

# A Panel Data Analysis of the Brain Gain\*

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## Abstract

In this paper, we revisit the impact of skilled emigration on human capital accumulation using new panel data covering 147 countries on the period 1975-2000. We derive testable predictions from a stylized theoretical model and test them in dynamic regression models. Our empirical analysis predicts conditional convergence of human capital indicators. Our findings also reveal that skilled migration prospects foster human capital accumulation in low-income countries. In these countries, a net brain gain can be obtained if the skilled emigration rate is not too large (i.e. does not exceed 20 to 30 percent depending on other country characteristics). On the contrary, we find no evidence of a significant incentive mechanism in middle-income and, unsurprisingly, in high-income countries.

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# 1 Introduction

An undeniably stylized fact of the last 50 years is that, with a few exceptions, the poorest countries of the world did not catch up with industrialized nations in any meaningful way. Although a considerable amount of research has been devoted to the understanding of growth and development, economists have not yet found how to make poor countries richer. Nonetheless, in the quest for growth, increasing human capital has usually been considered as an adequate policy. In this context, it has long been argued that the brain drain curbs human capital accumulation in poor countries and exacerbates inequality across nations, i.e. makes rich countries richer at the expense of the poor. The brain drain looks particularly harmful if concentrated in some strategic occupations (e.g. healthcare, teaching, etc.) and if skilled migrants were trained in their country of origin. Under the leadership of Jagdish Bhagwati, a series of models were developed throughout the 1970s to emphasize the negative consequences of the brain drain for those left behind, a literature which has been reformulated in an endogenous growth framework twenty years later<sup>1</sup>. According to this traditional or pessimistic view, reducing the brain drain lowers the development potential of sending nations.

On the contrary, a new wave of research has emerged since the mid-1990s around the idea that skilled migration also generates beneficial effects for sending countries. Those effects can partly or totally compensate the costs of losing talents. More precisely, the brain drain cost is attenuated if origin countries receive larger amounts of remittances, benefit from diaspora externalities or from brain circulation and return migration<sup>2</sup>. One particular strand of this new literature is even more optimistic and reveals that the brain drain ambiguously impacts human capital accumulation in developing countries. Several authors such as Mountford (1997), Stark et al. (1997,

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<sup>1</sup>See among others Bhagwati and Hamada (1974), McCulloch and Yellen (1977), Miyagiwa (1991) or Haque and Kim (1995).

<sup>2</sup>Surveys of the literature can be found in Commander et al. (2004) or Docquier and Rapoport (2009).

1998), Vidal (1998), Beine et al. (2001, 2008), Stark and Wang (2002) argue that ex-ante (i.e. before emigration occurs), migration prospects foster education investments in sending countries. Ex-post, some educated individuals will effectively leave whereas others will stay put. The net/global impact on human capital accumulation becomes ambiguous. If the ex-ante effects is strong enough, the origin country may end up with a higher level of human capital after emigration is netted out than under autarky. The debate is now shifted to the empirical ground.

Evidence of an ex-ante incentive effect has been found at the micro level. In their survey on medical doctors working in the UK, Kangasniemi et al. (2008) report that about 30% of Indian doctors surveyed acknowledge that the prospect of emigration affected their effort to put into studies; Commander et al. (2007) provide clear indications that the software industry's booming has been met with a powerful educational response, partly related to migration prospects. Lucas (2004) argues that the choice of major field of study (medicine, nursing, maritime training) among Filipino students respond to shifts in the international demand for skilled workers. Batista et al. (2007) estimate that migration prospects are responsible for the bulk of human capital formation in Cape Verde. Gibson and McKenzie (2009) show that Tonga's "best and brightest" students contemplated emigration while still in high school, which led them to take additional classes and make changes in their courses choices. Chand and Clemens (2008) compare education choices of ethnic Fijians and Fijians of Indian ancestry in the aftermath of the 1987 military coup and interpret differences as quasi-experimental evidence on the incentive mechanism.

To investigate the extent to which the incentive effect can be generalized to other countries and whether it is strong enough to generate a brain gain (i.e. a positive global effect on human capital), macro-level analyzes are needed. Taking advantage of new cross-country databases on international migration by education attainment<sup>3</sup>,

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<sup>3</sup>See Docquier and Marfouk (2006), Docquier, Lowell an Marfouk (2009), Beine Docquier and Rapoport (2007).

