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ABSTRACT *This paper analyses whether international migrants contribute to increasing technological advances in developing countries by inducing a transfer of productive knowledge from developed countries back to migrants' home countries. Using the Economic Complexity Index as a proxy for the amount of productive knowledge embedded in each countries and bilateral migrant stocks of 20 OECD destination countries, we show that international migration is a strong channel of technological transmission. Diasporas foster the local adoption of new technologies by connecting high technology countries with low ones, reducing the uncertainty surrounding their profitability. Our empirical results support the hypothesis that technological transfers are more likely to occur out of more technologically advanced destinations and when emigration rates are particularly high.*

'Accumulating productive knowledge is difficult. For the most part, it is not available in books or on the internet. It is embedded in brains and human networks.' (Haussman et al., 2011, p. 7)

1. Introduction

The Venetian travel merchant Marco Polo spent 24 years in Asia at the end of the thirteenth century, describing his travels in *The Book of the Marvels of the World*, which allowed Europeans to discover a number of Chinese innovations – such as paper money, the use of the coal and eyeglasses – that were subsequently adopted in the West. Although information about the existence of new technologies certainly spreads across the globe more easily today than in Marco Polo's time, this needs not to translate immediately into its local adoption, which represents the main form of innovation in developing countries (World Bank, 2008). The financial returns from adopting foreign technologies are uncertain, and no legal protection is granted to an entrepreneur who succeeds in adopting a foreign technology, so that rival domestic producers can rapidly erode ensuing profits. This risk can result in the under-provision of entrepreneurial efforts required for the adoption of foreign technologies (Hausmann & Rodrik, 2003).

This paper analyses whether international migrants can contribute to fostering innovation in developing countries, thus reducing the uncertainty surrounding the profitability of a local adoption of foreign technologies. Indeed, international migration can facilitate the transfer of technologies from the North to the South, by connecting high technology countries with low ones. Diasporas and emigrants are directly in touch with what is produced in developed countries and can act as scouts, exploring all the production possibilities for their origin country. They can more easily understand which technologies are suitable for

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local adoption and which are not, lifting the veil on the cost structure of their origin country.[1] To the best of our knowledge, the first empirical evidence of international knowledge diffusion at the country level was raised by Coe and Helpman (1995), who underlined the positive correlation between foreign R&D capital and total factor productivity. More recently, Bahar, Hausmann, and Hidalgo (2014) have shown that a country is 65 per cent more likely to add a new product to its export basket if a neighbouring country already exports this product. While not testing for the channels through which knowledge is spread across nations, Bahar et al. (2014) mention that trade, Foreign Direct Investments (FDI) and migration certainly play a role in that process. In this paper we empirically investigate this major issue, focusing on the role of international migration. We use the Economic Complexity Index as a proxy for innovation and productive knowledge embedded in each economy. Productive knowledge encompasses the largest definition of knowledge, taking into account not only explicit but also tacit knowledge, which is both harder to transfer and the lack of which is more likely to hamper the growth of countries (Hidalgo, Klinger, Barabási, & Hausmann, 2007). Measuring productive knowledge allows us to capture possible knowledge spillovers between products since proximity between goods matters, and capabilities required for one product are useful in many other different productions. To address endogeneity issues, we rely on the (System Generalized Method Moments) System GMM estimator (Blundell & Bond, 1998) which allows us to deal with identification issues of our variable of interest as well as other covariates. We alternatively use internal and external instruments and the predictions of a pseudo-gravity regression that includes interactions between year dummies and the geographic distances between each destination-origin pair (Feyrer, 2009). Our results demonstrate that international migrants foster the local adoption of foreign technology in their origin countries. We also provide evidence that our main results are not driven by trade, FDI or geographical or genetic distance and that they are robust to different technological indicators.

This present paper contributes to a recent and growing body of literature that studies the diffusion of technologies across borders as a result of international human mobility. The seminal paper by Kerr (2008) shows that diasporas strongly influence the international technology diffusion. Indeed, his results point out that a 10 per cent increase of a given origin country's researchers residing in the United States is associated with a 1 per cent increase in foreign output of the given origin country. His model supports the idea that scientists abroad ease the diffusion of knowledge to 'technology follower's economies' and then, spur the process of imitation. Similar results are presented by Mayr and Peri (2009) with a special look at return migration and by Andersen and Dalgaard (2011) who show that the intensity of temporary movements of workers is a very good predictor of global productivity levels. Lodigiani (2008) also shows that high-skill migrants positively influence productivity levels in their origin countries as an increase in emigration rates is associated with an increase in productivity back home. In the same way, Naghavi and Strozzi (2015) concentrate their study on 34 developing countries and study the interaction between emigration and innovation performances, measured by the number of granted patents. They show that diasporas create a new source of knowledge for domestic innovators under sound intellectual property rights in the origin country. Moreover, they find that this positive inflow of knowledge overcomes the country's direct loss from emigration. At the micro level, Agrawal, Kapur, McHale, and Oettl (2011) use patent citation data from Indian inventions to show that diasporas abroad help inventors back home maintain access to a foreign source of knowledge and therefore spur innovation in the origin country, but only when it comes to high-quality patents. These mixed results are confirmed by Breschi, Lissoni, and Miguelez (in press) who, while demonstrating evidence of a positive diaspora effect for Asian countries, do not find significant technology transfers from the Indian diaspora to its origin country. Finally, as far as the emergence of global inventor teams is concerned, Miguélez (in press) and Kerr and Kerr (2015) study the rise in international migration which increases co-patenting and fosters the transmission of technology from developed to developing countries.

While most of the previously cited papers study technology transfers through inventor diasporas and patents, our paper uses trade and international migration data that allows us to take into account technology transfers from the least to the most highly technologically advanced exported products. Bahar and Rapoport (in press) is therefore the closest paper to our analysis since they test the hypothesis of knowledge diffusion through international migration with an analysis at the product level (1984 to 2010 UNComtrade data at the 4-digit Standard International Trade Classification). With this high level of disaggregation, they find that migration, ahead of trade and FDI, is a strong driver of the evolution of comparative advantage. An increase of 10 per cent in the migrant stock at destination is associated with a 3 per cent increase in the probability to export one product for which the destination country already has a comparative advantage. Our paper enables us, using a more aggregate analysis, to capture additional indirect effects of migration on the development of new comparative advantages. Indeed, we allow migrants' origin countries to develop new comparative advantages, not only in products for which migrants' host countries have a comparative advantage, but also in products that require close productive knowledge. For instance, migrants residing in a country that exports cars (SITC 781.2) could help to promote the development of the exports by the origin country of closely related products, such as motor cycles (SITC 785.1) or motor vehicle accessories (SITC 784.3), an effect that goes beyond that identified by Bahar and Rapoport (in press).

The remainder of the paper is organised as follows. Section 2 discusses the data that we use, first looking at international migration data, and second focusing on the Economic Complexity Index. Next, we bring to light some stylised facts in international migration flows and technology levels. We show that recent convergence in technology is possibly associated with changes in international migration patterns. Section 3 presents our empirical specification and all the challenges associated with it. Section 4 outlines the baseline results and Section 5 provides some robustness checks. Finally, Section 6 concludes.

2. Data

This section describes the data we use in our empirical analysis. We start with international migration data and then move to the Economic Complexity Index, our index of technology.[2]

2.1. Emigration data

A growing body of empirical literature has recently emerged as a result of the availability of new migration data. We take advantage of these new databases and use the (Institut für Arbeitsmarkt- und Berufsforschung) IAB brain-drain database developed by Brücker, Capuano, and Marfouk (2013), which breaks down by country of origin the stocks of migrants (defined as foreign-born individuals) of 20 OECD destination countries. These destination countries are Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. We rely on this dataset since migration stocks are computed on the basis of national census and population register statistics in 20 OECD countries that are among the richest migrant destinations in the world.[3] Using only 20 destination countries may be seen as problematic since we ignore half of total world migration. However, these 20 OECD countries receive 85 per cent of high-skilled migrants worldwide. In our paper, emigration rates are defined as the share of migrants (25 years and above) in the pre-emigration population. Unfortunately, several limits emerge from migration data. It is worth noting that, although we use migration stocks, ideally researchers would be interested in flows that reflect the dynamics of the migration process. Indeed, some people that belong to a diaspora, such as retired workers for instance, do not play a huge role in technology transfers that occur to their origin country. Moreover, we know that the evolution over time of these migrant stocks reflects some demographic events that are unrelated to migration such as death or return migration, for example. Another limit is the omission of illegal migrants who are not present in census data aside from high-skilled migrants who mainly use legal channels in order to change their country of residence. We detail further some stylised facts related to recent international migration changes.

