Global Mobile Inventors[*]

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August 19, 2024

Abstract

The number of Global Mobile Inventors (GMIs), inventors moving across borders during their career, has increased more than tenfold over the past two decades, and the corridors of mobility have shifted towards a growing presence of emerging markets. We document that GMIs that have patented in a given technology before moving are 70% more likely to be among the pioneering inventors in that technology once they arrive at destination, which we interpret as evidence of knowledge diffusion across borders. Returnees, which are typically inventors from emerging markets that go back after having spent some time in the US and other advanced economies, are twice as likely to file pioneering patents once returned than migrants when arriving abroad. Finally, we find that the more central the GMIs in the network of inventors during the early stages of the technology life-cycle at destination, the faster the technology-specific knowledge is absorbed by local inventors.

Keywords: innovation, migration, patent, technology, knowledge

JEL Classification Numbers: O31, O33, F22

[*]Miguelez acknowledges financial support from the French National Research Agency (TKC project – reference: ANR-17-CE26-0016) and the French State's framework of the Investments for the Future programme IdEx université de Bordeaux / GPR HOPE. The authors thank Frank Chiu for excellent research assistance. All errors are our own.
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1 Introduction

Albert Einstein's legacy goes beyond his own contributions to science. He, as well as many other German Jewish scientists who fled Nazi Germany to the United States, are given credit for having "revolutionized US innovation", especially in fields such as chemistry (Moser et al., 2014). In other fields such as Mathematics, the post-1992 influx of Soviet mathematicians to the United States has been attributed to an increase in the production of "Soviet style Mathematics" in the United States (Borjas and Doran, 2012). These studies, conducted in specific fields of science and in specific epochs of history, raise the question: Can we systematically trace back the *origin* and *rise* of a country's inventive activity in specific fields to geographically mobile inventors transferring knowledge from abroad? This paper aims to answer this question.

Using the universe of USPTO records over the past 50 years, which include 6.1 million patents and 3.4 million inventors traceable across time and space, our paper demonstrates how this "Einstein" phenomenon is not an isolated one. Inventors who move across borders –or Global Mobile Inventors (GMIs) as we refer to them– are a rising global phenomenon leaving a clear footprint in the diffusion of technologies in the global stage.

Our analysis starts by enunciating a conceptual framework of knowledge diffusion across space based on insights from several strands of literature and lays out testable empirical predictions on the contexts in which we expect mobile inventors to be particularly effective at spreading innovation. In sum, knowledge does not move freely across space because learning is localized and is subject to search costs and contextual frictions.[1] In this type of environment, we theorize, GMIs act as brokers of information from their location of origin to their location of destination.

We then move to our empirical analysis, starting by describing in detail the GMI phenomenon

[1]This is consistent consistent with the observation using patent data that shows that knowledge moves with incredible difficulty across geography and that spillovers are highly localized (see Jaffe et al. (1993); Thompson (2006); Singh and Marx (2013); Murata et al. (2014); Figueiredo et al. (2015); Balsmeier et al. (2023)).

to provide some key insights. In particular, we document a substantial increase in the proportion of GMIs within the inventor population over the past few decades. The share of GMIs went from negligible levels in 1990 to consisting of 10% of all inventors and being present in 30% of all patents by 2015, surpassing the well-established parallel phenomenon of Global Collaborative Patents (GCPs), patents in which inventors located in different countries collaborate as a team (Kerr and Kerr, 2018). Interestingly, the main corridors of geographic mobility have also evolved, transitioning from primarily Western countries and Japan to encompass a growing number of emerging markets such as China, India, and Korea. This shift highlights the importance of these nations as innovation hubs and signals a changing landscape of global knowledge flows. In particular, the largest 10 corridors of inventor mobility include the US as a source or destination, and we can establish that most of these moves concern inventors from China, Korea, India, and Japan (and Taiwan to a lesser extent) that migrate in the US for a period of time and subsequently return to their home country. Finally, as a last stage of our descriptive analysis, we show that GMIs are "superstars" in a number of dimensions, such as their patenting activity and the quality of their innovations.

Next, we explore the link between GMIs and the diffusion of technology between nations. In particular, we study the life cycle of 623 technology classes (as per the Cooperative Patent Classification, or CPC) in over 200 countries of residence of inventors, and uncover two main findings with regards to GMIs. First, GMIs are about 70 percent more likely to innovate in the early stages of technologies new to the countries where they reside after moving (i.e., we measure early stage as the first chronological decile of patents filed by inventors in that country and in that technology), as compared to patents in the later stages. This pattern is much more pronounced when GMIs have previous experience patenting that same technology abroad before moving, suggesting that they function as a vector of diffusion of knowledge across borders. This first set of results validates the role of GMIs predicted by our conceptual framework. We further show that the over-representation of GMIs in the early stages of the technology life-cycle is more pronounced for (i) more complex technologies, (ii) when the destination of the GMIs is a developing country (which are further away from the technological frontier).[2]

We also show that, on average, the relative abundance of GMIs becomes negligible roughly half way through the life cycle of a technology-country pair, implying that after a period of time the ability to continue to innovate becomes fully embedded in local inventors. Based on this empirical regularity, we create a novel measure of the speed of local absorptive capacity (Cohen and Levinthal, 1990) that aims to capture how quickly knowledge is transferred from GMIs to local inventors. Our findings demonstrate that this local absorptive capacity grows faster when GMIs are more central in the network with local coauthors in early stages of the life cycle of technology-country pairs, and this is especially true when the local coauthors of the GMIs are themselves central in the network, and thus more productive.

While we acknowledge that our study lacks the type of exogenous variation allowing us to draw definitive conclusions on causal effects –though we carefully estimate a series of increasingly demanding specifications that leave little room for concerns regarding endogeneity– we believe our results shed a new light on an understudied phenomenon and on the mechanisms underlying it.

Our paper contributes to a growing literature that links immigrant inventors to positive effects on innovation in terms of their ability to diffuse knowledge across borders.[3] In particular, our study generalizes the fact that immigrant inventors serve as agents of knowledge diffusion. This fact has been documented for specific historical events (Moser et al., 2014; Bernstein et al., 2022) and for specific migration corridors (Prato, 2022). Our paper finds this empirical regularity to be robust to using the universe of countries filing patents for the

[2]Consistently, we have an additional finding that shows that the effect is mostly driven by instances where the GMI is a returnee, which is more common for corridors from developed (technologically advanced) to developing (technologically laggard) countries.

[3]Major contributions in this direction include Kerr (2008); Agrawal et al. (2008); Hunt and Gauthier-Loiselle (2010); Kerr and Lincoln (2010); Hornung (2014); Ganguli (2015); Bosetti et al. (2015); Choudhury (2016); Akcigit et al. (2017); Breschi et al. (2017); Bernstein et al. (2018); Lissoni (2018); Miguélez (2018); Choudhury and Kim (2018); Doran and Yoon (2019); Bernstein et al. (2022); Prato (2022); Miguelez and Morrison (2023).

USPTO and over a period of approximately 50 years.

Furthermore, we contribute to the literature documenting the link between aggregate migration flows and knowledge diffusion (Bahar and Rapoport, 2018; Bahar et al., 2020), delving into the mechanisms underlying the relationship. In particular we highlight the crucial role played by mobile inventors, especially when central in the network of local coauthors. We also contribute to the limited literature on the crucial role returned workers play in fostering innovation in developing countries and emerging markets, in part due to the difficulties in identifying them.[4]

Finally, we make a significant methodological contribution by moving away from patent citations to measure technological diffusion, which is recognized to be a noisy measure (Thompson and Fox-Kean, 2005; Jaffe and De Rassenfosse, 2017).

Our findings and contributions have important implications. When it comes to economics, by linking human mobility to the ability of countries to innovate in new technologies, our results speak to human mobility as a central determinant of economic growth through innovation.[5] This is particularly important in the context of developing countries, where our results tend to be consistently stronger.

Consequently, our results have direct policy implications. First, countries can benefit from encouraging scientists and inventors to move and bring with them their accumulated knowledge and experience, to foster the diffusion of knowledge, which is key to foster innovation and productivity. Second, the integration of newcomers is crucial, as team collaboration is crucial to facilitate the dissemination of knowledge to local inventors.[6]

[4] Related to this literature is the work by Fry (2022) showing that sub-Saharan African scientists returning home after a stay in the US significantly increase publishing and the size of their local network of colleagues who never left.

[5] The link between innovation and economic growth has been well established theoretically and empirically. A recent example is Akcigit et al. (2017).

[6] In this context our paper also contributes to a growing literature on the role of teams on innovation. In this literature, for example, it is shown that inventors are increasingly working in teams due to the growing specialization of knowledge (Uzzi and Spiro, 2005; Jones, 2009). In addition, teamwork comes with division of labor and hierarchy, with senior inventors holding precious assets capable of transferring them to the rest of the team (Balconi et al., 2004; Singh, 2005; Jaravel et al., 2018; Bernstein et al., 2022).

The remaining of the paper is organized as follows: Section 2 lays out theoretical considerations to better understand our results; Section 3 describes the data used; Section 4 presents some stylized facts about GMIs; Section 5 presents the main analysis on the link between inventor mobility and technological diffusion; Section 6 explores the mechanisms behind local absorption; and Section 7 concludes. This paper is accompanied by an Online Appendix that further details data sources, methodological approaches, and robustness results.

2 Theoretical Considerations

There is longstanding research across multiple literatures on how knowledge might be confined within geographic regions and may not easily spread to distant geographies. In the innovation economics literature, it is well known that knowledge spillovers are spatially localized (e.g., Jaffe et al., 1993)[7] and this insight relates to agglomeration economies and the spatial concentration of knowledge clusters (e.g., Glaeser and Gottlieb, 2009; Rosenthal and Strange, 2001).

There are three main mechanisms that explain the geographic concentration of knowledge within regions.

The first of these mechanisms is the high effectiveness of localized learning between individuals during serendipitous face-to-face interactions (as opposed to not face-to-face learning). This mechanism was highlighted by Marshall (1920) and Jacobs (1969) and is salient to a stream of recent research in economics and management (e.g., Duranton and Puga, 2001; Nardi and Whittaker, 2002; Choudhury, 2017; Bahar and Rapoport, 2018; Battiston et al., 2021; Lane et al., 2021; Atkin et al., 2022).

The second mechanism relates to the intuitive proven fact that, when it comes to finding

[7]Other papers that document and relate to geographic localization of knowledge spillovers include Almeida and Kogut (1999); Thompson and Fox-Kean (2005); Breschi and Lissoni (2009); Gambardella and Giarratana (2010); Belenzon and Schankerman (2013); Singh and Marx (2013); Murata et al. (2014); Contigiani and Testoni (2023).

sources of knowledge, the search costs are for the recipient of such knowledge are considerably lower in proximate geographies. This applies to what is often referred to as a proximate macro geography (e.g., within the same city or state) or even a proximate micro geography (e.g., being in the same floor of a building Vs. different floors), as opposed to distant macro or micro geographies (e.g., Bahar et al., 2014; Bahar, 2020; Sandvik et al., 2020; Roche et al., 2024).

The third mechanism relates to the contextual frictions, i.e., language, culture and the tacitness component of knowledge, that prevent the dissemination of "sticky knowledge" across geographies. The literature has argued that knowledge might be "sticky" and may not traverse across geographies, especially if such knowledge is non-codified or un-codifiable (e.g., Szulanski, 2000; Cowan et al., 2000). A more recent stream of research documents how language and culture can represent frictions in disseminating knowledge across regions (e.g., Choudhury and Kim, 2019; Bahar et al., 2023).

Given the geographic localization of knowledge, and the mechanisms that explain such fact, we theorize the following.

First, individuals who move between regions can act as catalysts to spread the otherwise geographically constrained knowledge, especially by acting as "knowledge brokers" between groups of individuals within their professional and social networks. By doing so, geographically mobile inventors are potentially critical actors behind the origin and rise of a country's inventive activity in specific fields. As such, GMIs can facilitate the spread of knowledge from the territory where the knowledge was originally produced to the host country where the GMI is now located.[8]

Second, we also theorize that GMIs will disproportionately benefit knowledge diffusion when more central in the host territory network, speeding up local absorptive capacity (Cohen and

[8]Related research on inventors as knowledge brokers includes Hargadon and Sutton (1997); Balconi et al. (2004); Fleming et al. (2007b); Breschi and Catalini (2010); Forti et al. (2013); Choudhury (2016); Paruchuri and Awate (2017); Balachandran and Hernandez (2018); Zacchia (2020); Bahar et al. (2023); Fry and Furman (2023).

Levinthal, 1990). This idea builds on the longstanding literature on networks and brokerage, especially the literature on "small world" networks in sociology and management. Networks research (e.g., Watts and Strogatz, 1998; Watts, 1999)has highlighted the existence of "small worlds" in the production and dissemination of knowledge. Small worlds have been defined as "clusters of locally dense interactions connected via a few bridging ties" (Fleming et al., 2007a, p. 938).[9] Given the existence of small worlds in knowledge production and knowledge dissemination where such small worlds are tethered to geographic regions, GMIs can also serve as "knowledge brokers" locally when sharing geographically constrained knowledge to local peers in their host areas.

Heterogenous Effects

The sociology literature has offered two conceptual views on brokerage: Structural holes (e.g., Burt, 2004), and structural folds (e.g., Vedres and Stark, 2010). In the structural holes view, individuals at the intersection of two small-world networks can derive social capital by brokering knowledge and information across the structural hole. In the structural folds view, individuals serve as "multiple insiders" (i.e., have inside-access to two or more small world networks) and can facilitate the transfer of knowledge between such disparate small world networks.

We argue that GMIs could represent either or both, structural holes or structural folds, between two small world networks (i.e., the small world network pertaining to the country originally producing the knowledge, and small-world network pertaining to the country where the GMI is now located). Building on Szulanski (2000) and Cowan et al. (2000), we further theorize that the effectiveness of the GMI as a knowledge broker between the two countries would be accented if the knowledge being transferred was more complex (i.e., the knowledge comprised more tacit and non-codified components), as their adoption and acquisition is

[9]The idea that social networks might be driving the innovativeness of regions has been long theorized in the economics literature, too (e.g., Marshall, 1920; Piore and Sabel, 1984).

more costly (Tamer Cavusgil et al., 2003; Balland and Rigby, 2017). We also hypothesize knowledge transfers to be more important when the destination country lays further away from the technological frontier (i.e., a developing country), and thus has more to learn. This is even reinforced when the GMI is a returnee, as usually returnee flows occur from technological leaders to laggard countries. Further, returnees can be particularly important knowledge brokers as they share language and cultural traits with their colleagues in their home country with whom they will share the newly acquired knowledge. Finally, we theorize that the effectiveness of the GMI as a knowledge broker between the two regions would be accented if the GMI had a rich and dense network of local collaborators in the host territory that are also in turn well connected into the network (i.e., the small world of the receiving country).

These theoretical considerations guide the empirical analysis throughout the rest of the paper.

