as in Equation 4 of the paper. NLLS estimated coefficients and (standard errors) are reported. Standard errors are bootstrapped with 500 replications. In Columns (1)-(2), the estimated parameter ϕ is obtained using the GBARD proximity-weighted version of the high-skilled migration matrix. In Columns (3)-(4), the estimated parameter ϕ is obtained using the GBARD proximity-weighted version of the medium-skilled migration matrix. In Columns (5)-(6), the estimated parameter ϕ is obtained using the GBARD proximity-weighted version of the low-skilled migration matrix. A precise definition of control variables can be found in Section 3 of the paper. Summary statistics for these variables are reported in Table A1. *, **, *** indicate statistical significance at the 10, 5 and 1 percent level.

Table 4. Average indirect effects of government R&D.

	Standard	Proximity	Welch two samples t-test	p-value
Model 1	0.0013	0.0015	5.7472	0.0000
Model 2	0.0009	0.0012	5.0220	0.0000

Note: Columns "Standard" and "Proximity" report the average marginal indirect effects of the variable GBARD obtained from model 4 of the paper when using the high-skilled migration net- work, and when adopting its proximity-weighted version, respectively. Model 1 refers to the model specifications adopted in Column (1) of Tables 2 and 3, respectively. Model 2 refers to the model specifications adopted in Column (2) of Tables 2 and 3, respectively. Average marginal indirect effects are obtained with the procedure described in Section 2. Column "Welch two samples t-test" reports the value of Equation A.6 testing the difference between the average marginal indirect ef- fects of the variable GBARD reported in Columns "Standard" and "Proximity". Column "p-value" indicates the p-value of the test reported in the previous column.

in innovation policies (i.e. those from Table 3). Interestingly, we find that the average indirect effect associated to the variable GBARD is lower when adopting the original network if compared to the case in which the network is weighted by the bilateral policy proximity, regardless of the model specification considered.

We further test whether the average indirect effects of GBARD obtained from the standard and the proximity-weighted matrices are statistically different. The statistical comparison of the indirect effects obtained from the two models is conducted by calculating the mean and the standard deviation of the indirect effects of GBARD, i.e. $(I - \phi \times G)^{-1} \times \frac{GBARDstock}{GDP}$, when using the original and the weighted network, and then performing a Welch two sample t-test, under the assumption that the variance is equal among the samples (B. K. Moser and Stevens 1992). Formally, the test takes the form:

$$t = \frac{x_o - x_w}{\sqrt{\frac{S_{2x0}}{x_0} + \frac{S_{2xw}}{x_w}}} \tag{10}$$

where the notation s and w indicate the metrics obtained from the estimates with the original and the proximity-weighted network, respectively. The null hypothesis $H0 : x = y$ is tested against the alternative $H1 : x > y$. Results are reported in Columns (3) and (4) in Table 4. The p-value lower than 0.05 is in favour of the alternative hypothesis: the two coefficients are statistically different and the indirect effects estimated by our model when using the proximity-weighted network are greater than that obtained using the original one. These results, which confirm **RH2**, suggest that the incoming flows of high-skilled migrants act as a stronger channel for diffusing knowledge when we account for the (origin destination) countries' proximity in pursuing alternative socio-economic goals through their research and innovation policy. Indeed, when putting more weight on the migration flows between host (i) and origin (j) countries, if i and j dedicate similar shares of their R&D budget to the same missions and technologies, the recombination of internal knowledge with the (external) skills and competencies conveyed by high-skilled migrants is more effective.

As a result, the positive impact on patent production of the foreign R&D policies mediated by the migration network is stronger.

4.2. Heterogeneity in network spillovers

This section is dedicated to the exploration of our third research hypothesis (**RH3**), positing that the external knowledge conveyed by high-skilled migrants generate larger innovation benefits in countries characterised by weaker efforts in their national innovation systems. The aim of this last exercise is to understand whether the external knowledge conveyed by high-skill immigrants is relatively more beneficial for countries lagging behind in terms of domestic innovation efforts, as opposed to the case in which countries better equipped in terms of the multiple features shaping the national innovation system are also those able to catch larger advantages from knowledge spillovers.