2.2. The Economic Complexity Index

We rely on the Economic Complexity Index (ECI) by Haussman et al. (2011) as a proxy for the technology levels of countries. The ECI summarises the number of available capabilities embedded in each economy according to what countries are able to export.[4] Capabilities are captured through two dimensions, namely Diversity and Ubiquity. Diversity gives the number of distinctive products exported by a country while Ubiquity gives the number of countries that export a given product. A complex economy is therefore a country which exports a diversified set of goods and/or exports products that are only exported by a small number of countries.[5] The ECI ranks the different countries from the least to the most highly technologically advanced country according to these two dimensions. An increase in the ECI of a given country represents either new available knowledge in the economy or an increase in the ability for people to match pre-existing knowledge (process or organisational innovations). A more detailed description of this variable and its computation is available in the Supplementary Materials.

2.3. Stylised facts

Figure 1 depicts the average worldwide ECI between 1980 and 2010.[6] Not surprisingly, technology is unevenly distributed across the globe and sophisticated exports take place in only a few developed countries in North America and Western Europe. As a matter of fact, the correlation between the ECI and the GDP per capita is about 0.75. Figure 2(a) confirms the gap that exists between the export sophistication of the different income groups using a simpler version of the ECI namely the EXPY. The EXPY is the export weighted average PRODY values for products exported by each country; PRODY being itself for each product, the weighted income level associated with exporters of this products (Hausmann, Hwang, & Rodrik, 2007). However, Figures 2(b) and 2(c) indicate that this gap significantly narrowed over the period, leaving the scope for some convergence between the least and the most technologically advanced countries. Indeed, from 1980 to 2000, the EXPY increased twice as much in upper-middle- and lower-middle-income countries, than in high-income countries. Even low-income countries have started to achieve a relative convergence to the levels of the most technologically advanced countries.

Over the same period from 1960 to 2010, international migration from the South to the North increased from 16 to 60 million people (Özden, Parsons, Schiff, & Walmsley, 2011). These migration flows of people have not only increased but also changed in their composition. Indeed, the number of high-skilled migrants residing in OECD countries increased by 70 per cent during the 1990s, as opposed to 30 per cent for low-skilled migrants (Docquier & Rapoport, 2012). Larger and more educated diasporas therefore represent greater opportunities for developing countries that would like to adopt the technologies already developed in high-income countries. These opportunities are even greater since half of all international migrants are concentrated in only 10 countries which are, for the most part, leaders in technology. This paper attempts therefore to investigate the link between the

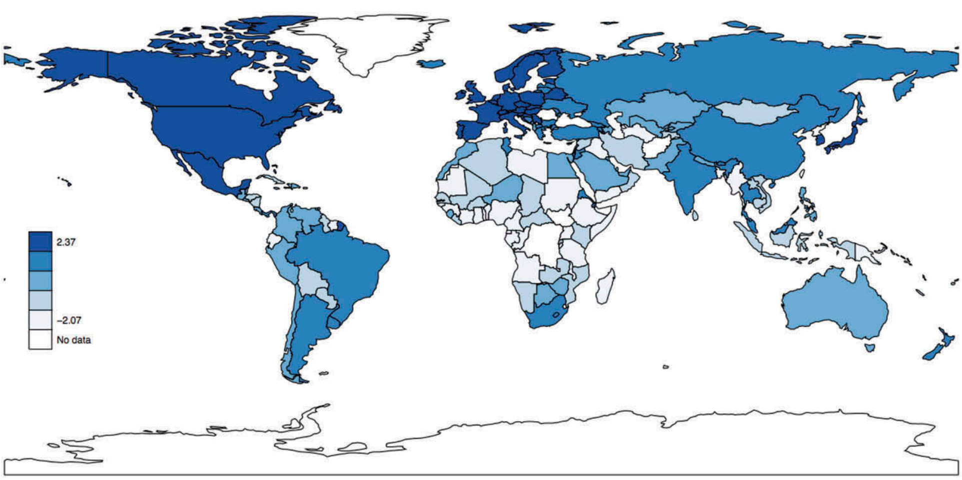

Figure 1. Average ECI by country from 1980 to 2010.
Source: Author's elaboration on Haussman et al. (2011).

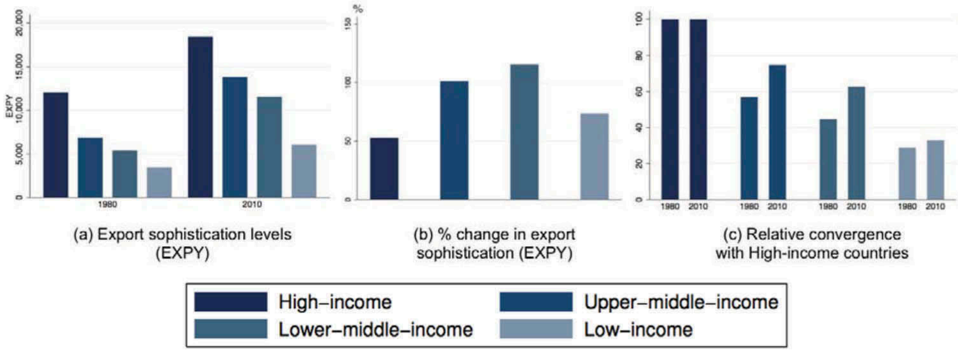

Figure 2. Gaps in technology remain strong … but convergence emerges.
Source: Author's elaboration on United Comtrade database.

increase in migration stocks from the South to OECD countries and the convergence in technology observed over the last decades.

3. Empirical analysis

Our aim is to investigate whether migrants transfer productive knowledge back to their origin countries. We follow Haussman et al. (2011), restricting our analysis only to countries with a population above 1.20 million between 2008 and 2010.[7] Our sample, therefore, includes 120 countries between 1980 and 2010 in five-year intervals.[8]

3.1. Benchmark specification

Our benchmark specification links the ECI in migrants' home countries with its values in foreign countries. Following Lodigiani and Salomone (2015) who study the transfer of gender norms related to political participation at the international level, our estimated equation is written as follows:[9]

$$ECI_{it} = \beta_1 ECI_{it-5} + \beta_2 \overline{ECI}_{it-5} + \boldsymbol{\lambda}'\boldsymbol{X}_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{1}$$

where the dependant variable ECI_{it} is the Economic Complexity Index in origin country i at time t and ECI_{it-5} is its lagged value of five years. The ECI in our sample ranges from −2.78 to 2.58. $\overline{ECI}_{it-5}$ is our variable of interest. It is the weighted average value of the ECI in migrants' destination countries and thus captures the amount of technology to which a given country is exposed to through its diasporas. It is computed as:

$$\overline{ECI}_{it-5} = \boldsymbol{\omega}'_{t-5}\boldsymbol{ECI}_{jt-5} \tag{2}$$

The weight vector $\boldsymbol{\omega}'_{t-5}$ in our benchmark specification is the emigration rates from i to j.[10] Emigration rates are the stock of migrants from origin country i residing in destination country j, overall the total pre-emigration population of i. It is worth noting that the weight for the origin country itself is zero. $\boldsymbol{ECI}_{jt-5}$ is the vector of complexity in the 20 OECD destination countries. By construction, our variable of interest increases, either if the ECI in any destination country increases or if the emigration rate increases to destinations for which the ECI is higher than the average ECI of the 20 OECD destination countries, or both. The average $\overline{ECI}_{it-5}$ in our sample equals 0.06 with a standard deviation of 0.09. Our specification allows for technology transfers even if the amount of productive knowledge at destination is lower than the level of productive knowledge at home. This relies on the nature of the ECI variable which not only summarises the amount of productive knowledge embedded in each economy but also its composition. As a result, migrants can move to a foreign country with a lower level of technology but with a completely different export basket and still transfer new productive knowledge to their origin county. $\boldsymbol{X}_{it}$ is a vector of controls described in Subsection 3.2 and μ_i and η_t are country and time fixed effects, respectively, whereas ε_{it} is the remaining error term. Standard errors are clustered at the country level in order to correct for heteroskedasticity and serial correlation.