3 Data

We base our analysis on patents and inventors from *PatentsView*. This open data platform contains the universe of patents granted by the USPTO for the period from 1970 until 2015, which we assign to countries based on the country of residence of their inventors, and to one of 623 technology classes according to its first listed Cooperative Patent Classification (CPC). Our final sample includes 6,146,440 granted patents belonging to 3,490,075 inventors. In our main analysis, we look at the prevalence of GMIs among the inventors of the first patents of a technology class ever filed in a given country. In a robustness test, we show that results are robust to considering all CPC classifications mentioned in the patent, and not just the first. To define a time span for each patent, our analysis uses the filling date (or the priority date if earlier). This follows the practice in the literature that considers filing dates as the most closely related to the date the knowledge creation occurred.[10] Although this data source only includes patents that were (also) filed in the USPTO, we argue that it includes all patents that can be considered as transformational, since it is the second largest patent office in the world, after China, and by far the largest repository of non-resident patents (WIPO, 2022).[11]

PatentsView uses complex algorithms to disambiguate the names of inventors and firms, resulting in a unique identifier for both (Monath et al., 2020).[12] It also registers the location of residence of each inventor at the time of patent filing, which together with the individual identifier, allows us to follow inventors across time and space and thus identify cross-border moves (consistent with patent activity).[13]

We define as GMIs all inventors that patent in a country other than the one that they have been observed patenting previously. An open question for this definition is for how long an inventor who moved across borders is to be considered a GMI. One possibility is to consider that after the first move an inventor remains a GMI during the rest of her career. The other extreme case is to only assign the GMI label to the first patent filed after a given move. In the main analysis of this paper, we define an inventor as a GMI since the moment she files the first patent in a country other than the one in which she filed her previous patent and during all patenting activity that occurs *within the year after that.* In this instance, a GMI is identified as such for patents filed within one year of observing the first patent filing in a different country. In our approach the one-year clock is reset following a new cross-border move. In the Online Appendix Section B.1 we show that the results are robust to assigning

[10]We drop patents filed after 2015 to avoid right-censoring, which is due to the time delay existing between the time of the filing and the time of acceptance. Our results, however, are robust to including the full dataset.

[11]In Online Appendix B.4 we show that the results are robust to excluding from the sample technology-country pairs where the very first patents filed do not appear in the USPTO, as indicated by the PATSTAT dataset. We also show that our results are robust to the reproducibility of the analysis using data from the European Patent Office (EPO).

[12]Extensive prior work describes both the USPTO data and assignee disambiguation efforts (see Hall et al. 2001; Li et al. 2014) and the role of patent data as an indicator of innovation (Trajtenberg, 1990; Hall et al., 2001).

[13]The most common practice is that an inventor reports her address, or the address of her work office, at the moment of filing the patent. This information is thus useful both for measuring inventor mobility across borders and for determining the countries where the MNE has offices around the world.

the GMI status to the inventor's entire career following the first move.

As opposed to the micro data used by Miguelez and Fink (2017), PatentViews contains no information on inventor's nationality, implying that GMIs cannot be directly classified into immigrants or returnees. In order to obtain this distinction, we perform a name analysis using the cultural origin of inventors' names (Kerr, 2008; Breschi et al., 2017).[14] If a GMI moves to a country where her name and surname are not common (highly frequent), we define her as "immigrant", otherwise we define her as "returnee". If they are common in both home and host countries (e.g., when both countries share the same linguistic group), then we grant her origin country where she filed her first patent (more details available in Breschi et al., 2017; Coda-Zabetta et al., 2021).

4 The Rise of Global Mobile Inventors

Figure 1a reveals that by 2015 nearly 30 thousand patenting inventors have moved internationally at some point in their career, corresponding to about 70 thousand patents, going from 1 thousand and 2 thousand in 1980 respectively.[15] Figure 1b shows that while the mobility of inventors was a negligible phenomenon until the 1990s, it grew massively since then, reaching almost 10% of all inventors and 30% of all patents by 2015.[16] Figure 1c shows that, while in the 1980s and 1990s the largest flows of inventors were taking place within Western countries and Japan, with the United States as the focal point, since the beginning of the 2000s emerging markets such as China, Korea and India entered the top 10 of the most important corridors of inventor mobility, rendering it a truly global phenomenon.

[14] We rely on IBM's Global Name Recognition (GNR) system, which includes 750k full names + computer-generated variants for each name or surname that were originated by Immigration authorities in the US at the beginning of the 1990's, to run ethno-linguistic analysis on inventors' names and surnames. For each of them, it provides (among other things) a list of countries of association, together with information on the name's/surname's frequency in each country (expressed in deciles).

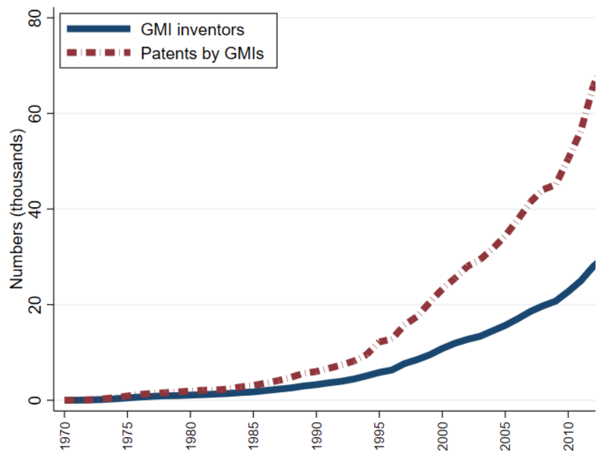
[15] For this graph, we consider a GMI every inventor that has moved at some point in the past and throughout his following career.

[16] For comparison, note that the share of patents that classify as Global Collaborative Patents Kerr and Kerr (2018), another form of the internationalization of innovation, has grown from nearly 0.5% of all patents in the early 1970s to over 8% of all patents in the mid 2010s (see Online Appendix figure A5).

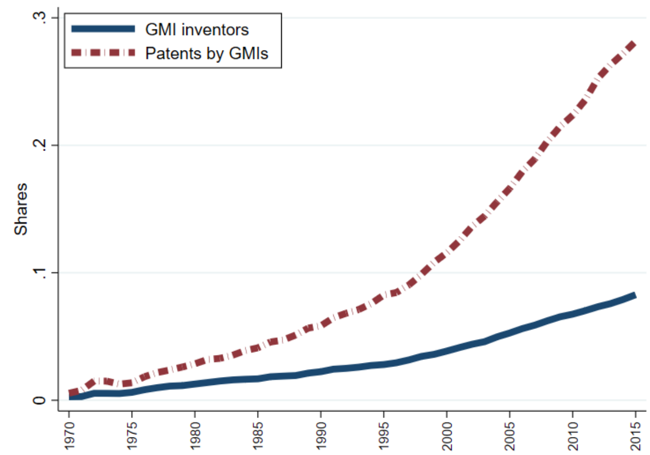
Online Appendix figure A1 show a similar picture for the evolution of the number of patents filed by country. While the US and Japan remain the global leaders in 2015 as measured by aggregate patents filed, China, South Korea and Taiwan show an impressive progression over the period and by the end they surpass France and the U.K.

Figure 1: The rise of mobile inventors and the shifting corridors

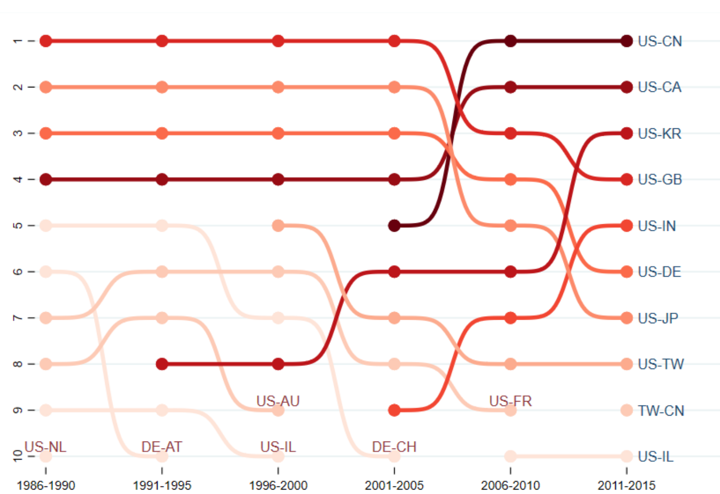
(a) N. of GMI inventors and patents



(b) Shares of GMI inventors and patents



(c) Shifting corridors of mobility



Panel a. and b. count the mobile inventors and the patents they file globally each year (in numbers and shares, respectively). Panel c. shows the evolution of the top 10 largest corridors of mobility over the period, with the largest corridor at the top.

Online Appendix A provides additional descriptive statistics, including the breakdown of the main corridor by migrant versus returnee status (see Figures A2 and A3). What we can observe is that by 2015 the three largest returnee flows concern inventors returning to China, Korea, and India after a stay in the US.

GMIs are highly productive, highly capable inventors, called "superstars". As such, they are among the few inventors able to transfer knowledge across borders, sharing it with locals, and pioneer the development of new technological life-cycles in the receiving countries. In Table 1 we present summary statistics comparing GMIs to non-GMIs.[17] Since in our sample, by definition, a GMI must have at least two patents, we highlight the comparison between GMIs and never moving inventors with at least two patents. Compared to non-GMIs with at least two patents, GMIs patent significantly more (17.17 vs 7.13). We also find that 44% of all GMIs patents in firms that belong to the top 100 in terms of the number of patents filed globally, whereas the corresponding figure for non-GMIs with two or more patents is 29%. GMIs are almost three times as likely to participate in Global Collaborative Patents than non-GMIs. Finally, GMIs have a patenting career that is longer, almost twice or three times as long as for non-GMIs, and receive more citations.

5 GMIs and the Diffusion of Technologies

In this section, we move on to investigate whether GMIs play a special role in explaining the dynamics of technology diffusion across countries. We focus in particular on GMIs with previous experience in a given technology, defined as an inventor that has filed at least one patent in that technology class *before* moving. We first provide preliminary evidence by regressing a dummy identifying GMIs with prior experience (or experienced GMI) in a given technology class on a series of dummies identifying each decile of all patents filed within that technology in the destination country, chronologically ordered by priority date. For

[17] Any person that was ever a GMI according to all definitions above is considered a GMI for this exercise, even before the first international movement.

Table 1: GMIs vs. non-GMIs

	μ_{GMI}	μ_{nonGMI}	Δ	μ^{2+}_{nonGMI}	Δ^{2+}
Number of patents	17.17	3.94	13.23***	7.13	10.04***
Number of assignees	3.95	1.24	2.71***	1.72	2.22***
Filed in Top 100 assginee	0.44	0.21	0.23***	0.29	0.15***
Number of active years	14.72	4.64	10.08***	8.59	6.13***
Share of GCPs	0.23	0.08	0.15***	0.08	0.15***
Multiple Fields	0.48	0.43	0.05***	0.45	0.02***
NPL Citations	6.59	3.97	2.61***	4.94	1.65***
Citations (5-year)	9.88	6.52	3.37***	8.28	1.60***
Sample Size	97192	3391954	-	1626550	-

This table presents averages for a number of measures for GMIs and non-GMIs. Averages for GMIs are denoted by μ_{GMI}. For non-GMIs we provide averages for the overall sample of non-GMIs (μ_{nonGMI}) as well as for the sub-sample of non-GMIs with two or more patents filed throughout the patenting career of the inventors (μ^{2+}_{nonGMI}). The table also presents difference of the means between GMI and non-GMIs (denoted by Δ) as well as for GMI and non-GMI with 2 or more patents (denoted by Δ^{2+}). Statistical significance of t-test are presented using stars as follows: ${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

example, the dummy for the first decile equals one if the patent is among the first 10% of all patents ever produced in that technology within that country; while the dummy for the 10th decile equals one if the patent is among the latest -or most recent- 10% of patents filed in that technology in that country, according to our sample. By doing this, we estimate the probability that a "pioneering" patent (within any given country-technology pair) is linked to at least one experienced GMI. We omit the dummy for the 10th decile so that the other coefficients can be interpreted as the additional concentration of experienced GMIs in earlier deciles relative to the final decile. Finally, we control for fixed effects for country-year, technology-year, and assignee-year combinations to absorb shocks that affect a particular technology over time and changes in overall R&D investments in a given country or a given multinational firm, all of which could be correlated with the flow of GMIs and the emergence of new technologies simultaneously. Formally, we estimate the following model :

$$GMI^{prev\_exp}_{i,p,k,c,t} = \sum_{d=1}^{10} \beta_d decile^{d}_{p,k,c} + \theta_{c,t} + \varphi_{k,t} + \eta^{assignee}_{p,t} + u_{i,p,k,c,t} \tag{1}$$

where subscript i is an inventor, p is a patent, k is a technology class, c is the country of residence of the inventor, and t is the year of patent filing. The data set is thus uniquely identified by the inventor ID and patent ID. $GMI^{prev\_exp}_{k,i,p,c,t}$ is a binary outcome that takes the value 1 if the inventor i is a GMI with prior experience in technology k *before* time t in a country other than c. $decile^{d}_{p,c}$ is a dummy variable that takes the value 1 if the patent p is in the d_{th} decile of all patents within each technology class k and country c chronologically order by the date of application (or priority date, whatever is earliest). For example, $decile^{1}_{i,p,c} = 1$ if patent p is among the first 10% of all patents ever produced in country c and in technology k; while $decile^{10}_{i,p,c} = 1$ if patent p is among the latest –or most recent– 10% of patents filed in country c and technology k, according to our sample. In this sense, β_1 is an estimator of the probability that a "pioneering patent" (within any given country-technology pair) is related to at least one experienced migrant inventor.

Figure 2 summarizes the result of this estimation by plotting the probability of observing a mobile inventor with past experience in a given technology, across the life cycle of that same technology in the country of destination. Panel (a) shows the results for all countries pooled together, while panel (b) distinguishes between OECD and non-OECD countries.[18]

If GMIs with previous experience abroad were randomly distributed across the technology lifecycle, we would see no differences in their presence across deciles. However, that is not the case. For Panel (a), we observe that patents in the first decile have around 0.5 percentage points higher probability of having been invented by at least one experienced GMI than the latest 10% patents filed in the same country and technology. Since in our sample the unconditional probability of seeing any experienced GMI across all deciles is

[18] Our choice to define deciles by splitting the total number of patents filed in a given country and technology pair, rather than splitting the calendar time between the first and last patent filed, is justified by the fact that the very first patents take longer to be invented than those that come later on in the life-cycle. Appendix table B2 shows that, on average, it takes 6 years to invent the first decile of patents, while the length quickly converges to 2 years for the deciles after. If we define deciles according to equally sized periods of time, we obtain a median of 2 patents in the first decile instead of the 5 obtained with our preferred definition, reducing considerably the number of observations considered as "pioneering inventions". Nonetheless, in Appendix figure B2 we reproduce our main figure according to the alternative calendar time definition, and show that a similar pattern arises, even though much more noisily when using the "GMI 1 year" definition and only significant when using the "GMI always" definition.