Importantly, we reiterate that our empirical strategy does not allow us to determine why high-skilled migrants would move to countries characterised by weaker efforts in their national innovation systems.[25] The drivers of their relocation are in fact modelled as an omitted variable of our analysis, and dealt with an *ad hoc* strategy building on a standard control function approach a la´ Heckman. At the same time, our analytical framework allows us to determine the impact of migrants presence when these are found in countries with given characteristics (e.g. countries lagging behind).

In practice, this is done by using the model including heterogeneous spillover effects (Equation A.6). Specifically, domestic innovation efforts (i.e. the characteristics z) are measured using the following indicators of public/business expenditure and presence of high-skilled human capital: i) GBARD/GDP ratio (i.e. the variable 'GBARD stock'), ii)

[25]A number of different reasons may explain this. First, each destination country (even those relatively lagging behind in term of R&D policy) may offer other attractive features to high-skilled migrants. These could include favourable economic conditions, access to advanced infrastructure and resources, specific sectors where the country holds a relative advantage and/or grow potential, academic and entrepreneurial ecosystems, or simply better quality of life (e.g. safety, healthcare, and education for their families). Second, some countries implement policies specifically designed to foster mobility and attract workers' from abroad, for example, by offering favourable immigration paths or tax benefits. Even in countries where the overall R&D policy environment is not as advanced, these incentives can make the destination country more attractive. Finally, migrants may have personal reasons for choosing a destination country beyond just its R&D policies. Factors such as family ties, cultural affinity, lifestyle preferences, or political stability could also play a significant role in their decision-making process.

BERD stock/GDP ratio (henceforth 'BERD stock'), iii) GERD stock/GDP ratio (henceforth 'GERD stock'), iv) dummy median GERD, and v) total economy researchers/population ratio. Results are reported in Columns (1) to (5) in Table 5.

First, we observe that all results previously uncovered are qualitatively confirmed. Furthermore, the coefficients associated to the additional variables measuring the national innovation system (i.e. related to BERD, GERD and the number of researchers), when statistically significant, are positive.

More interestingly, we notice that ϕ_{baseline} is positive while ϕ_{host} is negative, and both are statistically significant. It is worth remembering that, while the former registers the baseline effect, ϕ_{host} quantifies the extent to which a country benefit more (or less) from knowledge spillover given the characteristic z of the country. Hence, our results suggest that all countries benefit from the knowledge spillover conveyed by high-skilled immigrants ($\phi_{\text{baseline}} > 0$), but economies featured by stronger national innovation system (i.e. characterised by higher value of the characteristic z) capture relative smaller benefits from spillover effects ($\phi_{\text{host}} < 0$). This evidence is compatible with existing findings suggesting that stronger spillovers exist when receiving countries feature a lower technological advantage with respect to sending countries (P. Moser, Voena, and Waldinger 2014).

Table 5. Heterogeneity in network spillovers controlling host country characteristics.

	Dep. var: Total Patents per capita				
Lagged interaction variables	GBARD stock	BERD stock	GERD stock	Dummy Median GERD	Researchers per capita
Lagged variables	(1)	(2)	(3)	(4)	(5)
ϕbaseline	0.08264***	0.0660***	0.06092***	0.0571***	0.0848***
	(0.0114)	(0.0116)	(0.0131)	(0.0122)	(0.0143)
ϕhost	−0.0044*	−0.0019*	−0.0038*	−0.0086*	−0.0043*
	(0.0012)	(0.0014)	(0.0016)	(0.0052)	(0.0027)
GBARD stock	0.5416***	0.5668***		0.5831***	0.5939***
	(0.0734)	(0.0722)		(0.0666)	(0.0747)
GDP per capita	0.5709***	0.5447***	0.4609**	0.5065***	0.5169***
	(0.1381)	(0.1512)	(0.1574)	(0.1478)	(0.1496)
BERD stock		0.0379			
		(0.0504)			
GERD stock			0.3358***		
			(0.0809)		
Dummy Median GERD				0.0005	
				(0.0303)	
Researchers per capita					−0.0072
					(0.0386)
Unobservables	−0.1806***	−0.1634**	−0.1364**	−0.1729***	−0.1664***
	(0.0575)	(0.0378)	(0.0452)	(0.022)	(0.0372)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	560	560	560	560	560
AIC	0.07	2.95	44.06	0.6	3.81