Our choice to rely on a dynamic panel specification borrows both from theoretical and empirical requirements. First, it takes into account the persistence in technology levels evidenced in Section 2. Second, it allows us to distinguish between the short-run and the long-run technological transfers that occur through emigration. Indeed, it is very likely that a given diaspora that leaves its origin country at year t will not only transfer productive knowledge to its origin country in the next five years but also in the subsequent periods. In other words, technological transfers through emigration are very unlikely to fully materialise within five years. However, the use of a dynamic panel specification calls for a careful interpretation of the coefficients. Specifically, β_2, our coefficient of interest, gives us evidence of whether international migration acts as a channel of technological transfer from destination to migrants' origin country in the short-run. Our testable hypothesis in this paper is therefore a positive and significant β_2. Long-run effects can be obtained by dividing β_2 with the adjustment rate, namely, $1-\beta_1$.[11] It is important to note that usual approaches such as OLS or fixed effects are not appropriated with dynamic panel estimates. Indeed, OLS estimates are upward biased since the lagged dependent variable is correlated with the individual component of the error term. Fixed effects are not even more consistent (downward-biased) since the within transformation, in the case of samples with small T and large N, creates a correlation between the error term and the lagged dependent variable (Nickell, 1981). Our analysis relies, therefore, on the System GMM estimator (Blundell & Bond, 1998) which deals with problems of endogeneity of the lagged dependent variable. The System GMM estimator takes into account both the endogeneity of the variable of interest and all the regressors using their own lags as instruments. It combines into one system the regression in differences (Arellano & Bond, 1991) and the regression in levels (Arellano & Bover, 1995). Differences equations are instrumented with instruments in levels and levels equations are instrumented with instruments in differences. Operating in differences also permits us to control for unobserved heterogeneity. The overidentification test proposed by Hansen (1982) and the autocorrelation test proposed by Arellano and Bond (1991) check for the validity of the instruments.[12]

A legitimate concern that arises from our specification is the endogeneity of the variable of interest. In the next subsection we discuss both the threats to identification that prevent us from a causal interpretation of the estimated effect and our identification strategy to overcome these issues.

3.2. Identification strategy

Endogeneity in our context may arise from either confounding factors or reverse causality. In order to mitigate the possibility of an omitted variable bias, our estimated equation includes both country and time fixed effects that account for country- and time-specific omitted variables such as institutions, for instance. Our equation also includes a vector of controls with time-varying variables that simultaneously affect the ECI in migrants' origin countries and the weighted-average ECI in migrants' destination countries. For the origin country i, $\boldsymbol{X}_{it}$ contains the average level of adult's education aged 25 and older, the logarithm of the GDP at purchasing power parity per capita, the logarithm of the population aged 25 and older, the logarithm of trade openness and FDI net inflows as a share of gross domestic product. Hausmann et al. (2007) shows that population, education and income positively influence export sophistication. There is indeed a positive self-perpetuating cycle between income and the adoption of foreign technologies. Larger populations also induce a larger knowledge diversity (Kuznets, 1960; Simon, 1977) as they increase the probability of having innovators who foster intellectual networks and increase markets' potential and the incentives for individuals to invest in new products (Grossman & Helpman, 1991). In terms of human capital, education is recognised as a strong determinant for the adoption of new technologies (Arrow, 1962; Grossman & Helpman, 1991; Romer, 1990) thus it increases the range of discoverable goods in a given economy (Hausmann et al., 2007). Finally, we include trade and FDI controls since we know that these international flows can be channels for technological transfers between nations and because they are strongly correlated with migration flows. Foreign-invested firms can directly increase the quality of exports by producing higher quality products but may also foster the production of higher technology goods in domestic firms (Javorcik, 2004). However, despite these hypotheses, the literature on FDI and knowledge transfers remains inconclusive (Görg & Strobl, 2001). Regarding trade, Madsen (2007) shows that trade openness positively impacts international knowledge transmission. In addition, developing countries are more and more frequently exposed to high technology goods, particularly if they import large quantities of intermediate goods in response to the fragmentation of world production. These intermediate products automatically imply an increase in the export sophistication when they are re-exported as finished products (Xu, 2010).

Regarding reverse causality, Beine, Docquier, and Schiff (2013) show the potential biases that emerge from our specification and which can create a spurious correlation between the ECI at home and the ECI at destination. First, the interdependence of countries' weighted-average ECI in migrants' destination countries generates a reflection problem. Indeed, our variable of interest is constructed such that the weighted-average ECI in a given destination country includes the complexity of every partner with which it has developed an emigration relationship and vice versa. This means that, at the global level, each country's ECI depends on the other country's ECI. Second, migration is not an exogenous phenomenon; the decision to migrate is not random and poverty constraints influence the location choice of migrants. More precisely, the distribution of migrants from one country across various destinations is influenced by the level of income per capita at origin. However, we know that ECI levels are highly correlated with the level of GDP per capita in origin countries. There is, therefore, a reverse causality from the ECI at origin to our variable of interest. This can be easily illustrated by comparing Burkina Faso, a developing country, 80 per cent of whose migrants have migrated to Ivory Coast, a neighbouring country with a low ECI, and France, a developed country where one of the first migrants' destinations is the United States, a distant technology leader.

This paper relies on two methods to identify whether migrants transfer productive knowledge back to their origin countries. First, we rely on the System GMM estimator, which uses lags for endogeneity issues of the variable of interest and other covariates. However, a legitimate concern with the System GMM estimator arises since it only uses internal instruments to establish causation. To tackle this issue, our analysis makes use of an external instrument for the weighted-average ECI in migrants' destination countries. We rely on Feyrer (2009) who, with panel data, extends the seminal contribution of Frankel and Romer (1999). Using the predicted values from a pseudo-gravity equation, we compute a predicted weighted-average ECI in migrants' destination countries used as an instrument for our variable of interest. As in Feyrer (2009), our time-varying source of exogeneity for bilateral migration stocks comes from the inclusion of interactions between year dummies and the log of distance between each OECD destination country and each migrants' origin country. Interactions between year dummies and the log of distance in our pseudo-gravity equation capture all of the time-varying effects of distance on migration. For instance, while the decrease in transportation and communication costs, captured through year dummies is shared by all countries, its interaction with distance generates differential changes for all country pairs.[13] Our pseudo-gravity equation is written as follows:

$$\log\left(\mathrm{Stock}_{\mathrm{ijt}}\right) = \beta_{\mathrm{t}} \log\left(\mathrm{Dist}_{\mathrm{ij}}\right) + \mathrm{Bord}_{\mathrm{ij}} + \mathrm{Lang}_{\mathrm{ij}} + \mathrm{Colony}_{\mathrm{ij}} + \gamma_{\mathrm{i}} + \gamma_{\mathrm{j}} + \gamma_{\mathrm{t}} + \varepsilon_{\mathrm{ijt}} \qquad (3)$$

where $\log(Dist_{ij})$ is the log of the geographical distance between origin country i and destination country j, $Bord_{ij}$ is a dummy equal to 1 if i and j share a common border, $Lang_{ij}$is a dummy equal to 1 if at least 9 per cent of the populations of the two countries speak a common language, γ_i, γ_j, and γ_t are the origin, destination and year fixed effects.

Obviously the exogeneity of our instrument is conditional on the other covariates included in the estimated equation. Another legitimate concern in our analysis would be that our instrument is acting through other proxies of integration such as bilateral trade or FDI, for example. In Table S3 (Supplementary Materials) we provide the evidence that our results combining System GMM with an external instrument are robust to the inclusion of bilateral trade, FDI or geographical distance as controls. This strongly reduces concern for violation of the exclusion restriction.[14] In order to address the issue of the large number of zeros in migration stocks, we rely on the Poisson pseudo-maximum likelihood estimator (see Santos Silva & Tenreyro, 2006) for our pseudo-gravity equation.[15] Standard errors are clustered at the country pair level.