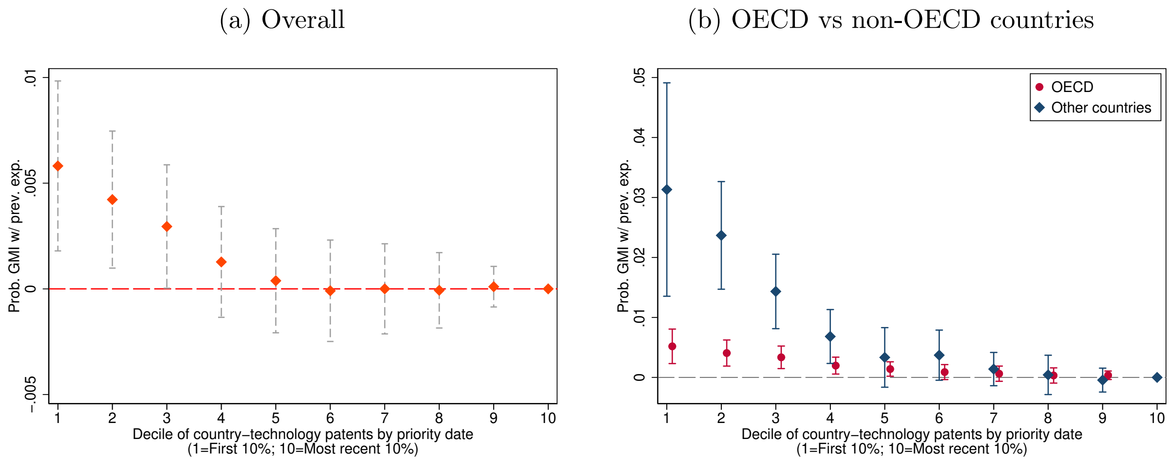
0.7%, this implies that an experienced GMI is over 70% more likely to file a patent in the earliest decile of any given country-technology pair. Noticeably in the figure, the probability keeps dropping and becomes statistically insignificant after the third decile (based on the confidence intervals at the 90% level). We can interpret the fact that the over-representation of GMIs fades out in patents invented later in the life cycle of a technology as evidence that the ability to innovate in that technology, as time goes by, becomes fully embedded in local inventors.

Panel (b) shows that, while this relationship holds true in both OECD and non-OECD countries, it is much more pronounced in non-OECD countries, where there is a 3 percentage points higher probability that a patent in the first decile is invented by experienced GMIs than a patent in the last decile (as opposed to under 1 percentage point for OECD countries). This heterogeneity highlights how GMIs are particularly crucial for technology diffusion in countries that are further away from the technological frontier (as predicted in Section 2).

In the Online Appendix B.1 we show that the figure remains unchanged if we use the "GMI Always" definition, which assigns the GMI status throughout the entire career of the inventor after the observed first change in country of residence. This definition of GMI is more conservative since it excludes the possibility of earlier GMIs being considered as locals after the first year spent patenting at destination. The fact that our results remain unchanged supports our interpretation of the figure as evidence of diffusion towards never-moving inventors. The OECD heterogeneity is also robust to this change.

Our main regression analysis aims to confirm the robustness of the link between the arrival of an experienced GMI and the introduction of a new class of technology in the country of destination. To do that, we regress the probability that a patent belongs to the first decile of the country-specific technology life cycle depending on the presence of a GMI with previous experience (relative to the other 9 deciles, thus a very stringent test), controlling for a battery of inventor-level and patent-level controls and several layers of fixed effects. We

Figure 2: Probability of patent by experienced GMI throughout life-cycle



This figure plots the probability of observing a mobile inventor with previous experience abroad across the 10 deciles of that technology life-cycle in the country of destination. The 10th decile (e.g the patents filed most recently) is used as the comparison one, and the whiskers represent the 90% confidence intervals (based on standard errors clustered at the country level). The underlying regression controls for technology $\times$ year, country $\times$ year, and firm $\times$ year fixed effects to absorb differences explained by specific technology, country and firm trends. Panel (a) shows the results for the entire sample, while Panel (b) distinguishes between OECD and non-OECD countries.

then explore the heterogeneity of the effect across types of mobility to test whether GMIs are particularly relevant for technology diffusion in contexts consistent with the theoretical considerations discussed in Section 2, and we perform several robustness checks to rule out alternative explanations. Formally, we estimate:

$$\begin{aligned} decile^{1}_{p,k,c} = \beta^{GMI} GMI^{prev\_exp}_{i,p,k,c,t} + controls_{i,p} + \\ + \theta_{c,t} + \varphi_{k,t} + \eta^{assignee}_{p,t} + u_{i,p,k,c,t} \end{aligned} \tag{2}$$

where subscript i is an inventor, p is a patent, k is a technology class, c is the country of residence of the inventor and t is the year of patent filing. $GMI^{prev\_exp}_{k,i,p,c,t}$ is a binary outcome that takes the value 1 if the inventor i is a GMI with previous experience in technology k *before* time t in a country other than c. $decile^{1}_{p,c}$ is a dummy variable that takes the value 1 if patent p is in the first decile of all patents within each technology class k and country c in chronological order by application date. In this sense, β^{GMI} is an estimator of the probability that a "pioneering" patent (within any given country-technology pair) is linked to at least one experienced GMI. Controls include patent characteristics and inventor characteristics. In the first category, we include a dummy equal to one if the patent is a GCP, the number of citations to non-patent literature, the number of claims included in the patent, the team size, a dummy for foreign priority, and the lag between application and granting. In the second category, we include the experience of the inventor computed as the number of years since the first patent she produced and the productivity of the inventor computed as the total stock of patents filed over her entire career. Finally, we control for the length, in calendar time, of the first decile of technology diffusion. All continuous variables are included using the inverse hyperbolic sine (IHS) transformation, which controls for skeweness similarly to the logarithm, but it is also defined in zero. Given this set of controls, our aim is to control for the fact that GMIs are generally more productive, as shown in the previous section. The model also includes country-year fixed effects to capture any country-level trends in the likelihood of introducing new technologies that might be correlated with GMI flows and technology-year fixed effects to capture broad evolutions of technology across all countries. Finally, it controls for assignee-year fixed effects to capture any specific trends in innovation within firms that might be correlated with both their inventor mobility and their likelihood to introduce a new technology in another country.

Results from estimating equation 2 are presented in Table 2. Column 1 presents the estimation of our coefficient of interest. The interpretation is that the likelihood of seeing a GMI with prior experience in the first decile of the technology lifecycle is approximately 0.2 percentage points higher than in the remaining 90% of patents filed, equivalent to a 30% increase from the baseline.[19]

Column 2 of Table 2 presents an important robustness test. Our claim is that the coefficient β^{GMI} captures the role of GMIs in the emergence of new technologies for a country. This

[19]The baseline is the unconditional probability of seeing a GMI in our sample which is 0.7%.

statement might be violated if the differential effect captured by β^{GMI} is simply driven by the fact that GMIs are particularly productive inventors. In addition to the set of controls already added in the main analysis, Column (2) shows that the estimate is much smaller for GMIs that do not have prior experience in that technology before moving. This suggests that our finding is not driven only by highly productive inventors but rather by specific knowledge diffusion (below we also show results that include inventor fixed effects, which further control for the innate ability of the inventor). Another possibility that would invalidate our results is a mechanical one: If mobile inventors are more present at the beginning of the country-technology cycle because of the temporary definition that we adopt (e.g., for the first year after the move). In the online Appendix Section B1 we show that results remain virtually unchanged if we use the "GMI always" definition, consisting of assigning the GMI status for the entire career of the inventor following the move, thus ruling out this possibility.

One might also wonder whether the effects are driven by the strategy of multinational firms to start operating in a new country, and thus rotate experienced talent from abroad to facilitate it. Column 3 of Table 2 shows that the over-representation of GMIs is similar if we compare inventors that moved internationally within the same firm or across firms, suggesting that what we observe is not the mere reflection of firm-specific strategies combining technology adoption and international human capital management. Furthermore, the inclusion of assignee-year fixed effects in all of our specifications is also meant to control for this possibility.

The remaining columns of Table 2 test the heterogeneity of the effect across different subsamples to verify some theoretical ideas exposed in Section 2. First, as already shown in Figure 2, Column 4 confirms that the over-presence of GMIs in the early phases of technology life-cycle is more pronounced in non-OECD countries. This is consistent with the claim that GMIs are particularly useful for technology diffusion in countries that lie further away from the technological frontier. Column 5 shows that returnees are twice as likely to be present in the first decile of technology diffusion than immigrants. This result is consistent with what shown by others in the literature (Fry, 2022) and highlights that returnees are particularly effective knowledge brokers because they possess both the experience accumulated abroad and the ability to effectively communicate it with those inventors that never left their own countries. Given the description of the main bilateral corridors concerning returnee mobility presented in Appendix Table A3, this result suggests that the knowledge transmitted by inventors that spent some time in the US is particularly valuable for the innovation in emerging markets such as China, Korea and India.

Column (6) shows that the effect is driven particularly for technologies that are complex. We define technology complexity by applying the Hidalgo and Hausmann (2009) method to measure complexity to technologies instead of trade: In short, complex technologies are those that are rare and only diversified innovation hubs are able to patent in them.[20] We expect complex technologies to contain more tacit knowledge, and thus to be particularly slow to diffuse without the presence of knowledge brokers such as our GMIs. In the main table we define complexity using the most recent period of USPTO data (2016-2020). In Appendix section B.3 we show that the results are robust to measuring complexity in various periods further back in time.

Finally, Column (7) splits the sample according to the time period of a given technology diffusion in the country.[21] The fact that GMIs are particularly effective at spreading technologies in countries after the beginning of the 1990s is consistent with the previous results highlighting the importance for diffusion in non-OECD countries, that started innovating more recently and can thus learn from the technological leaders. It is also consistent with the fact that the main flows of returnees going from OECD countries towards emerging markets become larger in the 2000s, while in the early periods most inventor mobility took place within OECD.

Finally, in many of these tests the question of the expected direction of causality arises.

[20] See Moscatelli et al. (2024) for a detailed description of the methodology.

[21] We define the period based on the date of the first patent that follows the first decile of diffusion.

While we lack an exogenous treatment that explains the movement of inventors, and thus we cannot ultimately disregard some other explanations, we find comfort in the survival of our estimation after the estimation of several specifications and inclusion of a battery of fixed effects. Certainly a possible story driving our results is that countries systematically put forward plans to enter a new technological field of innovation, and to achieve it, they adopt policies aiming to attract foreign workers with the right knowledge and qualifications. If this were the case, it would still be consistent with our results that in order for countries and firms to drive their innovation in a new direction, the role that GMIs play is instrumental for the diffusion of knowledge across borders.

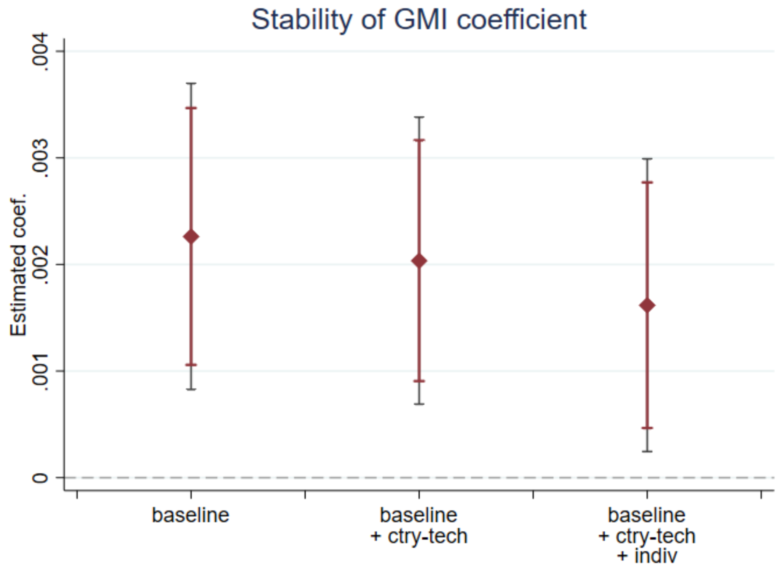
Figure 3 reports how the coefficient associated with GMI with previous experience evolves with the inclusion of increasingly demanding layers of fixed effects. Vertical bars represent the confidence intervals at the 10% and 5% level. Standard errors are clustered at the country level. The first specification includes country-year, technology-year, and firm-year fixed effects, in addition to all the controls described in the main analysis. Thus, it controls for all country-specific time trends common to all technologies, for all the technology-specific time trends common to all countries, and for all firm-specific time-variant factors. This corresponds to our baseline specification. In the second specification, we further add technology-country fixed effects, which absorb all factors specific to a technology-country pair that are time invariant. Finally, the last specification adds inventor fixed effects. In the latter case, the coefficient captures the additional presence of GMIs with previous experience in early stages of technology diffusion during the year following the inventor's mobility to another country, as compared to all other periods of her career. We believe that this last specification can capture the vast majority of unobservable factors that might confound our relation of interest. We find that the effect remains significant at the 5% level and preserves a similar size between specification 1 (our preferred one) and specification 3, the most restrictive one.

Table 2: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: First Decile						
GMI, previous exp.	0.00226***	0.00235***					
	(0.000732)	(0.000761)					
GMI, no previous exp.		0.000802***					
		(0.000271)					
GMI, same assignee			0.00232***				
			(0.000830)				
GMI, diff. assignee			0.00216**				
			(0.00107)				
GMI, OECD				0.00202***			
				(0.000748)			
GMI, non OECD				0.00304**			
				(0.00124)			
GMI, immigrant					0.00247***		
					(0.000920)		
GMI, returnee					0.00565***		
					(0.00124)		
GMI, high complex tech.						0.00322**	
						(0.00138)	
GMI, low complex tech.						0.000919	
						(0.000680)	
GMI, prior 1990							-0.000358
							(0.00139)
GMI, post 1990							0.00368***
							(0.00137)
Observations	13,621,698	13,621,698	13,621,698	13,621,698	13,621,698	13,621,612	13,621,698
R-squared	0.867	0.867	0.867	0.867	0.867	0.867	0.867

Notes: Country-level standard errors in parentheses. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar time of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

Figure 3: Main coefficient after adding increasingly demanding fixed effects



Notes: The figure reports the evolution of the main coefficient of interest - associated with GMI with previous experience - after the addition of increasingly demanding levels of fixed effects. The "baseline" specification includes country-year, technology-year, and firm-year fixed effects, in addition to all the controls (a dummy equal to one if the patent is a GCP, the number of citations to nonpatent literature, the number of claims included in the patent, the size of the patent team, a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days, the experience of the inventor computed from the first patent she produced, the stock of patents produced by the inventor over her career), and the length in calendar time of the first decile of technology diffusion. The second specification adds country-technology fixed effects. The third column adds individual inventor fixed effects.

Additional Robustness

In the Online Appendix we perform several additional robustness tests.

In Section B.4 we address the concern that what we measure as the pioneering patents in a country-technology cell is not indeed pioneering as USPTO patents in that cell might have been preceded by patents in another patent country office. To address this selection problem, we look at all patents from all national and regional patent offices worldwide, grouped by patent family (from the PATSTAT database) for all technology-country pairs and show that our main results are robust to restricting the sample to the cases where: (1) there is at least one USPTO patent in the first decile of the life-cycle of the pair; and where (2) the very first patent of the life-cycle is a USPTO one. The latter restriction is much more stringent, since it reduces the sample from 13.6 millions to 1.4 million observations, but all the coefficients and heterogeneities of interest remain consistent and very similar in magnitude. This reveals that our results are not driven by country-technology cells that appear as pioneering in the USPTO data but are not such when incorporating information from other patent offices.

We also show that our results are robust to including all technology classes listed in the patent instead of only the first one (Section B.5); to using different GMI definitions (Section B.1); to collapsing the data at the patent level (Section B.6); and to conducting the same analysis using data from the EPO instead of the USPTO (Section B.7). The latter is an additional test to ensure our results are not driven by selection into the USPTO. The Online Appendix does not just report the results for these tests, but also includes a description of our interpretation.

