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Highly Skilled Migration and Knowledge Diffusion

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Abstract

Highly Skilled Migration and Knowledge Diffusion Ernest Miguelez, 1/2/3 Claudia Noumedem Temgoua 1/§ 1 GREThA UMR CNRS 5113 – Université de Bordeaux 2 AQR-IREA (Barcelona, ES) 3 CReAM (London, UK) Year of enrolment: 2013, Expected final date: Dec. 2016 § contact author: claudia.noumedem-temgoua@u-bordeaux.fr Abstract This paper documents the influence of diaspora networks of highly-skilled individuals on international knowledge diffusion. In a context where highly skilled emigration has been for long considered as "lost" of human capital to the home country, a number of case studies have been produced, which looks into whether substantial knowledge "remittances" may compensate for the loss. However, systematic empirical evidence is still scarce, with few recent works looking at the role highly skilled migrants play on the diffusion of knowledge from the US to their homelands. In particular, no study has yet tested for the exact nature of the link between highly skilled migrants and knowledge spillover to their home economies at a global scale. This paper intends to fill this gap, adding to the growing literature on highly-skilled international migration and its contribution to knowledge and so economic growth in migrants' home countries. More precisely, it explores knowledge feedbacks to home countries generated by migrant inventors, a representative category of high-skilled migrants, most of them scientists and engineers. In line with a recent strand of literature on migration and innovation studies, we make use of patent and inventor data to measure migration flows between countries, and test our hypothesis in a country-pair gravity model framework, for the period 1990-2010, using patent citations across countries as a measure of international knowledge diffusion. Our results confirm our initial assumption on the positive impact of highly skilled migrants on knowledge diffusion to their homelands. We find a 10% increase in the number of inventors of a given nationality at a destination country, leads to 1- percentage point knowledge diffusion to their home economy from that same host land. And these results are not driven neither by the U.S. as a traditional country of highly skilled immigration, nor by India and China as the biggest highly skilled sending countries, since we obtain similar results even after having dropped these three countries.
Jelcodes:O33,J61

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Abstract

This paper documents the influence of diaspora networks of highly-skilled individuals on international knowledge diffusion. It adds to the growing literature on highly-skilled international migration and its contribution to knowledge and so economic growth in migrants' home countries. In particular, it explores knowledge feedbacks to home countries generated by migrant inventors, a representative category of high-skilled migrants, most of them scientists and engineers. In line with a recent strand of literature on migration and innovation studies, we make use of patent and inventor data to measure migration flows between countries, and test our hypothesis in a country-pair gravity model framework, for the period 1990-2010, using patent citations across countries as a measure of international knowledge diffusion. Our results confirm our initial assumption on the positive impact of highly skilled migrants on knowledge diffusion to their homelands. We find a 10% increase in the number of inventors of a given nationality at a destination country, leads to 1- percentage point knowledge diffusion to their home economy from that same host land. And these results are not driven neither by the U.S. as a traditional country of highly skilled immigration, nor by India and China as the biggest highly skilled sending countries, since we obtain similar results even after having dropped these three countries.

Keywords: migration, brain gain, diaspora, diffusion, inventors, patents, PCT patents

JEL classification: C8, J61, O31, O33

I- INTRODUCTION

Highly skilled workers are an important asset for a country's growth as they impact directly on knowledge production and diffusion (Nelson and Phelps, 1966; Vandenbussche et al., 2006). The network of knowledge exchanges developing around these highly skilled workers generates externalities to the actors being part of this network (Lodigiani, 2008; Breschi and Lissoni, 2009). Special attention has been given in the literature to the international dimension of such networks, with a focus on highly skilled migrants as the main actors and their contribution to knowledge transfer to their homelands (e.g. Brinkerhoff, 2006; Kapur, 2001; Kuznetsov, 2006; Saxenian, 1999). In a context where highly skilled emigration has been for long considered as "lost" of human capital to the home country, a number of case studies have been produced, which looks into whether substantial knowledge "remittances" may compensate for the loss. However, systematic empirical evidence is still scarce, with few recent works looking at the role highly skilled migrants play on the diffusion of knowledge from the US to their homelands (Agrawal et al., 2011; Kerr, 2008a). In particular, no study has yet tested for the exact nature of the link between highly skilled migrants and knowledge spillover to their home economies at a more global scale.

This paper intends to fill this gap of knowledge. In particular, it explores knowledge feedbacks to home countries generated by migrant inventors, a representative category of high-skilled migrants, most of them scientists and engineers. In line with a recent strand of literature on migration and innovation studies, we make use of patent and inventor data (as proxies for scientists and engineers and their output) to measure bilateral migration flows between countries, and test our hypotheses in a gravity model framework. In particular, we look for how highly skilled migration (our focal regressor) affects knowledge diffusion, as measured by patent citations (our dependent variable). The present empirical analysis is made possible by the use of a novel dataset of inventors with migratory background as a proxy for a highly-skilled diaspora (Miguelez and Fink, 2013).

Results from our regressions confirm our initial assumption on the positive impact of highly skilled migrants on knowledge diffusion to their homelands. More precisely, we find that a 10%

increase in the number of inventors of a given nationality at a destination country, leads to 1-percentage point knowledge diffusion to their home economy from that same host land. And these results are not driven neither by the U.S. as a traditional country of highly skilled immigration, nor by India and China as the biggest highly skilled sending countries, since we obtain same results even after having dropped these three countries.

The rest of the paper is organized as followed: the next section presents selected literature on highly skilled migration and innovation. Section III focuses on the research method, including the description of our data and variables, a presentation of the model and a discussion on the results. We conclude in the last section.