3.3. Alternative specification

While our specification borrows from Lodigiani and Salomone (2015), we also show that our results are robust to the use of the seminal equation estimated by Spilimbergo (2009). This equation can be written as follows:

$$ECI_{it} = \beta_1 ECI_{it-5} + \beta_2 M_{it-5} + \beta_3 \overline{ECI}^S{}_{it-5} + \beta_4 \overline{ECI}^S{}_{it-5} \times M_{it-5} + \boldsymbol{\lambda}' \boldsymbol{X}_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{4}$$

This interaction model links the ECI at home with the emigration rate M_{it-5} and a weighted-average ECI in migrants' destination countries $\overline{ECI}^S{}_{it-5}$. Weights in the variable of interest are no longer emigration rates, as in our first specification, but rather emigration shares. This corresponds to the number of migrants from origin country i settled in destination j, overall the total number of migrants of i. The interaction variable crosses each constitutive term, namely $\overline{ECI}^S{}_{it-5}$ and M_{it-5}. The coefficient in front of the interaction, β_4, gives us the intuition whether emigration rates and ECI at destination play simultaneously on ECI at home.[16] In other words, this equation allows us to test whether technological transfers are more likely to occur when emigration rates are particularly high and vice versa. Our testable assumption is a positive and significant coefficient for the interaction variable. We are not particularly interested in the coefficients of the two constitutive terms, β2 and β3, since they represent marginal effects for particular values of the conditional variables. By contrast, we plot in Section 4 the total effect of emigration rates and the total effect of the weighted-average ECI in migrants' destination countries for different deciles of the conditional variables following Brambor, Clark, and Golder (2006). Conditional variables are emigration rates when we look at the total effect of the weighted-average ECI in migrants' destination countries and vice versa.[17]

4. Results

Table 1 reports our benchmark results. From columns 1–3, we first investigate using OLS and fixed effects whether migrants transfer productive knowledge back to their origin countries. Year fixed effects in columns 2 and 3 account for all of the time-varying variables which similarly affect the productive knowledge levels of all of the countries in our sample. Country fixed effects in column 3 prevent our estimates from being biased due to the omission of time-invariant country-specific factors that determine their own levels of complexity. The three estimates support the use of a dynamic panel specification since the lagged dependent variable is positive and highly significant. This highlights a strong persistence in the ECI of countries which has to be taken into account in our analysis. Regarding our variable of interest, $\overline{ECI}_{it-5}$ is always positive and significant at the 5 per cent level. As far as the other covariates are concerned, human capital, income and population are positively correlated with the levels of productive knowledge in migrants' home countries. However, while trade openness seems to act as a channel of technological transfer in columns 1 and 2, this is no longer the

Table 1. The effect of ECI in migrants' destination countries on ECI at home Benchmark estimates (Dep $=ECI_{it}$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pooled OLS	Fixed effects	Fixed effects	System GMM	System GMM	System GMM Ext. Instrument	System GMM
ECI_{it-5}	0.778***	0.752***	0.165***	0.724***	0.716***	0.756***	0.690***
	(0.038)	(0.042)	(0.058)	(0.069)	(0.068)	(0.072)	(0.067)
$\overline{ECI}_{it-5}$	0.439**	0.446**	2.042**	0.940**		0.614**	
	(0.182)	(0.201)	(0.809)	(0.416)		(0.284)	
$\overline{ECI}^{INI}{}_{it-5}$					0.821*		
					(0.419)		
$\overline{ECI}^{S}{}_{it-5}$							−0.001
							(0.135)
M_{it-5}							−1.991
							(1.657)
$\overline{ECI}^{S}{}_{it-5} \times M_{it-5}$							2.102*
							(1.083)
$log(GDP_{it})$	0.133***	0.140***	−0.123	0.047	0.049	0.045	0.082*
	(0.026)	(0.027)	(0.078)	(0.052)	(0.047)	(0.053)	(0.044)
$log(Pop_{it})$	0.069***	0.083***	0.390**	0.108***	0.099***	0.084**	0.118***
	(0.015)	(0.017)	(0.156)	(0.035)	(0.033)	(0.036)	(0.038)
Hum_{it}	0.012*	0.021***	0.089**	0.066***	0.070***	0.062***	0.064***
	(0.007)	(0.008)	(0.036)	(0.024)	(0.023)	(0.023)	(0.021)
$log(Trade_{it})$	0.070*	0.104**	0.107	−0.092	−0.046	−0.100	−0.101
	(0.040)	(0.045)	(0.108)	(0.083)	(0.077)	(0.090)	(0.093)
FDI_{it}	−0.004	−0.003	−0.001	0.010	0.011	0.009	0.007
	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)	(0.007)	(0.007)
Observations	600	600	600	600	600	600	600
Nb. countries	120	120	120	120	120	120	120
Nb. instruments				84	84	77	100
R-squared	0.908	0.911	0.154				
Country fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)				0.000	0.000	0.000	0.000
AR(2)				0.449	0.493	0.431	0.434
Hansen J (p-value)				0.237	0.236	0.278	0.170

Source: Author's elaboration on Haussman et al. (2011) and Brücker et al. (2013). *Notes*: Standard errors in parentheses are clustered at the country level (***p <0.01, **p < 0.05, *p < 0.1). From Equations (4)–(7) the lagged dependent variable is treated as predetermined and instrumented with its own first to five lags. In columns (4), (5) and (7) all the variables are treated as endogenous and instrumented with their own second lag. In column (6), $\overline{ECI}_{it-5}$ is instrumented using its predicted value obtained from the pseudo-gravity model described in Appendix Table A3.

case when country fixed effects are included. Finally, FDI net inflows have no significant impact on the ECI. This underlines the mixed results in the literature on the effect of FDI on export sophistication.

While these initial estimates suggest that variations in the weighted-average ECI in migrants' destination countries are positively associated with variations in the ECI at home, it is worth remembering from Section 3 that OLS and fixed effects are biased with panel dynamic estimates. Thus, we turn to System GMM estimates from columns 4–7 that correct for the endogeneity of the lagged dependent variable and other covariates.[18] The coefficient of the lagged dependent variable β_1 with the System GMM estimator ranges between 0.690 and 0.756, and is always significant at the 1 per cent level. This means that it takes between 11 and 14 years after a shock (2.236 and 2.841 periods of five years) before closing half of the gap with the long-run level of the ECI (see Vu [2013] for the interpretation of beta-convergence effects). As expected, this coefficient ranges between the lower (0.165) and the upper bounds (0.778) given by the previous OLS and fixed effects estimates.

Column 4 reports the results of our preferred specification. The short-run coefficient for the variable of interest is positive and significant. This indicates that migrants transfer technology to their origin countries in the next five years after they have left their origin country.[19] As far as the magnitude of the effect is concerned, a one unit increase of the weighted-average ECI in migrants' destination countries is associated with a 0.940 increase of the ECI at origin in the five years following emigration. Such an interpretation of the coefficient is not intuitive since a one-unit increase of the variable of interest corresponds to two times the highest observed value in the sample and thus is very unlikely to occur for any country. A more self-explanatory interpretation of this coefficient requires, therefore, that we compute the variation of the ECI at home for a one standard deviation of the variable of interest. Using a simple transformation we find that an increase of one standard deviation of the weighted-average ECI in migrants' destination countries, that is, an increase of 0.088 units, is associated with an increase of 0.083 units of the ECI at origin. Mexico, the majority of whose emigration is to the United States (more than 98% in 2010), represents a suitable case to illustrate the economic implications of the estimated coefficient. It allows us to easily quantify the contribution of migrants to the evolution of the ECI in their origin country. Indeed, if no emigrants had left Mexico for the United States in 2005, then its weighted-average ECI at destination would have been equal to zero rather than 0.210. This implies that Mexico's ECI would have been 0.197 units lower than its observed value in 2010. This decrease corresponds to a drop of three places in the 2010 ECI overall ranking. In the long-run, using the adjustment rate in the dynamic panel specification, the ECI of Mexico would be 0.715 units lower, which corresponds to a drop of 25 places.

Another difficulty of interpreting ECI variations arises from the fact that the index is computed independently for each year of our period of analysis, between 1980 and 2010. This implies that changes in the world trade structure may affect the ECI trend, making interpretation of the indicator more difficult over time. In order to control for the possible bias related to the use of the ECI in a dynamic framework, Jarreau and Poncet (2012) and Poncet and Starosta de Waldemar (2013) propose looking at the sensitivity of the results using a time-invariant measure of the ECI.[20] In the same way, we compute our variable of interest no longer using the ECI at year t but rather its initial value in 1980. This allows us to keep the amount of productive knowledge in our destination countries constant over the period. It also means that the variability over time of the latter variable now only comes from the weights vector $\boldsymbol{\omega}'_{t-5}$. Results are reported in column 5. The coefficient for $\overline{ECI}^{INI}_{it-5}$ remains positive and significant, which underlines that removing the dynamic of productive knowledge accumulation at destination does not affect therefore our main result. The amount of technology in migrants' destination countries still positively influences the amount of productive knowledge in migrants' origin countries. Concerning endogeneity of the variable of interest, column 6 reports the results of the System GMM estimator combined with an external instrument. It is worth noting that, while our variable of interest is instrumented using the predicted bilateral migration stocks obtained from our pseudo-gravity model, following Feyrer (2009), we still use internal instruments in order to correct for the endogeneity of other covariates. Despite a slight decrease in the coefficient, we still observe a