6 Mechanisms of Local Absorption: Network centrality

The over-representation of GMIs in the life cycle of a technology-country cell decreases gradually over time, so that by the fourth decile, on average, GMIs and local inventors become as likely to be involved in an innovation as predicted by their overall share (Figure 2). As such, we can interpret the slope of the graph as a novel measure of the speed of the *local absorptive capacity* between local inventors (Cohen and Levinthal, 1990): The more negative the relationship between time and share of patents by GMIs, the faster local inventors have the embedded capacity to continue to innovate.

We exploit the relationship described in Figure 2 by adopting a similar approach to estimate the speed of local absorptive capacity (Cohen and Levinthal, 1990) in each country-technology cell, using the following specification:

$$Sh\_GMI^{exp}_{m,y} = \alpha^{speed} \times pctile_{m,y} + u_{m,y} \tag{3}$$

where $Sh\_GMI^{exp}_{m,y}$ captures the share of GMIs with previous experience out of all inventors patenting in a given month m and year y, and $pctile_{m,y}$ records the percentile of patents filed in each time period (from 0 to 100), as our counter.[22] Thus, α^{speed} captures the speed of local absorptive capacity: The more negative it is, the faster the over representation of GMIs fades out. We ran about 11 thousand regressions: one for each technology-country pair that has a large enough sample in our data. This approach introduces a novel measure of local diffusion, or local adoption that focuses on the time it takes for locals to fully absorb the know-how imported by inventors from abroad.[23]

Appendix Figure C1a shows graphically how the coefficient of local absorption speed is recovered for the example of the medical instrument technology class in India. Appendix Figure C1b shows the distribution of the diffusion parameter speed obtained in all countries and classes, where the outcome in the regression is the share of GMIs. The summary statistics of the speed measures are reported in the Appendix Table C1. The mean and median of the coefficient are positive and very close to 0 in magnitude. This can potentially be due to a combination of two effects. First, the negative relation documented in the previous section comes from the fact that the technology slowly becomes embedded in the local pool of inventors, and second, the general increase in the share of GMIs across the globe documented in the summary statistics, which makes it generally more likely to find GMIs in more recent years[24] To eliminate the second effect, we also perform the analysis using a

[22]Our findings are robust to use a RCA-like measure of GMI share, which account for the global trend in GMIs in each technology. Results are reported in the robustness analysis.

[23]One common approach adopted by the literature to capture technological diffusion is to measure the cumulative share of adopters at each point in time, which typically proceeds following an S-shape (initially very few adopt, then there is an acceleration when the majority starts adopting, and finally it slows down again when it reaches the group most averse to adoption) (Rogers et al., 2014). This approach is suitable for applications that use technology usage data, but not for applications using patent data. Patents record new inventions in a given technology that typically do not behave according to the same patterns.

[24]This effect is absorbed by the year fixed effects in Figure 2.

Relative Comparative Advantage (RCA) type variable as the outcome, which is simply the share of GMI observed in a given technology-country percentile divided by the share of GMIs observed globally at the same moment in time. Appendix Figure C1c plots the distribution of the speed of diffusion parameter obtained when the outcome is the RCA. Here, the mean and the median are both negatives (mean =-0.0085, median = -0.0014), consistent with what was shown when combining all technology-country cells. Next, we keep all the coefficients in our data set, regardless of their sign, and we store the t-statistic to be able to weight the observations according to their significance level.[25]

For the rest of our analysis and for easier interpretation, we flip the sign so that the *larger* it is, the *faster* the speed of the local absorptive capacity. Thus, we define $speed_{c,k} = -\widehat{\alpha^{speed}}$. To explore whether the number of collaborations between experienced GMIs and local inventors can predict the speed of knowledge absorption, we then regress the speed on different measures of network centrality of the GMI using the following model.

$$\begin{aligned} speed_{ck} &= \beta_1 \mathbb{1}(Sh\_GMI^{exp}_{d=1} > 0) + \beta_2 NetworkGMI^{exp}_{d=first} \\ &\quad + \beta_3 \mathbb{1}(Sh\_GMI^{exp}_{d=1} > 0) \times NetworkGMI^{exp}_{d=first} + \beta_4 X_{ck} + \eta_c + \phi_k + u_{ck} \end{aligned} \tag{4}$$

where $\mathbb{1}(Sh\_GMI^{exp}_{d=1} > 0)$ is a dummy equal to one if there is at least one GMI with previous experience within the first decile of the development of the technology k in the country c. $NetworkGMI^{exp}_{d=first}$ is a measure of the centrality of the GMI network with previous experience in the first decile of the life cycle where they are found. If in a given country-technology there are no GMIs with previous experience in the first 3 deciles of

[25] We remain agnostic on why in some cases the estimated speed of diffusion is positive or negative. It might be noise caused by estimations with very small samples or something more structural about the different country-technology cells. In this paper we take the estimates at face value but use the weights to make sure our results are not driven by noisy estimates. Properly investigating these differences, though, is an important part of our ongoing research agenda.

patents filed, we take the average network of the experienced GMIs in the 4th decile. Third, we include an interaction between the dummy indicating whether there is at least a GMI in the first decile and the network centrality measure. We use four distinct measures of network centrality : i) degree centrality, which captures the number of local co-inventors with whom the GMI is patenting; ii) eigenvector centrality, which is similar to degree centrality but weights the local coauthors by how central they themselves are in the network; iii) closeness centrality, which measures its average closeness (inverse of distance) to all other local inventors. GMIs with a high closeness score have the shortest distances to all other inventors; iv) betweenness centrality, which measures the shortest paths between all pairs of GMIs and local inventors in the country. This measure is often used to find individuals in the network that serve as a bridge between different groups (see summary statistics in the Online Appendix Table C1). All measures of speed and network centrality are standardized to have mean 0 and standard deviation 1 to facilitate interpretation. Regressions also include fixed effects for the country and for technology, and a number of controls X_{ck} including the total number of days in the country's technology life cycle, the duration of each decile in days, the number of days since the first patent was filed in country technology and the total number of inventors in the 1st decile (all in IHS). Standard errors are clustered at the country level. We perform four types of regressions: unweighted, weighted by the number of observations in the technology country cell, weighted by the absolute value of the t-statistic obtained in the speed regression (equation 3), and unweighted on the sub-sample of speed values that are statistically significant in equation 3. The weighted regressions aim to give more emphasis to the observations where the speed estimation is more precise, while the last column only considers the observations where this speed is significantly different from 0. We expect β_1 to be positive: Given that our absorption speed is directly computed using the slope of GMI intensity across deciles, the speed is more likely to be higher if there is at least one GMI with previous experience patenting in the first decile. Here we are thus mainly interested in β_3, which compares country-technology pairs with at least one GMI in the first decile and tests whether the speed of local absorptive capacity is higher when these GMIs have a larger network of local coinventors.

Table 3 reports the main results of our regression analysis. They confirm our hypothesis that the earlier the presence of GMI with previous experience in the life-cycle of the technology, and the more central these GMI are among the network of inventors, the faster the speed of absorptive capacity of locals. In particular, the first column and first row of Table 3 Panel A show that, conditional on the presence of at least one GMI in the first decile of the technology-country pair (as opposed to later deciles), a standard deviation higher degree centrality of the GMI in the network of local inventors increases the speed of local absorptive capacity by about half a standard deviation.[26] Using other measures of network centrality or adding different weighting to the regressions results in qualitatively similar effects. Interestingly, the coefficients on the interaction are even slightly larger when using the eigenvector centrality measure, which gives more importance to coauthors in the network that are themselves central. This suggests that the diffusion of knowledge from GMIs to local inventors is even faster when the latter are better connected themselves. On the contrary, we note a smaller and barely statistically significant coefficient in two of the coefficients of panel D, implying that the betweenness centrality of the GMI (its capacity to bridge separate networks) might be less important in facilitating local knowledge absorption than measures of interaction intensity within a given network (such as degree centrality, eigenvector centrality and closeness centrality)[27].

Our interpretation of this final result is consistent with what we spelled out in Section 2, namely the idea that the more the GMIs are interconnected with the local network through co-inventorship, the faster the new knowledge they bring into the country is absorbed by the local inventors, and this is especially true when local coauthors are themselves central in

[26]Note in the second row that the presence itself of a GMI in the first decile of the patenting activity of the technology-country pair also explains faster speed, thus the overall explanatory power is of one full standard deviation (0.521+0.598). However, this second effect could also happen partly by construction, so we focus on the interaction term as our main effect of interest.

[27]The coefficients on the various network measures are comparable in size because they have been standardized.

the network. Appendix Table C2 extends the measure of degree centrality to the number of local inventors with whom the GMIs co-work within the same subsidiary of the firm, while not directly patenting together, and recovers the robustness of results to defining the speed coefficient using the RCA measure, and to define GMI with previous experience using the GMI always definition, always using degree centrality as the measure of the network. Both tests give rise to remarkably similar results, while the network of co-workers that are not co-inventors does not affect the speed of local absorptive capacity. Finally, Appendix Table C3 introduces triple interactions between the dummy of having a GMI in the first decile, the degree centrality in the network of local coauthors, and a measure of productivity of the network of local coauthors. The latter is computed as the average number of patents filed per year until that point in time by all local inventors that coauthor with a GMI. Results are not always significant but generally point in the direction that higher productivity of the local network is associated with fastest diffusion, which both corroborates our conceptual framework and what found by others in the literature.

7 Conclusion

Our results in this paper speak to the importance of human mobility in facilitating the process of knowledge diffusion across borders, especially for emerging markets.

This non-trivial result, we believe, has important implications for global dynamics. The Schumpeterian view argues that innovation –by boosting productivity– translates into higher economic growth. As such, within this framework, our results suggest that human mobility is a central determinant of growth and development by effectively spreading ideas globally.

Further, our result showing that the local capacity of inventors to continue producing knowledge in technologies that arguably arrived with GMIs shows that this process is sustainable, as GMIs seem to ignite innovation, but local inventors are the ones that maintain the production of knowledge over time.

In our future research agenda we aim to further investigate this nonconventional relationship, and continue to push the frontier of our knowledge surrounding the effect of human mobility –and migration– on outcomes that go beyond innovation, which also would carry important policy implications.

If the relationship we uncover here is representative of the role human mobility could play in other determinants of economic growth, then one could argue that human mobility is a core part of the solution to bridge the long-standing gaps between developing and developed nations.

Table 3: Determinants of the speed of diffusion

	(1)	(2)	(3)	(4)
	Outcome : speed of diffusion			
	unweighted	wgt by obs.	wgt by T-stat	Only significant coefs.
	Panel A) Network measure: Degree centrality			
1 * [GMI in 1st decile]	0.598***	0.531***	0.774***	0.998***
	(0.0655)	(0.0567)	(0.0875)	(0.180)
1 * [GMI in 1st decile] *network local coauthors	0.521***	0.546***	0.674***	0.673**
	(0.0743)	(0.0704)	(0.0968)	(0.320)
Observations	4,843	4,843	4,842	925
R-squared	0.322	0.296	0.432	0.595
	Panel B) Network measure: Eigenvector centrality			
1 * [GMI in 1st decile]	0.586***	0.534***	0.770***	1.121***
	(0.0544)	(0.0474)	(0.0741)	(0.168)
1 * [GMI in 1st decile] *network local coauthors	0.573***	0.560***	0.766***	0.969***
	(0.0714)	(0.0636)	(0.0943)	(0.209)
Observations	4,843	4,843	4,842	925
R-squared	0.321	0.295	0.430	0.593
	Panel C) Network measure: Closeness centrality			
1 * [GMI in 1st decile]	0.653***	0.524***	0.859***	1.179***
	(0.0814)	(0.0694)	(0.113)	(0.162)
1 * [GMI in 1st decile] *network local coauthors	0.299***	0.286***	0.399***	1.221***
	(0.0717)	(0.0641)	(0.112)	(0.229)
Observations	4,843	4,843	4,842	925
R-squared	0.270	0.242	0.369	0.578
	Panel D) Network measure: Betweenness centrality			
1 * [GMI in 1st decile]	0.622***	0.485***	0.813***	1.027***
	(0.0872)	(0.0753)	(0.120)	(0.182)
1 * [GMI in 1st decile] *network local coauthors	0.0287*	0.0362***	0.0221	0.491**
	(0.0152)	(0.0129)	(0.0170)	(0.230)
Observations	4,843	4,843	4,842	925
R-squared	0.261	0.233	0.359	0.537

Notes : Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
All columns include country and technology fixed effects. It includes as controls the following variables: network of local coauthors and coworkers (not interacted with), total days of the country-tech life cycle, duration of each decile in days, total days until first patent filed in tech-country, and total number of inventors in country-tech in the 1st decile (all in IHS). We show the unweighted regressions as in the main text, and the robustness to weighting by the number of observations and the t-statistics obtained from the speed regression (equation 3), and finally restricting observations to those with a significant coefficient in equation 3 (significance defined at the 10% level).

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Online Appendix

Global Mobile Inventors

By Bahar, Choudhury, Miguelez and Signorelli

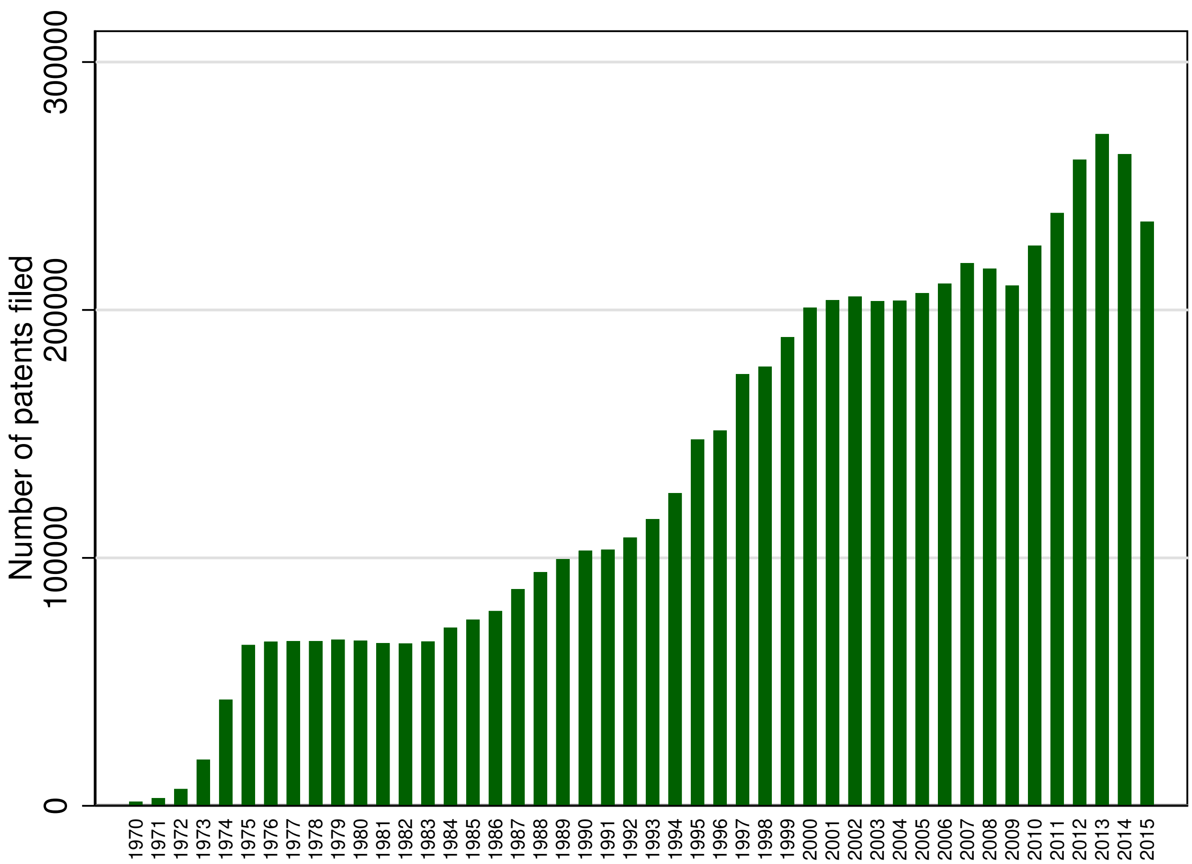
August 19, 2024

A Descriptive Statistics and Stylized Facts

Figure A1 plots the total number of patents filed per year in our sample (using the earliest between application and priority dates). As expected, the number of filings increases over time, reaching over 250,000 patents filed per year during the mid 2010s, up from just above 50,000 patents filed per year in the 1970s and 1980s. While we do not report it in this figure, we also see that the number of filings is steeply reduced for the most recent years (after 2015), due to the right censoring in the data (some of the most recent innovations have yet to be granted a patent, given the time delays in the process). Hence, all of our analysis is based on patents filed up to 2015, as noted in the main body of the text.