I- BACKGROUND LITERATURE

Innovation can be viewed as an outcome of cumulative efforts in R&D in the domestic country or region. Early empirical evidences of technological diffusion have shown that a country's R&D capital stock – a measurement for the stock of knowledge – could positively impact on its own total factor productivity (Coe and Moghadam, 1993; Griliches, 1988), but also on the one of its trade partners (Coe and Helpman, 1995). However, Keller (1997) casts some doubts on Coe and Helpman's (1995) findings showing that similar results were obtained when using random numbers for trade patterns. In a further analysis, other scholars (Eaton and Kortum, 1996; Keller, 2001) suggested technological diffusion could be as well be a consequence of other regional effects not linked to trade or could come from the simultaneous effect of several other channels like geographical distance, Foreign Direct Investment (FDI) and language similarity. Yet, Coe and Helpman's (1995) study provides an early empirical evidence of international diffusion of knowledge from trade. In recent years, new techniques have been developed allowing to explore more into depth what drives the international diffusion of knowledge.

In a study by MacGarvie, (2005) , a gravity model[1] is applied to a data from the U.S. Patent and Trademark Office (USPTO), taking the number of patent citations between country pairs as the dependent variable and a proxy to knowledge diffusion. Patent citations information for ten countries are retrieved from the USPTO for the period 1980–1995. The author then includes some dyadic control variables such as the technological and cultural proximity – a dummy for common language – and geographical distance between pair of countries and the citing country's imports from the cited country, adding country's specific variables like the citing country's employment of R&D workers, FDI and the yearly number of telephone calls. The author finds that FDI, geographical, technological and cultural proximity favors knowledge diffusion between two countries. Meanwhile, trade is associated with knowledge diffusion only in inventions within the same fields of technology. These findings from MacGarvie confirm results from previous empirical studies exploiting various methods which have highlighted the role played by FDI (Almeida, 1996; Frost, 2001; Singh, 2002), bilateral trade, geographical distance and technological proximity (Peri, 2003; Sjöholm, 1996) as determinants of international knowledge spillovers. Besides these traditional determinants, there is one channel of knowledge spillovers which is slowly gaining some attention from the literature, which is migrants, highly skilled in particular. A study by Miguelez (2014) for instance exploits the gravity model to explain co-the internationalization of innovation as proxied by inventorship and R&D offshoring with highly skilled migration and more particularly inventors diaspora. The author finds a positive, strong and robust relationship between the inventors diaspora variable and both variables on co-inventorship and R&D offshoring. One implication of this study is that highly skilled migration has some positive repercussion on sending countries in terms of innovation. This positive repercussion to home economies is what has been referred to as brain gain in the highly skilled migration literature, as opposed to the brain drain phenomenon which had been for decades predicted by early migration scholars. There is indeed a well-established theoretical literature on the brain drain phenomenon (Beine et al., 2001; Berry and Soligo, 1969; Bhagwati, 1975; Grubel and Scott, 1966; Johnson, 1967; Lucas, 1990; Mountford, 1997, 1995;). At a first glance, the conventional migration literature seems to depict brain drain mainly as the concern of developing nations or south-north migration. This could be explained by developing nations' relatively low endowment in human capital as compared to other nations' groups. It thus makes them more likely to be vulnerable to any human capital loss, particularly a loss of their highly qualified one. This explains why countries such as India and China are often cited among the winners – along with developing nations – in the brain drain debate, as their high endowment in human capital seems to make impact of the massive highly skilled emigration they experience negligible in relative terms. However, considering the basic definition of brain drain as the permanent emigration of qualified workers[2] (Straubhaar, 2000), it should be acknowledged that brain drain is not only restricted to developing countries as high income nations such as Germany, France and the United Kingdom have to face a considerably high rate of emigration of their highly skilled workers. From a data on emigration rates by country group in 1990 and 2000, Docquier et al. (2007) report the proportion of highly skilled workers among migrants to be much higher than the proportion of highly skilled workers among residents, this for every income groups. Furthermore, many high income countries have adopted local policies aiming at keeping their talents home and attracting foreign ones. Therefore, as brain drain is a concern for all countries and as the rate of highly skilled emigration will probably maintain a growing trend over the years, instead of focusing on questions such as which countries are the biggest losers or winners of brain drain, much attention should be given to finding strategies in order for sending as well as receiving countries to benefit from highly skilled migration. This is partly what has been at the core of a new trend of studies that has emerged during the past two decades – pioneered by Stark et al., 1998, 1997; Stark and Wang, 2002 – and which advocates the possibility of some brain gain for sending countries from their highly skilled workers outflow.

Indeed, the recent empirical migration literature has outlined several ways through which a brain gain could occur to sending countries. One of these mediums is returnee migrants. For instance, Chacko, (2007) provided evidences of the important role of Indian professional immigrants who returned home, in the development of the IT industry in the city of Bangalore. Other studies have reported higher intentions to return among various groups of skilled diaspora (see Bollard et al., 2011; Gibson and McKenzie, 2012; Kangasniemi et al., 2007). Another approach to brain gain in the empirical literature has been to show how co-ethnic ties eased knowledge flow among inventors of same origin not only at the destination place (Breschi et al., 2013), but also to the source country (Agrawal et al., 2011, 2008; Almeida et al., 2009). Using patent data from the USPTO, Kerr, (2008) showed that ethnic ties increased knowledge diffusion and technology production in source countries. The effect is even stronger for high-tech industries and Chinese industries. The author applies an ethnicity identification technique based on inventor's names – which has inspired several other empirical work such as the one by Breschi and Lissoni, (2013).

Besides, the brain gain effect, sending countries might as well gain some economic benefit from the outflow of their highly skilled. Indeed, migrant networks and ethnic ties have been positively linked to a set of variables such as Foreign Direct Investment (FDI) (Javorcik et al., 2011; Kugler and Rapoport, 2007), R&D off shoring (Miguelez, 2014) and international trade (Gould, 1994) in the literature. In these studies, highly skilled diasporas are depicted as a direct – from diaspora members deliberately interacting with their home economies – and an indirect – from diaspora members serving as an intermediate for easing transactions between host and home economies – vector of economic and knowledge development to their home countries (Kapur and McHale, 2005).