Note: Results for model as in Equation A.6 of the paper. NLLS estimated coefficients and (standard errors) are reported. Standard errors are bootstrapped with 500 replications. The estimated parameters ϕ_{baseline} and ϕ_{host} are obtained using the high-skilled migration matrix. A precise definition of control variables can be found in Section 3 of the paper. Summary statistics for these variables are reported in Table A1. *, **, *** indicate statistical significance at the 10, 5 and 1 percent level.

5. Conclusions

This paper investigates the impact of high-skilled migrants on the production of knowledge in host countries. Consistent with previous and well-established literature, we argue that high-skilled migrants are a crucial driver of innovation diffusion, as their presence can amplify the effect of internal knowledge on national innovation performances, thereby indirectly capturing aspects of knowledge transfer across borders.

To this purpose, we assess how national innovation performance improves when a country holds a central position (as measured by its Katz-Bonacich centrality) in the high-skilled migration network. Since high-skilled migrants likely relocate in countries with a better innovation performance, we employ a novel identification strategy based on a control function approach to account for migrants' self-selection process into the migration network, and addresses potential endogeneity concerns.

Our findings reveal that international high-skilled migration magnifies the effect of internal knowledge in improving national innovation performances, even when controlling for other common drivers of innovation, as well as time and country-fixed effects. By contrast, middle- or low-skilled migration flows exhibit no statistically significant effect on innovation (here measured in terms of production of triadic patents per capita). In other words, by becoming more central in the international high-skilled migration network, countries get access to the external (technological, organisational and institutional) knowledge embedded in high-skilled migrants, with beneficial effects on the country's patents production. This implies that the international network of high-skilled migration is a channel of knowledge diffusion, and host countries can enhance their position in the technological system thanks to the innovation externalities driven by the high-skilled people migrating from their place of origin.

Furthermore, we find that the knowledge spillovers from high-skilled immigrants are stronger if the origin and destination countries allocate a similar share of their public R&D budget across the same technological and socio-economic goals (i.e. similar budget allocation to the same technological clusters to support research activities performed by public, business, private non-profits and higher education sectors). This result is compatible with existing evidence showing that migrants' contribution to knowledge diffusion across borders may be technology-specific, i.e. host countries are more likely to gain a technological advantage in the same fields in which the migrants' origin country is specialised (Bahar, Choudhury, and Rapoport 2020).

Finally, our findings highlight the critical role of absorptive capacity in determining the magnitude of innovation spillovers facilitated by high-skilled migration since the contribution of high-skilled migrants is heterogeneous across countries. Indeed, their positive impulse to innovation performances is higher in host countries characterised by a relatively weaker national innovation system, as the relative marginal contribution brought by immigrants is stronger with respect to already technologically advanced economies. This suggests that skilled migration is valuable to innovation regardless of national specificities, but it is most beneficial for host countries in the earlier stages of a learning path. An important policy implication is that countries aiming to technologically upgrade could improve their innovation performance by designing recruitment policies of high-skilled migrants (who will magnify the effect of local efforts), even if their internal efforts to advance knowledge are relatively lower than the rest of the network.

This is consistent with previous evidence according to which hybrid skill-selective migration policies could help countries addressing both long-term weakness in human capital formation and short-term labour market failures, while boosting their innovation performances through the positive effect generated by knowledge spillover effects (Chand and Tung 2019; Czaika and Parsons 2017). Although there is no coordinated international response yet, some countries (e.g. Canada, France, Germany, Ireland) have started (or considered) revising their labour immigration policies to facilitate the admission of foreign workers (or to prevent their repatriation) with the aim of meeting employment needs (Ferrucci 2020).