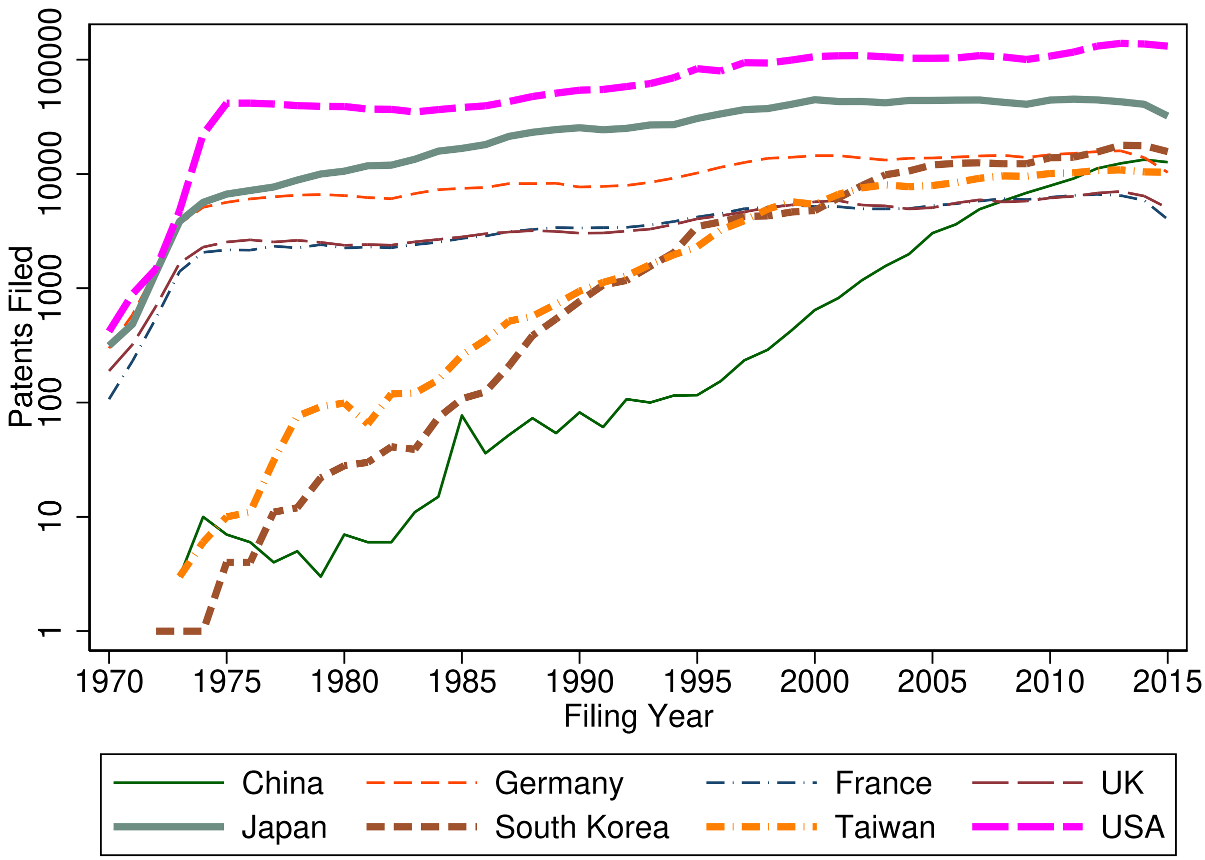
On average, these patents have 2.44 inventors per patent, with half of them filed by 2 or less inventors, while the maximum is 76. The size of teams filing a patent has increased slightly over the period, going from about 1.7 in the middle of the 1970s to about 2.8 in the early 2010s. Inventors in our sample reside in 94 different countries. However, it is only a handful of countries that account for the majority of the inventors' countries of residence. Figure A2 plots the number of inventors observed patenting each year by country of residence, for the countries that for at least five years in the whole sample (1970 to 2019) were among the five countries with the largest number of patenting inventors. The US is the country with the largest number of patenting inventors during the entire period in our sample, with

Figure A1: Total patents filed by year



This figure plots the number of patents filed by year of application in our sample. Please note that the scale on the Y-axis is non-linear, to better visualize the progression of emerging markets.

Figure A2: Top countries filing patents by inventors' residence and year



This figure plots the number of patenting inventors by year and country of residence. The list of countries included is limited to those countries that for at least five years during the whole sample (1970 to 2015) were in the top five countries with the largest number of patenting inventors.

Japan as a close second throughout. China, South Korea and Taiwan stand out in the figure because of their impressive rise in number of inventors between 1970 until the present. On the contrary, Germany, France, and the UK - which counted within the innovation leaders in the 1970s - have had a stable number of patenting inventors since, and have been surpassed by the Asian countries in recent years.

With the growth in the number of mobile inventors, we also observe an expansion in the number of major international corridors. Figure A3 plots the intensity of movements in the top 50 international corridors for the period 2015 to 2019 (which represent 85% of all movements in that period). The graph shows how the United States is the largest country

Table A1: Main corridors by 5-year periods

Rank	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2015
1	GB → US	GB → US	GB → US	GB → US	US → CN	US → CN
2	US → GB	JP → US	JP → US	JP → US	CN → US	CN → US
3	JP → US	US → GB	DE → US	US → DE	GB → US	CA → US
4	DE → US	US → JP	US → GB	DE → US	CA → US	US → CA
5	US → JP	US → DE	US → DE	CA → US	US → GB	KR → US
6	US → DE	DE → US	US → JP	US → GB	US → CA	US → KR
7	CA → US	CA → US	CA → US	US → JP	US → DE	GB → US
8	US → CA	US → CA	US → CA	US → CA	JP → US	US → GB
9	CH → DE	DE → CH	US → TW	US → CN	US → JP	US → IN
10	DE → CH	CH → DE	FR → US	CN → US	DE → US	IN → US

This table presents the top ten international corridors for moving inventors for every five-year period during 1985 to 2015, in terms of absolute number of movements.

of origin and of destination for mobile inventors, with China being the second largest. The two largest flows, accordingly, are from the US to China and from China to the US. Other countries that stand out as the origin and destination of the main international corridors are South Korea, Taiwan, Japan, Hong Kong, India, Canada, the United Kingdom, Germany, and France, consistent with figure A2.

It is important to note that the main international corridors for inventors have undergone important changes over the years. Table A1 presents the top ten corridors for every five-year period since 1985 to 2015 (using total movements for each period, based on application year). For instance, during the 1985 to 1989 period, the top five international corridors for inventors were: from the United Kingdom to the United States, from Japan to the United States, from the United States to Japan, from Germany to the United States, and from the United States to the United Kingdom. In the most recent period in the sample (2010-2015), the main corridors are from China to the United States, from the United States to China, from South Korea to the United States, from Canada to the United States, and from the United Kingdom to the United States. Indeed, consistent with Figure A2, the rise of China and South Korea in patenting activity is also correlated with their inclusion in the major corridors of international mobility of inventors over time.

Figure A3: Top 50 international corridors for inventors (2015-2019)

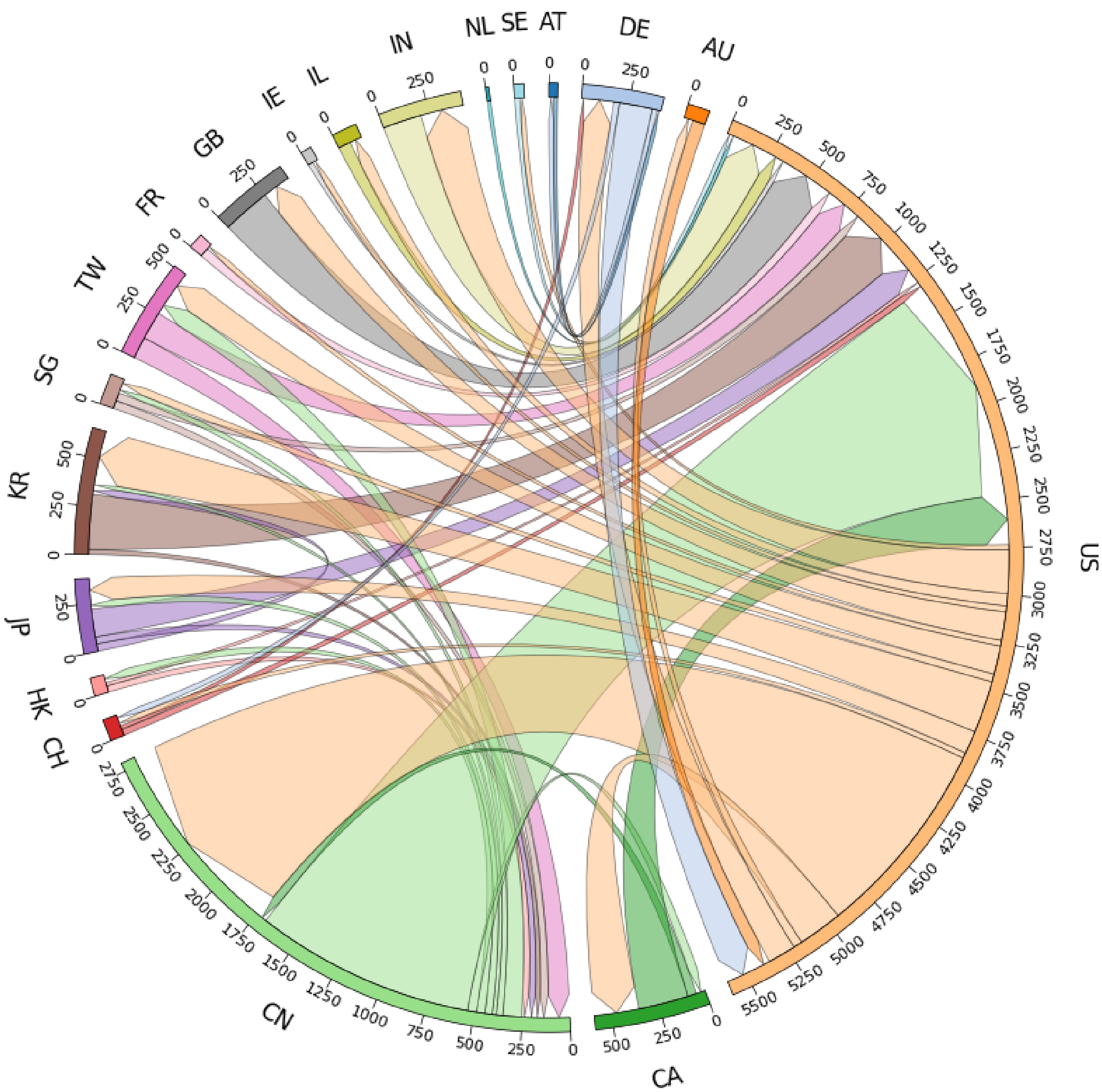


Table A2: Main corridors for GMI migrants by 5-year periods

Rank	**1985-1989**	**1990-1994**	**1995-1999**	**2000-2004**	**2005-2009**	**2010-2015**
1	JP → US	JP → US	JP → US	JP → US	CN → US	CN → US
2	GB → US	GB → US	GB → US	US → CA	JP → US	KR → US
3	US → GB	US → GB	US → GB	GB → US	US → CA	US → CA
4	DE → US	DE → US	DE → US	US → GB	US → GB	CA → US
5	US → CA	US → CA	CA → US	DE → US	KR → US	US → GB
6	CA → US	CA → US	US → CA	CA → US	GB → US	JP → US
7	US → DE	US → DE	US → DE	CN → US	CA → US	IN → US
8	DE → CH	DE → CH	FR → US	US → DE	DE → US	GB → US
9	CH → DE	FR → US	KR → US	KR → US	US → DE	DE → US
10	DE → AT	CH → DE	DE → CH	TW → US	TW → US	TW → US

This table presents the top ten international corridors for immigrant inventors for every five-year period during 1985 to 2015, in terms of absolute number of movements.

Interestingly, the top ten corridors differ if we consider immigrant separately from returnee GMIs. We use our name recognition approach to divide GMIs into these two categories and reclassify corridors accordingly. The results are reported in Tables A2 and A3. In particular, if we take the most recent period, we see that the two largest corridors of migration go from China and South Korea towards the US. Moreover, the US are the destination of 8 out of the top 10 immigrant corridors, the remaining two being from the US to Canada and the UK. Clearly, the direction of inventor migration goes from emerging markets towards advanced economies. Consistently, the opposite is observed if we look at the main corridors for returnees. The four largest flows consist of movements from the US towards Asia (in order towards China, Korea, India, and Japan). This fact is strongly suggestive of the temporary nature of most immigrants' stay in the US, and reinforces our finding that returnees having accumulated new knowledge abroad are key players in the diffusion of such knowledge in their countries of origin upon their return.

Table A3: Main corridors for GMI returnees by 5-year periods

Rank	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2015
1	US → JP	US → JP	US → JP	US → JP	US → CN	US → CN
2	GB → US	GB → US	US → DE	US → CN	US → KR	US → KR
3	US → DE	US → DE	GB → US	US → DE	US → JP	US → IN
4	US → GB	CA → US	DE → US	GB → US	GB → US	US → JP
5	CA → US	US → GB	CA → US	US → KR	CA → US	CA → US
6	DE → US	DE → US	US → TW	CA → US	US → TW	GB → US
7	CH → DE	US → KR	US → GB	US → TW	US → IN	US → TW
8	AT → DE	CH → DE	US → KR	DE → US	US → DE	US → DE
9	DE → CH	US → CA	US → CA	US → GB	DE → US	US → CA
10	US → CA	US → TW	US → IL	US → IN	US → GB	US → GB

This table presents the top ten international corridors for returnee inventors for every five-year period during 1985 to 2015, in terms of absolute number of movements.

