Journal of Economic Geography (2022) **22**, 423–448 https://doi.org/10.1093/jeg/lbab044
Advance Access Publication 29 November 2021

The ties that bind and transform: knowledge remittances, relatedness and the direction of technical change

Valentina Di Iasio *,† and *Ernest Miguelez***,***

*Department of Economics, University of Southampton, Southampton, UK
**Bordeaux School of Economics, University of Bordeaux, CNRS, Avenue Léon Duguit, 33608, Pessac, France
***AQR-IREA, University of Barcelona, Barcelona, Spain
†Correspondence to: *valentinadiiasio@gmail.com*

Abstract

This study investigates whether high-skilled migration in a sample of OECD countries fosters technological diversification in the migrants' countries of origin. We focus on migrant inventors and study their role as vectors of knowledge remittances. Further, we particularly analyze whether migrants spark related or unrelated diversification back home. To account for the uneven distribution of knowledge and migrants within the host countries, we break down the analysis at the metropolitan area level. Our results suggest that migrant inventors have a positive effect on the home countries' technological diversification, particularly for developing countries and technologies with less related activities around—thus fostering unrelated diversification.

Keywords: Migration, inventors, diversification, technical change
JEL classifications: O31, O33, F22
Date submitted: 1 March 2020 **Editorial decision:** 28 September 2021 **Date Accepted:** 28 October 2021

1. Introduction

Innovation and technical change are well-known drivers of economic growth of countries (Romer, 1994). Yet, technical change relies heavily on the countries' past technological trajectories, which tend to be path-dependent (Dosi, 1997). When countries manage to diversify into different activities, they tend to do it to technologically adjacent domains, as shown by the principle of relatedness (Hidalgo et al., 2007; Kogler et al., 2013; Boschma et al., 2015; Petralia et al., 2017; Hidalgo et al., 2018). However, in order to avoid technological lock-in, they must move into technological paths located far away from their current knowledge base (unrelated diversification) (Saviotti and Frenken, 2008). Unrelated diversification might be more difficult to create and more likely to fail, but if achieved, it can potentially foster structural change (Neffke et al., 2018), making countries less vulnerable to technology shocks and more prone to economic growth in the long run (Pinheiro et al., 2018). This might be especially relevant for developing countries, as they rely on a relatively low number of actual activities from which they can diversify into new technologies (Hidalgo et al., 2018). The question remains, however, on who are the agents able to spark (related and unrelated) technological change.

This article investigates the relationship between skilled migration (proxied by inventors) in a sample of Organization for Economic Cooperation and Development (OECD) countries and technological diversification in the migrants' country of origin.[1] Using the framework of the branching literature (Hausmann and Klinger, 2007; Hidalgo et al., 2007; Essletzbichler, 2015; Rigby, 2015; Boschma, 2017), we test the hypothesis that migrant inventors abroad (inventor diasporas) stimulate new patent applications in their countries of origin in technologies in which the destination area is relatively specialized—while the country of origin is not, and therefore foster technical change at home. While this literature has generally focused on the internal factors driving technological diversification, external factors have been mostly overlooked (Neffke et al., 2018; Whittle et al., 2020). This includes the potential role of international migrants (Bahar et al., 2020). Further, the literature has generally focused on the process of related diversification, and unrelated diversification has received less attention (Boschma, 2017). Thus, building upon the concept of relatedness (Hidalgo et al., 2018), which refers to the similarity between activities (products, industries and research areas) in terms of scientific knowledge, technical principles, heuristics and common needs (Petralia et al., 2017), we test whether migration-induced diversification tends to be related or unrelated to the current knowledge base.

Migration, especially of the highly-skilled, is nowadays a widespread phenomenon. The third wave of globalization opened new opportunities for human capital to reallocate, generating an increase in international migration of college-educated workers (Kerr et al., 2016). This has given rise to an increasing number of studies showing the influence of high-skilled migration on innovation in host countries (Stephan and Levin, 2001; Chellaraj et al., 2008; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Moser et al., 2014; Bosetti et al., 2015; Ganguli, 2015; Akcigit et al., 2017; Choudhury and Kim, 2019). The relationship between high-skilled diasporas and home countries' access to foreign technology—knowledge remittances—has been also studied (Kerr, 2008; Agrawal et al., 2011; Breschi et al., 2017; Bahar et al., 2020; Fackler et al., 2020; Miguelez and Temgoua, 2020).[2] However, the role of diasporas in fostering technical, structural change at home is less known.

To understand the role of inventor diasporas on home country technological diversification, we rely on an original database with information on worldwide patent families (Miguelez et al., 2019; WIPO, 2019). We focus on the five most common destination countries for migrant inventors: USA, Germany, Switzerland, UK and France. They are also among the most technologically advanced countries in the world, and sources of international knowledge spillovers (Coe and Helpman, 1995; Keller, 2004; Coe et al., 2009). As sending countries of these inventors, we work with a sample of 137 economies (both high-income and developing ones). We classify patent families in 636 technologies according to the first four digits of the International Patent Classification (IPC). As measures of diversification and technical change, we look at the growth of patents per country and technology, as well as entry into new specializations. For that we calculate a Revealed Technological Advantage (RTA) index (Soete, 1987) to measure relative specialization,

1 We use inventors as a proxy for high-skilled workers. Although we are aware that they are not exactly the same, the former is a critical component of the latter, and a good proxy for knowledge or STEM workers. Even though in parts of the text we refer to high-skilled migration, our empirical analysis is focused on inventors migration only.

2 For an exhaustive review on skilled migration and knowledge diffusion, see Lissoni (2018); for a review on the effects of diasporas on home countries' development, see Bahar (2020).

and the time evolution of this index to look at countries that became specialized in classes in which they were not specialized in the past.

As in Bahar et al. (2020), we build our migration proxy exclusively based on inventors' migration data using the database by Miguelez and Fink (2017). Focusing on inventor migration as captured in patent applications can overcome many of the limitations associated with census-based data. It captures one specific class of high-skilled workers, more homogeneous than the group of tertiary-educated workers as a whole, often behind the creation and diffusion of ideas.

All in all, we introduce three main novelties with respect to the existing literature. First and foremost, we study the capacity of inventor diasporas to foster technological change in their home countries. Differently from Bahar et al. (2020), we account for the fact that geographic areas within host countries tend to specialize in very different technologies and skills (Kogler et al., 2013). Moreover, migrants do not evenly distribute within a country, but tend to agglomerate in highly innovative, urban areas (Kerr, 2010; Verginer and Riccaboni, 2021). Further, they tend to settle where previous co-nationals migrated (Munshi, 2003; Beine et al., 2011), thus leading to within-country specialization in specific foreign nationalities. For instance, in the USA, the Metropolitan Statistical Area (MSA) of San José is highly specialized in technologies such as telecommunications, computer technology or semiconductors, while Detroit specializes in engines, turbines or mechanical tools. Meanwhile, San José largely welcomes inventors from India, followed by inventors from China and, to a lesser extent, Germany. Detroit is home of mainly German inventors, followed at a distance by Indians and Chinese.

Second, as our most novel contribution, we qualify the direction of technical change by investigating whether inventor diasporas are more prone to foster unrelated technological change—whose development would have been more difficult had they relied upon the actual knowledge base of the country, which potentially may lead to structural change (Neffke et al., 2018).

Finally, we investigate heterogeneous effects based on the level of economic development of sending countries. Externally driven technological change might be particularly important for developing countries, as they lack the preconditions necessary for diversifying into new technologies (Petralia et al., 2017). While, as argued above, related diversification is not a negative process per se, the risk is to become locked in the development of a certain group of technologies, narrowing down diversification opportunities and complicating the catching-up process with high-income countries (Hidalgo et al., 2007).

To anticipate the results to come, we find a positive and significant coefficient associated to migration, suggesting a positive relationship with technological diversification, in line with the literature earlier mentioned. We also find a negative and significant coefficient for the interaction between migration and relatedness density, supporting the hypothesis that external knowledge flows aid countries to diversify into new, unrelated technologies and break path dependency. Moreover, when analyzing the heterogeneity between high-income and developing countries, we find that our core results specifically hold for the latter. This supports the hypothesis that having a diaspora abroad does not necessarily imply a brain drain for developing countries. By bringing new ideas, skilled diasporas may help compensate for the lack of domestic knowledge and foster technological development and diversification. Contrarily, high-income economies seem not to benefit that much from their skilled nationals abroad.

We partially deal with endogeneity adopting different strategies, including an instrumental variables approach. Following Frankel and Romer (1999), Ortega and Peri (2014) and

Bahar and Rapoport (2018), we use the prediction of a gravity model of migration to build a suitable instrument for our focal explanatory variables. Our results are robust to our Instrumental Variable (IV) strategy, the inclusion of control variables, and a large number of fixed effects.

The remaining of the article is organized as follows: Section 2 surveys the literature on technological diversification, and the contribution of migration to knowledge diffusion and innovation; Section 3 describes the data with some more detail, and explains our methodology and empirical strategy; Section 4 presents the step by step results; finally, Section 5 concludes.

2. Related literature

While the production of new technologies is a widely unquestioned track to growth and development, less is known on the factors moving technological change one way or another. As diversification usually follows a path-dependent process (Dosi, 1997), it is assumed that the actual set of capabilities conditions which new activities will countries be able to develop (Boschma, 2017), in accordance with the concept of relatedness (Hidalgo et al., 2018). Several empirical studies show that the diversification possibilities at the country (Hidalgo et al., 2007; Petralia et al., 2017), region (Boschma, 2017; Rigby, 2015; Balland et al., 2019) and firm (Jaffe, 1986; Breschi et al., 2003) levels are affected by the related capabilities present in the country, region and firm. For instance, at the country level, Hidalgo et al. (2007) show that countries have a higher probability to add to their basket of export products that are related to the ones they already produce/export. An important implication is that developing countries are usually located in the periphery of the product space, with consequently fewer opportunities for diversification. Petralia et al. (2017) confirm the role of relatedness in binding countries' technological diversification patterns, particularly of countries at early stages of development, concluding that developing countries tend to be more exposed to the risk of technological lock-in. Developing countries seem, therefore, the places with more potential to benefit from the introduction of diversification from abroad.