Unfortunately, empirical work on brain gain is limited to a group of countries, mainly high income ones, India and China. The focus on India and China in the brain gain literature is somehow due to all the success stories that have been reported by studies on their highly skilled migrants in the U.S. And this is at the expenses of studies on highly skilled from other regions like Africa and South Asia. The case of Africa is particularly interesting as most studies on migration in this region have addressed it from an internal or rural-urban migration perspective and its implication in terms of growth and development. The relatively low quality of data on highly skilled migration to and from Africa is one of the reasons why this topic remains empirically unexplored, although existing statistics have reported a relatively high proportion of talents leaving the continent to Europe or to the U.S. A study by Kabore (2013) depicts the extent of brain drain from Africa to OECD countries based on a data on immigrants living in OECD countries. Out of the total African immigrants living in OECD, there is on average 28% immigrants with tertiary education, while the proportion of tertiary educated living in the continent is only 5%. The author also reported the top sending African countries in absolute terms to be Northern African countries followed South Africa, Nigeria, Ethiopia, Ghana and Somalia, while France, the U.S., Canada and Spain were the top destination countries in the OECD. Moreover, the trend of tertiary education brain drain has been increasing for most of the top sending African countries. Besides, Bhargava and Docquier (2008) have compared medical brain drain in Sub-Saharan Africa to the situation in South-Asia, and it appears that the average brain drain for the former is above 20%, while the average rate of medical brain drain in South-Asia is around 13%. The above-mentioned figures would sound alarming when omitting to mention the potential to positive feedback to African sending countries.

Batista et al. (2007) showed that the prospect of emigration considerably increases educational attainment in Cape Verde, from a study based on migrants' individual histories. Similar results were found by Chojnicki and Oden-Defoort (2011) when focusing on medical brain drain. Indeed, their findings suggested that emigration of their medical workers resulted to higher education decision in some African countries, but under specific restrictive conditions on medical doctor's emigration rates. Additionally, Clemens (2007) documented an increase in the production of health workers in Africa, from health professional emigration. These findings contrast previous studies whose outcomes are more pessimistic. For instance, Connell et al. (2007) found that migration of the healthcare work force from Sub Saharan Africa was economic costly for these countries, diminished the effectiveness of health care delivery and reduced the morale of the remaining workforce.

One common observation that is outlined from the above literature is the lack of any common measurement for concepts such as highly skilled or knowledge spillovers. For the former, it should be pointed out to the fact that skill level definition is often driven by the data in hands. First existing data on highly skilled migrants referred to occupation for defining and classifying skills (Koser and Salt, 1997). Some countries have used the level of wages paid to measure skills. However, in most data or studies in migration nowadays, skills level is captured by the level of education. In this case, a highly skilled means anyone holding a tertiary education qualification or with a certain number of years of schooling. Each of the three criteria of skill identification has its own specific features[3]. Some scholars have found a way to reconcile all three of them by working on inventors as highly skilled, a category which seems to embody all aspects of skill (see for instance Kerr, 2008; Miguelez, 2014; Breschi and Lissoni, 2013). As for knowledge, some variables such as trade, R&D and FDI have been used to proxy the extent of knowledge exchange between countries. But measuring knowledge diffusion in general could be cumbersome. The use of patent citations has emerged as a way of doing so. This technique was pioneered by Jaffe et al. (1993). Indeed, using patent citations from the United States Patent and Trademark Office (USPTO), Jaffe et al. (1993) investigates patterns of technology diffusion in the U.S. After geo-localising patents on the basis of their inventors' addresses, they find a higher likelihood for U.S. patents to be cited by other patents coming from the same state as the cited

[3] For a detailed discussion see Chaloff et al. (2009)

patent than by patents from other states, pointing out to the existence of localized of knowledge spillovers. Since then, the use of patent citations has been widely applied in various other studies – as no better measurement of knowledge spillover or technology diffusion has been found up to date – which have attempted to investigate channels of knowledge diffusion.

All in all, to the best of our knowledge, very few studies have empirically investigated the actual nature of the link between highly skilled migration and knowledge spillover. There have been some case studies that have looked into the question on how knowledge diffuses across multiple ethnicities in a given country or to origin countries through ethnic communities, by analyzing the distribution of citations from source countries to migrants from the same ethnicity. Additionally, these studies have looked into the link between technological production or productivity in home and host economies and the size of ethnic research community in the host country (Breschi and Lissoni, 2013; Kerr, 2008). However, this literature has not reached any consensus so far. Some studies have found some positive impacts in terms of knowledge diffusion as well as development, while the results from other studies remain inconclusive. This might be due to the specificities attached to samples used altogether with the model specifications, which call for some cautions when generalizing findings from these studies. In the present analysis, we will borrow from the model specifications applied by Miguelez (2014) who investigated the role of highly skilled in the internationalization of knowledge and the one by McGarvie (2005) who looked into the determinants of knowledge diffusion. Both papers apply a gravity model using patent data.

II- RESEARCH METHOD

1- The international mobility of inventors

For the present analysis we make use of a new dataset on patent citations and inventors from Patent Cooperation Treaty (PCT) patents application, the patent database from the World International Patent Office (WIPO) for the period 1990 to 2010 (see Miguelez and Fink, 2013 for a detailed description of the dataset), from which we are able to identify inventors with a migratory background on the basis of their nationality. However, the latter can be considered as

an imperfect proxy of origin to the extent there is a great chance of underestimating migrants unlike with other origin proxy such as country of birth which is the most commonly used proxy in most migration datasets like the DIOC (Database on Immigrants in OECD Countries) dataset. Patents data and inventors' data in particular have been used in a few highly skilled migration studies, especially studies on immigration to the U.S. The development of new techniques for origin identification has rendered possible this widespread application. Moreover, these data that rely on inventor migrants are said to cover a more homogenous category of highly skilled migrants, unlike with similar data where skill levels are obtained from educational levels. However, one point that makes the PCT dataset stands one step ahead from other existing datasets from country or regional patent offices is its international dimension, which thus makes it rather more convenient for the present analysis. Indeed, these other datasets will tend to be more biased towards one or another origin/destination country or region. Another advantage of using this dataset is that it is the only international migration dataset where information on inventors' nationalities and residence are provided by inventors themselves[4]. It is therefore possible to identify migrant inventors by contrasting information on nationality with those on residence. Furthermore, the dataset yearly coverage enables it to be organized into a time-series data with information on both patent citations and migrant inventors for a wide range of countries that can be coupled into citing/cited countries or sending/receiving country pairs. Around 80% share of inventors' observations got information on nationality and residence[5].
Country-pair yearly aggregated data on migrant inventors from the WIPO dataset are the starting point compute our focal explanatory variable, that is to say, the number of inventors from sending country j residing in receiving country i, annually from 1990 to 2010.