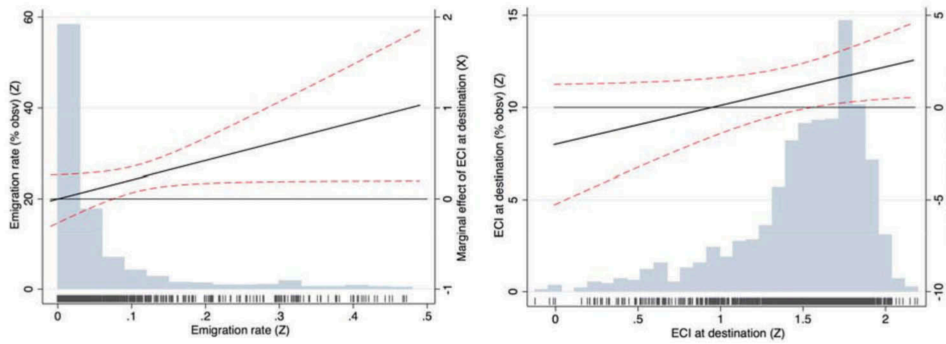

Figure 3. Total effect of ECI at destination and emigration rates.
Source: Author's elaboration on Haussman et al. (2011) and Brücker et al. (2013).
Notes: The solid line represents the marginal effect of X conditional on all values of the modifying variable Z. The histogram indicates the percentage of observations of the modifying variable and each bar on the rug plot represents one observation for this one. The dashed lines are the upper and the lower bound of the 95 per cent confidence interval, respectively.

positive and significant relationship between the weighted-average ECI in migrants' destination countries and the ECI at home. In fact, the coefficient is not statistically different from our benchmark coefficient reported in column 4.

Finally, column 7 reports the results of the alternative specification that follows the seminal equation estimated by Spilimbergo (2009). Results for this interaction model are depicted in Figure 3 and shows that the ECI in migrants' destination countries has no effect on the ECI at origin when emigration rates are at their lowest levels. However, when emigration rates increase, we observe a positive and significant effect of the technology at destination on the technology in origin countries. This effect gets stronger as emigration rates increase. In the same way, emigration rates begin to have a positive and significant effect on the ECI at home only for higher levels of the technology at destination, that is, the more sophisticated the foreign technology, the stronger the effect. The seminal specification of Spilimbergo (2009) thus supports the hypothesis of technological transfers through international emigration but highlights that this diffusion is more likely to occur with high emigration rates and high levels of technology at destination.

5. Robustness checks

This section first investigates whether our previous results are robust to the introduction of additional controls and sub-samples and then explores some transmission channels.

5.1. Sub-samples and additional control variables

Table 2 reports our results with sub-samples and additional control variables. Column 1 replicates our benchmark specification for the sake of comparison. In columns 2 and 3 we split our baseline sample between developing and developed countries. In both cases the weighted-average ECI in migrants' destination countries remains significant at the 5 per cent level. While this indicates that our results are not only driven by high-income countries, the higher coefficient for high-income countries suggests that knowledge circulation is stronger among OECD countries than among others. As a second robustness check and to dismiss alternative explanations, we introduce a new set of weighted-average ECI variables which take into account other proxies of integration and distances between migrants' destination and home countries. More precisely, we successively replace the weight vector $\boldsymbol{\omega}'_{t-5}$ in our variable of interest with bilateral trade and FDI and the inverse of geographical and genetic distances.[21] It is worth noticing that this exercise is particularity challenging given the strong correlations that exist between the different weighted-average ECI computed with different weights. As a matter of fact, Table S2

Table 2. Sub-samples and additional controls System GMM (Dep $=ECI_{it}$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Non OECD	OECD	All	All	All	All	All
	1980–2010	1980–2010	1980–2010	1980–2010	1980–2010	1980–2010	1980–2010	1985–2010
ECI_{it-5}	0.724***	0.549***	0.681***	0.647***	0.694***	0.714***	0.580***	0.717***
	(0.069)	(0.076)	(0.143)	(0.088)	(0.065)	(0.077)	(0.085)	(0.055)
$\overline{ECI}_{it-5}$	0.940**	0.865**	1.584**	0.844**	0.937**	0.992**	0.969***	0.586*
	(0.416)	(0.366)	(0.746)	(0.374)	(0.377)	(0.408)	(0.364)	(0.305)
$\overline{ECI}^{DIS}{}_{it-5}$				17.634***			21.451***	14.945***
				(5.995)			(6.427)	(5.571)
$\overline{ECI}^{GEN}{}_{it-5}$					0.110**		0.038	−0.002
					(0.052)		(0.053)	(0.043)
$\overline{ECI}^{IMP}{}_{it-5}$						−0.131	−0.180	0.076
						(0.101)	(0.126)	(0.127)
$\overline{ECI}^{FDI}{}_{it-5}$								−0.035
								(0.124)
$log(GDP_{it})$	0.047	0.098*	0.129	0.078	0.052	0.076*	0.087**	0.086**
	(0.052)	(0.057)	(0.173)	(0.050)	(0.047)	(0.045)	(0.044)	(0.038)
$log(Pop_{it})$	0.108***	0.053	0.196**	0.113***	0.101***	0.098***	0.114***	0.079***
	(0.035)	(0.047)	(0.095)	(0.036)	(0.035)	(0.033)	(0.035)	(0.027)
Hum_{it}	0.066***	0.073***	0.015	0.050**	0.070***	0.056**	0.059***	0.026*
	(0.024)	(0.028)	(0.042)	(0.022)	(0.024)	(0.025)	(0.022)	(0.015)
$log(Trade_{it})$	−0.092	−0.087	0.248	−0.130	−0.113	−0.093	−0.121	−0.028
	(0.083)	(0.120)	(0.272)	(0.084)	(0.079)	(0.086)	(0.085)	(0.075)
FDI_{it}	0.010	−0.014	−0.004	0.005	−0.002	0.005	−0.009	−0.009*
	(0.006)	(0.012)	(0.011)	(0.007)	(0.006)	(0.005)	(0.007)	(0.005)
Observations	600	411	189	600	598	600	598	404
Nb. countries	120	83	37	120	119	120	119	117
Nb. instruments	84	84	35	92	92	92	108	101
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.449	0.527	0.413	0.470	0.382	0.443	0.476	0.253
Hansen J (p-value)	0.237	0.405	0.100	0.210	0.261	0.193	0.198	0.580

Source: Author's elaboration on Haussman et al. (2011) and Brücker et al. (2013).
Notes: Standard errors in parentheses are clustered at the country level (***p < 0.01, **p < 0.05, *p < 0.1). The lagged dependent variable is treated as predetermined and instrumented with its own first to five lags. All the other variables are treated as endogenous and instrumented with their own second lag. Genetic distance data are not available for Yemen. FDI data had no records for Tajikistan or Turkmenistan or the year 1980.

(Supplementary Materials) reports the Pearson correlations between the different weighted average ECI. As expected, these correlations are particularly high even if using immigration rates (for $\overline{ECI}_{it-5}$) rather than immigration shares (as in $\overline{ECI}^{S}_{it-5}$), mitigates the problem.