This literature is particularly rich at the regional level. Neffke et al. (2011), looking at the evolution of Swedish regions, show that these tend to enter new industries when related sectors are already present locally, way more than if the new industry is unrelated to the current industrial base. Similar results are found for the USA using technologies and patent data by Rigby (2015) and Boschma et al. (2015), among many others.

In general, this literature shows that related diversification in countries and regions reigns, while unrelated changes are more difficult to occur (Pinheiro et al., 2018). Yet, unrelated diversification is also possible, and has been shown to be beneficial for countries and regions—especially in the long run. Saviotti and Frenken (2008) stress the particular role of unrelated export diversification in ensuring long-term economic growth and development, for a sample of countries. Pinheiro et al. (2018) analyze the export diversification paths of countries over the long run, to show that unrelated diversification tends to occur in only 7.2% of the cases. However, countries entering more unrelated products tend to growth faster than those only entering related products, evidencing the importance of export diversity for development, which has been associated to higher resilient economic systems.

Here it is important to appreciate the role of external actors able to break lock-in and path dependency. Bahar et al. (2014) investigate the role of distance on the evolution of comparative advantages in trade, finding that countries are more likely to add in their basket of export products already exported by neighbor countries, even if they have different factors' endowments. These findings confirm that knowledge tends to be localized, therefore contributing to fuel the debate on the importance of human interactions for knowledge diffusion. Neffke et al. (2018) look at emerging economic activities in Swedish regions, and found that newcomer firms are more likely to introduce new, unrelated activities into regions, especially if they arrive reallocated from other regions. They are therefore the agents able to foster structural change in the economy. In a similar vein, Multinational Corporations (MNCs) have been regarded to be key agents of structural change in regions (Elekes et al., 2019; Crescenzi et al., 2020). To our knowledge, the role of international skilled migrants has received less attention.

In the literature of the early 1970s, the emigration of high-skilled individuals was widely seen as a potential threat for developing countries, relatively less endowed with human capital and more vulnerable to its loss (Bhagwati and Hamada, 1974; Bhagwati, 1976). Yet, an increasing number of studies in recent years have reported that migrants may create transnational communities keeping connections with their home countries and establishing links with migrants living in other places (Saxenian, 2007; McAuliffe and Ruhs, 2017). Thus, the existence of a high-skilled diaspora exposes their home countries to foreign technological knowledge and may constitute an important resource or, borrowing the expression from Agrawal et al. (2011), a brain bank.

Knowledge remittances may travel through different, non-mutually exclusive, forms. One channel of technology transfer is the transmission of knowledge and skills from high-skilled migrants to their social contacts back home (referred to as *ethnically driven* knowledge flows; Breschi et al., 2017), on a friendly or contractual basis. Knowledge transfers to home countries may occur also when high-skilled workers decide to return on a permanent or temporary basis, equipped with new skills and social networks (Baruffaldi and Landoni, 2012; Choudhury, 2016).[3]

Kerr (2008), by combining patents with industry-level manufacturing data, shows that the industry output of the sending countries increases as the respective ethnic communities develop knowledge in the USA. Breschi et al. (2017) define a brain gain effect when a foreign patent receives a higher number of citations in the home country of the inventor. The authors highlight a positive effect of high-skilled migration on brain gain for all the emerging countries except for India and underline the importance of absorptive capacity in the country of origin.

Kerr and Kerr (2018) scrutinize global collaborative patents, defined as patents where at least one inventor is located within the USA and at least one resides in a foreign country, of US public firms. According to the authors, global collaborative patents are more impactful than those where all team is located either in the USA or abroad. Moreover, US-based firms employing foreign inventors are more likely to engage in these collaborative patents. In a similar vein, Marino et al. (2019) analyze the citation patterns of global collaborative patents. The authors find that US-based inventors, whose foreign ethnicity matches the foreign region in which the other members of the team are located, act as bridges between the multinationals' headquarters and their home countries, facilitating the

3 Sending countries can also benefit from their diasporas abroad through the action of MNCs, by means of multi-establishment, international teams or through internal mobility of skilled labor (Branstetter et al., 2015; Choudhury and Kim, 2019).

access to foreign knowledge for the latter. Miguelez (2018) explores the impact of high-skilled diaspora on cross-country patent collaborations between developed and developing countries, finding a positive and robust effect. Choudhury (2016) investigates the role of return migrant managers on the patent activity of 50 US multinationals' R&D centers based in India. The study finds that returnee migrant managers facilitate greater innovation among their local employees, as they connect them with ideas and resources of the US headquarters.

The studies mentioned so far focus on whether migration allows countries of origin to access foreign knowledge, yet they do not analyze whether these knowledge flows to transform the home countries' economies. Moreover, the use of citations as a proxy for knowledge flows has been recently criticized as flawed (Arora et al., 2018; Jaffe and De Rassenfosse, 2019). A recent strand of literature focuses on the impact of migration, as a channel of knowledge diffusion, on the evolution of comparative advantages. Kerr (2018) finds that migrants networks contribute to technology transfers from the USA, and that those transfers are sufficiently strong to promote exports from migrants' homelands to other countries. Bahar and Rapoport (2018) examine the impact of migration on the extensive (whether a country starts to export a new product from scratch) and the intensive margin (whether a country increases the exports for a given product) of trade of both sending and receiving countries. A follow-up study by Bahar et al. (2020), using data on patents and migrant inventors, shows a positive and robust impact of inventor migration on their host countries and non-significant results for migrants' home countries patenting.

The last described strand of literature, although providing interesting results on the relationship between migration and diversification, is essentially silent on how external knowledge flows interact with countries' endogenous productive and technological capabilities. It does not speak therefore on the qualitative aspects of diversification (related or unrelated to the current knowledge base). In this vein, our article analyzes how relatedness and knowledge remittances interplay, and sheds light on whether or not inventors' migration creates social bridges between lagging-behind countries and developed areas where advanced knowledge is present, helping to break the technological path dependency of countries and promoting structural change.

3. Data and methods

3.1. Data and sample construction

To build the dependent variables (growth of number of patents and entry into new technology), we use an original database that gathers information on 34 million of worldwide patent families (Miguelez et al., 2019). The data cover all patent documents worldwide, filed in any patent office—provided that they are available in the European Patent Office's Worldwide Patent Statistical Database. We collapse all patents of the same family to the first filing of a given set of patent documents filed in one or more countries and claiming the same invention. Each set containing one first and, potentially, several subsequent filings is defined as a patent family.[4] Worldwide patents can be further split into internationally oriented and domestically oriented ones. Internationally oriented patent families refer to patents filed by applicants seeking patent protection in at least one jurisdiction other than their country of residence. Domestic patent families refer only to filings in a home

4 For a more extensive definition of patent families, see Martinez (2010).

country. While our analysis is based on the use of both types of patents together, robustness checks in the Supplementary Appendix repeats all main regressions using internationally oriented patents only, which we use as an indicator of minimum quality of the patent, allowing us to reduce noise related to the idiosyncrasy of each national patent system. Miguelez et al. (2019) database provides geocoding information of patent documents, based on the inventors' addresses (when possible).[5] We then attribute all geocoded patent data into Metropolitan Statistical Areas in the USA and metropolitan regions for the case of European countries.[6] Data are available from 1976 to 2017, and we use the period from 1996 to 2015 to build four non-overlapping 5-year time windows (tw).[7] We then classify the patents in technological classes according to the four digits IPC codes and focus the analysis on the classes that appear in all the tw.

For the migration variables, we use data from Miguelez and Fink (2017), who collect Patent Cooperation Treaty (PCT) applications containing information on inventors' nationality. This has to do with the requirement under the PCT that only nationals or residents of a PCT contracting state can file PCT applications. To verify that applicants meet at least one of the two eligibility criteria, the PCT application form asks for both nationality and residence. A limitation of this data is that we automatically exclude from the sample naturalized inventors. However, they still give a more precise measure of inventors migration than census data that are generally available only every 10 years, and provide a skills breakdown according to only three schooling levels. The database covers the period 1980–2010. Using the period 1991–2010, we build four 5-year non-overlapping tw. In the regressions we introduce this variable with a one-tw lag, in order to minimize issues of reverse causality.[8] Patent and inventor data from Miguelez and Fink (2017) are not provided at the metropolitan area level. In order to get that, we combine it with the OECD REGPAT database, where PCT patents are available at the NUTS3 and county levels (using inventors' addresses)—that we then group into, respectively, European metro regions and MSAs. We match both datasets using the available application number and the names of the inventors.

As inventors are often associated with more than one technological class (because their patents are, too), we prefer to group them into five technological areas (ta) (electrical engineering, instruments, chemistry, process engineering and mechanical engineering) according to the classification of Schmoch (2008). We do this in order to avoid fractionalizing head counts of inventors, or duplicating them across technologies (patents commonly belong to more than one technological class, IPC4, but are unlikely to belong to more than one ta).[9] We then calculate how many inventors of a given nationality are working in a given ta in the metropolitan area of destination.[10]

As mentioned in Section 1, we restrict the analysis to the most common destination countries for migrant inventors, that is, the USA, Germany, Switzerland, UK and France.

5 Geocoded data originally collected from Bergquist et al. (2017), Yin and Motohashi (2018), Morrison et al. (2017), de Rassenfosse et al. (2019) and PatentsView.org, among others.

6 Metropolitan regions in Europe are defined as NUTS3 regions or a combination of NUTS3 regions which represent all agglomerations of at least 250,000 inhabitants (see https://ec.europa.eu/eurostat/web/metropolitan-regions/background, accessed January 2020).

7 The 1991–1995 period will be occasionally used to build some explanatory variables.

8 The choice of the 5-year tw to compute our variables is customary in the related literature. Results using slightly different tw do not alter our results—provided upon request.