2- Patent citations as a measure of knowledge flows

Our dependent variable is built using cross-country citations to PCT patents. In particular, we retrieve backward citations to PCT patents from the "OECD Citations database, July 2014"

[4] The PCT requires at least one of the patent applicants to be a national of a PCT Contracting State, thus the requirement of filing applicants' nationalities and residences. And for international applications filed before 16 September 2012, inventors have to be listed as applicants for the purposes of the U.S. designation.
[5]Information on country of location of inventor come from the inventor's address provided upon application.

(Webb et al., 2005) and geo-reference both cited and citing patents across all countries. From an initial table with 8,748,399 bilateral patent citations observations – citing and cited patents pairs -, there are 5,994,806 of these observations where information on inventors' location are available, thus a coverage of 69% share of full citation pairs dataset between 1990 and 2010. Further, 3,638,847 of these observations (61%) are international citations and therefore constitute the focus of our analysis. However, this coverage is not evenly distributed across countries and over time. Again, citation data are aggregated into pairs at a country level.

3- Empirical approach

Our data configuration calls for an application of a gravity model of the following form:

$$KF_{ijt} = e^{\beta_0}.mig_{ijt}^{\beta_1}.Z_{ijt}^{\gamma_n}.e^{\tau_i}.e^{\tau_j}.e^{\delta_t}.\varepsilon_{ijt} \quad (1)$$

Where KF_{ijt} is the flow of knowledge from country i to country j in the year t as measured by the number of patent citations that have received country j from country i for that period t, β_1 is our parameter of interest for the bilateral migration variable, mig_{ijt} is the stock of inventors of j nationality residing in country i during the year t, Z_{ijt} is the set of dyadic and country specific control variables in year t, τ_i, τ_j and δ_t are country i, country j and time FE respectively. ε_{ijt} stands as the error term.

The gravity model in its initial form was used to explain migration patterns (Ravenstein, 1889). The model has been later on applied to trade flows by (Tinbergen, 1962) and thus extensively used and extended in several international trade studies. When applied to trade or migration, the gravity model faces the issue of the presence of too many zero in the data which implies skewness in its distribution with relatively few high values in the bottom end. Therefore, the common econometric usage when dealing with gravity models has been to transform the gravity equation – equation (1) in our case – into its logarithmic form – with a normal disturbance term, then estimate it with an Ordinary Least Squares (OLS). However, the latter practice may induce some heteroskedasticity in the error terms, thus some inconsistency of estimation as pointed out by Santos-Silva and Tenreyro (2006). The many zero that were calling for a logarithmic transformation are the factors leading to a violation of the normal distribution assumption since it will produce an important mass of the disturbance term at these zero values (Anderson, 2011). Consequently, Santos-Silva and Tenreyro (2006) recommend estimating the multiplicative form of the model using Poisson pseudo-maximum likelihood (PPML).

Given all what precedes, we choose to apply the PPML regression to the following conditional expectation of equation (1):

$$E(KF_{ijt} \mid X_{ijt}) = \exp\left[\beta_0 + \beta_1 \ln(mig_{ijt} + 1\right) + \gamma_{\mathrm{n}} \ln\ (Z_{ijt} + 1) + \tau_i + \tau_j + \delta_t + \varepsilon_{ijt}] \quad (2)$$

4- Descriptive statistics

Knowledge flow and migrant inventors' variables

Our variable, the knowledge flow variable, is a dyadic variable returning the fractional count of patent citations from one country to another per year, weighted by the total number of inventors per country. The highly skilled migration variable here is measured by the stock of inventors with a country nationality, living in a given country. These bilateral variables have been computed for the 163 countries of our sample which have been grouped into pairs, with the omission of same country pairs – as we are rather interested by international than intra-country knowledge diffusion. Before jumping into the regressions, some quick general overview of the statistical figures returned by both variables will allow us to see if there are some country or region pairs special caution needs to be paid on.

Citations and migration corridors

From Tables 1 and 2 we can have a quick glance at the top 20 biggest players when it comes to knowledge flow and migration flow, respectively, for the period 2006 to 2010 – due to the uneven distribution of this flows over the time, we choose to represent average of the last five years which are the periods where there is a higher concentration of records.

Table 1 shows the biggest flows of citations are amongst technology-leading or high income countries, with the US[6] being the largest origin of knowledge mainly to European countries, Japan, Canada, Israel and Australia respectively. There is a strong reciprocity to the extent that many top knowledge recipient countries are also origin countries to the countries they get knowledge from. Additionally, the knowledge flow distribution is very skewed, with the top 20 country pairs accounting for up 46% of the share of bilateral citations worldwide. All this implies the largest quantity of knowledge is exchanged and circulates amongst a small group of countries which are all high income countries. When eliminating high income countries from the list of knowledge recipient countries, China and India appear as important knowledge destinations, receiving altogether a good deal of 42% of the share of citations going to low and middle income countries (Table A1 in the appendix). Interestingly, the share of knowledge flowing from the US to South Africa – the only African country in this top 20 table – is the third highest share in this list of bilateral citations, with high income citing countries excluded. Again here, there is a skewed distribution of bilateral citations – 58% of knowledge flowing amongst top 20 country pairs – and high income countries remain the top origin of knowledge.

[6] The country itself accounts for around 29% of all knowledge origin in the entire sample.