A.1 The Rise of GMIs

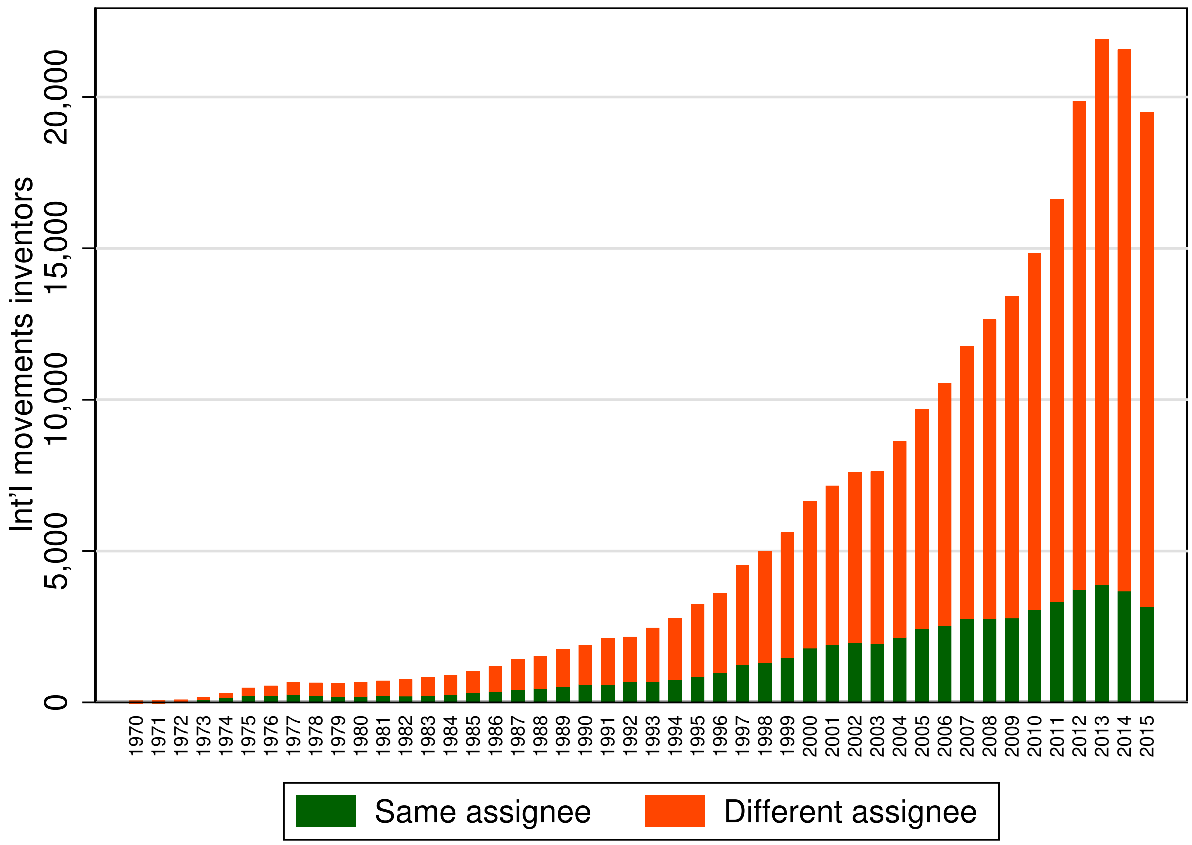
Figure A4 plots the total number of international movements observed in our sample by year.[28] The plot shows that the mobility of inventors across borders has grown significantly over the past decades, going from a few hundreds in the 1970s and 1980s to about 20,000 in the mid-2010s. The figure also shows that the vast majority of movements throughout the years take place outside the boundaries of the assignee (firm), though a non-negligible amount of movers that patent in different countries do so within the same assignee.

A known factor that defines the internationalization of knowledge production is the rising prominence of patents filed by teams of inventors residing in multiple countries, also known as global collaborative patents (GPCs) (Kerr and Kerr, 2018). The latter are typically large and ambitious projects involving international collaborations. The share of patents that are classified as GCPs in our sample has grown from nearly 0.5% of all patents in the early 1970s to more than 8% of all patents in the mid-2010s, a 16X growth.[29] The internationalization

[28] These movements are equivalent to the number of GMI (First Patent) in the sample every year, according to the definitions in the previous subsection.

[29] We identify GCPs in our sample as the patents filed by at least two inventors residing in at least two different countries at the time of application. The large growth observed is consistent with the findings of Kerr and Kerr (2018), who, using a sample of US public company patents, found that the share of GCPs went from 1% in 1982 to 6% in 2004. Our sample is not limited to US firms, which is explaining the differences in the overall figures, although the trends are quite similar. For comparison purposes, we report that in our sample the share of GCPs goes from

Figure A4: International movements of inventors, by. year

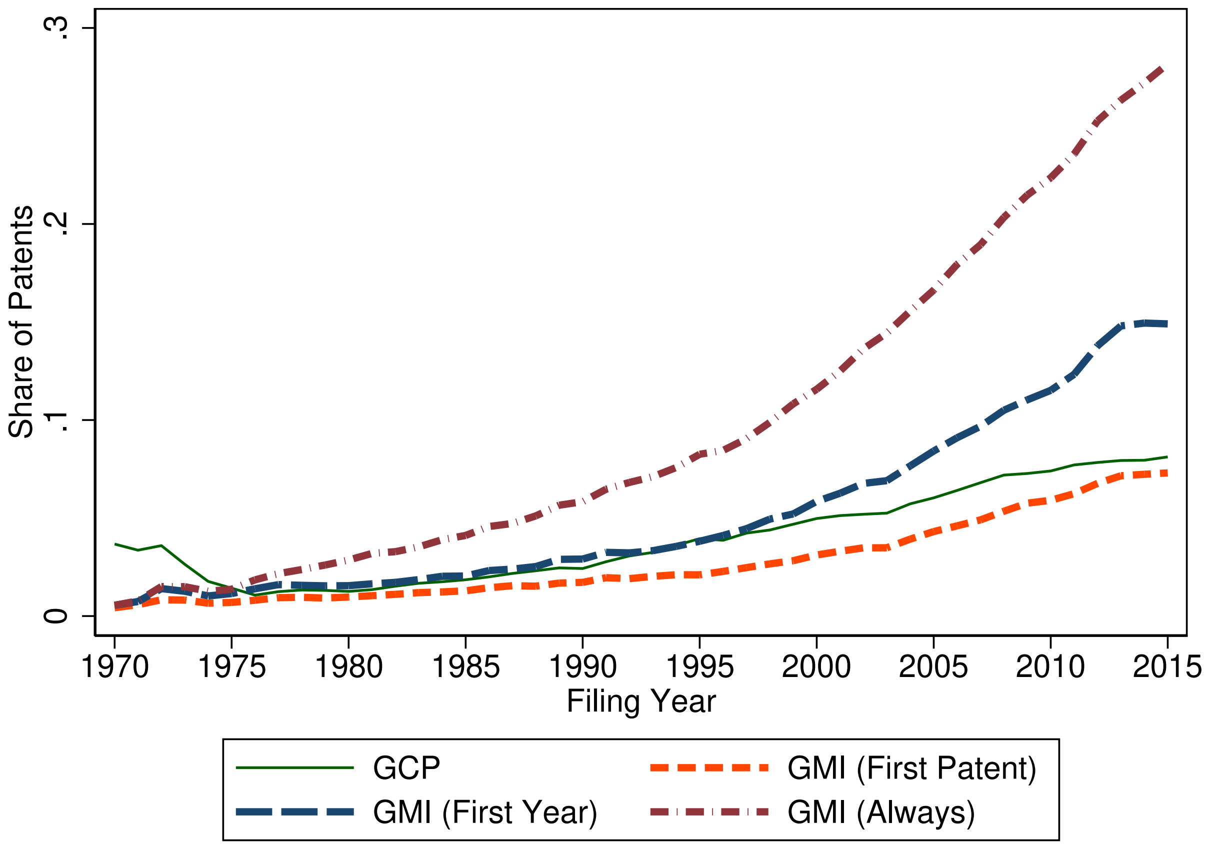


This figure plots the absolute number of international movements we see in our sample by year, using the year of application (or priority, if earlier) of a patent where the inventor's reported country of residence differs to the one reported in the immediately previous patent by the same inventor.

trend observed through the rise in GCPs is even more pronounced when we look at patents filed by teams with at least one GMI. Figure A5 plots the share of all patents that have at least one GMI year-by-year, using the three different definitions outlined above. The graph shows that in the early 1970s less than half a percent of all patents had at least one GMI, regardless of the GMI definition used. In fact, the share of patents with a GMI in the team was significantly lower than the share of GCPs in 1970. However, patents with at least one GMI in the team became much more common over the past decades. In 2015, about 7% of the patents in the sample had at least one GMI, using the "First Patent" definition. Naturally, because of the cumulative effect of how the variables are computed, when using the other definitions, the number is even larger, as seen in the figure. About 15% and 28% of the patents in the sample, by 2015, had a GMI defined using the "First Year" and "Always", respectively. Thus, regardless of how it is measured, the GMI phenomenon is as fast-growing, if not more, and often larger (depending on how GMI is defined) than GCPs.

1.5% in 1982 to nearly 6% in 2004, which are very similar figures.

Figure A5: Share of patents by categories



This figure plots for every year of application (or priority if earlier) the share of patents with at least one GMI using three different definitions outlined in the main body of the text, as well as the share of patents that can be classified as a GCP.

B GMIs and the Life-Cycle of Technologies: robustness and heterogeneity

B.1 Using a different definition for GMIs

Given our preferred definition of GMIs, which consists in assigning the GMI status after each cross-country move of an inventor and for the year that follows such move, it could be the case that in some technology-country cells the mobile inventors are the only ones patenting, and that the decreasing slope in Figure 2 in the main text is explained by the fact that they gradually become "locals" according to our definition. To ensure that this fact is not biasing our results, we reproduce the same exercise but using the "GMI Always" definition instead, which continues to consider as GMIs all the inventors that move throughout the rest of their career. Results are presented in Figure B1. The picture is extremely similar to the one obtained using the "GMI 1 year" definition, both in magnitude and shape. We thus conclude that what we observe is indeed the fact that the technology-related knowledge gets slowly embedded into local inventors that have never moved before.

We also repeat the regression results, but we consider that an inventor remains a GMI for her entire career after the first move. Table B1 shows the results. The coefficients are smaller than in the main analysis, which is to be expected since the role of the knowledge transmitter is fading after having spent many years in the destination country. However, the heterogeneity of effects remains consistent with the main analysis and confirms the patterns previously discussed.

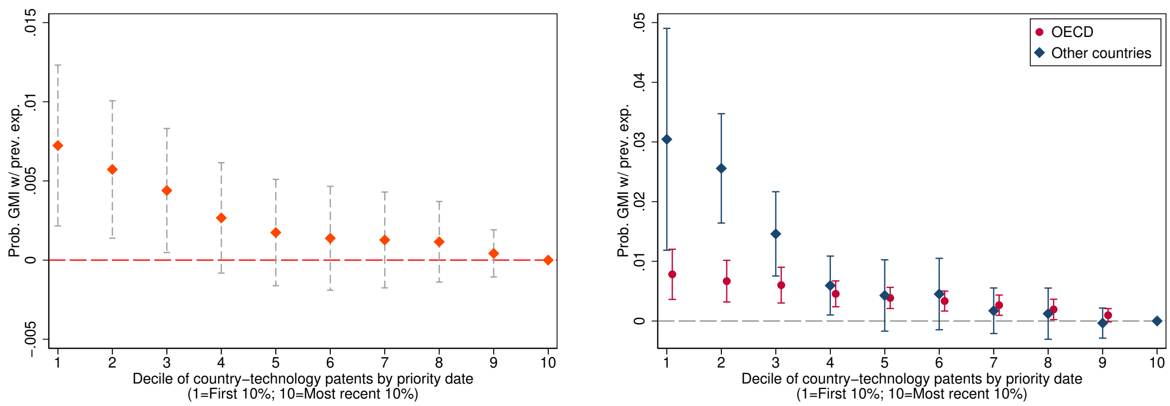
Table B1: Using the "GMI always" definition of movers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: First Decile						
GMI, previous exp.	0.00126**	0.00134**					
	(0.000543)	(0.000575)					
GMI, no previous exp.		0.000431**					
		(0.000177)					
GMI, same assignee			0.00111**				
			(0.000528)				
GMI, diff. assignee			0.00160*				
			(0.000885)				
GMI, OECD				0.00121**			
				(0.000546)			
GMI, non OECD				0.00148			
				(0.00100)			
GMI, immigrant					0.00248***		
					(0.000915)		
GMI, returnee					0.00564***		
					(0.00124)		
GMI, high complex. tech.						0.00200*	
						(0.00103)	
GMI, low complex. tech.						0.000240	
						(0.000536)	
GMI, prior 1990							0.00176*
							(0.00101)
GMI, post 1990							0.000439
							(0.000990)
Observations	13,621,698	13,621,698	13,621,698	13,621,698	13,621,698	13,621,612	13,621,698
R-squared	0.867	0.867	0.867	0.867	0.867	0.867	0.867

Notes: Country-level standard errors in parentheses. Main regressor of interest: presence of a GMI with previous experience, defined as any individual who has previously patented abroad in the same technology. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

Figure B1: Patents by experienced mobile inventors - GMI always definition - across the technology life-cycle

(a) Overall (b) OECD vs non-OECD countries



This figure plots the probability of observing a mobile inventor with previous experience abroad across the 10 deciles of that technology life-cycle in the country of destination. The definition of GMI used here is the one of "GMI Always", which assigns the GMI status to the entire career of the inventor after the first cross-country move. The 10th decile is used as the comparison one, and the wiskers represent the 90% confidence intervals (based on standard errors clustered at the country level). The underlying regression controls for technology × year, country × year, and firm × year fixed effects to absorb differences explained by specific technology, country and firm trends. Panel A) shows the results for the entire sample, while Panel B) distinguishes between OECD and non-OECD countries.

B.2 Definition of deciles

Our analysis defines deciles of a technology life-cycle within a given country according to the total number of patents filed within that pair. This choice is motivated by the fact that pioneering patents take longer to be introduced than patents coming later on, which are more incremental rather than transformational. Table B2 shows that, on average, the first decile of patents takes 6 years to be invented, while the second takes 3 years and later the length stabilizes at around 2 years per decile. If we take the alternative approach of defining deciles by splitting evenly the calendar time observed between the first and last patent, we would obtain deciles of about 2 years of length each, at the expense of reducing the number of patents included among the pioneering one.[30] While the average number of patents in the first decile remains high with both definitions (59 using our preferred one vs 32 using

[30]The length is not exactly the same across the calendar time deciles because in some technology-country pairs we observe less than 10 patents and it is thus not possible to define 10 distinct deciles. The same reasoning applies to the fact that the number of patents found in each decile of our main approach is not exactly the same.

the calendar time one), the median drops from 5 patents to 2 patents, highlighting how for half of the country-technology cells we would have very few observations left within the pioneering inventions.

We nonetheless provide the figure obtained with the alternative calendar time definition of deciles for comparison (see figure B2). When we consider the presence of GMIs defined as GMIs only for the first year after the move, the descending pattern remains visible in the decile coefficients but the standard errors become much larger (panel A). This is probably due to the fact that in many technology-country pairs in our sample we observe very few patents in the first calendar deciles, and it becomes even rarer to observe a GMI "1 year" among their inventors. Nonetheless, Panel B shows that the descending relation becomes again significant when using the "GMI Always" definition, which we have argued in the previous section of the Appendix to be a more conservative measure of GMIs. Overall, these results highlight that the main finding of the paper re-emerges, albeit more noisily, with the calendar time definition of deciles.