9 Table A19 in Supplementary Appendix A15 confirms our main results when we calculate migration at the IPC4 level.

10 The correspondence between technological classes and ta is unique (Schmoch, 2008).

Figure 1 shows the percentage of migrant inventors hosted by these five countries, showing that the USA hosts 54% of the total. Focusing on these countries, we take into account 76% of the total inventor migration.

As it is shown in the next section, our main explanatory variables combine information on the RTA index (built using information from all patent families) in destination cities, as well as the uneven settlement of migrants in space. We exploit the metro region desegregation level for European countries and MSAs for the USA. This is possible since our database geocodes 80% of the total patent families at a fine geographical detail (Miguelez et al., 2019). Our final sample consists of 137 countries of origin (24 high-income and 113 developing countries), 636 technological classes, 4 tw and 447 metropolitan areas of destination.

Table 1 shows the main migration corridors for the US MSAs and European metropolitan areas.[11] For the USA, the main corridors are from China and India to San Diego, San José and Boston. In Europe, corridors are dominated by intra-European flows, and the main ones are from Germany to Zürich and Basel, from the Netherlands to London and Paris, and from France to London and Lausanne. In Table 2, we remove China and India as possible countries of origin for the USA, and other high-income countries for European metropolitan areas as possible origins. For the USA, the table shows that the main sources of migrant inventors are from Canada and the UK and the most attractive MSAs remain San Diego, San José and Boston. For Europe, the main origin countries are India, China and Russia, and the most attractive metropolitan areas are London and Paris—refer to the Supplementary Appendix A2 for a detailed descriptive analysis.

3.2. Empirical approach and variable construction

In order to explore the role of skilled diaspora on the technological diversification of migrants' home countries, we estimate the following regression, at the country-technology level, that accounts for heterogeneity in destination countries by building our variables of interest (migrants and relative specialization) exploiting information at the metropolitan level:

$$\begin{aligned} Y_{c,t,tw} = \alpha + \beta_1 \text{Migration}_{c,t,tw-1} + \beta_2 \text{Rel\_dens}_{c,t,tw-1} + \beta_3 \text{Migration}_{c,t,tw-1} * \\ \text{Rel\_dens}_{c,t,tw-1} + \beta_4 \text{Controls}_{c,t,tw-1} + \gamma_{c,tw} + \delta_{t,tw} + \epsilon_{c,t,tw} \end{aligned} \tag{3.1}$$

where we denote with c the inventors' home countries, t the technological class (belonging to one single ta), tw.

β_1 is the first coefficient of interest, that is associated with our main explanatory variable—labeled Migration for simplicity. This is calculated at the origin country level as the sum of the interactions between the number of migrants from country c working in ta in tw, resident in metropolitan area met and a dummy R that takes the value 1 if the metropolitan area of destination has a comparative advantage in technology t (part of the ta):

$$\text{Migration}_{c,t,tw-1} = \sum_{\text{met}} \text{MIG}_{c,\text{met},ta,tw-1} * R_{\text{met},t\in ta,tw-1} \tag{3.2}$$

11 Cross-country migration corridors are depicted in Figure A3 in Supplementary Appendix A2.

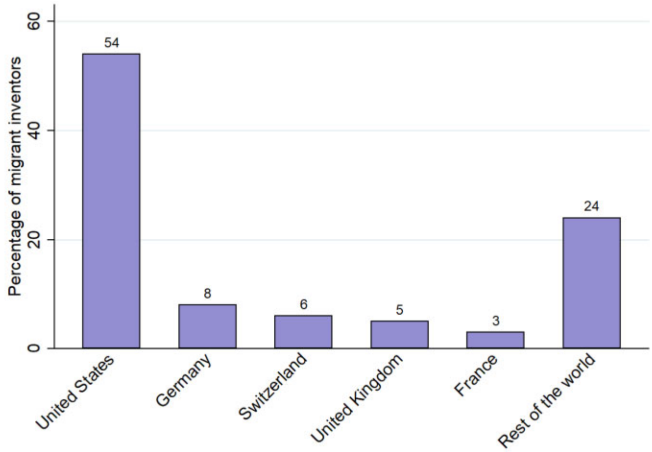

Figure 1 Migrant inventors stock
Source: Author's calculations based on Miguelez and Fink (2017) data.

Table 1. Top 20 migration corridors, 2000–2009

USA			Europe		
Origin	Destination	Inventors	Origin	Destination	Inventors
India	San Diego, CA	4736	Germany	Zürich, CH	1848
India	San José, CA	4439	Germany	Basel, CH	1615
China	San Diego, CA	4176	Netherlands	London, UK	1331
China	San José, CA	4153	France	London, UK	837
China	Boston-Worcester, MA	3123	France	Lausanne, CH	831
India	Boston-Worcester, MA	2099	Netherlands	Paris, FR	676
Canada	San Diego, CA	1845	Germany	London, UK	597
Canada	Boston-Worcester, MA	1818	UK	Basel, CH	595
China	Middlesex-Somerset, NJ	1678	USA	München, DE	589
China	Oakland, CA	1537	USA	London, UK	586
China	Chicago, IL	1507	UK	Paris, FR	484
Canada	San José, CA	1436	Germany	Paris, FR	460
India	Chicago, IL	1358	Germany	Lausanne, CH	450
China	San Francisco, CA	1332	Italy	London, UK	441
China	Philadelphia, PA-NJ	1328	France	Basel, CH	351
UK	Boston-Worcester, MA	1319	France	Genéve, CH	338
India	Oakland, CA	1262	Italy	Paris, FR	314
India	Middlesex-Somerset, NJ	1191	USA	Paris, FR	305
UK	San Francisco, CA	1169	Greece	Mannheim-Lüdwigshafen, DE	278
Canada	San Francisco, CA	1144	UK	Frankfurt Am Main, DE	272

Source: Authors' calculations based on Miguelez and Fink (2017) data and OECD REGPAT database.

Table 2. Top 20 migration corridors, 2000–2009: no India and China for the USA, only developing countries for Europe

USA			Europe		
Origin	Destination	Inventors	Origin	Destination	Inventors
Canada	San Diego, CA	1845	India	London, UK	222
Canada	Boston-Worcester, MA	1818	China	London, UK	197
Canada	San José, CA	1436	Russia	Mannheim-Lüdwigshafen, DE	141
UK	Boston-Worcester, MA	1319	China	München, DE	127
UK	San Francisco, CA	1169	China	Paris, FR	126
Canada	San Francisco, CA	1144	Tunisia	Paris, FR	100
UK	San Diego, CA	1071	Russia	Berlin, DE	87
UK	San José, CA	1049	China	Cambridge, UK	86
Germany	Boston-Worcester, MA	948	Algeria	Paris, FR	81
Korea	San Diego, CA	943	Russia	London, UK	79
Germany	San José, CA	898	India	Paris, FR	74
Korea	San José, CA	799	India	Mannheim-Lüdwigshafen, DE	73
Germany	San Diego, CA	799	Russia	Paris, FR	70
Israel	San José, CA	726	China	Stüttgart, DE	69
Germany	San Francisco, CA	711	South Africa	London, UK	69
Japan	San José, CA	646	Malaysia	London, UK	66
France	San Diego, CA	641	Ukraine	Rührgebiet, DE	66
Canada	Oakland, CA	632	Morocco	Paris, FR	65
France	San José, CA	602	Russia	Rührgebiet, DE	63
France	Boston-Worcester, MA	596	Romania	Paris, FR	63

Source: Authors' calculations based on Miguelez and Fink (2017) data and OECD REGPAT database.

We consider that a metropolitan area met has a comparative advantage in technology t if its relative specialization index is equal or greater than 1. The RTA of metropolitan areas is calculated as follows:

$$\mathrm{RTA}_{\mathrm{met,t,tw}} = \frac{\mathrm{pat}_{\mathrm{met},t,tw} / \sum_{\mathrm{t}} \mathrm{pat}_{\mathrm{met,tw}}}{\sum_{\mathrm{c}} \mathrm{pat}_{t,tw} / \sum_{\mathrm{c}} \sum_{\mathrm{t}} \mathrm{pat}_{tw}} \tag{3.3}$$

where c refers to all countries.

The dependent variable is, for each specification, either the growth of number of patents or the entry of a new technology. As a measure of growth we use the compound average growth rate in technology t for country c between the 5 years separating tw and tw−1, conditional on $\mathrm{pat}_{tw-1} > 0$, that is:

$$\mathrm{Growth}_{c,t,\mathrm{tw}} = \left(\frac{\mathrm{pat}_{c,t,\mathrm{tw}}}{\mathrm{pat}_{c,t,\mathrm{tw}-1}}\right)^{1/5} - 1 \quad \text{if} \quad \mathrm{pat}_{tw-1} > 0 \tag{3.4}$$

Entry of a new technology in a given country is computed as follows: first, we measure the relative technological specialization for each country of origin, using the RTA:

$$\mathrm{RTA}_{c,t,\mathrm{tw}} = \frac{\mathrm{pat}_{c,t,\mathrm{tw}} / \sum_{\mathrm{t}} \mathrm{pat}_{c,\mathrm{tw}}}{\sum_{\mathrm{c}} \mathrm{pat}_{t,tw} / \sum_{\mathrm{c}} \sum_{\mathrm{t}} \mathrm{pat}_{\mathrm{tw}}} \tag{3.5}$$

where $\text{pat}_{c,t,\text{tw}}$ is the number of patents that country c produced in technology t in tw. The Entry proxy measures whether country c starts to develop a comparative advantage in a new technology. The variable is a dummy that takes the value 1 if the RTA of country c is smaller than 1 in technology t in tw-1 and equal or greater than 1 in time window t.[12] When using Growth as dependent variable we introduce a control for the total number of patents lagged one tw ($\text{Tot\_pat}_{c,t,tw-1} = \sum_t \text{pat}_{c,t,\text{tw}-1}$), while when using Entry we control for the continuous value of the actual RTA, always at tw-1.