<u>Table 1.</u> Citations corridors (Total flow of citations for the top 20 country pairs for the period 2006-2010)

Citing country	Cited country	# of citations	Citation share Cum. (%)	High income	High income
Germany	USA	31535,83	5,55	yes	yes
USA	Japan	30436,24	10,9	yes	yes
UK	USA	26071,23	15,49	yes	yes
USA	Germany	19469,17	18,91	yes	yes
France	USA	14961,82	21,54	yes	yes
Germany	Japan	14487,21	24,09	yes	yes
Japan	USA	13766,22	26,51	yes	yes
Netherlands	USA	12971,89	28,79	yes	yes
USA	UK	12328,78	30,96	yes	yes
Canada	USA	11642,68	33,01	yes	yes
Israel	USA	9803,344	34,73	yes	yes
Sweden	USA	9785,602	36,45	yes	yes
Italy	USA	9206,611	38,07	yes	yes
Australia	USA	9084,947	39,67	yes	yes
Switzerland	USA	8699,053	41,2	yes	yes
USA	Canada	7716,963	42,56	yes	yes
UK	Japan	6769,336	43,75	yes	yes
Denmark	USA	6745,993	44,94	yes	yes
USA	France	6461,959	46,08	yes	yes
USA	Republic of Korea	6302,805	47,19	yes	yes

Source: WIPO Statistics Database, October 2013

The figures depicted by Table 2 for migration flow corridors are quite similar to those of citation corridors, with striking differences though. Unsurprisingly, out of the top 20 destination countries, the US is the most common residence migrant inventors from 14 countries. China-US and India-US come up as the pairs with the highest inventor migration stocks, with the latter accounting for close to one fourth of the whole dataset bilateral migration flows. Additionally, there is a high stock of migrant inventors from Europe residing in the US, mostly from the UK, Germany and France which are also technology-leading countries.

<u>Table 2.</u> Migration corridors (Total flow of inventor immigrants for the top 20 country pairs for the period 2006-2010)

Origin country	Destination country	Total migration flow	Cum. Migration share (%)	High income	High income
China	USA	27696	13.48	no	yes
India	USA	21712	24.04	no	yes
Canada	USA	11364	29.58	yes	yes
UK	USA	8313	33.62	yes	yes
Germany	USA	5895	36.49	yes	yes
Germany	Switzerland	4952	38.9	yes	yes
Republic of Korea	USA	4877	41.27	yes	yes
France	USA	3898	43.17	yes	yes
Japan	USA	2844	44.55	yes	yes
Russian Federation	USA	2309	45.58	no	yes
France	Switzerland	1880	46.59	yes	yes
Israel	USA	1878	47.51	yes	yes
Australia	USA	1783	48.37	yes	yes
Netherlands	USA	1670	49.19	yes	yes
France	Germany	1492	49.91	yes	yes
Italy	USA	1492	50.64	yes	yes
China	Japan	1463	51.35	no	yes
Germany	Netherlands	1335	52	yes	yes
Austria	Germany	1308	52.63	yes	yes
Turkey	USA	1233	53.24	no	yes

Source: WIPO Statistics Database, October 2013

5- Control variables

Drawing from MacGarvie (2005) and Miguelez (2014) , we control for geographical distance as well as cultural and historical ties between citing/sending and cited/receiving countries. Two variables are included for the geographical distance; one is a dummy variable for contiguity, taking the value 1 if the two countries share a common border and 0 otherwise. The other one is a variable measuring the distance – in km – between the biggest cities of both countries, weighted by the share of that city's population in the overall country's population. Cultural ties are proxied with a dummy for common language taking the value 1 if both countries share at least one language and 0 otherwise. For controlling for historical ties, we include a dummy taking value zero if there has been a colonial link between both countries and 0 otherwise[7]..

Additionally, we include an index of technological proximity between pair of countries in order to control for whether they both share common fields of technological specialization. This index is computed as followed:

$$Tech.proximity_{ij} = \frac{\sum f_{ih} f_{jh}}{(\sum f_{ih}^2 \sum f_{jh}^2)^{1'2}} \tag{3}$$

Where f_{ih} stands for the share of patents of one technological class h according to the 30-class reclassification of IPC codes[8] of country i, and f_{jh} for the share of patents of one technological class h of country j. Values of the index close to the unity indicate that a given pair of countries are technologically similar, and values close to zero indicate that they are technologically different (Jaffe, 1986).

Lastly, we control for each country level of technological production or its technological capacity with its total number of inventors per year. This variable is informative to the extent it is a signal to the size of country innovation systems, which clearly determines a country's capacity to collaborate with foreigners, as well as its capacity to attract inventors from abroad or send them to other location.

[7] All of the above control variables come from the *'Centre d'Etudes Prospectives et d'Informations Internationales'* (CEPII). A detailed description of these variables can be found in Mayer and Zignago (2011)
[8] This 30-class reclassication of IPC codes was originally proposed by the OST (Observatoire des Sciences et Techniques). For more details see Coffano and Tarasconi (2014).

<u>Table 3.</u> Variables definition

Variables	Definition
Knowledge Flow	Fractional count of citations from one citing country i to a cited country j, weighted by the number of inventors per patent
Migrant inventors	Total inventors from one origin country i residing at a given destination country j
Technological similarity	Index of technological proximity between countries i and j at a given year, varying from 0 to 1
Contiguity	Dummy variable for taking value 1 if countries i an j share same border
Colony	Dummy variable taking value 1 if country i is a former colony of country j
Com. official langage	Dummy variable taking value 1 if countries i and j share at least one common national language
Distance	Distance in kilometres between the biggest cities of both countries i and j, weighted by the share of that city's population in the overall country's population
# of inventors in country i	Total number of inventors with country i nationality
# of inventors in country j	Total number of inventors with country j nationality