Along with the contributions, also the limitations of our study should be acknowledged. First, our measure of national innovation performance is derived from patent statistics, however not all inventions are patented, and different forms of innovation can be over/under- represented (e.g. product innovations are usually over-represented). We adopt the standard approach for measuring innovation output, widely used in economics of innovation and in innovation–migration studies, but further research could use alternative proxies for measuring the innovation output. Furthermore, due to data availability, our empirical analysis is constrained to a sample of 20 OECD countries and does not encompass all global migration flows. Yet, this represents more than half of the OECD countries, about 75% of the total GDP of countries in this group, and 40% of the entire high-skilled migrant population. To the extent that other sources of bilateral and skill-specific migration data become available, a more comprehensive picture on the role of migration in fostering knowledge diffusion could emerge from a global perspective. Finally, while our empirical approach allows us to control for the unobserved reasons why migrants move from one country to another (and sort out endogeneity concerns), further research could explicitly disentangle some of these drivers.

Importantly, our paper also speaks to the research dedicated to the analysis of the unequal distribution of income, resources and labour opportunities across countries. The spatial sorting of workers has in fact been recognised as a significant source of spatial inequality (Behrens, Duranton, and Robert-Nicoud 2014; Davis and Dingel 2020). This arises when developed countries facing a shortage of skilled workers recruit foreign-born workers by offering them better opportunities, and leave migrant-sending countries with a scarcity of skilled professionals, reducing opportunities for local firms and workers.[26] New research, however, offers a more mixed picture of the effects of high-skilled migration. Evidence in fact suggests that sending countries may also receive benefits from high-skilled migration in terms of return flows of income, investment, expertise from returning migrants, and skill acquisition in the local population (Beine, Docquier, and Rapoport 2001; Docquier and Rapoport 2012; Gibson and McKenzie 2011). The bidirectional links between emigration and migrant-sending countries' outcomes can thus induce both vicious and virtuous circles.

Indeed, the evidence produced by the literature on spatial sorting following high-skilled migration waves stimulated a number of policy considerations for migrant-sending countries that are relevant to this paper for completing the discussion on the policy lessons that we draw from our study. While the literature agrees that countries

[26]This is, for instance, the case of the brain drain of medical workers (Taylor and Dhillon 2011).

with different characteristics will have different optimal strategies in dealing with high-skilled migration, in the last decade several suggestions emerged to effectively look at this particular form of migration. On the one hand, governments could obtain a fiscal gain if they react to the departure of the highly educated by adjusting the public supply of higher education (Docquier and Rapoport 2012) or public infrastructure (Grossmann and Stadelmann 2011) and free riding on destination countries' foreign education programmes. On the other hand, however, the fiscal gain obtained by encouraging students to obtain their education abroad has a downside: by outsourcing tertiary education, countries make access to education more unequal for the local popula tion (Rosenzweig 2005). Therefore, the coping strategy should be considered with caution, identifying the correct balances to correct its unintended consequences. More recently, Abarcar and Theoharides (2024) provided new evidence in support of a model of human capital formation where emigration and high prospective returns to skill in foreign countries lead to skill acquisition at home (Beine, Docquier, and Rapoport 2001; Fackler, Giesing, and Laurentsyeva 2020; Mountford 1997; Stark, Helmenstein, and Prskawetz 1997). These recent findings suggest the adoption of alternative policy measures, based on well-designed partnerships between migrant-sending and receiving countries that can in principle facilitate both migration and human capital accumulation.

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Appendix

A.1 *Model description*

We propose a model of national innovation, where the innovation performance of country i at time t ($y_{i,t}$), proxied by its number of registered triadic patents, is determined by its national efforts to advance internal knowledge here measured in terms of Government R&D budget ($KNint_{i,t}$) and its external knowledge. This latter factor is obtained as a weighted sum of the innovation performance produced by i's network-connected countries, with weights measuring the percentage of immigrants received by i from each of these countries ($g_{i,j}$). In addition to this, we consider that the innovation performance of country i is the result of a factor common to all countries (δ), time-varying country-specific characteristics, $X_{i,t}$[27] unobserved time-invariant factors controlled using country (η_i) and time (ι_t) fixed effects, and an idiosyncratic factor ($u_{i,j}$). Formally, the model takes the form:

$$ln(y_{i,t}) = \delta + \beta ln(KNint_{i,t}) + \gamma ln(X_{i,t}) + \phi^{I}_{j=i} g_{i,j,t} ln(y_{j,t}) + \eta_i + \iota_t + u_{i,t} \tag{A.1}$$

where ϕ is the measure of the effect of i's external knowledge on its innovation performance: i.e. the spillover effects stemming from the innovation advances of i's network-connected countries and conveyed by immigrants.