Next, the main goal of this article is to understand how knowledge remittances and relatedness interplay in shaping the path of technological diversification of the countries of origin. We compute relatedness density between technologies following Rigby (2015), Boschma et al. (2015) and Balland et al. (2019), among others. First, we measure technological relatedness counting the frequency with which technologies i and j appear on the same patent and normalizing this count by total number of patents that record claims for i and j, in order to avoid the influence of size effects—technological relatedness is recomputed from scratch for every tw.[13] The outcome is a $t * t$ network where the nodes are the technologies and the links their degree of relatedness. We then generate a dummy variable that takes the value 1 if the degree of relatedness of two technologies is $\geq$1. We then calculate the relatedness density that measures the relatedness of the technology of interest to the set of technologies in which the country is already specialized. This measure is derived from the technological relatedness ($\phi_{i,j}$) of technology i to all the technologies j in which the country has relative specialization index $>$1 (Equation (3.5)), divided by the sum of technological relatedness of technology i to all the other technologies j:

$$\text{Rel\_dens}_{c,t,tw-1} = \frac{\sum_{j \in c, j \neq i, tw-1} \phi_{i,j,tw-1}}{\sum_{j \neq i} \phi_{i,j,tw-1}} * 100 \tag{3.6}$$

We then introduce in Equation (3.1) an interaction variable between migration and relatedness density. A positive coefficient associated with this variable would suggest that relatedness reinforces the effect of knowledge remittances, confirming that knowledge brought in from abroad requires absorptive capacity to be understood (Cohen and Levinthal, 1990). On the other hand, a negative coefficient would imply that knowledge remittances act as substitute for relatedness, helping to diversify beyond the set of countries' technological capabilities and preventing the risk of lock-in.

This specification can incur in endogeneity issues due to omitted variables, reverse causality and measurement error. We partially address the omitted variables issue including country per time ($\delta_{c,tw}$) and technology per time ($\delta_{t,tw}$) fixed effects, that allow us to control for time-variant characteristics that may correlate with both migration and diversification (such as the relative size of a technological class or country income). Yet, the choice of destinations of foreign inventors might be correlated with dynamics of specialization at both origin and destination. Bahar and Rapoport (2018) and Bahar et al. (2020) address this issue introducing a control for bilateral trade and FDI. A weakness of these measures is that they are not technology-specific and consider the overall bilateral flows. In our

12 In Supplementary Appendix A6, we present a robustness check in which we define *Entry* as a dummy that takes the value 1 if the RTA of country c in technology t is equal or smaller than 0.5 in tw-1, and equal or greater than 1 in tw. Supplementary Appendix Table A6 shows that our main conclusions on developing countries hold even when defining Entry in this stricter, alternative way.

13 Using the association measure presented in Eck and Waltman (2009).

specification, we introduce an alternative control that is the total number of collaborative patents between the migrants' country of origin c and the metropolitan area of destination met in technology t in which the city of destination is specialized ($\text{RTA}_{\text{met},t,\text{tw}} \geq 1$):

$$\text{Copatents}_{c,t,\text{tw}-1} = \sum_{\text{met}} \text{Pat}_{c,\text{met},t,tw-1} * R_{\text{met},t,\text{tw}-1} \tag{3.7}$$

In this way, we control for innovative collaborative activities between origin and destination that may drive inventors relocation.[14]

Next, lagging the variables of interest by one tw to minimize reverse causality does not completely resolve the issue, as both migration at time tw-1 and diversification at time tw could be affected by long-term human capital investments in sending countries. We address these concerns by implementing an IV strategy. Following Frankel and Romer (1999), Ortega and Peri (2014) and Bahar and Rapoport (2018), we estimate a gravity model to compute predicted bilateral migration flows as follows:

$$\begin{aligned}\text{Migrants}_{c,\text{met,tw}} &= \alpha + \beta_1 \text{Mig\_less\_skilled}_{c,\text{dc,tw}} * \text{share\_pop}_{\text{met}\hat{I}\text{dc},1980} + \beta_2 \text{Distance}_{\text{met}\in dc,c} \\ &+ \beta_3 \text{Contiguity}_{\text{met}\in\text{dc},c} + \beta_4 \text{Colony}_{\text{dc,c}} + \beta_5 \text{Common\_language}_{\text{dc},c} \\ &+ \beta_6 \text{Common\_religion}_{\text{dc},c} + \gamma_{\text{met}} + \omega_c + \delta_{\text{tw}} + \epsilon_{c,\text{met,tw}}\end{aligned} \tag{3.8}$$

where the left-hand side is the actual stock of migrant inventors from country c in metropolitan area met in tw. On the right-hand side we introduce three dummy variables at the country level: $\text{Colony}_{\text{dc},c}$ indicating whether the two countries ever had a colony–colonizer relationship, $\text{Common\_language}_{\text{dc},c}$ whether the two countries share the same language, and $\text{Common\_religion}_{\text{dc},c}$ whether they share the same religion. The data come from the CEPII Gravity dataset. To introduce variability at the metropolitan area level, we introduce a dummy indicating whether the metropolitan area of destination and the country of origin share a border $\text{Contiguity}_{\text{met}\in\text{dc},c}$. We also introduce the straight line distance between the metropolitan areas of destination and the countries of origin ($\text{Distance}_{\text{met}\in\text{dc},c}$). Finally, we proxy pre-existent diasporas at destination multiplying the stocks of less skilled migrants Mig_less_skilled by origin country c, in destination country dc and tw with the population shares share_pop of metropolitan area met in a destination country dc. Data for unskilled migrants come from the Institute for Employment Research and population data for metropolitan areas come from the History Database of the Global Environment. We acknowledge that these variables may affect technology diffusion in different ways, above and beyond skilled migration (e.g. via trade or FDI), thus not meeting the exclusion restriction. Note, however, that our dependent variables are technology-specific. It is therefore more likely that our gravity variables would affect diversification into a new technology only by influencing skilled migrants working in that specific technology, rather than through other channels. Moreover, note that our instruments are not these variables per se, but the predicted influence of them on inventor migration flows.

Due to the high number of zeros in our dependent variable and its count nature, we estimate the equation by means of Pseudo-Poisson Maximum Likelihood (Silva and Tenreyro,

14 We are aware that our Copatents variable is not a substitute for bilateral trade and FDIs. Supplementary Appendix Table A4 presents the results when we add trade and FDI instead of Copatents. The results are robust to this alternative estimation.

2006). Once we estimate the predicted migration flows, we multiply them by a fixed value of R, based on the RTAs of metropolitan areas in the pre-sample period 1981–1985, which takes the value 1 if the metropolitan area of destination had a relative advantage in the technology under consideration, and finally we sum them up at the country level:

$$\mathrm{IV}_{c,t,\mathrm{tw}} = \sum_{\mathrm{met}} \widehat{\mathrm{Migrants}}_{c,\mathrm{met},\mathrm{tw}} * R_{\mathrm{met},t,1981\_1985} \tag{3.9}$$

To account for the potential endogeneity of the interaction between Migration and Rel_dens, we interact the IV with Rel_dens and use it as an additional exclusion restriction.

Moreover, since our main variable of interest is the sum of the product between specialization at destination and the number of migrants, we provide two falsification tests to rule out the possibility that our results are driven by only one of these dynamics. First, to verify that our results are not only driven by specialization at destination, we substitute the actual migration variable by randomizing the number of migrants. Second, to confirm that specialization at destination matters, we change the meaning of the dummy R that this time takes the value 1 if the metropolitan area of destination met does not have a comparative advantage in technology t.

To compute Growth and the various RTAs, we use fractional counting, meaning that if a patent belongs to a number x of technologies (locations), it will be counted proportionally per technology (location): $1/x$. We transform Migration and Copatents using the inverse hyperbolic sine, a linear monotonic transformation similar to a logarithmic one, except that it is defined at zero (MacKinnon and Magee, 1990).

Table 3 presents basic descriptive statistics for the dependent variables, the variables of interest, and the control variables, firstly all together and then by type of country of origin. Not surprisingly, the average values in Table 3 witness a gap between developing countries and high-income economies in patenting activity. Also, the average number of collaborative patents is higher for high-income countries. Concerning migration, we notice that developing countries present a lower mean value but a higher maximum value, suggesting that migrants from developing countries may be more concentrated. Table A5 in Supplementary Appendix presents the correlation matrix which shows that no concerns on collinearity are present. We add all these variables parsimoniously (in unreported results), to be sure that collinearity does not drive our results.

4. Results

4.1. Baseline results

Table 4 estimates our main regressions on the pooled sample. As discussed earlier, our focal variable, Migration, is computed as the sum of the interactions between the number of migrants from country c working in ta in tw and a dummy R that takes the value 1 if the metropolitan area of destination has a comparative advantage in technology t, part of the ta.

In Columns 1–3, we use the growth in the number of patents per technological class as the dependent variable. The coefficients of Migration and Relatedness density are positive and statistically significant in all the specifications, while the interaction between these two variables presents a negative and significant coefficient. The coefficient for the number of collaborative patents is negative and significant at the 1% level. This result is

Table 3. Descriptive statistics

	Growth sample											
	Pooled (Obs = 93,510)				Developing (Obs = 42,016)				High income (Obs = 51,494)			
	Mean	sd	Min	Max	Mean	sd	Min	Max	Mean	sd	Min	Max
Growth	−0.09	0.46	−1	6	−0.21	0.57	−1	6	0.01	0.32	−1	4
Migration	158.86	709.67	0	19,561	132.51	866.11	0	19,561	180.35	549.06	0	9412
Tot_pat	96.16	760.25	0	76,351	38.09	409.14	0	31,428	143.55	952.89	0	76,351
Rel_dens	35.52	16.58	0	100	30.80	17.48	0	100	39.37	14.74	0	100
Copatents	5.03	50.26	0	3607	0.22	2.85	0	189	8.95	67.43	0	3607
	Entry sample											
	Pooled (Obs = 397,500)				Developing (Obs = 318,000)				High income (Obs = 79,500)			
	Mean	sd	Min	Max	Mean	sd	Min	Max	Mean	sd	Min	Max
Entry	0.06	0.23	0	1	0.05	0.22	0	1	0.08	0.28	0	1
Migration	44.44	359.61	0	19,561	22.93	328.35	0	19,561	130.49	454.00	0	9412
RTA	1.21	19.81	0	5036	1.19	22.01	0	5036	1.27	4.95	0	489
Rel_dens	16.92	17.94	0	100	11.87	14.78	0	100	37.13	14.99	0	100
Copatents	1.52	21.74	0	3581	0.29	9.62	0	2516	6.41	44.31	0	3581