6- Results

Baseline estimations

Table 3 reports the results from the baseline PPML regression, with robust, country-pair clustered standard errors. The explanatory variable here is the logarithm of the number of inventors of nationality i living in country j plus one unit. This variable altogether with a set of control variables are used to explain the flow of citations from country i to country j. First column returns results from the simple model specification without any interaction of control variable. The estimator of our variable of interest, the migrant inventors' variable is of an order of 0.101, positive and statistically significant. In other words, a 10% increase in the number of inventors from one country residing in another country leads to a one percentage point increase in the knowledge diffusion from the destination country to the source country. Similarly, sharing a border and having some colonial ties seem to positively impact on knowledge diffusion between two countries, but the coefficients for both of these two variables is not significant. Meanwhile, cultural ties appear to be an important factor of knowledge diffusion, with a positive and significant estimator for the common language variable. As expected, the coefficient for technological similarity is positive and significant, with a value of 1.45 – close to what have been found by MacGarvie (2005) – confirming the hypothesis that there are more knowledge diffusion between countries that are close in their technological space. Other expected results are the strong and positive estimators for the variables measuring both countries inventive capacity – log of number of inventors – and the negative and significant coefficient of the distance variable, meaning diffusion of knowledge fades with distance. However, assuming the latter relationship to be linear would be a mistake, since there could be other factors at work for better capturing the knowledge diffusion between two countries than the distance and which could help explaining why there is more knowledge diffusion from the US to India or China than from the U.S. to Mexico for instance. In other words, in some cases, the cost of distance or its negative effect will be much lower than in others, and this does not only depend on the number of kilometers but on additional attributes attached to distance. In the model specification (2), we introduce the square of the log of distance in order to account for the non-linearity in the relationship between distance and knowledge diffusion. In this new model specification, the results for the other coefficients remain pretty much the same while the estimator for the distance variable remains negative and significant but becomes stronger and the coefficient for contiguity loses its significance. The coefficient for the square of distance is positive and significant. All this suggests there are some country pairs for which the distance does not really matter for knowledge diffusion while for others there is actually an inverse relationship between both variables.

Besides, we are interested to see how the variable of interest here, which is the migration variable, interacts with country pairs underlying ties such as historical and cultural ties. We therefore add two variables representing respectively the product of the migration variable and colonial ties dummy – results shown in column (3) and the product of the migration variable and common language dummy – results shown in column (4). The results we get from both columns (3) and (4) are not very different from the results we got from the baseline model, except for changes in the significance of variables for contiguity, same colony and geographical distance. What is worth to mention here are both negative signs and significance of the coefficients of the two interaction variables from columns (3) and (4). This can be interpreted as; in the absence of historical and cultural ties between two countries, migration serves as a channel to and eases knowledge spillovers between pairs of countries. In other words, the effect or importance of highly skilled migrants as medium of knowledge diffusion between pairs of countries is much stronger when these countries do not share any common history or culture. In the last column we see the results of the model when the two interaction terms are added simultaneously.

<u>Table 3:</u> Baseline estimations for the period 1990 – 2010

	PPML (1)	PPML (2)	PPML (4)	PPML (3)	PPML (5)
Ln(migrant inventors + 1)	0.101*** (0.00999)	0.0994*** (0.00992)	0.102*** (0.0100)	0.107*** (0.0103)	0.107*** (0.0103)
Contiguity	0.0435* (0.0222)	0.0356 (0.0229)	0.0332 (0.0228)	0.0517** (0.0233)	0.0474** (0.0235)
Colony	0.0152 (0.0217)	0.0199 (0.0215)	0.150*** (0.0427)	0.0235 (0.0214)	0.0898* (0.0492)
Common official language	0.0817*** (0.0206)	0.0777*** (0.0210)	0.0869*** (0.0216)	0.212*** (0.0337)	0.192*** (0.0363)
Ln(distance 1)	-0.0514*** (0.0122)	-0.272** (0.119)	-0.236** (0.119)	-0.156 (0.121)	-0.159 (0.120)
[Ln(distance)]^2		0.0139* (0.00728)	0.0117 (0.00733)	0.00680 (0.00740)	0.00700 (0.00738)
Colony*ln(migrants + 1)			-0.0271*** (0.00891)		-0.0140 (0.0107)
Common language *ln(migrants + 1)				-0.0290*** (0.00669)	-0.0236*** (0.00820)
Technological similarity	1.451*** (0.0739)	1.452*** (0.0739)	1.446*** (0.0740)	1.466*** (0.0737)	1.460*** (0.0740)
Ln(# of inventors in country i + 1)	0.516*** (0.0308)	0.517*** (0.0308)	0.515*** (0.0308)	0.516*** (0.0309)	0.515*** (0.0309)
Ln(# of inventors in country j + 1)	0.350*** (0.0325)	0.351*** (0.0325)	0.349*** (0.0327)	0.350*** (0.0325)	0.349*** (0.0326)
Constant	-8.659*** (0.535)	-7.820*** (0.709)	-7.989*** (0.714)	-8.384*** (0.716)	-8.365*** (0.715)
N	382,304	382,304	382,304	382,304	382,304
Pseudo R2	0.970	0.970	0.970	0.970	0.970
Country I FE	Yes	Yes	Yes	Yes	Yes
Country j FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Robustness checks: Are the biggest players driving the results?

We replicate the PPML regressions for the baseline model with the square of distance and the model with the interaction of migration and distance variables, but this time omitting China and India as sending/citing countries and the U.S. as the receiving/cited country alternatively. The results are displayed in Table 4. These results are very similar to those from the baseline model, especially in the sign of coefficients. The first two columns (1) and (2) display results of the regression for all country pairs except those with the U.S. as the receiving/cited country. In columns (3) (4) and (5) (6) we dropped all pairs with India and China as sending/citing countries respectively. In all cases, the coefficient for our variable of interest remains positive and significant in all model specifications although it slightly drops for the two cases where we omit the U.S. – 0.071 and 0.072 – and slightly increases for all cases where we omit India and China – from 0.108 to 0.112. All this suggests although the U.S. top position as a highly skilled receiving country and a knowledge source economy might considerably impact on the magnitude of our results, this position might not be sufficient enough to explain the positive sign of the migration coefficient. While India and China position as highly skilled top sending countries do not affect much our coefficients of interest, if not to slightly lower them.