For ease of notation, we re-write this equation in matrix form, and we omit the terms referring to fixed effects and the idiosyncratic factor. Consequently, Equation A.6 becomes:

$$ln(Y_t) = \delta + \beta ln(KNint_t) + \gamma ln(X_t) + \phi G ln(Y) \tag{A.2}$$

(A.2) In order to make estimation feasible, we rearrange E q (A.2) as follows:

$$(I - \phi G) ln(Y_t) = \delta + \beta ln(KNint_t) + \gamma ln(X_t) \tag{A.3}$$

Then, provided that the parameter ϕ is smaller than the spectral radius of matrix G, $(I - \phi G)$ is invertible and we obtain the reduce form of our model, that is:

$$ln(Y_t) = (I - \phi G)^{-1}(\delta + \beta ln(KNint_t) + \gamma ln(X_t)) \tag{A.4}$$

This is a general formulation in which the traditional linear regression model is nested. In fact, if spillover effects are not at play (i.e. external knowledge conveyed by migrants has no statistically significant impact on the national performance of a country), then $\phi = 0$ and the first term on the right-hand side of Eq (A.4), $(I{-}\phi G)^{-1}$, reduces to the identity matrix I, and the model becomes $ln\ (Y_t) = \delta + \beta\ ln(KNint_t) + \gamma\ ln(X_t)$, where the innovation performance of the country is only determined by its internal knowledge and other characteristics.

Now, assume that $\phi < |1|$, and denote $q = (\delta + \beta\ ln(KNint_t) + \gamma\ ln(X_t))$, so that the right-hand side of Eq (A.4) becomes $(I - \phi G)^{-1}q$. The Taylor expansion of this term is:

$$(I - \phi G)^{-1} \times q \approx^{I\infty}_{k=0} \phi^k G^k \times q \tag{A.5}$$

In the formulation of Eq (A.5), the i^th row of the matrix G^k keeps tracks of the countries that are connected to i in the network G in k steps. It follows that this measure approximates the number of all countries that can be reached by country i through a direct or indirect path in the network, penalising through the parameter ϕ the contributions of distant countries. In other words, Eq (A.5) indicates the degree of exposure of country i to the spillover effects flowing in the international high-skilled migration, or, put more simply, its centrality in the network. Specifically, the literature refers to the term $(I - \phi G)^{-1}q$ as to Katz-Bonacich centrality (Bonacich 1972, 1987; Katz 1953).

[27]Variables included in the set $X_{i,t}$ are discussed in details in Section 3.

Table A1. Summary statistics.

Variables	Obs	Min	Max	Mean	Median	CV
Total Triadic patents per million population	600	0	234.809	38.0075	24.3354	1.0687
GBARD stock	600	0.0018	0.0679	0.0334	0.0321	0.4496
GDP per capita	600	7545.62	107895.8	40824.01	39147.38	0.3803
High-skilled employment/population	600	0.0373	0.3289	0.1313	0.1273	0.4014
GERD stock	600	0.0035	0.2238	0.0853	0.0815	0.5462
BERD stock	600	0.0009	0.1642	0.0541	0.0483	0.6742
Total economy researchers/population	600	0.0005	0.0119	0.0049	0.0046	0.4699

Note: Summary statistics for the variables presented in Section 3. Values are computed before log-transformation.

Table A2. Main results - first step.