Table 4. Pooled sample

	Growth			Entry		
	(1)	(2)	(3)	(4)	(5)	(6)
Migration	0.0097***	0.0368***	0.0367***	0.0017*	0.0066***	0.0065***
	(0.0027)	(0.0058)	(0.0057)	(0.0008)	(0.0011)	(0.0011)
Rel_dens	0.0057***	0.0089***	0.0087***	0.0011***	0.0017***	0.0015***
	(0.0004)	(0.0007)	(0.0007)	(0.0002)	(0.0002)	(0.0002)
Mig*rel	—	−0.0007***	−0.0007***	—	−0.0002***	−0.0001***
	—	(0.0001)	(0.0001)	—	(0.0000)	(0.0000)
Copatents	—	—	−0.0104**	—	—	−0.0217***
	—	—	(0.0035)	—	—	(0.0018)
Tot_pat	−0.1295***	−0.1292***	−0.1263***	—	—	—
	(0.0064)	(0.0063)	(0.0065)	—	—	—
RTA	—	—	—	−0.0002***	−0.0002***	−0.0002***
	—	—	—	(0.0001)	(0.0001)	(0.0001)
Country per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,494	93,494	93,494	318,000	318,000	318,000
R^2	0.4427	0.4447	0.4450	0.0641	0.0645	0.0661

Notes: Standard errors clustered at the country level in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All Right hand side (RHS) variables are lagged of one tw. Migration, Tot_pat and Copatents are transformed using the inverse hyperbolic sine.

somewhat counterintuitive. A potential explanation is that, as international collaborations mainly happen among a subset of countries, the variable is highly skewed and the coefficient reflects a spurious relationship due to the collinearity with the country-time fixed effects.

These results suggest that the presence of a high-skilled diaspora working in a destination specialized in a given technology has a positive impact on the number of patents that the country of origin files in that technology in the next 5 years. More specifically, doubling the number of migrant inventors working in a metropolitan area specialized in technology *t* increases the total number of patents filed in the country of origin in that technology by 3.7%. Although the coefficient may seem small, it is worth noting that a 2-fold increase implies a moderate number of inventors, as the average number of migrant inventors for the Growth sample is 158.86 (Table 3). Moreover, the negative coefficient associated with the interaction between migration and relatedness density (Mig $*$ rel) suggests that the effect is stronger for technologies with lower degrees of relatedness, implying that knowledge remittances may act as substitute for relatedness. When Rel_dens is equal to the mean, doubling the stock of migrants increases the total number of patents filed by 1.1%. The effect of Migration is either positive or non-significant for 90% of the observations, when sorted by the level of relatedness density.[15]

Results are similar in Columns 4–6 for the case of Entry, our proxy of technological change, where we find a positive and statistically significant coefficient for migration and relatedness density, and a negative and significant coefficient for the interaction between the two. In this case, doubling the number of migrant inventors working in a metropolitan area specialized in technology *t* increases the probability that the country of origin starts to specialize in that technology by 6.5%. Note that in this sample the average number of migrant inventors is 44.44, suggesting that a relatively small increase in the number of inventors working abroad has a positive and highly significant effect on the probability of entry of a new technology in the country of origin. Here again, the negative coefficient associated to the interaction between migration and relatedness density implies that this effect specifically holds for technologies with a low degree of relatedness density, suggesting that having a high skilled diaspora helps the country of origin to diversify in technologies that will, otherwise, be unlikely to appear. Comparing our results to Bahar et al. (2020), we see that their equivalent coefficient is not always significant, which we attribute to the territorial breakdown by metro areas in destination countries we do.[16]

Doubling the stock of migrants when Rel_dens is equal to the mean increases the probability of entering in a new technology by 4%. The effect of Migration is positive and significant for the 75%, and either positive or non-significant for the 90% of the observations, again when sorted by the level of relatedness density.[17]

In Table 5, we split the sample into developing and high-income countries. We notice that when isolating the group of high-income countries, the coefficients of Migration are only significant at the 10% level in the Growth sample, while the interaction between migration and relatedness density is never significant, for both our dependent variables. On the other hand, the results on developing countries largely confirm the ones on the pooled

15 Additional computations are available in Supplementary Appendix A3.

16 We repeat our baseline results in Supplementary Appendix Table A7 without breaking down migration and specialization data by metropolitan areas in our five destination countries. Interestingly, results barely hold, suggesting how important is to account for territorial differences in specialization and migration patterns.

17 Additional computations are available in Supplementary Appendix A3.

Table 5. Developing and high income

	Growth					
	High-income			Developing		
	(1)	(2)	(3)	(4)	(5)	(6)
Migration	0.0093**	0.0187*	0.0187*	0.0141**	0.0516***	0.0515***
	(0.0031)	(0.0072)	(0.0073)	(0.0049)	(0.0070)	(0.0071)
Rel_dens	0.0044***	0.0056***	0.0056***	0.0066***	0.0106***	0.0105***
	(0.0005)	(0.0010)	(0.0010)	(0.0009)	(0.0008)	(0.0008)
Mig*rel	—	−0.0003	−0.0003	—	−0.0011***	−0.0011***
	—	(0.0001)	(0.0002)	—	(0.0002)	(0.0002)
Copatents	—	—	0.0005	—	—	−0.0212
	—	—	(0.0038)	—	—	(0.0121)
Tot_pat	−0.1181***	−0.1184***	−0.1185***	−0.1408***	−0.1391***	−0.1379***
	(0.0089)	(0.0090)	(0.0089)	(0.0086)	(0.0085)	(0.0087)
Country per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,489	51,489	51,489	41,967	41,967	41,967
R^2	0.3250	0.3254	0.3254	0.4842	0.4872	0.4874
	Entry					
Migration	0.0020	0.0050	0.0049	0.0033***	0.0070***	0.0070***
	(0.0023)	(0.0046)	(0.0045)	(0.0008)	(0.0012)	(0.0012)
Rel_dens	0.0009***	0.0013**	0.0013**	0.0014***	0.0019***	0.0018***
	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Mig*rel	—	−0.0001	−0.0001	—	−0.0002***	−0.0002***
	—	(0.0001)	(0.0001)	—	(0.0000)	(0.0000)
Copatents	—	—	−0.0036	—	—	−0.0281***
	—	—	(0.0026)	—	—	(0.0074)
RTA	−0.0044**	−0.0044**	−0.0044**	−0.0002***	−0.0002***	−0.0002***
	(0.0013)	(0.0013)	(0.0013)	(0.0000)	(0.0000)	(0.0000)
Country per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,600	63,600	63,600	254,400	254,400	254,400
R^2	0.0707	0.0708	0.0709	0.0804	0.0807	0.0811

Notes: Standard errors clustered at the country level in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All RHS variables are lagged of one tw. Migration, Tot_pat and Copatents are transformed using the inverse hyperbolic sine.

sample. This suggests that, for this group of countries, a 2-fold increase in the number of migrant inventors working in a metropolitan area specialized in technology t increases the total number of patents filed in the country of origin by 5.2% and the probability that the country starts to specialize in that technology by 7%. This last result is particularly significant since, on average, as for the pooled sample, a 2-fold increase on the number of inventors working abroad implies a relative small number of people (22.93). The negative sign of the interaction between migration and relatedness density confirms that the effect specifically holds for technologies with a low degree of relatedness density and that knowledge remittance to developing countries act as a substitute for the presence of absorptive capacity. Supplementary Appendix A8 digs deeper into the analysis of migration and relatedness across income levels by plotting the interaction of our focal variables with Gross Domestic Product (GDP) per capita. The evidence presented there is coherent with the results shown when splitting the sample according to the income level.

4.2. Instrumental variables

Tables 6 and 7 present the results for the IV strategy, respectively, on the pooled sample and separately on developing and high-income countries.[18] We report the Kleibergen–Paap *F*-statistics for all the estimations to test if our instrument is weak. As the values are always larger than 10—and in most of the cases larger than 100 (Lee et al., 2020), we are confident that there are no reasons for concern. The IV estimations largely confirm our baseline results, suggesting a positive and significant relationship between inventors' migration and home countries technological diversification for the pooled sample and for developing countries. Next, as in the baseline results, we find a negative coefficient associated to the interaction between migration and relatedness, suggesting a substitution effect between external knowledge flows and developing related activities.

IV coefficients are very similar in magnitude compared to OLS when considering Entry in the pooled sample regression, and between 0.5 and 2 times larger for the rest of the estimations. As we hypothesize endogeneity to be driven by reverse causality, we would have expected our OLS coefficients to be biased upwards. We believe that there might be substantial reasons behind the downward bias in OLS estimates. First, as MNCs are important drivers of the international mobility of these skilled workers (international recruitment, cross-country transfers, etc.), they possibly internalize some of the gains and spillovers migrants produce (Ganguli, 2015). As our analysis aggregates the data by country-areas, we cannot break down the reinforcing effect of migration and MNCs, as found in Breschi et al. (2017). Second, skilled migration and proximity (geographical and others) tend to be substitutes (Oettl and Agrawal, 2008; Breschi et al., 2017). If this is the case, skilled people will tend to move to places where knowledge flows are more scarce, precisely because these flows cannot be accessed in any other way (e.g. between high-income and developing economies). In this scenario, OLS estimates would underestimate the true relationship due to a negative correlation between migration and the errors.

4.3. Falsification tests

To rule out that our results are only driven by specializations in the metropolitan area of destination, we estimate two random models that randomize the stock of migrants 500 times (Bahar et al., 2020). In the first model, we use a uniform distribution, while in the second model, we shuffle the real number of migrants so to obtain a random variable with the same distribution of the original one. Figure 2 presents the results for the first model, which clearly shows that none of the estimated coefficients using the random variable is statistically significant, both for Migration and the interaction between Migration and Rel_dens. Figure 3 shows the results for the second model and also in this case the vast majority of coefficients estimated using the random variable are not significant (the number of significant coefficients ranges from 1 to 13).