<u>Table 4:</u> Estimations without some of the biggest players for the period 1990 – 2010

	PPML (1)	PPML (2)	PPML (3)	PPML (4)	PPML (5)	PPML (6)
Ln(migrant inventors + 1)	0.0705***	0.0724***	0.108***	0.112***	0.104***	0.112***
	(0.00983)	(0.0103)	(0.00998)	(0.0104)	(0.0101)	(0.0106)
Contiguity	0.0446*	0.0446*	0.0185	0.0228	0.0319	0.0438*
	(0.0243)	(0.0246)	(0.0228)	(0.0234)	(0.0229)	(0.0234)
Colony	0.0465*	0.137**	0.00890	0.130***	0.0193	0.0939*
	(0.0255)	(0.0580)	(0.0218)	(0.0500)	(0.0217)	(0.0495)
Common official language	0.0712***	0.0861**	0.0936***	0.152***	0.0739***	0.192***
	(0.0223)	(0.0385)	(0.0209)	(0.0372)	(0.0210)	(0.0365)
Ln(distance + 1)	-0.344***	-0.329**	-0.359***	-0.279**	-0.276**	-0.158
	(0.131)	(0.130)	(0.119)	(0.120)	(0.119)	(0.120)
$[\text{Ln(distance + 1)}]^2$	0.0174**	0.0166**	0.0196***	0.0147**	0.0142*	0.00701
	(0.00813)	(0.00808)	(0.00729)	(0.00740)	(0.00731)	(0.00739)
Colony*ln(migrants + 1)		-0.0256		-0.025**		-0.0149
		(0.0156)		(0.0111)		(0.0107)
Common language *ln(migrants + 1)		-0.00302		-0.0109		-0.025***
		(0.0104)		(0.00858)		(0.00829)
Technological similarity	1.699***	1.698***	1.396***	1.395***	1.467***	1.474***
	(0.0735)	(0.0734)	(0.0748)	(0.0748)	(0.0750)	(0.0748)
Ln(# of inventors in country i + 1)	0.507***	0.508***	0.488***	0.485***	0.485***	0.483***
	(0.0300)	(0.0302)	(0.0313)	(0.0314)	(0.0342)	(0.0343)
Ln(# of inventors in country j + 1)	0.541***	0.541***	0.344***	0.342***	0.347***	0.345***
	(0.0327)	(0.0329)	(0.0327)	(0.0329)	(0.0329)	(0.0329)
Constant	-8.194***	-8.286***	-7.537***	-7.92***	-7.795***	-8.364***
	(0.711)	(0.712)	(0.709)	(0.716)	(0.711)	(0.715)
N	376,682	376,682	379,451	379,451	379,451	379,451
Pseudo R2	0.973	0.973	0.970	0.971	0.970	0.971
Country I FE	Yes	Yes	Yes	Yes	Yes	Yes
Country j FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Without the U.S. as cited/receiving country	Yes	Yes	No	No	No	No
Without India as citing/sending country	No	No	Yes	Yes	No	No
Without China as citing/sending country	No	No	No	No	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Are low income-high income Africa-high income and country pairs different?

We now turn to an analysis focusing on how immigration to high income economies – which are the largest highly skilled receiving economies and largest knowledge source economies – from all income groups impact on knowledge diffusion to these sending income groups. More precisely we are interested to see what poor countries get – or lose – from sending their highly skilled to rich countries as it has been shown in the empirical literature that small and poor countries in general were the ones experiencing intensive brain drain and suffering the most from it (Docquier et al., 2007; Docquier and Rapoport, 2011). Our goal is therefore to test for this hypothesis for our sample case. We report the results for the regressions for the case of "low income[9]-high income" country pairs – columns (1) and (2) –, "Africa-high income country pairs – columns (5) and (6) – and "low, middle, high-high income" country pairs – columns (3) and (4). We take the model specifications from the middle columns (3) and (4) as a benchmark for comparison. The results show that for all pairs the relationship between highly skilled migrants and innovation remains positive and significant. What is striking though is the coefficients from the first two columns which are six times higher – 0.602 and 0.646 – than what we get from our benchmark models – see first row columns (3) and (4). This means a 10% increase in the stock of highly skilled from poor economies living in rich economies leads to a 6 percentage point increase in knowledge diffusion from these high income economies to the low income ones. However, historical ties seem to negatively impact on knowledge diffusion for this same income group pair. This means low income economies do not benefit from their high income past colonialist economies in terms of knowledge diffusion but rather from high income economies with which they have no historical ties. This result could as well be driven by the fact that these low income economies get the most of their knowledge from the U.S. which is itself a past colony. Additionally, we find the coefficient for the sending country total number of inventors variable to be higher in model specifications (1) and (2) than in all other model specifications – 1.135 and 1.152 respectively – , this suggests the size of highly skilled in low income countries or more generally their inventive capacity are an important asset for them to benefit from the knowledge diffusing back from their highly skilled diaspora.Another interesting result is the negative sign and the significance of the coefficient for the technological similarity variable. This

[9] India and China are not part of this group.

tells us that the kind of knowledge or technology that diffuses back to low income economies from high income ones is pretty different from the kind of technology in which these two groups of countries actually specialize in. These results are different from those obtained in the benchmark model where technological similarity played an important role for knowledge spillover – columns (3) and (4). Similar negative sign of the technological similarity coefficient is obtained from the regressions of "Africa-high income" country pairs in columns (5) and (6), although they are not statistically significant. All this suggests migrant inventors from low income economies and African economies in particular might not only channel back some knowledge home, as they could also serve as a window to access and discovery of new knowledge or technology by their people back home. Another interesting result from these two last columns is the positive and statistically significance of the coefficient for the geographical distance variable. This obviously comes from the fact that all high income countries from which African countries get knowledge are countries from outside the African continent, thus from other regions of the world. But again here, this relationship is far from being linear as confirmed by the negative and significance coefficient of the distance square variable. This means some African countries – more likely North African countries – might actually be getting knowledge externalities from high income countries geographically closer to them.