In column 4 of Table 2 we first weight the ECI of foreign countries using the inverse of the bilateral great-circle distance between each destination-origin pair. Indeed, Bahar et al. (2014) show that knowledge diffusion decreases with geographical distance and that closer countries are more likely to share common technologies. The coefficient of the geographical distance weighted-average ECI ($\overline{ECI}^{DIS}_{it-5}$), is positive and highly significant which confirms that distance is crucial in technological transfers. The greater the distance between two countries, the lower the technological transfers. Interestingly, adding this new control does not significantly affect the coefficient of our variable of interest, which is still positive and significant at the 5 per cent level despite a small decrease. We repeat the same exercise in column 5 using the inverse of the genetic distance as a weight for the ECI in foreign countries. The rationale is given by by Spolaore and Wacziarg (2009), who demonstrate that genetic distance acts as a barrier to the diffusion of development from the world technological frontier. Genetically closer societies are more likely to exchange and to learn from each other. As the authors argue, similarities in terms of genetics facilitate the diffusion and the adoption of 'complex technological and institutional innovations' (Spolaore & Wacziarg, 2009, p. 471). As for geographical distance, the coefficient of our variable of interest remains positive and strongly significant while the coefficient of $\overline{ECI}^{GEN}_{it-5}$ suggests that genetic distance plays a role in technological transfers. Another legitimate concern in our analysis would be that confounding proxies of integration such as trade and FDI could prevent us from showing evidence of an effect of emigration on technological transfers. Indeed, trade openness captures the fact that, the more a country is trading, the more it is exposed to a diversified set of productive knowledge. However, while trade theories predict that openness to trade increases a country's specialisation, they underline that this specialisation depends on the initial patterns of comparative advantages. A country with comparative advantages in low-technology products will specialise in these kinds of goods as it opens its economy to trade and vice versa. Column 6 includes $\overline{ECI}^{IMP}_{it-5}$, a weighted average ECI in trade import partners. $\boldsymbol{\omega}^{\prime}_{t-5}$ is the share that each OECD destination country represents in the total imports of the origin country. The coefficient of the weighted-average ECI in trade import partners is not significant. However, its negative sign might reflect the fact that importing a large share of products from high-complex economies reflects a strong inability for low ECI countries to produce high-technology goods locally. Still, our variable of interest remains robust to this new control. Due to data limitations in FDI, we first introduce in the same equation (in column 7) all of the previous additional controls added separately along the previous lines. Despite the inherent problems of collinearity, our main coefficient remains positive and becomes significant at the 1 per cent level. Next, in column 8 we add $\overline{ECI}^{FDI}_{it-5}$, a weighted average ECI in foreign countries where the weights are the share that each OECD destination country represents in the total FDI that the origin country i receives from its partners. It is worth noting that the estimated sample is restricted to the 1985–2010 period.[22] Migration ahead of trade and FDI is still found to be a strong channel of technology transmission between countries. Despite a slight decrease, the coefficient of $\overline{ECI}_{it-5}$ remains positive and significant.

5.2. Alternative channels of transmission

While the focus of the previous section was to change the weight vector in our variable of interest, this section investigates some transmission channels, adjusting the second component of the weighted-average ECI in migrants' destination countries, namely, the indicator of technology at destination. We replace the ECI in foreign countries using different proxies for the level of productive knowledge in migrants' destination countries. It is worth noting that due to collinearity we cannot add all of these new variables and $\overline{ECI}_{it-5}$ in the same regression. While this would have been a suitable way to test

Table 3. Channels of transmission System GMM (Dep $=ECI_{it}$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ECI_{it-5}	0.724***	0.725***	0.725***	0.721***	0.730***	0.720***	0.720***
	(0.069)	(0.070)	(0.070)	(0.071)	(0.069)	(0.070)	(0.066)
$\overline{ECI}_{it-5}$	0.940**						
	(0.416)						
$\overline{log(GDP_{it-5})}$		0.137*					
		(0.074)					
$\overline{log(TFP_{it-5})}$			0.127*				
			(0.069)				
$\overline{log(EXPY_{it-5})}$				0.150*			
				(0.083)			
$\overline{log(Patent_{it-5})}$					0.119*		
					(0.061)		
$\overline{log(RDexp_{it-5})}$						0.138**	
						(0.065)	
$\overline{log(RDwork_{it-5})}$							1.037**
							(0.404)
$log(GDP_{it})$	0.047	0.045	0.045	0.042	0.046	0.046	0.054
	(0.052)	(0.049)	(0.049)	(0.048)	(0.047)	(0.049)	(0.049)
$log(Pop_{it})$	0.108***	0.102***	0.102***	0.102***	0.098***	0.103***	0.096***
	(0.035)	(0.037)	(0.036)	(0.037)	(0.034)	(0.036)	(0.030)
Hum_{it}	0.066***	0.068***	0.068***	0.070***	0.068***	0.069***	0.066***
	(0.024)	(0.023)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
$log(Trade_{it})$	−0.092	−0.049	−0.049	−0.050	−0.079	−0.050	−0.080
	(0.083)	(0.084)	(0.084)	(0.083)	(0.078)	(0.082)	(0.082)
FDI_{it}	0.010	0.010	0.010	0.010	0.009	0.010	0.007
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Observations	600	600	600	600	600	600	600
Nb. countries	120	120	120	120	120	120	120
Nb. instruments	84	84	84	84	84	84	84
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.449	0.475	0.476	0.488	0.452	0.476	0.456
Hansen J (p-value)	0.237	0.228	0.230	0.227	0.337	0.243	0.302

Source: Author's elaboration on Haussman et al. (2011) and Brücker et al. (2013).
Notes: Standard errors are in parentheses are clustered at the country level (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). The lagged dependent variable is treated as predetermined and instrumented with its own first to five lags. All of the other variables are treated as endogenous and instrumented with their own second lag.

for some transmission channels, collinearity forces us to add the variables separately in different regressions, excluding our variable of interest from the latter.

Column 1 in Table 3 replicates our baseline result for comparison. In column 2 and 3 we first use the logarithm of the GDP per capita and the logarithm of the TFP as proxies for technology at destination. Indeed, wealthier countries with higher levels of productivity are more likely to present greater stocks of productive knowledge. In both cases the coefficient of the variable of interest is positive while only significant at the 10 per cent level. Similar results are obtained in column 4 using the EXPY.

Since traditional economic indicators support the idea of a technological transfer through migration but only with low levels of significance we move to innovation indicators from columns 5–7. We sequentially use the logarithm of the number of patent applications made by residents, the logarithm of research and development expenditures (in million US dollars) and the logarithm of the number of researcher per 1000 employed as indicators for technology in migrants' destination countries.[23] While the coefficient of the variable of interest computed using patents data is still only significant at the 10 per cent level, coefficients using indicators of the research sector in destination countries are significant at the 5 per cent level. This highlights the importance of the research sector at destination when it comes to transfer of technology to migrants' home countries, as first underlined by Kerr (2008).

6. Conclusions

Technology has been recognised as one of the main determinants of development, while the distribution of productive knowledge is still unevenly distributed across the world and the majority of regions significantly lag behind in terms of export sophistication.

This paper has shown that international migration acts as a transmission channel for technology from migrants' destination to origin countries. Using economic complexity, as a proxy for export sophistication and productive knowledge embedded in foreign countries, allows us to capture knowledge spillovers in the production process. Our results are robust to different estimation methods, to the introduction of different weights in the average ECI in migrants' destination countries and to different technology indicators. Endogeneity issues have been addressed using the System GMM estimator with internal and external instruments. Moreover, using the seminal specification proposed by Spilimbergo (2009), we have found that technological transfers are more likely to occur when the intensity of emigration is high and when technology levels in destination countries are high. Our results, therefore, support the statement that productive knowledge is deeply embedded in brains and human networks (Haussman et al., 2011). They also link the increase in international migration stocks from Southern to Northern countries with the convergence in technology levels observed over recent decades.

While our paper underlines that migrants transfer technology to their origin countries, our study is inconclusive about the total effect on emigration at origin. It is worth noting that the departure, particularly of high-skilled inhabitants, may also deter the adoption of foreign technology by taking away those most likely to engage in entrepreneurial activities. Future research is therefore needed to investigate whether the transmission of productive knowledge from diasporas is able to exceed the negative impact of the brain drain in developing countries. Analysis at the firm level should also allow for better tracking of the channels through which migrants spur the development of new comparatives advantages in their origin countries. Nevertheless, our results encourage migrants' origin countries to foster a close relationship with their diaspora and facilitate the ease of return migrants.

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Disclosure statement

No potential conflict of interest was reported by the author.

Notes

1. Our paper only focuses on the effect of international emigration on migrants' origin countries. We do not investigate the effect of immigration since immigration from the North to the South only represents 6 per cent of total international migration (Özden et al., 2011). Also, immigration stocks in developing countries require many imputations that lower the quality of the estimates.
2. Definitions, sources and statistics of all other variables can be found in Appendix Table A2.