B.3 Measurement of technology complexity

One of the key heterogeneities of our results is that GMIs are particularly instrumental to favor the diffusion of technologies that are complex, and thus expected to contain a greater amount of tacit knowledge difficult to transmit across borders. As explained in the main text, we define a measure of technology complexity using the methodology first introduced by Hidalgo and Hausmann (2009) to define countries' production complexity using trade data and applied to technologies by a recent WIPO report (Moscatelli et al., 2024). High complexity technologies are thus defined by splitting our dataset at the median of the level of complexity measured using the most recent data (2016-2020). One might wonder whether the results hold if we measure complexity using data from further back in time, since our analysis focuses on a period that extends much further in the past. Table B3 shows the results

Table B2: Summary statistics for different definitions of life-cycle deciles

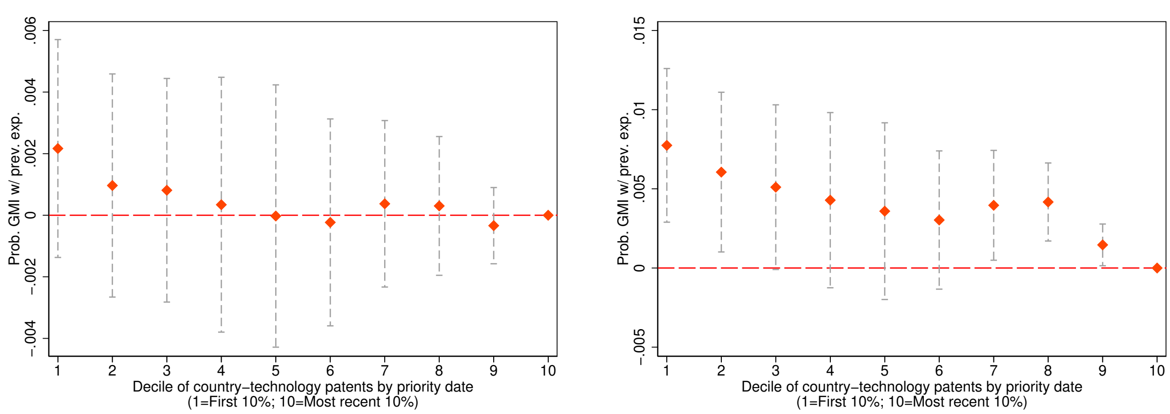
	Deciles def: N. of patents				Deciles def: calendar time			
	N. years		N. patents		N. years		N. patents	
Decile	mean	median	mean	median	mean	median	mean	median
1	6.1	5	59	5	2.2	2	32	2
2	3.2	3	57	5	2.1	2	35	4
3	2.6	2	57	5	2.1	2	35	5
4	2.2	2	57	5	2.2	2	42	5
5	2.3	2	56	5	2.2	2	52	6
6	1.7	1	58	5	2.3	3	68	7
7	2.0	2	55	5	2.4	3	86	7
8	1.9	2	57	5	2.4	3	89	7
9	2.1	2	55	5	2.4	3	92	8
10	2.6	2	55	5	2.5	3	96	7

Notes: this table compares the number of patents and the length expressed in years of each decile according to two different definition. Our preferred definition, which consists in splitting the total number of patents observed in a given technology-country pair in equally sized deciles; and an alternative definition consisting in splitting the calendar time observed between the first and last patent filed in a given technology-country pair in equally sized deciles.

Figure B2: Probability of patent by experienced GMI throughout the life-cycle defined by calendar time

(a) GMI 1 year definition

(b) GMI Always definition



This figure plots the probability of observing a mobile inventor with previous experience abroad across the 10 deciles of that technology life-cycle in the country of destination, defined by calendar time between the first and last patent filed. The definition of GMI used in Panel A) is our preferred one, which consists of considering an inventor a GMI during the first year after the move, while the definition in Panel B) is the one of "GMI Always", which assigns the GMI status to the entire career of the inventor after the first cross-country move. The 10th decile is used as the comparison one, and the wiskers represent the 90% confidence intervals (based on standard errors clustered at the country level). The underlying regression controls for technology × year, country × year, and firm × year fixed effects to absorb differences explained by specific technology, country and firm trends.

obtained if we measure complexity in different periods: i) 2016-20 (our baseline measure), ii) 2012-16, iii) 2008-12, IV) 2004-08, and v) 2000-04. Importantly, while the complexity measures are correlated across time, as we would expect, the correlation is far from perfect: if we take the continuous measure of complexity in 2000-2004 and 2016-20 their correlation is of 0.57 and only 60% of technologies classified as high-complexity in 2004 remain classified as high complexity in 2020. Nonetheless, regardless of the measure used, the same empirical regularity arises : GMIs are particularly instrumental in introducing complex technologies to countries that have yet to innovate in that domain.

B.4 Testing the role of selection into the USPTO dataset

The USPTO dataset has the great advantage of providing both assignee and inventor disambiguation over a large period of time (1970 onward). However, the dataset only includes patents that are filed with the US office, and does not record patents that are only filed in other country offices. We argue that the USPTO is by far the largest and more attractive patent office in the world, and that it should include all the transformational patents, since avoiding to file a patent in the US implies that the invention is not protected there. One might still wonder whether our results are biased by the missing patents in the data, especially in the case where the earliest patents produced in a given technology-country cell are only filed in a country office other than the USPTO. To check whether our results are affected by missing patents, we construct a subsample of country-technology cells where at least one patent within the first decile was filed in the USPTO (99% of our sample), and a sub-sample of country-technology cells where the very first patent was filed in the USPTO (32% of our sample). The data cover all patent documents worldwide filled in any office, geolocalized at the country level, and come from the European Patent Office's (EPO) Worldwide Patent Statistical Database (PATSTAT). Patents are treated at the family level. The results are shown in Tables B4 and B5. As expected, nothing changes when we exclude the 1% of the sample for which none of the patents in the first decile appear in the USPTO.

Table B3: Heterogeneity by technology complexity measured at different points in time

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Dependent variable: First Decile				
GMI, high complex. tech. (2016-20)	0.00322**				
	(0.00138)				
GMI, low complex. tech. (2016-20)	0.000918				
	(0.000680)				
GMI, high complex. tech. (2012-16)		0.00460**			
		(0.00189)			
GMI, low complex. tech. (2012-16)		-0.00247			
		(0.00283)			
GMI, high complex. tech. (2008-12)			0.00280**		
			(0.00140)		
GMI, low complex. tech. (2008-12)			0.00165**		
			(0.000766)		
GMI, high complex. tech. (2004-08)				0.00415**	
				(0.00192)	
GMI, low complex. tech. (2004-08)				0.000324	
				(0.00102)	
GMI, high complex. tech. (2000-04)					0.00469**
					(0.00209)
GMI, low complex. tech. (2000-04)					-0.000112
					(0.00119)
Observations	13,621,612	13,621,612	13,621,612	13,621,612	13,621,612
R-squared	0.867	0.867	0.867	0.867	0.867

Notes: Country-level standard errors in parentheses. The table shows the heterogeneity of the role of GMIs for technologies with high and low levels of complexity, measured in different periods of time. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

More interestingly, the coefficients become even stronger in the 32% of the sample where the very first patent was filed within the USPTO. Therefore, we conclude that, if anything, the selection of the USPTO sample attenuates the magnitude of the effect.

B.5 Including all technology classes of patents

In the main analysis we have only considered the first class of technology that appear on the patent. Here we repeat the exercise by considering all the technology classes appearing on the patent, which in practice consists in duplicating patent observations across all technology classes. The dataset becomes much larger, from 13 mio observations to 23 mio, but the coefficients obtained are largely unchanged, as shown in Table B6.

B.6 Patent level regressions

In the main analysis we kept the observations at the level of inventor-patent. Here we collapse the data at the patent level, where the GMI dummy equals one if at least one of the inventors within the team is a GMI with previous experience. The same is done for all the GMI indicators. Note that in this case a patent can have both the dummy for GMI with and without experience equal to one if both types of inventors are part of the team. The inventor level controls are averaged within the patent. The results reported in table B7 show coefficients that are very similar to those of our main specification.

B.7 Using data from the European Patent Office (EPO)

USPTO patents neither cover all patenting activity worldwide nor constitute the largest patent repository. Since 2011, the Chinese patent office (CNIPA) outnumbered the USPTO as the leading patent office, and currently receives 3 times the number of applications received at the USPTO. Yet, the large majority of applications at the CNIPA come from Chinese

Table B4: Sample of country-tech cells where USPTO is in the first decile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: First Decile						
GMI, previous exp.	0.00211***	0.00220***					
	(0.000701)	(0.000733)					
GMI, no previous exp.		0.000858***					
		(0.000274)					
GMI, same assignee			0.00221**				
			(0.000852)				
GMI, diff. assignee			0.00195*				
			(0.00106)				
GMI, OECD				0.00192***			
				(0.000703)			
GMI, non OECD				0.00279*			
				(0.00143)			
GMI, immigrant					0.00224***		
					(0.000840)		
GMI, returnee					0.00591***		
					(0.00116)		
GMI, high complex. tech.						0.00307**	
						(0.00140)	
GMI, low complex. tech.						0.000823	
						(0.000687)	
GMI, prior 1990							0.00343**
							(0.00141)
GMI, post 1990							-0.000204
							(0.00136)
Observations	13,386,443	13,386,443	13,386,443	13,386,443	13,386,443	13,386,357	13,386,443
R-squared	0.869	0.869	0.869	0.869	0.869	0.869	0.869

Notes: Country-level standard errors in parentheses. The sample excludes all the technology-country cells for which none of the patents appearing in the first decile are filed at the USPTO. The latter excludes a very small minority of our sample. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

Table B5: Sample of country-tech cells where the 1st patent is in the USPTO

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: First Decile						
GMI, previous exp.	0.00222**	0.00234**					
	(0.000957)	(0.000930)					
GMI, no previous exp.		0.000478					
		(0.000510)					
GMI, same assignee			0.00236*				
			(0.00139)				
GMI, diff. assignee			0.00205***				
			(0.000755)				
GMI, OECD				-0.000335			
				(0.00197)			
GMI, non OECD				0.00326***			
				(0.000891)			
GMI, immigrant					0.00333		
					(0.00246)		
GMI, returnee					0.00359**		
					(0.00167)		
GMI, high complex. tech.						0.00377***	
						(0.000860)	
GMI, low complex. tech.						0.000339	
						(0.00137)	
GMI, prior 1990							0.00267**
							(0.00102)
GMI, post 1990							-0.000482
							(0.00241)
Observations	1,444,767	1,444,767	1,444,767	1,444,767	1,444,767	1,444,767	1,444,685
R-squared	0.931	0.931	0.931	0.931	0.931	0.931	0.931

Notes: Country-level standard errors in parentheses. The sample excludes all the technology-country cells for which the very first patent was not filed in the USPTO. The latter excludes a large portion of our sample. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

Table B6: Sample including all tech. classes mentioned in patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Dependent variable: First Decile			
GMI, previous exp.	0.00226***	0.00244***					
	(0.000491)	(0.000523)					
GMI, no previous exp.		0.00140***					
		(0.000288)					
GMI, same assignee			0.00225***				
			(0.000594)				
GMI, diff. assignee			0.00229***				
			(0.000810)				
GMI, OECD				0.00198***			
				(0.000456)			
GMI, non OECD				0.00320***			
				(0.000937)			
GMI, immigrant					0.00269***		
					(0.000497)		
GMI, returnee					0.00415***		
					(0.00121)		
GMI, high complex. tech.						0.00445***	
						(0.00169)	
GMI, low complex. tech.						-0.000346	
						(0.00142)	
GMI, prior 1990							0.00398***
							(0.00101)
GMI, post 1990							-0.000268
							(0.00130)
Observations	22,588,748	22,588,748	22,588,748	22,588,748	22,588,748	22,588,748	22,588,748
R-squared	0.660	0.660	0.660	0.660	0.660	0.660	0.660

Notes: Country-level standard errors in parentheses. The sample considers all the CPC technology classes listed in each patent. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

Table B7: Sample collapsed at the patent level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: First Decile						
GMI, previous exp.	0.00232**	0.00236**					
	(0.000906)	(0.000929)					
GMI, no previous exp.		0.000678**					
		(0.000334)					
GMI, same assignee			0.00234**				
			(0.000952)				
GMI, diff. assignee			0.00231*				
			(0.00124)				
GMI, OECD				0.00201**			
				(0.000872)			
GMI, non OECD				0.00340**			
				(0.00162)			
GMI, immigrant					0.00231**		
					(0.00110)		
GMI, returnee					0.00596***		
					(0.00173)		
GMI, high complex. tech.						0.00294*	
						(0.00150)	
GMI, low complex. tech.						0.00143**	
						(0.000705)	
GMI, prior 1990							0.00367**
							(0.00159)
GMI, post 1990							-0.000166
							(0.00151)
Observations	5,099,117	5,099,117	5,099,117	5,099,117	5,099,117	5,099,074	5,099,117
R-squared	0.857	0.857	0.857	0.857	0.857	0.857	0.857

Notes: Country-level standard errors in parentheses. The sample is collapsed at the patent level, and GMI is a dummy equal to one if at least one of the inventors filing the patent is a GMI with previous experience. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

resident applicants, while the USPTO is the largest receiving office of non-resident applicants. In fact, together with the European Patent Office (EPO), they are the only ones with more applications from non-residents than from residents (WIPO, 2022). Given these numbers, it is clear that data from the USPTO are the best candidates for the present analysis, on the emergence of new technologies in countries as a result of cross-border diffusion. Yet, it could be argued that certain "home bias" still remains when using USPTO data, as US-based applicants are, naturally, way more likely to apply (Akcigit et al., 2018). The home-centered bias is less likely to be present in the data from the EPO. While European and, particularly, German applicants may have a higher tendency to apply to the EPO, the leading countries remain the US and Japan, and the origins of the applications at the EPO are better distributed according to the countries' size (Akcigit et al., 2018). The EPO is, however, considerably smaller, and presents other drawbacks that make it less suitable than the USPTO for this analysis. Nevertheless, in order to show that our analysis is not driven by USPTO-specific features, we reproduce our main results using EPO data.

EPO data are retrieved from EPO's Worldwide Patent Statistical Database (PATSTAT). In coherence with the main approach taken in the paper, we only take granted patents for this analysis. The disambiguation of inventors' names (crucial for the present exercise) is slightly different, but follows similar principles of cleaning and parsing the raw data, matching same/similar names, and filtering the matched names based on similarity of characteristics, such as common backward citations, among others (Pezzoni et al., 2014). All in all, our final dataset consists of almost 2 million patents and over 2 million unique inventors.