Table 5: Estimations for "low income-high income" and "Africa-high income" pairs for the period 1990 - 2010

	PPML (1)	PPML (2)	PPML (3)	PPML (4)	PPML (5)	PPML (6)
Ln(migrant inventors + 1)	0.602***	0.646***	0.101***	0.108***	0.075**	0.126***
	(0.211)	(0.245)	(0.0105)	(0.0109)	(0.0349)	(0.0452)
Contiguity	-0.827	-1.050	0.0219	0.0340	2.533*	2.556*
	(3.076)	(3.375)	(0.0229)	(0.0233)	(1.351)	(1.350)
Colony	-0.888*	-1.101*	0.0115	0.0850*	0.203	0.259
	(0.529)	(0.623)	(0.0215)	(0.0515)	(0.248)	(0.289)
Common official language	0.835	0.896	0.0870***	0.205***	0.0208	0.194
	(0.540)	(0.617)	(0.0211)	(0.0378)	(0.188)	(0.221)
Ln(distance + 1)	-0.732	-1.360	-0.371***	-0.254**	6.662**	6.191**
	(7.583)	(8.562)	(0.121)	(0.123)	(2.860)	(2.861)
$[\text{Ln(distance + 1)}]^2$	-0.0199	0.0173	0.0203***	0.0132*	-0.407**	-0.380**
	(0.452)	(0.512)	(0.00746)	(0.00755)	(0.174)	(0.176)
Colony*ln(migrants + 1)		0.412		-0.0147		-0.0602
		(0.583)		(0.0110)		(0.0824)
Common language *ln(migrants + 1)		-0.0933		-0.024**		-0.0727
		(0.314)		(0.00846)		(0.0509)
Technological similarity	-3.169**	-3.224**	1.459***	1.466***	-0.549	-0.556
	(1.527)	(1.534)	(0.0776)	(0.0778)	(0.442)	(0.442)
Ln(# of inventors in country i + 1)	1.135***	1.152***	0.514***	0.512***	0.269**	0.261**
	(0.271)	(0.272)	(0.0307)	(0.0309)	(0.116)	(0.116)
Ln(# of inventors in country j + 1)	0.584	0.579	0.298***	0.296***	0.271***	0.247**
	(0.607)	(0.606)	(0.0372)	(0.0373)	(0.0955)	(0.0971)
Constant	-0.946	1.693	-1.902**	-2.41***	-30.05***	-27.90**
	(33.94)	(37.75)	(0.801)	(0.803)	(11.62)	(11.53)
N	9,616	9,616	123,534	123,534	21,979	21,979
Pseudo R2	0.256	0.255	0.970	0.971	0.983	0.983
Country I FE	Yes	Yes	Yes	Yes	Yes	Yes
Country j FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Low income-High income	Yes	Yes	No	No	No	No
Low, middle, high income-High income	No	No	Yes	Yes	No	No
African countries-High income	No	No	No	No	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

In general, the results presented above for the “African-high income” and “low income-high income” country pairs sound pretty optimistic to the extent that they show low income countries in general can actually benefit from their highly skilled diaspora with some new knowledge. However, we are aware of the fact that these results might as well been driven by some intra company citations from multinational cooperation (MNC). In other words, we might get high chances to see many citations from some affiliate companies of high income MNC that are located in low income countries and that actually seek to protect an existing invention that has just been adapted to local markets. We intend to text it further in an extension of the paper.

III- CONCLUSION

In this paper, we have used the gravity model to show how bilateral highly skilled migration – as measured by the number of migrant inventors – affects bilateral knowledge diffusion – as measured by patent citations. Our results suggest that migrant inventors residing in a given country are an important channel of knowledge diffusion back to their home countries. This implies there are some knowledge externalities from the network developed around the ties that these migrants keep with their people home. Our estimates remain positive and significant even after having dropped India, China and the U.S. from the regressions, confirming a general brain gain for all countries from highly skilled migrants and not only for the case of Chinese and Indian migrants in the U.S. as shown by case studies analysis. Contrary to what have been advocated in the migration literature for decades, on the detrimental effect of highly skilled migration from low income countries and an alarming brain drain, we found that low income countries as well as African countries technologically benefit from their migrant inventors living in high income countries. And this benefit was in the form of new technology, meaning a field of knowledge different from the field in which these countries specialize in. However, the size of these low income economies or more precisely their total number of highly skilled matters more for knowledge diffusion than for all other sending countries. This implies they should emphasize more on policies leading to an increase of their highly skilled capacity like more investment on education for instance. And for all countries, one general recommendation is that, instead of focusing the debate on brain drain, the attention of home and host countries policy makers should be more oriented towards finding strategies in order to establish and strengthen connections between hs diaspora and those remaining home, through adequate knowledge networks.

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APPENDIX

Table A1 Citations corridors – without citing high income countries (Total flow of citations for the top 20 country pairs for the period 2006-2010)

Citing country	Cited country	Total share of citations	Citation share Cum. (%)	Oecd citing	Oecd cited
China	USA	4000,56	12,87	no	yes
India	USA	3022,53	22,59	no	yes
South Africa	USA	1284,15	26,72	no	yes
China	Japan	1244,64	30,72	no	yes
Brazil	USA	880,34	33,55	no	yes
India	Japan	836,27	36,24	no	yes
China	Germany	800,25	38,81	no	yes
China	Republic of Korea	768,13	41,28	no	yes
Russian Federation	USA	735,64	43,65	no	yes
India	Germany	595,93	45,57	no	yes
Turkey	USA	588,45	47,46	no	yes
Mexico	USA	499,72	49,07	yes	yes
India	UK	467,49	50,57	no	yes
Turkey	Germany	387,786	51,82	no	yes
Malaysia	USA	375,76	53,03	no	yes
China	UK	368,66	54,22	no	yes
Brazil	Germany	336,44	55,3	no	yes
Argentina	USA	325,65	56,34	no	yes
India	France	315,64	57,36	no	yes
India	Israel	309,93	58,36	no	yes

Source: WIPO Statistics Database, October 2013

Table A2. Descriptive statistics

Variables	Observations	Mean	Std. Dev.	Min	Max
Knowledge Flow	524,244	4.92	250.69	0	56,146.39
Migrant inventors	537,731	8.12	547.39	0	110,001
Ln(migrant inv. + 1)	537,731	0.08	0.48	0	11.61
Technological similarity	557,949	0.12	0.22	0	1
Contiguity	478,821	0.02	0.15	0	1
Colony	478,821	0.01	0.11	0	1
Com. official language	478,821	0.12	0.33	0	1
Distance	478,821	7,286.83	4,251.73	8.45	19,650.13
# of inventors in country i	557,949	2.37	2.91	0	11.64
# of inventors in country j	557,949	2.37	2.91	0	11.64