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DIASPORA EXTERNALITIES AND TECHNOLOGY DIFFUSION

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ABSTRACT. In this paper, we analyze how skilled migration contributes to TFP growth in the sending countries when diaspora effects in technology diffusion are introduced. To investigate this issue, we start from a previous paper by Vandenbussche, Aghion and Meghir (2006), who examine the contribution of human capital to economic growth theoretically and empirically. By using a panel dataset covering 19 OECD countries between 1960 and 2000, they show that a marginal increase in the stock of skilled human capital contributes to productivity growth the closer a state is to the technological frontier. In this framework, we also consider the impact of a positive externality in the adoption sector from skilled migration. By using a panel dataset covering 92 countries, including both developed and developing nations, between 1980 and 2000, we reconfirm Vandenbussche *et al.*'s findings. Additionally, we show that migration increases growth in areas far from the frontier.

JEL Classification: F22; O15 ; O30; O40; Z13.
Keywords: Economic growth; Imitation; Innovation; Migration; Brain Drain; Diaspora.

RÉSUMÉ. Cet article analyse dans quelle mesure la migration de main-d'œuvre qualifiée contribue à la hausse de la productivité totale des facteurs dans le pays d'origine, lorsque sont pris en compte les effets de diffusion de la technologie introduits par la diaspora. Ce travail part de l'article de Vandenbussche, Aghion et Meghir (2006) qui étudient la contribution du capital humain à la croissance économique, tant sur le plan théorique qu'au niveau empirique. En s'appuyant sur des données de panel disponibles pour dix-neuf pays de l'OCDE pour la période 1960-2000, ces auteurs montrent qu'un accroissement marginal dans le stock de capital humain engendre une hausse de la productivité d'autant plus significative que le pays est proche de la frontière technologique. Partant de là, nous étudions aussi l'effet d'une externalité positive apportée dans le secteur d'adoption par une migration de personnel qualifié. Le recours à des données de panel pour 92 pays, incluant des nations développées et en développement, pour les années 1980 à 2000, permet de confirmer les résultats obtenus par Vandenbussche *et al.*. De plus, nous montrons que la migration stimule la croissance dans les pays éloignés de la frontière.

Classification *JEL* : F22 ; O15 ; O30 ; O40 ; Z13.
Mots-clefs : Croissance économique ; imitation ; innovation ; migration ; fuite des cerveaux ; diaspora.

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1. Introduction

The pace of international migration from poor to rich countries has accelerated during recent decades. In particular, recent data suggest that emigration of highly skilled people from developing countries continues unabated. What will be the consequences for both receiving and sending countries? This issue seizes the attention of politicians and scholars across the world.

While early literature maintains that skilled migration is unambiguously detrimental for those left behind, a new perspective emerged in the early 1990s that showed the possible emergence of a "brain gain" in the "brain drain". Indeed, positive effects of skilled emigration on home countries have been demonstrated, taking the form of either "incentive" (*ex ante*) effects on investments in education in the sending economy (e.g., Mountford, 1997; Beine *et al.*, 2001, 2007, 2008) or "feedback" (*ex post*) effects, such as remittances, return migration after additional knowledge and skills have been acquired abroad (e.g., Dos Santos and Postel-Vinay, 2003), and the creation of business and scientific networks. The importance of expatriate networks has been highlighted in recent debate, given the successful examples of the Indian and Chinese mature diasporas that have greatly contributed to growth of the information technology sector (see, e.g., Biao, 2006; Saxeenian, 1999, 2001, 2002; Opiniano and Castro, 2006 or Pandey *et al.* , 2006).

Moreover, network or diaspora externalities, by creating trust, providing market information, and reducing transaction costs, can promote trade and investment in the originating country (e.g., for trade Gould, 1994; Head and Rees, 1998; Combes *et al.*, 2005; Rauch and Trindade, 2002; Rauch and Casella, 2003; for FDI, Kugler and Rapoport, 2007, Docquier and Lodigiani, 2009, Javorcik *et al.*, 2006). By strengthening trade and investment linkages, diaspora contributes to technology transfers and adoption. However, this is just one channel.

The diaspora can also create technology and knowledge transfer without being embedded in trade and FDI, but also by relying on informal networks that are interested in helping promote scientific and economic development in their home countries. Meyer and Brown (1999) and Meyer (2001) provide anecdotal evidence on knowledge diffusion and "brain circulation," but very few studies are aimed at addressing this question (for instance, Dos Santos and Postel-Vinay, 2003, stress the importance of returnees, not diaspora, and knowledge transmission). Only in a very recent paper, using data on international patent citations, Kerr (2005) finds that a larger ethnic research community in the U.S. improves technology diffusion to less advanced countries of the same ethnicity. Along the same lines, Agrawal, Kapur, and McHale (2008) use patent citation data for Indian inventors and show that spatial and social proximity increase the probability of knowledge flows between individuals, even if the co-location effect is larger than the diaspora effect.

Our study contributes to this literature and shows that skilled diaspora stimulates productivity growth through technology diffusion and adoption if the source country is far from the frontier. The basic idea is that brain drain and skilled diaspora facilitate adoption of foreign technologies in the home country, therefore contributing to its economic growth. Given that adoption is more productive in countries that are far from the economic frontier, brain drain has a greater positive effect on lagging economies.