18 Supplementary Appendix Table A8 presents the results for the first stage.

Table 6. IV estimations

	(OLS)		(IV)	
	(1) Growth	(2) Entry	(3) Growth	(4) Entry
Migration	0.0367***	0.0065***	0.0618***	0.0068**
	(0.0057)	(0.0011)	(0.0103)	(0.0024)
Rel_dens	0.0087***	0.0015***	0.0105***	0.0018***
	(0.0007)	(0.0002)	(0.0008)	(0.0002)
Mig*rel	−0.0007***	−0.0001***	−0.0012***	−0.0002***
	(0.0001)	(0.0000)	(0.0002)	(0.0001)
Country per time FE	Yes	Yes	Yes	Yes
Technology per time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	93,494	318,000	93,494	318,000
R^2	0.4450	0.0661	0.4444	0.0660
Underidentification test	—	—	0.000	0.000
Kleibergen–Paap statistics	—	—	107.873	389.814

Notes: Standard errors clustered at the country level in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. Estimations reported in Columns 1 and 3 include Tot_pat and Copatents as controls, while estimations in Columns 2 and 4 include RTA and Copatents. All RHS variables are lagged of one tw. Migration, Tot_pat and Copatents are transformed using the inverse hyperbolic sine transformation.

Next, to rule out that the impact is only driven by migrant inventors stocks, we replicate the main specification reversing the sense of the dummy variable R that takes the value 1 if the metropolitan area of destination has 0 patents in technology t. Thus, our main variable of interest is the sum of the interactions between the actual number of migrants from country c working in ta in tw and the dummy R that takes the value 1 if the RTA of the metropolitan area of destination is equal to 0 in technology t. Table 8 presents the results. We find that the coefficient of Migration is not significant in all the specifications. On the other hand, some coefficients for the interaction between migration and relatedness density are significant, but positive, which we attribute to spillovers brought in by emigrants in different, but related technologies.

4.4. International inventions

So far, we computed our measure of growth and technological change on all patent families regardless of the quality of inventions. To consider this latter element, we replicate the analysis restricting the sample only to internationally oriented patents—around 25% of the total, which we define as those whose families include applications to several countries' patent offices as well as those including applications in just one country, but filed by foreign firms (the patent applicant's country, as per its address, does not coincide with that of the patent office). The underlying hypothesis is that since the procedure to protect an idea internationally is particularly costly, these inventions represent the most valuable ones. Thus, we analyze the effect of knowledge flows on the development of high-quality inventions.

Table 7. IV estimations—developing and high-income

	Developing			
	(OLS)		(IV)	
	(1) Growth	(2) Entry	(3) Growth	(4) Entry
Migration	0.0515***	0.0070***	0.0712***	0.0116***
	(0.0071)	(0.0012)	(0.0113)	(0.0022)
Rel_dens	0.0105***	0.0018***	0.0117***	0.0022***
	(0.0008)	(0.0003)	(0.0009)	(0.0003)
Mig*rel	−0.0011***	−0.0002***	−0.0014***	−0.0003***
	(0.0002)	(0.0000)	(0.0002)	(0.0001)
Country per time FE	Yes	Yes	Yes	Yes
Technology per time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	41,967	254,400	42,016	254,400
R^2	0.4874	0.0811	0.4877	0.0809
Underidentification test	—	—	0.000	0.000
Kleibergen–Paap statistics	—	—	57.815	309.660
	High-income			
	(OLS)		(IV)	
	(1) Growth	(2) Entry	(3) Growth	(4) Entry
Migration	0.0187*	0.0049	0.0558*	−0.0039
	(0.0073)	(0.0045)	(0.0246)	(0.0174)
Rel_dens	0.0056***	0.0013**	0.0076***	0.0015*
	(0.0010)	(0.0004)	(0.0016)	(0.0006)
Mig*rel	−0.0003	−0.0001	−0.0007*	−0.0001
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Country per time FE	Yes	Yes	Yes	Yes
Technology per time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	51,489	63,600	51,494	63,600
R^2	0.3254	0.0709	0.3239	0.0706
Underidentification test	—	—	0.001	0.000
Kleibergen–Paap statistics	—	—	52.8508	64.595

Notes: Standard errors clustered at the country level in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimations reported in Columns 1 and 3 include Tot_pat and Copatents as controls, while estimations in Columns 2 and 4 include RTA and Copatents. All RHS variables are lagged of one tw. Migration, Tot_pat and Copatents are transformed using the inverse hyperbolic sine transformation.

Table A10 in the Supplementary Appendix provides the results for the pooled sample, confirming the results of Table 4. Concerning Growth, results confirm the magnitude of the Migration's coefficient, that remains quite stable with a slight increase (0.1%), while for Entry we notice a slight decrease from 0.7 to 0.5. In Supplementary Appendix Table A11, we split the sample into developing and high-income countries. Also in this case the results are similar to Table 5, with the exception that we find a significant coefficient of Migration and the interaction on the sample of high-income countries when using Growth as dependent variable. The magnitude of the coefficient (2.1) is lower than for developing

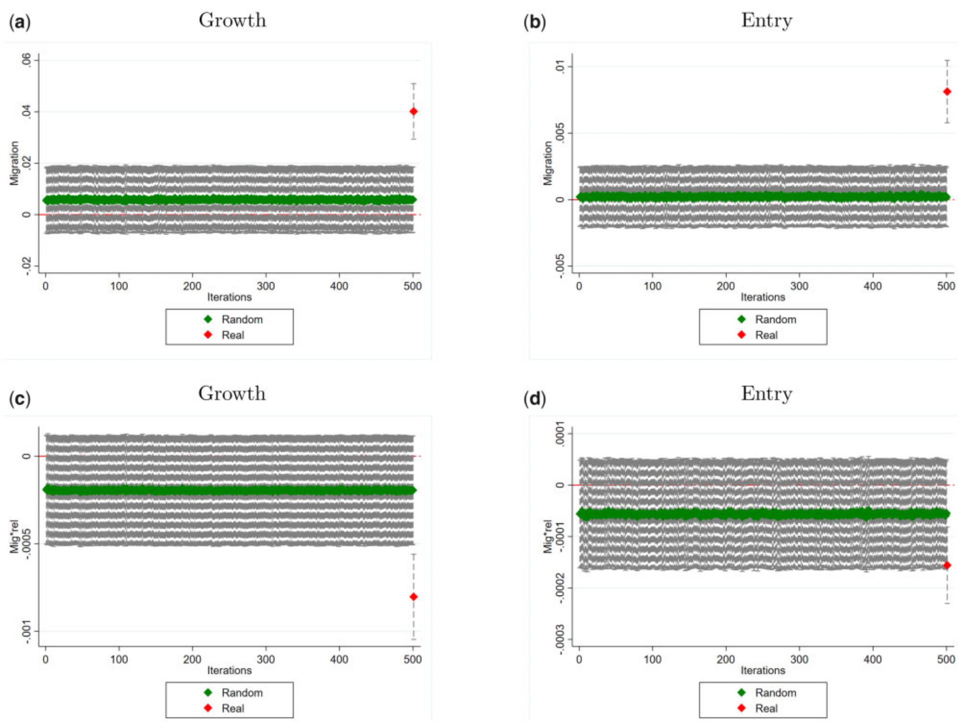

Figure 2 Random model 1. (a) Growth. (b) Entry. (c) Growth. (d) Entry.
Notes: Summary of 500 estimations using random inventor figures (OLS). Figure (a) and (b) plot the estimators of β_1Migration from the baseline equation when substituting the real number of migrant inventors between countries with a random one, for each of 500 iterations. Figure (c) and (d) repeat the same exercise and plot the estimators of β_3Mig $*$ rel.The figure is based on a randomization approach that replaces the actual number of inventors with a random number, with no restrictions distributed uniformly from 0 to 1. The figure also includes, for reference, the estimation using the actual number of migrant inventors (in blue). Whiskers represent 95% confidence intervals, based on SE clustered at the country level.

countries (5.2). Overall, we can conclude that the results are confirmed when we restrict the sample to international inventions only.

4.5. Further robustness checks

To assess the robustness of our results, we run a number of alternative estimations. The estimations in Supplementary Appendix A12 mitigate concerns on our results being driven by a group of outliers by replicating the analysis excluding the countries with the most sizeable diaspora, namely China (Supplementary Appendix Table A13) and India (Supplementary Appendix Table A14). In the same spirit, we exclude the USA as destination country (Supplementary Appendix Table A15). Following Bahar and Rapoport (2018) and Bahar et al. (2020), we test the robustness of our results including additional controls for bilateral trade and FDI (Supplementary Appendix Table A4). Supplementary Appendix A13 is dedicated to the estimations with alternative dependent variables. In Supplementary Appendix Table A16, to address concerns on possible reverse causality, we