3. It is worth noting that other databases provide more destination countries. However, these databases use many imputations, particularly for migration stocks in developing countries, which strongly reduces the quality of the estimates.
4. Haussman et al. (2011) restrict their analysis to exported goods for which countries have a revealed comparative advantage. Balassa (1965), defines that a country c has an RCA in a product p only if this country exports p in larger proportions than the share of p in world trade and is computed as: $RCA \equiv \frac{x_{cp}}{\sum_c x_{cp}} / \frac{\sum_p x_{cp}}{\sum_{cp} x_{cp}}$ where x_{cp} is the monetary value of p exported by country c.
5. Both Ubiquity and Diversity are affected by the existence of rare capabilities. The iterative method called 'the method of reflections' described in the Supplementary Materials tackles this issue.
6. Post Soviet states have particularly strong average ECI here since they only present data between 1992 and 2010.
7. As with Haussman et al. (2011), we assume that it is impossible to infer on the export structure of countries that are too small.
8. Due to the lack of observations, the panel is unbalanced. Table S1 (Supplementary Materials) reports the number of observations for each country in the sample.
9. Our paper borrows its main specifications from the 'transfer of norms' literature. Since the seminal paper by Spilimbergo (2009) who studied the diffusion of democracy through international students, norms transferred by international migrants refer to politics (Barsbai, Rapoport, Steinmayr, & Trebesch, in press; Docquier, Lodigiani, Rapoport, & Schiff, 2016), fertily rates (Beine et al., 2013; Bertoli & Marchetta, 2015) or gender norms for instance (Lodigiani & Salomone, 2015; Tuccio & Wahba, 2016).
10. In Section 5 we test for the robustness of our results using different weight vectors accounting for bilateral trade and FDI or genetic and geographic distances.
11. Our main results are all robust to the exclusion of the lagged dependent variable. Estimates with non dynamic panel specification with fixed effects and 2SLS fixed effects are available upon request.
12. We chose to keep the number of instruments below the number of groups in order to remove the problem of instrument proliferation (Roodman, 2009a). All the variables, excluding the lagged dependant variable and time fixed effects, are treated as endogenous and are instrumented with their own second lag.
13. Miguelez and Moreno (2015) and Naghavi and Strozzi (2015) also rely on the same method but with different time-varying sources of exogeneity for bilateral migration stocks.
14. One may be concerned that origin fixed effects in the pseudo-gravity equation capture institutional variables that simultaneously affect migration and the level of productive knowledge. However, origin fixed effects are already included in our main equation, which prevents the exclusion restriction to be violated by any time-invariant country-specific variable.
15. Results of the gravity model are available in the Appendix, Table A3.
16. We can demonstrate that $\overline{(ECI)}^{S}_{(it-5)}$ is a transformation of our previous variable of interest such as: $\overline{(ECI)}^{S}_{(it-5)} = \overline{ECI}^{S}_{it-5} \times M_{it-5}$ However, it is important to note that the specification following Spilimbergo (2009) suffers from collinearity problems inherent to interaction models.
17. One may be concerned that our sample at destination always contains the same 20 OECD destination countries. However, the sample of destination countries is observed between 1980 and 2010 in five-year intervals, resulting in 140 different values for the ECI over the period. Figure S1 (Supplementary Materials) depicts the residual variability of the ECI in destination countries when country and year fixed effects are partialled out.
18. We check for the validity of the estimator in the last rows of Table 1. In every column, we always reject the null hypothesis of first-order serial correlation and do not reject the null hypothesis of no second-order correlation in the residuals. Moreover, the Hansen's J test confirms the overall validity of the instruments. It is important to note that our p-values for this last test are particularly low. It is a great support for the validity of System GMM estimates since Roodman (2009b, p. 129) recalls that Hansen test p-values way above 0.25 have to be seen as potential signs of trouble.
19. In Table S4 (Supplementary Materials), we provide evidence that our baseline result is robust to alternative lag structures either for the lagged dependent variables and other control variables.
20. In these two papers the authors test the effect of export sophistication on growth, first using a time invariant measure of export sophistication and then exploiting the variation of export sophistication over time.
21. This new set of estimates suffers from data constraints which reduces the size of the sample. For instance, genetic distance data are not available for Yemen while FDI data are only available from 1985 and not available for Tajikistan and Turkmenistan.
22. For comparison, in the same specification as column 7 that is without $\overline{(ECI)}^{FDI} it-5$ and over the same time span, the coefficient for $\overline{(ECI)}\, it-5$ equals to 0.972 and is significant at the 5 per cent level.
23. Patent data indicators are obtained from the World Development Indicators, while other innovation variables are obtained from the OECD Science, Technology and R&D statistics.

References

Agrawal, A., Kapur, D., McHale, J., & Oettl, A. (2011). Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. *Journal of Urban Economics*, *69*(1), 43–55. doi:10.1016/j.jue.2010.06.003

Andersen, T. B., & Dalgaard, C. J. (2011). Flows of people, flows of ideas, and the inequality of nations. *Journal of Economic Growth*, *16*(1), 1–32. doi:10.1007/s10887-011-9060-7

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297. doi:10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. doi:10.1016/0304-4076(94)01642-D

Arrow, K. (1962). The economic implications of learning by doing. *The Review of Economics Studies*, *29*(3), 155–173. doi:10.2307/2295952

Bahar, D., Hausmann, R., & Hidalgo, C. (2014). Neighbors and the evolution of the comparative advantage of nations: Evidence of international knowledge diffusion? *Journal of International Economics*, *92*(1), 111–123. doi:10.1016/j.jinteco.2013.11.001

Bahar, D., & Rapoport, H. (in press). Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal*. Forthcoming.

Balassa, B. (1965). Trade liberalisation and "revealed" comparative advantage. *The Manchester School*, *33*(2), 99–123. doi:10.1111/j.1467-9957.1965.tb00050.x

Barro, R., & Jong-Wha Lee, J.-W. (2013). A new data set of educational attainmentin the world, 1950–2010. *Journal of Development Economics*, *104*(1), 184–198. doi:10.1016/j.jdeveco.2012.10.001

Barsbai, T., Rapoport, H., Steinmayr, A., & Trebesch, C. (in press). The effect of labor migration on the diffusion of democracy: Evidence from a former Soviet Republic. *American Economic Journal: Applied Economics*. Forthcoming.

Beine, M., Docquier, F., & Schiff, M. (2013). International migration, transfer of norms and home country fertility. *Canadian Journal of Economics*, *46*(4), 1406–1430. doi:10.1111/caje.12062

Bertoli, S., & Marchetta, F. (2015). Bringing it all back home–return migration and fertility choices. *World Development*, *65*, 27–40. doi:10.1016/j.worlddev.2013.08.006

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. doi:10.1016/S0304-4076(98)00009-8

Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis*, *14*(1), 63–82. doi:10.1093/pan/mpi014

Breschi, S., Lissoni, F., & Miguelez, E. (in press). Foreign-origin inventors in the USA: Testing for diaspora and brain gain effects. *Journal of Economic Geography*. doi:10.1093/jeg/lbw044

Brücker, H., Capuano, S., & Marfouk, A. (2013). *Education, gender and international migration: Insights from a panel-dataset 1980-2010*. Mimeo. http://www.iab.de/en/daten/iab-brain-drain-data.aspx

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review*, *39*(5), 859–887. doi:10.1016/0014-2921(94)00100-E

Docquier, F., Lodigiani, E., Rapoport, H., & Schiff, M. (2016). Emigration and democracy. *Journal of Development Economics*, *120*(1), 209–223. doi:10.1016/j.jdeveco.2015.12.001

Docquier, F., & Rapoport, H. (2012). Globalization, brain drain, and development. *Journal of Economic Literature*, *50*(3), 681–730. doi:10.1257/jel.50.3.681

Feyrer, J. (2009). Trade and income: Exploiting time series in geography. NBER working paper No 14910. Cambridge, MA: National Bureau of Economic Research.

Frankel, J. A., & Romer, D. H. (1999). Does trade cause growth? *American Economic Review*, *89*(3), 379–399. doi:10.1257/aer.89.3.379

Görg, H., & Strobl, E. (2001). Multinational companies and productivity spillovers: A meta-analysis. *Economic Journal*, *111*(475), 723–739. doi:10.1111/1468-0297.00669

Grossman, G., & Helpman, E. (1991). *Innovation and growth in the global economy*. Cambridge: MIT Press.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029–1054.

Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of Economic Growth*, *12*(1), 1–25.

Hausmann, R., & Rodrik, D. (2003). Economic development as self-discovery. *Journal of Development Economics*, *72*(2), 603–633.

Haussman, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., & Yildirim, M. A. (2011). *The atlas of economic complexity*. Cambridge, MA: Puritan Press.

Head, K., Mayer, T., & Ries, J. (2010). The erosion of colonial trade linkages after the independence. *Journal of International Economics*, *81*(1), 1–14.

Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482–487.

Jarreau, J., & Poncet, S. (2012). Export sophistication and economic growth: Evidence from China. *Journal of Development Economics*, *97*(2), 281–292.

Javorcik, B. (2004). Does Foreign Direct Investment increase the productivity of domestic firms? In search of spillovers through backward linkages. *American Economic Review*, *94*(3), 605–608.

Kerr, S. P., & Kerr, W. R. (2015). Global collaborative patents. NBER Working Paper 21735. Cambridge, MA: National Bureau of Economic Research.

Kerr, W. R. (2008). Ethnic scientific communities and international technology diffusion. *The Review of Economics and Statistics*, *90*(3), 518–537.