To investigate this issue, we start from a paper by Vandenbussche, Aghion and Meghir (2006), who examine the contribution of human capital to economic growth, where technological improvements are a result of a combination between innovation and imitation (adoption). Considering that both imitation and innovation make use of high-skilled and unskilled labor, Vandenbussche, Aghion and Meghir show that skilled labor has a higher growth-enhancing impact closer to the technological frontier, given the assumption that innovation makes a relatively more intensive use of skilled labor. Conversely, the growth-enhancing effect of unskilled human capital decreases with proximity to the frontier. They provide evidence in favor of this prediction by considering a panel dataset covering 19 OECD countries between 1960 and 2000. In this framework, we consider the impact of a positive externality on growth from skilled migration. We confirm that a marginal increase in the stock of skilled human capital contributes to productivity growth more as a state is closer to the technological frontier. Additionally, we show that migration is likely to increase growth in an area far from the frontier. We provide evidence in favor of this prediction by using a panel dataset covering 92 (OECD and non-OECD) countries between 1980 and 2000.

In section 2, we present a theoretical model that shows how skilled migration can have an ambiguous impact on growth. In section 3, we present empirical evidence of our main theoretical predictions. Section 4 concludes.

2. The model

The aim of this theoretical section is to investigate the role that skilled migration has on TFP growth in the sending countries when diaspora effects in technology diffusion are introduced. The model we present is based on a previous paper by Vandenbussche, Aghion and Meghir (2006), who examine the contribution of human capital to economic growth.

2.1. Economic environment

Consider a world with two types of economies, one leader economy (for concreteness, we can think of the United States) and technological follower economies that take the leader's case as given. The economies are populated by workers and entrepreneurs. Skilled workers are allowed to migrate from the less technological economy to the leader economy. Time is discrete, and all agents live only for one period. We assume that, in the source country, the pre-migration worker population is exogenous and constant over time. It is made up of skilled workers $\bar{S}$ and unskilled workers $\bar{U}$, with $\bar{S} + \bar{U} = N$. Unskilled workers are immobile, $M_{u,t} = 0$, whereas the skilled ones are mobile, $M_{s,t} > 0$ ($M_{s,t}$ represents the stock of skilled worker abroad at time t). After migration, at time t, in aggregate an economy is endowed with s skilled and u unskilled units of labor.[2] We hypothesize that each worker in the economy is endowed with only one unit of labor; therefore, s and u represent the fraction of workers who are skilled and unskilled, respectively. After migration, the fraction of skilled workers s in the economy, at time t, is given by:

$$s_t \equiv \frac{\overline{S} - M_{s,t}}{\overline{S} + \overline{U} - M_{s,t}} = \frac{\overline{S} - M_{s,t}}{N - M_{s,t}} \tag{1}$$

The fraction of unskilled workers is given by:

$$u_t \equiv \frac{\overline{U}}{\overline{S} + \overline{U} - M_{s,t}} = \frac{N - \overline{S}}{N - M_{s,t}} \tag{2}$$

Following Vandenbussche, Aghion and Costa Meghir (2006), hereafter VAM, one final good is competitively produced using a continuum of intermediate inputs, indexed from 0 to 1, and a fixed factor (typically land) that without loss of generality is set equal to 1 according to a Cobb-Douglas production function.

$$y_t = l_t^{1-\alpha} \int_0^1 A_{i,t}^{1-\alpha} x_{i,t}^{\alpha}\, di \tag{3}$$

where $\alpha \in (0,1)$, $x_{i,t}$ is the quantity of intermediate input produced in sector i at date t, $A_{i,t}$ is the productivity in sector i (and it measures the quality of the intermediate input i in producing the final good), and l_t is the amount of land used in the final production at time t. We normalize the total supply of land to one (l_t=1 $\forall t$). The final good can be used either for consumption or as an input for the production of intermediate goods. The price of the final good is normalized to 1. In each intermediate sector i, only one firm (a local monopolist) is active in each period, and it produces intermediate input i with productivity $A_{i,t}$ using final good as input with a one-to-one technology.[3] It is easy to show that, for a given level of $A_{i,t}$, the equilibrium demand for good i is $x_{i,t} = \alpha^{\frac{2}{1-\alpha}} A_{i,t}$ and the corresponding equilibrium profit in intermediate sector i is equal to:

$$\pi_{i,t} = \varsigma A_{i,t} \tag{4}$$

where $\varsigma \equiv (\frac{1}{\alpha} - 1)\alpha^{\frac{2}{1-\alpha}}$

2.2. Productivity dynamics

At the initial stage of each period, firm i decides on its demand for skilled and unskilled workers for the purpose of maximizing productivity (and thereby profit). We assume that productivity can be improved by a combination of (i) innovation upon the local technological frontier and (ii) imitation/adoption from the world technological frontier. Both activities use

2. In this model, we consider both the fraction of skilled labor and the number of skilled migrants as given. We disregard any problems of incentive effects on human capital accumulation due to emigration prospects.