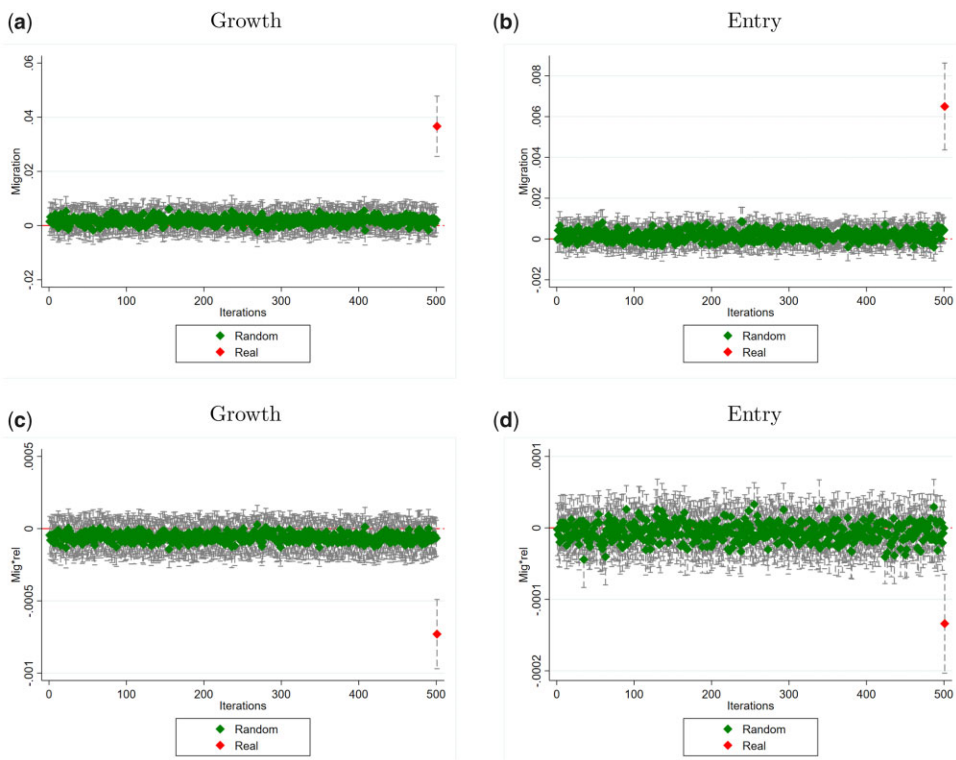

Figure 3 Random model 2. (a) Growth. (b) Entry. (c) Growth. (d) Entry.
Notes: Summary of 500 estimations using random inventor figures (OLS). Figure (a) and (b) plot the estimators of β_1Migration from the baseline equation when substituting the real number of migrant inventors between countries with a random one, for each of 500 iterations. Figure (c) and (d) repeat the same exercise and plot the estimators of β_3Mig $*$ rel. The figure is based on a randomization approach such that the real and the random number of inventors have the same sample mean and distribution. The figure also includes, for reference, the estimation using the actual number of migrant inventors (in blue). Whiskers represent 95% confidence intervals, based on SE clustered at the country level.

run the estimations by excluding international collaborations from the dependent variable. Following the same logic, in Supplementary Appendix Table A17, we exclude PCT applications. In Supplementary Appendix Table A18 presented in Supplementary Appendix A14, we transform our main variables of interest using a regular logarithmic transformation, which excludes zero cells from our estimations. Finally, in Table A19 of Supplementary Appendix A15, we compute migrant inventors at the IPC4 level. Most of our results and conclusions hold for all the specifications.

5. Conclusions

In this article, we analyze the relationship between high-skilled migration and the technological diversification of the migrants' countries of origin. In particular, we investigate whether migrant inventors transfer productive knowledge back home and encourage

Table 8. Falsification test 2: R = 1 if RTA = 0

	(Growth)			(Entry)		
	Pooled (1)	High-income (2)	Developing (3)	Pooled (4)	High-income (5)	Developing (6)
Migration (R = 1 if RTA = 0)	0.00515	−0.00284	0.00900	−0.000625	−0.00164	−0.00376*
	(0.00530)	(0.00532)	(0.0123)	(0.00187)	(0.00321)	(0.00222)
Rel_dens	0.00578***	0.00359***	0.00781***	0.000487**	0.000447	0.00103***
	(0.000486)	(0.000449)	(0.000733)	(0.000197)	(0.000375)	(0.000297)
Mig*rel	−0.0000484	0.000253**	−0.000455*	0.000214***	0.000150*	0.000157**
	(0.000108)	(0.0000951)	(0.000246)	(0.0000515)	(0.0000773)	(0.0000718)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech per time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,494	51,489	41,967	318,000	63,600	254,400
R^2	0.443	0.325	0.485	0.0666	0.0711	0.0808

Notes: Standard errors clustered at the country level in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Estimations reported in Columns 1–3 include Tot_pat and Copatents as controls, while estimations in Columns 4–6 include RTA and Copatents. All RHS variables are lagged of one tw. Migration, Tot_pat and Copatents are transformed using the inverse hyperbolic sine.

development of new technologies in which the destination areas are specialized. One of the main novelty of this article is that we take into account the uneven distribution of knowledge and the consequent migrants' concentration at destination (Carlino and Kerr, 2015) by breaking down at the metropolitan area level the way in which our focal explanatory variables are computed. Also, we aim at understanding whether the transfers of knowledge from abroad foster unrelated diversification, allowing the country of origin to extend the set of technological capabilities and preventing lock-in. As technological development is a strong predictor of economic and social development (Hidalgo et al., 2007; Hartmann et al., 2017), we specifically focus on developing countries and on the most common destinations, that is, the USA, Germany, UK, Switzerland and France.

Our results suggest a positive and statistically significant effect of high-skilled migration on the direction of technical change back home. More importantly, we find that external knowledge from abroad is particularly beneficial for the development of technologies with a low degree of relatedness, thus fostering unrelated diversification in the home countries, and promoting technological structural change (Neffke et al., 2018). Our results are confirmed when we restrict the sample to international inventions only and are robust to several alternative specifications and our instrumental variables approach.

Next, we also find that our results are critical for developing countries' innovation and diversification. That is, having a high-skilled diaspora helps developing economies to access foreign knowledge and catching-up with countries at the technological frontier. Moreover, fostering unrelated diversification, knowledge remittances help developing countries to prevent the risk of lock-in and promote long-term development (Saviotti and Frenken, 2008).

Our data provide detailed information on the localization of a great number of worldwide patent families. Yet, they do not allow us to identify the specific channel through which migrants transfer knowledge from destination areas to their home countries. We hypothesized that high-skilled migrants keep contacts with their countries of origin and transfer the knowledge acquired at destination to their social networks back in the country of origin. They may return back home, on a permanent or temporary basis, after some time abroad, with new skills and contacts. Future research, possibly at the micro-level, could investigate the specific mechanisms behind our results.

The focus of our analysis is on technological development. However, we did not investigate to which extent it translates into new production and export capacity for the migrants' countries of origin. This open question may guide further research aimed at understanding the role of knowledge flows in connecting technological and economic diversification.

Acknowledgments

We would like to thank Mathieu Clément, Eric Rougier and Georgios Tsiachtsiras for useful remarks. We also received valuable suggestions from participants at the 9th Annual Conference on 'Immigration in OECD Countries' (Paris, 2019), the CEMIR Junior Economist Workshop on Migration Research (Munich, 2019), PhD workshop (Insubria, 2019) and the 5th Geography of Innovation conference (Stavanger, 2020), as well as seminars at Beijing Normal University, the University of Bordeaux, the University of Sheffield and the University of Valencia. We also acknowledge financial support from the French National Research Agency (TKC project—reference: ANR-17-CE26-0016).

Funding

This study was supported by French National Research Agency (TKC project—reference: ANR-17-CE26-0016).

Conflict of interest

The authors declare that they have no known competing financial or personal interests that could have influenced the work reported in this paper.

Data availability statement

The data that support the findings of this study are openly available at 10.6084/m9.figshare.16867249.v3

Supplementary material

Supplementary data for this paper are available at *Journal of Economic Geography* online.

References

Agrawal, A., Kapur, D., McHale, J., Oettl, A. (2011) Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. *Journal of Urban Economics*, 69: 43–55.

Akcigit, U., Grigsby, J., Nicholas, T. (2017) Immigration and the rise of American ingenuity. *American Economic Review*, 107: 327–331.

Arora, A., Belenzon, S., Lee, H. (2018) Reversed citations and the localization of knowledge spillovers. *Journal of Economic Geography*, 18: 495–521.

Bahar, D. (2020) Diasporas and economic development: a review of the evidence and policy. *Comparative Economic Studies*, *62*, 200–214.
Bahar, D., Choudhury, P., Rapoport, H. (2020) Migrant inventors and the technological advantage of nations. *Research Policy*, 49: 103947.
Bahar, D., Hausmann, R., Hidalgo, C. A. (2014) Neighbors and the evolution of the comparative advantage of nations: evidence of international knowledge diffusion? *Journal of International Economics*, 92: 111–123.
Bahar, D., Rapoport, H. (2018) Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal*, 128: F273–F305.
Balland, P. A., Boschma, R., Crespo, J., Rigby, D. L. (2019) Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, 53: 1252–1268.
Baruffaldi, S. H., Landoni, P. (2012) Return mobility and scientific productivity of researchers working abroad: the role of home country linkages. *Research Policy*, 41: 1655–1665.
Beine, M., Docquier, F., Özden, Ç. (2011) Diasporas. *Journal of Development Economics*, 95: 30–41.
Bergquist, K., Fink, C., Raffo, J. (2017) *Identifying and Ranking the World's Largest Clusters of Inventive Activity*, pp. 161–176. Geneva, Switzerland: WIPO.
Bhagwati, J., Hamada, K. (1974) The brain drain, international integration of markets for professionals and unemployment: a theoretical analysis. *Journal of Development Economics*, 1: 19–42.
Bhagwati, J. N. (1976) Taxing the brain drain. *Challenge*, 19: 34–38.
Boschma, R. (2017) Relatedness as driver of regional diversification: a research agenda. *Regional Studies*, 51: 351–364.
Boschma, R., Balland, P. A., Kogler, D. F. (2015) Relatedness and technological change in cities: the rise and fall of technological knowledge in us metropolitan areas from 1981 to 2010. *Industrial and corporate change*, 24: 223–250.
Bosetti, V., Cattaneo, C., Verdolini, E. (2015) Migration of skilled workers and innovation: a european perspective. *Journal of International Economics*, 96: 311–322.
Branstetter, L., Li, G., Veloso, F. (2015) The changing frontier: rethinking science and innovation policy. *The Rise of International Convention*, pp. 135–168. Chicago IL: University of Chicago Press.
Breschi, S., Lissoni, F., Malerba, F. (2003) Knowledge-relatedness in firm technological diversification. *Research Policy*, 32: 69–87.
Breschi, S., Lissoni, F., Miguelez, E. (2017) Foreign-origin inventors in the USA: testing for diaspora and brain gain effects. *Journal of Economic Geography*, 17: 1009–1038.
Carlino, G., Kerr, W. R. (2015) Agglomeration and innovation. *Handbook of Regional and Urban Economics*, Vol. 5, pp. 349–404. Amsterdam, Netherlands: Elsevier.
Chellaraj, G., Maskus, K. E., Mattoo, A. (2008) The contribution of international graduate students to us innovation. *Review of International Economics*, 16: 444–462.
Choudhury, P. (2016) Return migration and geography of innovation in MNEs: a natural experiment of knowledge production by local workers reporting to return migrants. *Journal of Economic Geography*, 16: 585–610.
Choudhury, P., Kim, D. Y. (2019) The ethnic migrant inventor effect: codification and recombination of knowledge across borders. *Strategic Management Journal*, 40: 203–229.
Coe, D. T., Helpman, E. (1995) International R&D spillovers. *European Economic Review*, 39: 859–887.
Coe, D. T., Helpman, E., Hoffmaister, A. W. (2009) International R&D spillovers and institutions. *European Economic Review*, 53: 723–741.
Cohen, W. M., Levinthal, D. A. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 35: 128–152.
Crescenzi, R., Dyevre, A., Neffke, F. (2020) Innovation catalysts: how multinationals reshape the global geography of innovation. (No. 105684). London School of Economics and Political Science, LSE Library.
de Rassenfosse, G., Kozak, J., Seliger, F. (2019) Geocoding of worldwide patent data. *Scientific data*, *6*, 1–15.
Di Iasio, V., Miguelez, E. (2021) Ties that bind data. doi:10.6084/m9.figshare.16867249.v3.