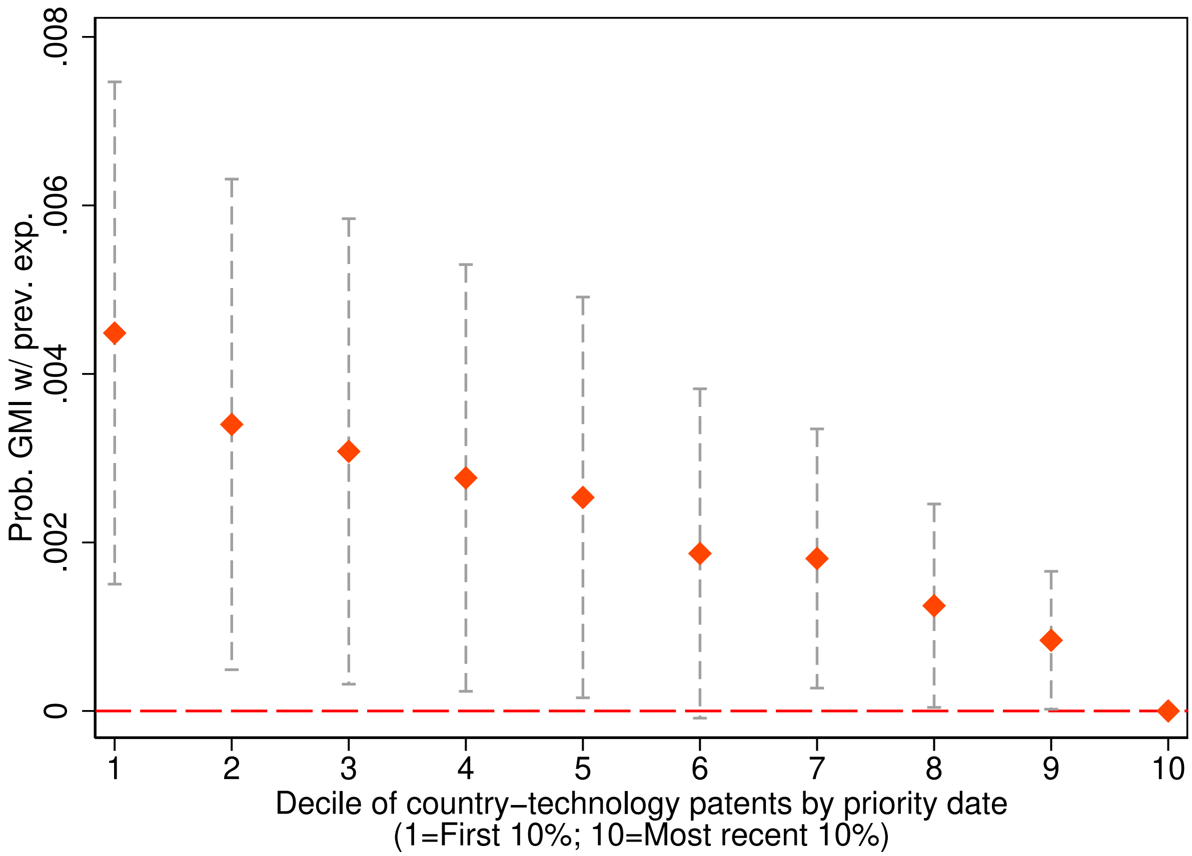
Contrary to the USPTO, the EPO does not have a main technological class assigned, and provides only a list of tech codes. To make the analysis comparable to the USPTO one, we arbitrarily assign one single technological class to each patent. To do so, we look at the CPC codes of applications, and assign them to the class with more CPC codes listed. If two or more classes are equally listed, we then prioritize the CPC codes written in the first line of the list of codes (CPC codes are not listed alphabetically, but there is no a priory rule to list them).[31] We drop the remaining applications for which we could not assign a unique technological class (around 9%).

Figure B3 reproduces the main graph of the paper, but with EPO data. The resulting figure resembles that obtained using USPTO, as one clearly sees a decreasing coefficient with increasing deciles. However, the drop is less pronounced and the coefficients are estimated with less precision. We see the same pattern in the regression analysis (table B8). Coefficients have the expected sign, but they are only significant at the 10% level.

All in all, results using EPO data seem to point to the same direction: GMIs play a crucial role in diffusing technologies across countries, and in infiltrating them to the local economy. Yet, coefficients seem to be estimated with less precision and some of the effect heterogeneities found in the USPTO dataset cannot be reproduced here, which we attribute to several characteristics of the EPO dataset (e.g., difficulties in assigning patents to an unequivocal technological class, smaller number of inventors - particularly GMIs returning to their home country) and to the fact that the EPO is not a national office, but a regional one (covering Europe, with US and Japan-based applicants on top). The latter makes us suspect that the EPO is not generally used to register the most novel technologies emerging in each country.

[31] The data on the position of the codes in the application come from PATSTAT - table TLS209.

Figure B3: Patents by experienced mobile inventors across the technology life-cycle - EPO data



This figure plots the probability of observing a mobile inventor with previous experience abroad across the 10 deciles of that technology life-cycle in the country of destination. The 10th decile is used as the comparison one, and the wiskers represent the 90% confidence intervals (based on standard errors clustered at the country level). The underlying regression controls for technology × year, country × year, and firm × year fixed effects to absorb differences explained by specific technology, country and firm trends.

Table B8: Main results using EPO data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: First Decile						
GMI, previous exp.	0.00383*	0.00387*					
	(0.00222)	(0.00224)					
GMI, no previous exp.		0.000923					
		(0.000904)					
GMI, same assignee			0.00375				
			(0.00264)				
GMI, diff. assignee			0.00415				
			(0.00259)				
GMI, OECD				0.00576***			
				(0.00167)			
GMI, non OECD				-0.0135**			
				(0.00535)			
GMI, immigrant					0.00662***		
					(0.00185)		
GMI, returnee					0.00150		
					(0.00604)		
GMI, high complex. tech.						0.000193	
						(0.00273)	
GMI, low complex. tech.						0.00734**	
						(0.00294)	
GMI, prior 1990							0.00376
							(0.00474)
GMI, post 1990							0.00389**
							(0.00174)
Observations	4,705,984	4,705,984	4,705,984	4,705,984	4,705,984	4,705,984	4,705,984
R-squared	0.863	0.863	0.863	0.863	0.863	0.863	0.863

Notes: Country-level standard errors in parentheses. GMI is a dummy equal to one if at least one of the inventors filing the patent is a GMI with previous experience. Control variables include a dummy equal to one if the patent is a GCP, the number of citation to non-patent literature (transformed using the inverse hyperbolic sine, IHS), the number of claims included in the patent (IHS), the size of the patent team (IHS), a dummy indicating whether the patent has a foreign priority, the time between application and granting, in days (IHS), the experience of the inventor computed from the first patent she produced (IHS), the stock of patents produced by the inventor over her career (IHS), and the length in calendar months of the first decile of technology diffusion (IHS). The regression further controls for country-year fixed effects, technology-year fixed effects, and assignee-year fixed effects.

C Mechanisms: speed of knowledge diffusion and network centrality of GMIs

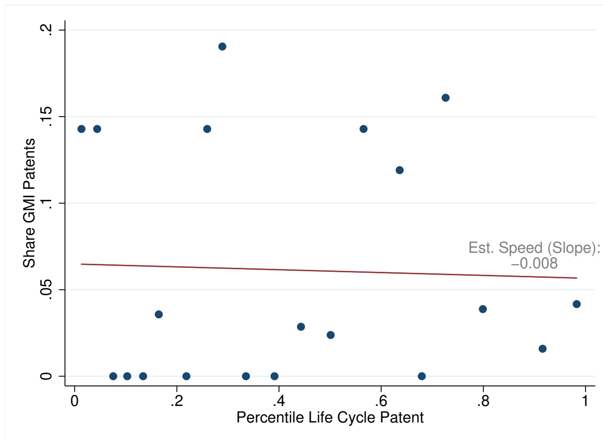
C.1 Measuring Speed

Figure C1a shows graphically how the coefficient of speed of local absorption is recovered for the example of the medical instrument technology class in India. Figure C1b plots the distribution of the speed of diffusion parameter obtained across all countries and classes, where the outcome in the regression is the share of GMIs. The summary statistics of the speed measures are reported in table C1. The mean and the median of the coefficient are positive and very close to 0 in magnitude. This can potentially be due to a combination of two effects : the negative relation documented in the previous section coming from the fact that the technology slowly gets embedded into the local pool of inventors, and the general increase in the share of GMIs across the globe documented in the summary statistics, which makes it generally more likely to find GMIs in more recent years.[32] To get rid of the second effect, we also perform the analysis using the RCA as the outcome, which is simply the share of GMI observed in a given technology-country-percentile divided by the share of GMIs observed globally at the same moment in time. Figure C1c plots the distribution of the speed of diffusion parameter obtained when the outcome is the RCA. Here the mean and the median are both negatives (mean =-0.0085 , median = -0.0014), consistent with what shown when pooling all technology-country cells. We keep all coefficients in our dataset, no matter their sign, and we store the t-statistic in order to be able to weight observations according to their significance level.

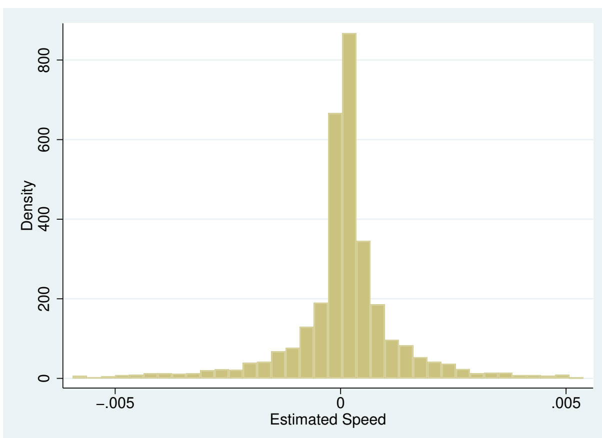
[32]This effect is absorbed by the year fixed effects in Figure 2.

Figure C1: Speed of Diffusion

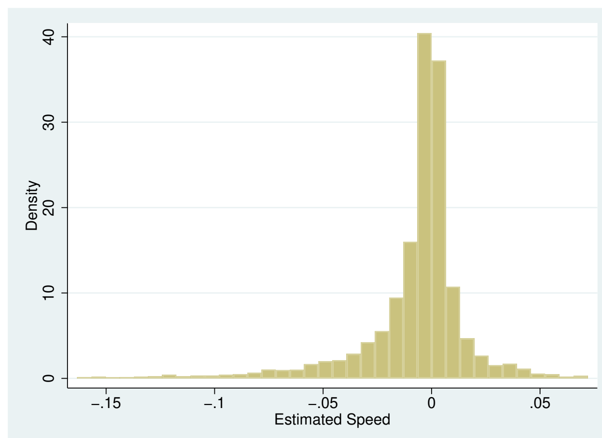
(a) India A61B (Medical Instruments)



(b) α^{speed} distribution, sh. GMI



(c) α^{speed} distribution, RCA GMI



Panel (a) plots the speed of diffusion α^{speed} obtained by estimating equation 3 for India in the medical instruments technology class. Panel (b) plots the distribution of the point estimate α^{speed} across all country-technology pairs. Panel (c) shows the distribution of the speed coefficient when the outcome used is the RCA instead of the share of GMIs (which simply divides the share of GMIs in the country with the global share observed that same year, thus controlling for time trends).

Table C1: Summary Statistics of variables of interest

	Speed measures		Network measures				
	speed (sh. GMI measure)	speed (RCA measure)	1st degree centrality	closeness centrality	betweenness centrality	eigenvector centrality	Productivity local coauthors
Mean	0.00006	-0.00854	0.086	0.045	0.001	0.141	0.390
25th percentile	-0.00020	-0.01182	0.000	0.000	0.000	0.000	0.000
50th percentile	0.00009	-0.00144	0.000	0.000	0.000	0.000	0.000
75th percentile	0.00048	0.00281	0.026	0.016	0.000	0.016	0.708
St. dev.	0.00173	0.03963	0.236	0.135	0.008	0.280	0.753
N	4895	4893	4896	4896	4896	4896	4896

Notes : The table reports the summary statistics for the speed measures as well as for the measures of network centrality.

C.2 Absorptive Local Capacity

Table C2 extends the measure of degree centrality to the number of local inventors with whom the GMIs co-work within the same subsidiary of the firm, while not directly patenting together, and recovers the robustness of results to defining the speed coefficient using the RCA measure, and to define GMI with previous experience using the GMI always definition, always using degree centrality as the measure of the network. Both tests give rise to remarkably similar results, while the network of coworkers that are not coauthors does not affect the local absorptive capacity (or if anything, affects it negatively). Finally, Table C3 corroborates the finding that the more productive is the network of local coauthors, the fastest is the diffusion of knowledge, but introducing a triple interaction. Productivity of local coauthors is computed as the average number of patents filed per year by all coauthors of the GMIs up until that point in time. The triple interaction is not always significant but generally corroborates the finding already suggested by the results on eigenvector centrality of the network.

Table C2: Robustness: Determinants of the speed of diffusion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcome: speed of diffusion (RCA)				Outcome: speed of diffusion (sh GMI always)			
VARIABLES	unweighted	wgt by obs.	wgt by t-stat	Only significant coefs.	unweighted	wgt by obs.	wgt by t-stat	Only significant coefs.
Dummy Exp. GMI in 1st decile x network local coauth.	0.184***	0.179***	0.250**	0.676**	0.328***	0.332***	0.435***	0.805**
	(0.0651)	(0.0576)	(0.0988)	(0.268)	(0.0578)	(0.0552)	(0.0756)	(0.359)
Dummy Exp. GMI in 1st decile x network local cowork.	-0.154*	-0.119*	-0.174	-0.733**	-0.129	-0.0899	-0.162	-0.166
	(0.0785)	(0.0641)	(0.108)	(0.360)	(0.0784)	(0.0590)	(0.102)	(0.236)
Dummy Exp. GMI in 1st decile	0.576***	0.486***	0.728***	1.177***	0.689***	0.565***	0.900***	0.983***
	(0.0779)	(0.0667)	(0.0949)	(0.212)	(0.0819)	(0.0683)	(0.114)	(0.217)
Observations	4,842	4,842	4,839	612	5,340	5,340	5,340	634
R-squared	0.228	0.208	0.318	0.532	0.240	0.218	0.329	0.630

Notes : Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
All columns include country and technology fixed effects. It includes as controls the following variables: network of local coauthors and coworkers (not interacted), total days of country-tech life cycle, duration of each decile in days, total days until first patent filed in tech-country, and total number of inventors in country-tech in the 1st decile (all in asinh). Columns (1) to (4) use the RCA measure in the regression to recover the speed of diffusion, while Columns (5) to (8) use the "GMI always" definition instead of GMI 1 year.

Table C3: Heterogeneity of speed of diffusion effect by productivity of local co-authors

	(1)	(2)	(3)	(4)
	Outcome : speed of diffusion			
	unweighted	wgt by obs.	wgt by T-stat	Only significant coefs.
1 * [GMI in 1st decile]	0.590***	0.526***	0.766***	1.012***
	(0.0617)	(0.0545)	(0.0834)	(0.170)
1 * [GMI in 1st decile] *network local coauthors	0.561***	0.564***	0.724***	0.871***
	(0.0781)	(0.0741)	(0.104)	(0.291)
1 * [GMI in 1st decile] *network local coauthors * avg. productivity local coauth.	0.174*	0.120	0.228	0.868***
	(0.101)	(0.0893)	(0.142)	(0.307)
Observations	4,843	4,843	4,842	925
R-squared	0.326	0.299	0.436	0.619

Notes : Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
All columns include country and technology fixed effects. It includes as controls the following variables: network of local coauthors (not interacted), productivity of local coauthors (not interacted), productivity of local coauthors interacted with the network of local coauthors, productivity of local coauthors interacted with the first decile dummy, total days of country-tech life cycle, duration of each decile in days, total days until first patent filed in tech-country, and total number of inventors in country-tech in the 1st decile (all in asinh).

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