3. To better explain, we consider that in each intermediate sector i, only one firm has access to the most productive technology, $A_{i,t}$, so this "leading firm" will have monopoly power. Moreover, each leading firm has access to a technology to transform one unit of the final good into one unit of intermediate good of productivity $A_{i,t}$.

skilled and unskilled labor as inputs. Following VAM (who followed Benhabib and Spiegel (1994) and Acemoglu *et al.* (2006)), technological progress is given by:

$$A_{i,t} = A_{i,t-1} + \varphi(M_{s,t})\, u^{\sigma}_{m,i,t}\, s^{1-\sigma}_{m,i,t}(\overline{A}_{t-1} - A_{t-1}) + \gamma u^{\phi}_{n,i,t}\, s^{1-\phi}_{n,i,t} A_{t-1} \qquad (5)$$

where:

i) $\overline{A}_{t-1}$ represents the world technological frontier at time $t-1$;

ii) A_{t-1} is the country's productivity frontier at the end of period $t-1$;

iii) $u_{m,i,t}$ and $s_{m,i,t}$ are the amounts of unskilled and skilled labor input, respectively, used in imitation in sector i at time t;

iv) $u_{n,i,t}$ and $s_{n,i,t}$ are the amounts of unskilled and skilled labor input, respectively, used in innovation activities in sector i at time t;

v) $\gamma > 0$ measures the relative efficiency of innovation compared to imitation in the productivity growth process.

The elasticity of skilled labor is assumed to be higher in innovation than in imitation, i.e. $\phi < \sigma$. This assumption is made to reflect the notion that skilled workers are relatively more productive in innovation than in adoption of existing techniques. This is plausible because we can imagine that skilled human capital is better suited to innovation because adoption and imitation are relatively straightforward activities (compared to innovation).[4] Furthermore, as we can see from equation (5), following Benhabib and Spiegel and VAM, we make the standard assumption that the world frontier technology diffuses from the most developed economy to the less developed one with a lag of one period. The rate of diffusion is positively related to the size of the gap between the two economies; i.e., the greater the distance from the frontier, the more technology can be adopted from abroad. This is quite intuitive because a larger technological gap means that more innovations can be usefully adopted from abroad. Local innovation, instead, becomes more productive the higher one's own technology level, A, becomes.

Extending VAM, we allow for a further effect on adoption from migration; i.e., the capacity to adopt also depends on a positive externality from skilled diaspora $\varphi(M_{s,t})$, with $\varphi'(M_{s,t}) > 0$ and $\varphi''(M_{s,t}) < 0$. The diaspora is represented by the number of skilled workers abroad to account for a size effect. Intuitively, the benefit of the networks is increasing in its network size. The larger the diaspora, the lower the information costs for technology diffusion are, and thus the effect of the externality will be increasing in the numbers of skilled migrants, but less increasing once that a certain number of migrants has been reached.

4. This assumption follows from VAM, but it also refers to Acemoglue, Aghion and Zilibotti (2006) and to the seminal paper of Nelson and Phelps (1966). As Acemoglue *et al.* underlines, "Nelson and Phelps (1966) ranks activities according to the degree they required adaptation to change. They write: 'At the bottom of this scale are functions that are highly routinied… In the other direction on this scale we have, for example, innovative functions which demand keeping of improving technology.' (p. 69). They argue that the importance of human capital increases with the innovative content of the tasks performed, or with the extent to which "it is necessary to follow and to understand new technological developments" (p.69)."

2.3. Optimal firms' behavior

From equation (5), the two kinds of labor inputs are employed in augmenting productivity, $A_{i,t}$. From equation (4), total operating profit depends on the productivity level. Solving the model consists of finding the optimal amount of skilled and unskilled labor that has to be allocated across imitation and innovation to maximize profits given a total labor supply and at a given distance from the technological frontier.

Assuming interior solutions, i.e. when both imitation and innovation are performed in equilibrium, the first-order conditions of this maximization problem imply the following factor intensities in technological improvement:

$$\frac{u_{m,t}}{s_{m,t}} = \frac{\Psi}{h(a_{t-1}, M_{s,t})} \tag{6}$$

$$\frac{u_{n,t}}{s_{n,t}} = \frac{1}{h(a_{t-1}, M_{s,t})} \tag{7}$$

where: $\Psi = \frac{\sigma(1-\phi)}{\phi(1-\sigma)} > 1$ as $\phi < \sigma$

$a_{t-1} \equiv A_{t-1}/\overline{A}_{t-1}$ is an inverse measure of the country's distance from the world technological frontier at $t-1$ and:

$$h(a_{t-1}, M_{s\,t}) = \left(\frac{(1-\sigma)\Psi^{\sigma}(1-a_{t-1})\varphi(M_{s,t})}{(1-\phi)\gamma a_{t-1}} \right)^{\frac{1}{\sigma-\phi}}$$

which is an increasing function in $M_{s,t}$ and a decreasing function in a_{t-1}, i.e. $h'_{M_{s,t}} > 0$ and $h'_{a_{t-1}} < 0$.

Equations (6) and (7) imply a reallocation effect (or Rybczynski effect). When u increases, firms will reallocate unskilled labor in the imitation sector because the productivity of unskilled labor is higher in the imitation sector than in the innovation sector, i.e., $\sigma > \phi$. Therefore, the marginal productivity of skilled labor increases more in imitation than in innovation, attracting skilled labor in the imitation sector. Because there is less skilled labor in innovation, the marginal productivity of unskilled labor decreases in innovation, so even more unskilled labor goes to imitation. In the end, employment of both types of labor input increases in the imitation sector (and decreases in innovation).