Dosi, G. (1997) Opportunities, incentives and the collective patterns of technological change. *The Economic Journal*, 107: 1530–1547.
Eck, N. J. V., Waltman, L. (2009) How to normalize cooccurrence data? An analysis of some well-known similarity measures. *Journal of the American Society for Information Science and Technology*, 60: 1635–1651.
Elekes, Z., Boschma, R., Lengyel, B. (2019) Foreign-owned firms as agents of structural change in regions. *Regional Studies*, 53: 1603–1613.
Essletzbichler, J. (2015) Relatedness, industrial branching and technological cohesion in us metropolitan areas. *Regional Studies*, 49: 752–766.
Fackler, T. A., Giesing, Y., Laurentsyeva, N. (2020) Knowledge remittances: does emigration foster innovation? *Research Policy*, 49: 103863.
Frankel, J. A., Romer, D. H. (1999) Does trade cause growth? *American Economic Review*, 89: 379–399.
Ganguli, I. (2015) Immigration and ideas: what did Russian scientists "bring" to the United States? *Journal of Labor Economics*, 33: S257–S288.
Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., Hidalgo, C. A. (2017) Linking economic complexity, institutions, and income inequality. *World Development*, 93: 75–93.
Hausmann, R., Klinger, B. (2007) *The Structure of the Product Space and the Evolution of Comparative Advantage*. Technical Report. Cambridge, MA: Center for International Development at Harvard University.
Hidalgo, C. A., Balland, P.-A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D. F., Morrison, A., et al. (2018) The principle of relatedness. *International Conference on Complex Systems*, pp. 451–457. Berlin/Heidelberg, Germany: Springer.
Hidalgo, C. A., Klinger, B., Barabási, A. L., Hausmann, R. (2007) The product space conditions the development of nations. *Science*, 317: 482–487.
Hunt, J., Gauthier-Loiselle, M. (2010) How much does immigration boost innovation? *American Economic Journal: Macroeconomics*, 2: 31–56.
Jaffe, A. B. (1986) Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value. *The American Economic Review*, *76*, 984-1001.
Jaffe, A. B., De Rassenfosse, G. (2019) Patent citation data in social science research: overview and best practices. *Research Handbook on the Economics of Intellectual Property Law*. Cheltenham: Edward Elgar Publishing.
Keller, W. (2004) International technology diffusion. *Journal of Economic Literature*, 42: 752–782.
Kerr, S. P., Kerr, W., Özden, Ç., Parsons, C. (2016) Global talent flows. *Journal of Economic Perspectives*, 30: 83–106.
Kerr, S. P., Kerr, W. R. (2018) Global collaborative patents. *The Economic Journal*, 128: F235–F272.
Kerr, W. R. (2008) Ethnic scientific communities and international technology diffusion. *The Review of Economics and Statistics*, 90: 518–537.
Kerr, W. R. (2010) The agglomeration of us ethnic inventors. *Agglomeration Economics, pp.* 237–276. Chicago, IL: University of Chicago Press.
Kerr, W. R. (2018) Heterogeneous technology diffusion and Ricardian trade patterns. *The World Bank Economic Review*, 32: 163–182.
Kerr, W. R., Lincoln, W. F. (2010) The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics*, 28: 473–508.
Kogler, D. F., Rigby, D. L., Tucker, I. (2013) Mapping knowledge space and technological relatedness in us cities. *European Planning Studies*, 21: 1374–1391.
Lee, D. L., McCrary, J., Moreira, M. J., Porter, J. (2020) Valid t-ratio inference for IV. (No. w29124). National Bureau of Economic Research.
Lissoni, F. (2018) International migration and innovation diffusion: an eclectic survey. *Regional Studies*, 52: 702–714.
MacKinnon, J. G., Magee, L. (1990) Transforming the dependent variable in regression models. *International Economic Review*, pp. 315–339. Hoboken, NJ: Wiley-Blackwell for the Economics Department of the University of Pennsylvania and Osaka University (United States).
Marino, A., Mudambi, R., Perri, A., Scalera, V. G. (2019) Ties that bind: the role of ethnic inventors in multinational enterprises' knowledge creation. *Academy of Management Proceedings*, Vol. 2019, p. 12100. Briarcliff Manor, NY: Academy of Management Briarcliff Manor.

Martinez, C. (2010) Insight into different types of patent families.(No. 2010/2). OECD Publishing.
McAuliffe, M., Ruhs, M. (2017) *World Migration Report* 2018. Geneva, Switzerland: International Organization for Migration.
Miguelez, E. (2018) *Inventor Diasporas and the Internationalization of Technology*. Washington, DC: The World Bank.
Miguelez, E., Fink, C. (2017) Measuring the international mobility of inventors. *The International Mobility of Talent and Innovation*, pp. 114–161. Cambridge: Cambridge University Press.
Miguelez, E., Raffo, J., Chacua, C., Massimiliano Coda-Zabetta, M., Yin, D., Lissoni, F., Tarasconi, G. (2019) *Tied in: The Global Network of Local Innovation*.
Miguelez, E., Temgoua, C. N. (2020) Inventor migration and knowledge flows: a two-way communication channel? *Research Policy*, 49: 103914.
Morrison, G., Riccaboni, M., Pammolli, F. (2017) Disambiguation of patent inventors and assignees using high-resolution geolocation data. *Scientific Data*, 4: 170064.
Moser, P., Voena, A., Waldinger, F. (2014) German Jewish émigrés and us invention. *American Economic Review*, 104: 3222–3255.
Munshi, K. (2003) Networks in the modern economy: Mexican migrants in the US labor market. *The Quarterly Journal of Economics*, 118: 549–599.
Neffke, F., Hartog, M., Boschma, R., Henning, M. (2018) Agents of structural change: the role of firms and entrepreneurs in regional diversification. *Economic Geography*, 94: 23–48.
Neffke, F., Henning, M., Boschma, R. (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87: 237–265.
Oettl, A., Agrawal, A. (2008) International labor mobility and knowledge flow externalities. *Journal of International Business Studies*, 39: 1242–1260.
Ortega, F., Peri, G. (2014) The aggregate effects of trade and migration: evidence from OECD countries. *The Socio-Economic Impact of Migration Flows, pp.* 19–51. Berlin, Germany: Springer.
Petralia, S., Balland, P. A., Morrison, A. (2017) Climbing the ladder of technological development. *Research Policy*, 46: 956–969.
Pinheiro, F. L., Alshamsi, A., Hartmann, D., Boschma, R., Hidalgo, C. (2018) Shooting low or high: do countries benefit from entering unrelated activities? *Papers in Evolutionary Economic Geography*, 18.
Rigby, D. L. (2015) Technological relatedness and knowledge space: entry and exit of us cities from patent classes. *Regional Studies*, 49: 1922–1937.
Romer, P. M. (1994) The origins of endogenous growth. *Journal of Economic Perspectives*, 8: 3–22.
Saviotti, P. P., Frenken, K. (2008) Export variety and the economic performance of countries. *Journal of Evolutionary Economics*, 18: 201–218.
Saxenian, A. (2007) *The New Argonauts: Regional Advantage in a Global Economy*. Cambridge, MA: Harvard University Press.
Schmoch, U. (2008) Concept of a technology classification for country comparisons. Final report to the world intellectual property organisation (wipo), WIPO.
Silva, J. S., Tenreyro, S. (2006) The log of gravity. *The Review of Economics and Statistics*, 88: 641–658.
Soete, L. (1987) The impact of technological innovation on international trade patterns: the evidence reconsidered. *Research Policy*, 16: 101–130.
Stephan, P. E., Levin, S. G. (2001) Exceptional contributions to us science by the foreign-born and foreign-educated. *Population Research and Policy Review*, 20: 59–79.
Verginer, L., Riccaboni, M. (2021) Talent goes to global cities: the world network of scientists' mobility. *Research Policy*, 50: 104127.
Whittle, A., Lengyel, B., Kogler, D. F. (2020) *Understanding Regional Branching Knowledge Diversification via Inventor Collaboration Networks*. *Papers in Evolutionary Economic Geography, 20*.
WIPO. (2019) *The Geography of Innovation: Local Hotspots, Global Networks*. Technical Report. Geneva, Switzerland: World Intellectual Property Organization.
Yin, D., Motohashi, K. (2018) *Inventor Name Disambiguation with Gradient Boosting Decision Tree and Inventor Mobility in China (1985–2016)*. Technical Report. Tokyo, Japan: Research Institute of Economy, Trade and Industry (RIETI).