	Dep. var: Total Patents TRIADIC per million population					
Lagged network migration by skills	High-skilled		Medium-skilled		Low-skilled	
Lagged variables	(1)	(2)	(3)	(4)	(5)	(6)
GBARD stock	0.0395***	0.0454***	−0.0086	−0.0064	−0.0606	−0.0513
	(0.0087)	(0.0087)	(0.0149)	(0.0151)	(0.0499)	(0.0504)
GDP per capita	0.0260*	0.0363*	0.0426	0.0465*	0.1466*	0.1629*
	(0.0154)	(0.0155)	(0.0264)	(0.0267)	(0.0884)	(0.0894)
High-skilled employment/Population		−0.0471***		−0.0178		−0.0741
		(0.0102)		(0.0592)		(0.0687)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	560	560	560	560	560	560

Note: Results for model in Eq (A.6) of the paper. OLS estimated coefficients and (standard errors) are reported. In Columns (1)–(2), the dependent variable is defined as the share of high-skilled migrants entering country i from country j at time t. In Columns (3)–(4), the dependent variable is defined as the share of medium-skilled migrants entering country i from country j at time t. In Columns (5)–(6), the dependent variable is defined as the share of low-skilled migrants entering country i from country j at time t. The independent variables capture differences in characteristics between i and j at time *t*-1. A precise definition of control variables can be found in Section 3 of the paper. Summary statistics for these variables are reported in Table A1. *, **, *** indicate statistical significance at the 10, 5 and 1 percent level.

From a theoretical standpoint then, our model predicts that the national innovation performance of a country is a weighted measure of its Katz-Bonacich centrality in the international high-skilled migration network, with weights given by its characteristics, i.e. its internal knowledge. The intuition behind this model is that the national innovation of a country depends from both its internal knowledge and its position in the network, and the extent to which a country benefits from its position in the network is determined by the term ϕ, that is the measure of the exposure to the external knowledge conveyed by immigrants (i.e. the spillover effects).

A concern with the estimation of our model is that G is endogenous with respect to Y because high-skilled migrants self select into countries with a better national performance in order to obtain the best working opportunities, hence a high national performance can be correlated with a large presence of high-skilled migrants, but not necessarily determined by it.

We tackle this problem by using a control function approach specifically suited for handling network data (Battaglini, Leone Sciabolazza, and Patacchini 2020, 2022; Costantini, Leone Sciabolazza, and Paglialunga 2022), similar to that proposed by Heckman (1979). This approach works in two steps.

First, we use a dyadic model to predict the expected number of incoming migrants from j to i at time t from the difference in their characteristics. The model takes the form:

$$g_{i,j,t} = \alpha +_{k}^{I:} \gamma |z_{k,i,t} - z_{k,j,t}| + \varepsilon_{i,j,t} \qquad \text{(A.6)}$$

Table A3. Robustness on main results - first step.

Lagged network migration by skills	*Dep. var:*	*Total Patents TRIADIC* High-skilled		*per capita*
Lagged variables	(1)	(1)	(2)	(2)
GBARD stock	0.0385***	0.0444***	0.0364***	0.0422***
	(0.0087)	(0.0088)	(0.0090)	(0.0091)
GDP per capita	0.0257*	0.0362**	0.0266*	0.0371*
	(0.0154)	(0.0155)	(0.0154)	(0.0156)
High-skilled employment/Population		-0.0477***		-0.0473***
		(0.0103)		(0.0103)
FDI stock inwards	0.0046*	0.0050*		
	(0.0027)	(0.0027)		
Total trade			0.0036	0.0038
			(0.0028)	(0.0028)
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	560	560	560	560

Note: Results for model in Eq (A.6) of the paper. OLS estimated coefficients and (standard errors) are reported. The dependent variable is defined as the share of high-skilled migrants entering country i from country j at time t. The independent variables capture differences in characteristics between i and j at time *t*-1. A precise definition of control variables can be found in Section 3 of the paper. Summary statistics for these variables are reported in Table A1. *, **, *** indicate statistical significance at the 10, 5 and 1 percent level.

Table A4. Robustness on main results - second step.