In contrast, an increase in s leads to an increase in the number of units of both skilled and unskilled labor used in innovation (activities that employed skilled labor more intensively) and to a corresponding decrease in labor input in imitation. When a increases, $h(a, M_s)$ decreases, and both types of work are reallocated from imitation to innovation. Far from the technological frontier, the catch-up effect for imitation is quite high. Therefore, for firms, it is more convenient to employ more labor input in imitation than innovation. On the other hand, the closer the economy is to the frontier, the more convenient it is to increase employment in innovation.[5]

5. For further details, see Vandenbussche, Aghion and Costa Meghir (2006).

An exogenous increase in skilled migration, M_s, leads to a decrease in the fraction of skilled labor, s, and therefore to a reallocation of resources toward imitation. In other words, recalling equations (1) and (2), an increase in migration leads to a decrease in s and an increase in u as $s + u = 1$ and, therefore, to a reallocation of both labor inputs toward imitation. Moreover, if migration increases, $h(a, M_s)$ also increases, and both types of work will be reallocated from innovation to imitation. Therefore, when both imitation and innovation are performed in equilibrium, given a, the optimal amount of skilled and unskilled labor in imitation will increase the greater the number of skilled migrants abroad.

2.4. Main predictions

Given the equilibrium productivity growth rate at date t :

$$g_{i,t} = \int_0^1 \frac{A_{i,t} - A_{t-1}}{A_{t-1}} di = \frac{A_t - A_{t-1}}{A_{t-1}} = g_t$$

it is possible to obtain the growth rate of the economy given by:

$$g = \gamma\,[\phi h(a, M_s)^{1-\phi}(1-s) + (1-\phi) h(a, M_s)^{-\phi} s] \tag{8}$$

Considering that:

$$\frac{1}{\gamma}\frac{dg}{dM_s} = \frac{\partial g}{\partial h(a, M_s)}\frac{\partial h(a, M_s)}{\partial M_s} + \frac{\partial g}{\partial s}\frac{\partial s}{\partial M_s} \tag{9}$$

then a marginal increase in the stock of skilled migrants has two effects on growth. One effect is through technological transfer thanks to the diaspora abroad. The other effect is through the reduction of the fraction of the skilled labor force. Consider these two effects separately. The first represents the effect of skilled migration through technology transfer:

$$\frac{\partial g}{\partial h(a, M_s)}\frac{\partial h(a, M_s)}{\partial M_s} =$$

$$= \phi\,(1-\phi)\,[h(a, M_s)^{-\phi}(1-s) - h(a, M_s)^{-(1+\phi)} s]\,\frac{\partial h(a, M_s)}{\partial M_s}$$

$$= \frac{\varphi(M_{s,t})'}{\varphi(M_{s,t})}\frac{\phi\,(1-\phi)}{\sigma - \phi}[h(a, M_s)^{1-\phi}(1 - s) - h(a, M_s)^{-\phi} s]$$

Given our assumptions of $\varphi\,(M_{s,t})$ and $\sigma > \phi$, this equation is always positive if $[h(a, M_s)^{1-\phi}(1-s) - h(a, M_s)^{-\phi} s] > 0$, which means if $\frac{s}{u} < h(a, M_s)$[6], therefore, if all the skilled labor is not allocated to innovation.

6. Condition for $s > s_n + s_m$ given $s = s_n + s_m$.

The growth-enhancing effect increases the greater the distance from the technological frontier and decreases as *s* becomes greater.[7]

In other words, an increase in the supply of skilled labor *s* attracts more labor inputs into innovation. This, in turn, implies that innovation will increase at the expense of imitation, and therefore the effect of migration through knowledge transfer in imitation is less effective because the imitation sector becomes less important. We have the same effect when the distance from the frontier decreases. Far below the technological frontier when the catch-up effect of imitation is sufficiently high, it is more convenient to allocate labor inputs in imitation. However, the closer the economy comes to the frontier, the more profitable it is to increase the innovation component of productivity growth. Again, the more important the innovation component becomes, the effect of migration through technology transfer becomes smaller.

Skilled migration has also an effect on growth through the reduction of the skilled labor force. In fact, remembering that

$$s = \frac{\overline{S} - M_s}{\overline{S} + \overline{U} - M_s} \tag{10}$$

then:

$$\frac{ds}{dM_s} = \frac{-\overline{U}}{(\overline{S} + \overline{U} - M_s)^2} \tag{11}$$

which is always negative.

Reduction of the skilled labor force is not always detrimental for the economy. Recall the main results of VAM. What matters for economic growth is the composition effect. At a given distance from the frontier, *u* and *s* have different marginal effects on the growth rate. Far from the frontier, unskilled labor is the prime driver of growth, and, as in VAM, an increase in *s* has an ambiguous effect on the growth rate:

$$\frac{\partial g}{\partial s} = -\phi h(a, M_s)^{1-\phi} + (1-\phi) h(a, M_s)^{-\phi} \tag{12}$$

that will be positive only if $\frac{1-\phi}{\phi} > h(a, M_s)$, i.e., given *h*, if the elasticity of skilled labor in innovation is high enough. In other words, an increase in *s* will be growth-enhancing only if the induced amount of innovation is enough to compensate for the loss in imitation, which, in our case, is driven not only by the distance from the frontier but also by the stock of migrants abroad that facilitate the adoption of new technology.

7.
$$\left(\frac{\partial g}{\partial h(a, M_s)} \frac{\partial h(a, M_s)}{\partial M_s}\right)\frac{\partial}{\partial a} = \frac{\varphi(M_s)'}{\varphi(M_s)}\frac{\phi(1-\phi)}{\sigma-\phi}[(1-s)(1-\phi)h(a, M_s)^{-\phi} + +s\phi h(a, M_s)^{-(\phi+1)}]\frac{\partial h(a, M_s)}{\partial a}$$

that is always negative, as *h* is a decreasing function in *a*. And :

$$\left(\frac{\partial g}{\partial h(a, M_s)} \frac{\partial h(a, M_s)}{\partial M_s}\right)\frac{\partial}{\partial s} = -\frac{\varphi(M_s)'}{\varphi(M_s)}\frac{\phi(1-\phi)}{\sigma-\phi}[h(a, M_s)^{1-\phi} + h(a, M_s)^{-\phi}]$$

that is always negative.