Kuznets, S. (1960). Population change and aggregate output. In *Demographic and economic change in developed countries* (pp. 324–351). Cambridge: Columbia University Press.
Lodigiani, E. (2008). Diaspora externalities and technology diffusion. *Economie Internationale*, *115*(3), 43–64.
Lodigiani, E., & Salomone, S. (2015). Migration-induced transfers of norms. The case of female political empowerment (June 23, 2015). University Ca' Foscari of Venice, Department. of Economics Research Paper Series No. 19/WP/2015. Retrieved from https://ssrn.com/abstract=2622394
Madsen, J. B. (2007). Technology spillover through trade and TFP convergence: 135 years of evidence for the OECD countries. *Journal of International Economics*, *72*, 464–480.
Mayr, K., & Peri, G. (2009). Brain drain and brain return: Theory and application to Eastern-Western Europe. *The BE Journal of Economic Analysis & Policy*, *9*(1), 1–52.
Miguélez, E. (in press). Inventor diasporas and the internationalization of technology. *World Bank Economic Review*. doi:10.1093/wber/lhw013
Miguelez, E., & Moreno, R. (2015). Knowledge flows and the absorptive capacity of regions. *Research Policy*, *44*(1), 833–848.
Naghavi, A., & Strozzi, C. (2015). Intellectual property rights, diasporas, and domestic innovation. *Journal of International Economics*, *96*(1), 150–161.
Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*, 1471–1476.
Özden, Ç., Parsons, C. R., Schiff, M., & Walmsley, T. L. (2011). Where on earth is everybody? The evolution of global bilateral migration 1960-2000. *World Bank Economic Review*, *25*(1), 12–56.
Poncet, S., & Starosta de Waldemar, F. (2013). Export upgrading and growth: The prerequisite of domestic embeddedness. *World Development*, *51*, 104–118.
Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), 71–102.
Roodman, D. (2009a). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, *71*(1), 135–158.
Roodman, D. (2009b). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, *9*(1), 86–136.
Santos Silva, J. M. C., & Tenreyro, S. (2006). The log of gravity. *Review of Economics and Statistics*, *88*(4), 641–658.
Simon, J. (1977). *The economics of population growth*. Princeton, NJ: Princeton University Press.
Spilimbergo, A. (2009). Democracy and foreign education. *The American Economic Review*, *99*(1), 528–543.
Spolaore, E., & Wacziarg, R. (2009). The diffusion of development. *Quarterly Journal of Economics*, *124*(2), 469–529.
Tuccio, M., & Wahba, J. (2016). Can I have permission to leave the house? Return migration and the transfer of gender norms. (IZA Discussion Paper 9216). Bonn: Institute for the Study of Labor (IZA).
Vu, K. M. (2013). A note on interpreting the Beta-convergence effect. *Economic Letters*, *118*(1), 46–49.
World Bank. (2008). *Global economic prospects 2008: Technology diffusion in the developing world*. Washington, DC: The World Bank.
Xu, B. (2010). The sophistication of exports: Is China special? *China Economic Review*, *21*(3), 482–493.

Appendix

Table A1. Summary statistics

	Mean	Std. Dev.	Min.	Max.	N
ECI_{it}	0,020	1,047	−2,783	2,582	600
$\overline{ECI}_{it-5}$	0,058	0,088	0,001	0,586	600
$log(GDP_{it})$	8,650	1,215	5,410	11,539	600
$log(Pop_{it})$	2,675	1,427	−0,690	7,184	600
Hum_{it}	6,912	3,078	0,534	13,270	600
$log(Trade_{it})$	4,178	0,529	2,406	6,071	600
FDI_{it}	3,071	4,949	−16,071	41,065	600

Source: Author's elaboration.
Notes: ECI is the Economic Complexity Index from Haussman et al. (2011). $\overline{ECI}_{it-5}$ is the weighted-average ECI in migrants' destination countries where the weights are the emigration rates computed using Brücker et al. (2013). GDP_{it} and Pop_{it} are respectively the GDP per capita at current PPPs and the total population aged 25 years and older in millions, respectively, taken from the Penn World Table 8.0. Hum_{it} is the average years of schooling attained for population aged 25 and over taken from Barro and Lee (2010). $Trade_{it}$ and FDI_{it} are respectively the sum of exports and imports of goods and services, respectively, measured as a share of GDP and the FDI net inflows in current US dollars measured as a share of GDP, from the World Development Indicators.

Table A2. Main variables

Variable	Description	Definition and Source
ECI_{it}	Economic Complexity Index	Measure of the knowledge in a society that gets translated into the products it makes. Hausmann et al. (2011).
$\overline{ECI}^{\rho}{}_{it}$	Average of the Economic Complexity Index at destination	Weighted average of the Economic Complexity Index where the weights are emigration rates ($\rho = \emptyset$), emigration shares (ρ = S), import shares (ρ = IMP), inverse of geographical distances (ρ = DIS), FDI shares (ρ = FDI) inverse of genetic distance (ρ = GEN) and initial value in 1980 (ρ = INI), respectively. Authors' calculations.
$log(M_{it})$	Emigration rate (log)	Proportion of migrants over the pre-migration population (25 years and older). Brücker et al. (2013).
$log(GDP_{it})$	GDP per Capita (log)	Output-side real GDP per capita at current PPPs (in mil. 2005 US dollars). Penn World Table 8.0.
$log(Pop_{it})$	Total population 25 years and older (log)	Penn World Table 8.0.
Hum_{it}	Adult Education	Educational Attainment for Population Aged 25 and Over: Average Years of Schooling Attained. Barro and Lee (2010).
$log(Trade_{it})$	Trade Openness (log)	Sum of exports and imports of goods and services measured as a share of gross domestic product. World Development Indicators.
FDI_{it}	Foreign Direct Investment	FDI, net inflows in current U.S. dollars as a share of gross domestic product. Foreign direct investments are the net inflows of investments needed to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. World Development Indicators.
Gravity model à la Feyrer (2009)		
$log(Stock_{ijt})$	Bilateral migration stock (log)	Stock of migrants from i residing in j at time t. Özden et al. (2011) and Brücker et al. (2013).
$log(Dist_{ijt})$	Distance (log)	Geographical distance between the biggest cities of the coutries i and j weighted by the share of the city in the total population of the two countries. Head, Mayer, and Ries (2010). Dummy equal to 1 if countries i and j share a common border and 0 otherwise. Head et al. (2010).
$Colony_{ij}$	Colonial past	Dummy equal to 1 if countries i and j share a colonial past and 0 otherwise. Head et al. (2010).
$Lang_{ij}$	Common language	Dummy equal to 1 if at least 9 per cent in countries i and j populations speak a common language and 0 otherwise. Head et al. (2010).
$Bord_{ij}$	Common border	Dummy equal to 1 if countries i and j share a common border and 0 otherwise. Head et al. (2010).

Table A3. Gravity model following Feyrer (2009)

	(1)
	$log(Stock_{ijt})$
$log(Dist_{ij}) \times I_{1980}$	−0.844***
	(0.128)
$log(Dist_{ij}) \times I_{1985}$	−0.759***
	(0.117)
$log(Dist_{ij}) \times I_{1990}$	−0.741***
	(0.114)
$log(Dist_{ij}) \times I_{1995}$	−0.738***
	(0.108)
$log(Dist_{ij}) \times I_{2000}$	−0.729***
	(0.103)
$log(Dist_{ij}) \times I_{2005}$	−0.689***
	(0.101)
$log(Dist_{ij}) \times I_{2010}$	−0.690***
	(0.100)
$Bord_{ij}$	0.357
	(0.247)
$Lang_{ij}$	1.215***
	(0.183)
$Colony_{ij}$	1.200***
	(0.181)
Constant	11.624***
	(1.032)
Observations	26,600
Nb. origin	191
Nb. destination	20
R-squared	0.792
Year dummies	Yes
Origin dummies	Yes
Destination dummies	Yes

Source: Author's elaboration on Haussman et al. (2011), Brücker et al. (2013) and Head et al. (2010).
Notes: Standard errors in parentheses are clustered at the country-pair level (*** p < 0.01, ** p < 0.05, * p < 0.1). $Dist_{ij}$ is the great-circle distance between the capitals of i and j. I_t are year dummies. $Bord_{ij}$ is a dummy variable equal to one if i and j share a common border. $Lang_{ij}$ is a dummy variable equal to one if at least 9 per cent of the populations of i and j speak a common language. $Colony_{ij}$ is a dummy variable equal to one if i and j share a colonial past.