Lagged network migration by skills	*Dep. var:*	*Total Patents TRIADIC* High-skilled		*per capita*
Lagged variables	(1)	(1)	(2)	(2)
ϕ	0.0610***	0.0457***	0.0612***	0.0463***
	(0.0110)	(0.0095)	(0.0109)	(0.0097)
GBARD stock	0.6131***	0.5674***	0.6115***	0.5665***
	(0.0661)	(0.0713)	(0.0675)	(0.0692)
GDP per capita	0.5028***	0.4484**	0.4614**	0.4441**
	(0.1421)	(0.1505)	(0.0083)	(0.1403)
High-skilled employment/Population		0.1270*		0.1272**
		(0.0686)		(0.0624)
Unobservables	-0.1153*	-0.1455*	-0.1236*	-0.1836***
	(0.0226)	(0.0194)	(0.0224)	(0.0196)
First step	FDI	FDI	Trade	Trade
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	560	560	560	560
AIC	3.2633	2.0017	3.4227	1.9935

Results for model in Equation 4 of the paper. NLLS estimated coefficients and (standard errors) are reported. Standard errors are bootstrapped with 500 replications. The estimated parameter ϕ is obtained using the high-skilled migration matrix. A precise definition of control variables can be found in Section 3 of the paper. Summary statistics for these variables are reported in Table A1. *, **, *** indicate statistical significance at the 10, 5 and 1 percent level.

where α is a rescaling factor, and $|z_{k,i,t} - z_{k,j,t}|$ accounts for the absolute difference between country i and j in their k^{th} characteristics at time t. Specifically, the characteristics used in our empirical model encompasses the full set of data at our disposal (i.e. the entire set of control variables in Eq (A.4)). Moreover, we include country i and country j fixed effects to control for time-invariant characteristics of the countries (e.g. cultural, physical, legal, etc.), and time-fixed effects to sort out contextual effects.

In this model, the residual term $\epsilon_{i,j,t}$ is the difference between the predicted and the actual number of j's citizens in the total population of i's immigrants at time t. Consequently, it measures the part of the decision of j's immigrants to move to i at time t that is unexplained by our data: i.e. those differences between i and j at time t which are not already accounted in our data motivating migrants' relocation in that time. Using standard assumptions (Battaglini et al. 2022), we use this term to compute:

$$\xi_{i,t} =_{j=i}^{I:} \varepsilon_{i,j,t}$$

that is the measure of all the unobserved reasons why migrants moved to i which were motivated by the difference in the (unobserved) characteristics between i and all other countries at time t. From an econometric standpoint, this is a measure of the selection bias threatening our main estimates.

In the second step, we plug the vector ξ into our empirical model to control for the endogeneity of the network with respect to the outcome, and sort out the selection bias. In practice, we implement a correction a` la Heckman by augmenting E q (A.2) as follows:

$$ln(Y_t) = \delta + \beta ln(KNint_t) + \gamma ln(X_t) + \phi G ln(Y) + \psi \xi_t \tag{A.7}$$

where ψ is the measure of migrants' self selection bias.

An important implication can be drawn from looking at the second step equation (Eq (A.7)). The correct identification of migrants' spillover effects (ϕ) does not depend on the set of controls (z) included in the model specification used in the first stage (Eq (A.6)), but it is achieved because of the non-linearities specific to the network structure of our model: i.e. the dyadic regressors used in the first stage are expressed in absolute values of differences, and these differences in characteristics do not appear in the second step equation. In other words, even when the model specification of Eq (A.6) suffers from an omitted variable problem, because it lacks some of the factors influencing the propensity of migrants to move from one country to another, Eq (A.7) is still correctly identified (because the term $\xi_{i,t}$ capture all omitted variables in Eq (A.6)). It follows that our method is only useful to assess the presence of spillover effects stemming from migration, not to model the drivers of migration.[28] In a robustness check however, we augment the model specification in Eq (A.6) with additional control variables. As expected, all our results are qualitatively unchanged.[29]

[28]This is why results from Eq. (A.6) will only be shown in the Appendix.

[29]As additional robustness checks we include in the first stage equation the amount of inward FDI and total trade flows between the two countries.