The complementary relationship between *s* and *a* is shown by:

$$\frac{\partial g}{\partial s}\frac{\partial}{\partial a}=[-\phi(1-\phi)\,h(a,M_s)^{-\phi}-\phi\,(1-\phi)\,h(a,M_s)^{-(1+\phi)}]\frac{\partial h(a,M_s)}{\partial a}$$

which is always positive, as *h* is a decreasing function in *a*. The growth-enhancing impact of skilled labor increases with a country's proximity to the frontier.

This complementary relationship arises because the labor reallocation from a marginal increase in the quantity of skilled labor is larger when the productivity of innovation is higher, therefore making its marginal contribution to growth larger.

On the contrary:

$$\frac{\partial g}{\partial s}\frac{\partial}{\partial M_s}=[-\phi(1-\phi)\,h(a,M_s)^{-\phi}-\phi\,(1-\phi)\,h(a,M_s)^{-(1+\phi)}]\frac{\partial h(a,M_s)}{\partial M_s}$$

which is always negative. The marginal contribution to growth of skilled labor is smaller when the stock of skilled migrants from abroad is higher. This is because more technology could be easily adopted, making it more profitable to allocate labor in imitation than in innovation.

We can summarize our main results:

- if skilled labor induces a negative effect on growth, i.e., $\frac{\partial g}{\partial s}<0$, migration will have a positive effect on growth due to both the reduction of *s* and its role in transferring technology from abroad. That is likely the farther the country is from the frontier and the higher the stock of migrants abroad;
- if skilled labor is growth-enhancing, i.e., $\frac{\partial g}{\partial s}>0$, (that it is more likely when country is closer to the frontier), two opposite effects on productivity growth arise: a growth-enhancing effect from the role of migrants in transferring technology from abroad and a growth-decreasing effect induced by the loss of skilled labor (that will be bigger the higher the stock of skilled migrants abroad, i.e. the more negative equation (11)).

A main prediction relative to migration emerges from our analysis:

- Migration should increase growth in areas far from the frontier. The coefficient of the interaction term between proximity and migration should be negative.

In the next section, we will test this implication using a panel dataset on skilled migration and productivity growth.

3. Empirical analysis

The purpose of this section is to empirically investigate the relationship between migration and growth. As discussed in section 2, the main implication that emerges from our theoretical analysis is that skilled migration can induce a negative effect on TFP growth if skilled labor is growth-enhancing, which is more likely when the country is closer to the frontier. In our empirical analysis, we can test these predictions by regressing a country's TFP growth on its proximity to the frontier, on the interaction between proximity and its fraction of skilled human capital and skilled emigration, and on the direct effects of human capital and skilled migration. If the model is correct, we will expect a negative coefficient on the interaction term between proximity and migration. On the other hand, we expect a positive coefficient on the interaction term between proximity to the frontier and the fraction of skilled human capital.

3.1. Data description

We combine different sources to construct our panel data, which covers 92 countries from 1980 to 2000. We follow the same procedure as VAM.

3.1.1. GDP and capital stock data

We use GDP and investment data from the World Development Indicators 2006. This source provides yearly data on total investments from the late of the 1970's (about 100 observations in 1975) and contains information on about 150 countries in the recent years. However, it does not provide a measure of capital stock by country. We construct this variable using a classical inventory method, based on the following formula:

$$K_{i,t} = K_{i,t-1}(1-\delta) + I_{i,t-1} \tag{13}$$

Initial capital stocks, in 1980, are calculated according to the following formula:

$$K_{i,80} = \frac{I_{i,75-82}}{\gamma + \delta + n} \tag{14}$$

where $I_{i,75-82}$ is the average amount of investment through 1975 and 1982, γ represents the average rate of economic growth over 1975-1985, δ represents the average rate of population growth over 1975-1985 and n represents the rate of depreciation, set equal to 3 %. We then apply the capital accumulation function sequentially to compute our measure of capital stocks for 1980-2000.

Following VAM, we construct total factor productivity, defined as the logarithm of the *output per* worker minus the logarithm of the capital *per* worker times the capital share:

$$\log A_{i,t} = y_{i,t} - 0.3 * k_{i,t} \tag{15}$$

where $\log A_{i,t}$ is the logarithm of total factor productivity, $y_{i,t}$ represents the logarithm of *output per* worker, $\log(Y/L)_{i,t}$, and $k_{i,t}$ represents the logarithm of the physical capital stock *per* worker, $\log(K/L)_{i,t}$.

Output per worker is constructed by dividing total GDP (constant U.S. \$ 2000) by the size of the worker population. We take labor shares to be constant across countries and equal to 0.7. We define proximity to the technological frontier as the ratio of a country's TFP level to that of the U.S.

3.1.2. Human capital and migration data

Data on the skilled population aged 25 and older (as a proxy for the skilled labor force) are computed following Docquier and Marfouk (2006). De la Fuente and Domenech's data (2006) are used for OECD countries and Barro and Lee's data (2001) are used for other countries. For countries where Barro and Lee measures are missing, Cohen and Soto's available indicators (2001) are used, or the skill sharing of the neighboring country with the closest rate of enrollment in education is transposed. For migration data, we used U.S. immigration data by educational attainment and by country of birth (source: U.S. Census).

3.1.3. Other data

Additional control variables are added in a separate section. For trade openness (imports plus exports as a percentage of GDP) and FDI (net inflows as a percentage of GDP), data were taken from the World Development Indicators 2006.

3.2. Empirical specification

Following VAM, we consider the following augmented empirical specification where we add the direct and composite effect for migration on TFP growth:

$$\begin{aligned} g_{i,t} = {} & \alpha_0 + \alpha_1 a_{i,t-1} + \alpha_2 h_{i,t-1} + \alpha_3 \log mig_{i,t-1} + \\ & + \alpha_4 a_{i,t-1} * h_{i,t-1} + \alpha_5 a_{i,t-1} * \log mig_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{16}$$

where $g_{i,t} = \log A_{i,t} - \log A_{i,t-1}$, $A_{i,t}$ is TFP in country *i* at period *t*, $a_{i,t-1} \equiv \log A_{i,t-1} - \log \bar{A}_{t-1}$ is the logarithm of the proximity to the total factor productivity frontier in the previous period (this last variable is a negative number), $h_{i,t-1}$ is the fraction of the population with higher education in the previous period (i.e., stock of tertiary educated workers divided by the total stock of population workers), $\log mig_{i,t-1}$ is the logarithm of tertiary educated migrants to the U.S. plus one (to avoid taking the logarithm of zero values), and α_0 reflects country dummy variables that control for unobserved country fixed effects in TFP growth. All regressions are run with time dummy variables to control for common time shocks. In addition to the country fixed effect, we consider $a_{i,t-1}$ and its interaction terms as endogenous. By construction, in fact, proximity to the frontier, $a_{i,t-1}$, is correlated with the lags of the dependent variable. We treat the lagged skilled emigration stock (in logarithms) and the fraction of skilled workers as sequentially exogenous variables.[8] As excluded instruments, we use the logarithm of proximity lagged two periods, $a_{i,t-2}$, the lagged two periods values of the fraction of human capital and of the logarithm of skilled emigrants, and the interacted terms lagged two periods.[9] To test the relevance of the instruments, we consider some tests and statistics from the first stage regression. Finally, we correct for heteroskedasticity, considering robust standard errors in a GMM framework.[10] The estimation method is the GMM method on within-group variation because we take out the country effects, i.e., a LSDV method, which we know can produce downward-biased estimates in small samples (Nickell, 1981). However, in this context, we believe that the within estimator is the most appropriate. As VAM suggest, "[E]ven if it is well known that within groups is biased in panels with a low time dimension, the first difference estimator would lead to much greater biases, because the instruments are not capable of predicting the first difference in the education and distance." Moreover, when T is small and there are highly persistent series, then even the first difference estimator, such as the Arellano-Bond estimator, is downward biased.[11] Second, even if the system GMM is shown to have better small sample performance, according to Islam (2003), the LSDV also shows very good performance in growth converging equations, despite the well-known Nickell bias.[12]

3.3. Estimation results

3.3.1. First stage regression

The estimation results for our first stage regression are represented in TABLE 1. All regressions are run with time and country dummy variables. The excluded instruments are the logarithm of proximity lagged twice (i.e., 10 years before), the lagged two period values both of the fraction of human capital and the logarithm of skilled migrants, and the two interaction terms lagged two periods. The included instruments are the fraction of tertiary educated workers lagged one period and the logarithm of tertiary migrants lagged one period. In the first reduced form for the logarithm of distance from the frontier in the previous period, its lagged values are highly significant. In the second reduced form for the interacted variable that refers to migration, we find that almost all of the excluded instruments are highly significant

8. We consider the logarithm of skilled emigration and the fraction of human capital as sequentially exogenous; i.e., the error term is uncorrelated with current and past values of the independent variables. As the logarithm of skilled emigration (lagged) is a stock measure, we think that it can be treated as exogenous (additionally in the contest of an over-identified model, given the fraction of human capital as exogenous, we consider a "C test" or "difference-in-Sargan" test, which suggests that we should treat it as exogenous.) Moreover, in contrast to VAM, here the fraction of human capital is also exogenous. In the contest of an overidentified model, given the logarithm of skilled migration as exogenous, we consider a "C test" or "difference-in-Sargan" test, which suggests that we can treat human capital as exogenous.

9. The choice of lagging twice is the result of trying to eliminate as much endogeneity as possible, but at the same time not going too far back in time to preserve observations for the empirical analysis, given the small number of data that we have.

10. Serial correlation is ruled out when country dummy variables are included in the regressions.

11. See Islam (2003) for a discussion.

12. He provides Monte Carlo Simulation with data from the PWT.

(except for the logarithm of proximity lagged twice). Finally, for the interaction variable that refers to skilled workers, both its lagged value and the double-lagged fraction of human capital are significant instruments. Moreover, our instruments have joint explanatory power.

Table 1 - First stage regression

	$a_{i,t-1}$	$a_{i,t-1} * lmig_{i,t-1}$	$a_{i,t-1} * h_{i,t-1}$
$h_{i,t-1}$	1.61260**	15.679**	−1.217***
	(0.72530)	(6.528)	(0.132)
lagged $h_{i,t-1}$	−1.95877*	−25.165***	0.884***
	(1.05145)	(8.761)	(0.216)
log $mig_{i,t-1}$	−0.03840	−3.001***	−0.004
	(0.028)	(0.124)	(0.003)
lagged log $mig_{i,t-1}$	−0.01544	1.467***	0.005
	(0.04342)	(0.351)	(0.004)
lagged $a_{i,t-1}$	0.71821***	0.478	−0.022
	(0.26522)	(1.594)	(0.015)
lagged $a_{i,t-1} * h_{i,t-1}$	−0.84538	−12.086**	0.711***
	(0.60780)	(4.846)	(0.119)
lagged $a_{i,t-1} * lmig_{i,t-1}$	−0.018	0.498***	0.003
	(0.026)	(0.185)	(0.002)
Intercept	−1.236	−1.328	−0.072*
	(0.783)	(4.796)	(0.043)
d95	−0.011	−0.020	0.000
	(0.020)	(0.154)	(0.003)
d00	−0.036	−0.204	0.002
	(0.032)	(0.235)	(0.004)
Country dummies	yes	yes	yes
N	276	276	276
Partial R^2 of excl. instr.	0.25	0.3065	0.537
Test of excl.instr.:			
$F_{(5,175)}$	7.18	12.08	17.84
Prob>F	0.000	0.000	0.000

Note: Robust Standard Errors in parentheses. Country dummies are not reported. A test for the joint significance of country dummies yields a P-value of 0.

* ** and *** indicate significance at 10, 5, 1 percent level respectively.

3.3.2. The estimates

Following VAM, we start with pure level regressions, without interaction terms.[13] First, we considered only variables related to human capital. Later, we added variables referring to migration.

Proximity. In all the specifications, the lagged distance from the frontier, the catch-up term, is always negative, as predicted by the theory (i.e., the further away from the frontier, the faster a country will catch-up). In TABLE 2, the effect of the lagged distance on growth, implying TFP convergence not mediated by education, is significant only when the country effects are included. In TABLE 3, when the interaction effect between skilled emigration and proximity to the frontier is included, the catch up term, not mediated either by education or by emigration, turns out to be not significant (models 7 and 8).

Fraction. The effect of the fraction of tertiary educated workers on TFP growth is positive, meaning that human capital is important for innovation. In our estimations, from model 1 to model 7 this effect is not very significant (10 % in models 3 and 7). However, when we include in the model both the interaction effect between proximity and skilled emigration and country fixed effects, the estimated coefficient turns out to be higher and statistically significant at the 5 % level.

Proximity*fraction. The interaction effect between proximity and the proportion of workers with tertiary education is positive (like VAM), meaning that skilled workers are more important for growth in economies closer to the frontier. In the model with migration variables and country dummy variables, its coefficient is positive and statistically significant at 10 %.

Proximity*emigration. The interaction effect between proximity and the logarithm of skilled emigrants is negative, implying that skilled emigration has a decreasing effect on growth when a country approaches the frontier. In other words, skilled migration seems to be more important for countries far from the frontier. This effect is significant with a coefficient equal to −0.055 when we allow for country fixed effects.

Skilled emigration (logs). The direct effect of migration on TFP growth has a positive sign from model 5 to 7, but it turns out to be negative when the interaction effect between migration and proximity is introduced.

13. We follow VAM, even if our analysis is a simplified one. Moreover, our sample also includes non-OECD countries. Therefore, data quality and availability are worse than for only OECD countries. The instruments used for education also are different. They used education expenditure, which is largely not available for non-OECD countries.

Table 2 - TFP growth equation

	(1)	(2)	(3)	(4)
Proximity	−0.012	−0.731***	−0.016	−0.760***
	(0.014)	(0.142)	(0.013)	(0.148)
Fraction	0.149	0.168	0.281*	0.942
	(0.137)	(0.482)	(0.144)	(0.714)
Proximity*fraction			0.215**	0.641
			(0.098)	(0.467)
d95	−0.010	−0.041**	−0.005	−0.042**
	(0.020)	(0.017)	(0.019)	(0.017)
d00	0.032*	−0.032	0.038**	−0.032
	(0.018)	(0.026)	(0.017)	(0.027)
country dummies	no	yes	no	yes
Anderson canon. corr. LR stat. (identif./IV relev. test)	776.290	76.054	899.19	81.414
Chi-sq(.) P-value	0.000	0.000	0.000	0.000
Hansen J stat.	eq. ex.	eq. ex.	0.302	0.939
(overid. test of all instr.)	ident.	ident.		
Chi-sq(.) P-value			0.583	0.333
N	276	276	276	276
R^2	0.03	0.69	0.041	0.69

Note: Robust standard errors in parentheses.

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

3.3.3. Additional controls

Given that migration could positively affect growth in home countries, inducing more trade and FDI, we start from our last and best specification (column 8 in TABLE 3), and we add as additional control variables a measure of openness and one related to FDI inflows in the country. For openness, we introduce the most basic measure of trade intensity: the ratio of exports plus import to GDP. As argued by many studies, we have to pay attention to the problem of reverse causality between trade and openness. Even if it is not the aim of this paper to study the relationship between trade and openness, we try to correct for it by using, as an explanatory variable, the averages of five previous years instead of contemporaneous values. The estimated coefficient is positive, meaning that countries with higher trade shares are likely to grow faster than other countries, but it is not statistically significant. We introduce also a measure of FDI (net inflows) as a percentage of GDP, using the averages of five previous years instead of contemporaneous values, for the same reason explained before. Also in this case the coefficient is positive but not statistically significant. Our coefficient of interest, i.e. proximity*emigration remains negative and statistically significant at 5 %, both when controlling separately for trade and FDI and when using a unique specification (TABLE 4).[14]

Table 3 - TFP growth equation

	(5)	(6)	(7)	(8)
Proximity	−0.028*	−0.738***	−0.019	−0.285
	(0.014)	(0.149)	(0.039)	(0.230)
Fraction	0.238	1.168	0.266*	1.436**
	(0.147)	(0.715)	(0.138)	(0.707)
Skilled emigration (logs)	0.012***	0.034***	0.009	−0.103*
	(0.003)	(0.016)	(0.010)	(0.052)
Proximity*fraction	0.331***	0.819*	0.346***	0.878*
	(0.104)	(0.475)	(0.112)	(0.476)
Proximity*emigration			−0.001	−0.055***
			(0.004)	(0.020)
d95	−0.006	−0.051***	−0.001	−0.037**
	(0.019)	(0.017)	(0.019)	(0.018)
d00	0.035**	−0.051**	0.038**	−0.031
	(0.017)	(0.025)	(0.017)	(0.026)
country dummies	no	yes	no	yes
Anderson canon. corr. LR stat. (identif./IV relev. test)	896.973	75.936	779.38	76.847
Chi-sq(.) P-value	0.000	0.000	0.000	0.000
Hansen J stat.	0.245	0.559	2.512	0.961
(overid. test of all instr.)				
Chi-sq(.) P-value	0.6205	0.4547	0.2847	0.6185
N	276	276	276	276
R^2	0.083	0.69	0.08	0.69

Note: Robust standard errors in parentheses.

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

14. In this case, given the number of missing values for openness and FDI, the panel is no more balanced.

Table 4 - TFP growth equation

	(1)	(2)	(3)
Proximity	−0.2852627	−0.3133213	−0.3176288
	(0.2381547)	(0.2336213)	(0.2402138)
Fraction	1.431283*	1.681911**	1.688829**
	(0.7361076)	(0.7606934)	(0.777624)
Skilled emigration (logs)	−0.1083366*	−0.0889749	−0.0940308
	(0.0563969)	(0.0576631)	(0.060961)
Proximity*fraction	0.8260568*	0.9924034**	0.973501*
	(0.4929105)	(0.5012964)	(0.5260284)
Proximity*emigration	−0.0565259**	−0.0502884**	−0.051669**
	(0.0214454)	(0.0214098)	(0.0223994)
OPENNESS	0.0001645		0.0002839
	(0.0006639)		(0.0006505)
FDI		0.0018675	0.0009718
		(0.0054674)	(0.0049742)
d95	−0.0406841**	−0.042224**	−0.0441509**
	(0.0180771)	(0.0186923)	(0.0185228)
d00	−0.0352871	−0.0379668	−0.0406314
	(0.0266679)	(0.0283058)	(0.0287613)
R^2	0.6895341	0.6925655	0.6913992
N	270	262	259
country dummies	yes	yes	yes
Anderson canon. corr. LR stat. (identif./IV relev. test)	78.166	70.765	74.639
Chi-sq(.) P-value	0.000	0.000	0.000
Hansen J stat. (overid. test of all instr.)	1.287	1.496	1.563
Chi-sq(.) P-value	0.5253	0.4734	0.4577
N	270	262	259
R^2	0.69	0.69	0.69

Note: Robust standard errors in parentheses.

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

4. Conclusion

Skilled emigrants can have an important role in the transfer of knowledge and technology from the most developed to the less developed world through informal networks. Therefore, even if the loss of human capital slows the growth process, the source economy can still benefit from the stimulation of growth through imitation and knowledge diffusion. To investigate the impact of skilled migration on growth from network externalities, we consider previous work by Vandenbussche, Aghion and Meghir (2006), who examine the contribution of human capital to economic growth. Considering that both imitation and innovation use both high-skilled and unskilled labor, Vandenbussche, Aghion and Meghir find that skilled labor has a higher growth-enhancing impact closer to the technological frontier and, conversely, that the growth-enhancing effect of unskilled human capital decreases with proximity to the frontier, assuming that innovation more intensely uses skilled labor. Extending this model and allowing for a positive effect of migration on adoption, we show that a marginal increase in the stock of skilled human capital increasingly contributes to productivity growth as a state moves closer to the technological frontier, and *vice versa*. On the contrary, skilled migration is likely to increase growth in areas far from the frontier. We also provide evidence in favor of this prediction by using a panel data set consisting of 92 countries, both developed and developing, between 1980 and 2000. The results are robust to the inclusion of trade and FDI as explanatory variables.

E. L.[15]

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Appendix 1

Countries in the sample

Albania, Algeria, Antigua and Barbuda, Argentina, Australia, Austria, Bangladesh, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cameroon, Canada, Chile, China, China Hong Kong SAR, Colombia, Comoros, Congo, Republic of the Costa Rica, Côte d'Ivoire, Denmark, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Finland, Gabon, Gambia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, India, Indonesia, Iran, Ireland, Italy, Jordan, Kenya, Korea, Lesotho, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Nicaragua, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Rwanda, Saint Kitts and Nevis, Saint Vincent and the Grenadines, Senegal, Singapore, South Africa, Spain, Sri Lanka, Swaziland, Sweden, Syria, Thailand, Togo, Trinidad and Tobago, Tunisia, Uruguay, Venezuela, Zambia, Zimbabwe

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