Beine et al. (2008) confirm that migration prospects positively and significantly impact human capital formation in a cross-section of 127 developing countries. Depending on the magnitude of the migration rate and initial human capital stock, the global effect of the brain drain (after migration is netted out) can be positive or negative. Beine et al. (2008) use counterfactual simulations to estimate the short-run net effect of the brain drain for each country and region. The counterfactual experiment consists in reducing the high-skill emigration rate to the level of the low-skill rate. Comparisons between observed and simulated human capital levels show that the brain drain depletes human capital in 53.4 percent of developing countries. These “losers” include many small and medium-sized countries exhibiting skilled emigration rates above 50 percent. On the contrary, the brain drain has a positive but moderate net impact on human capital in countries combining low levels of human capital (below 5%) and low skilled migration rates (below 20%). The group of “winners” includes the main "globalizers" (e.g., China, India, Brazil) and other countries such as Indonesia, Thailand, Mongolia, Venezuela, Argentina, or Egypt. Beine, Docquier and Rapoport (2009) and Docquier, Faye and Pestieau (2008) complement the previous study by testing several functional forms for the incentive mechanism, endogenizing educational policies at origin or using adjusted measures of the brain drain to account for country of training. In most cases, the incentive mechanism is significant and the group of net winners remains the same.

In spite of these encouraging results, the debate remains controversial since, due to data availability, existing empirical studies are all relying on cross-country regressions. Hence, they may suffer from misspecification biases and the impossibility to capture unobserved heterogeneity between countries (see Islam, 1995). In addition, the exact causality between human capital formation and skilled migration is not easy to detect in a cross-country setting, although instrumentation techniques are implemented. A panel data extension seems appropriate to address some of those criticisms.

Therefore, the purpose of this paper is to revisit the macro-level analysis of the

brain gain using a recent and original panel database on international migration and human capital with 6 observations by country (from 1975 to 2000). We first test for the existence and robustness of the incentive hypothesis in  $\beta$ -convergence regression models of human capital accumulation. Second, we examine whether the magnitude of the incentive mechanism varies with the country level of development. Finally, we conduct numerical experiments based on the estimated model to assess the net/global effect of the brain drain on human capital accumulation at origin.

The remainder of this paper is organized as follows. In Section 2, we develop a simple theoretical model characterizing human capital accumulation in developing countries. We model the effect of skilled migration on the decision to educate and on the proportion of educated in the remaining labor force. We demonstrate that the relationship between skilled migration and human capital accumulation ambiguously depends on the level of development of the sending country, a prediction which has been relatively disregarded in the exiting literature. Our theoretical model also demonstrates that it is important to treat the probability of migration as an endogenous variable. Section 3 presents the original panel data on skilled migration and human capital, which can be used to test the model predictions. Section 4 gives the empirical results. Based on a cross-section  $\beta$ -convergence model, our results provide some support in favor of a conditional convergence process of human capital accumulation. Skilled migration prospects have a positive impact on human capital accumulation. However this incentive effect is only perceptible in low-income countries. It is not significant in lower-middle, upper-middle and, unsurprisingly, in high-income countries. Hence, the brain drain ambiguously impacts human capital accumulation in low-income countries; however, it unambiguously decreases the average level of schooling in rich and middle-income countries. Section 5 concludes.

## 2 Theory

This section describes the theoretical mechanisms underlying our empirical model and derive the main testable predictions. Our framework is similar to that used in the recent brain gain literature, except that we explicitly emphasize the way the level of development at origin affects the size of ex-ante incentive mechanism. This link was disregarded in previous contributions but will prove to be important in our empirical analysis.

Each economy is populated by two-period lived heterogeneous individuals. Young individuals work and may invest in human capital. In adulthood, individuals supply all their time on the labor market.

Technology is endogenous. The proportion of educated workers affects the wage rate through a static Lucas-type externality (see Lucas, 1988). Hence, if skilled migration modifies the proportion of educated in the labor force (used as a proxy for the stock of human capital), it affects the welfare of those left behind. We assume a linear production function with labor in efficiency unit as a single input. High-skill and low-skill workers are thus perfect substitutes: each low-skill worker supplies one efficiency unit of labor whereas each highly skilled supplies  $\sigma > 1$  such units. At each period  $t$ , the gross domestic product is given by  $Y_t = w_t L_t$  where  $L_t$  is the total labor force in efficiency unit, and the wage rate per efficiency unit of labor,  $w_t = w(H_t)$ , is an increasing function of the proportion of high-skill adults remaining in the country (with  $w' \equiv \frac{\partial w}{\partial H} > 0$  and  $w'' \equiv \frac{\partial^2 w}{\partial^2 H} \leq 0$  to allow for increasing marginal returns).

Regarding individual preferences, the expected utility depends on the first-period income and the (potentially uncertain/expected) second-period income ( $y_{1,t}$  and  $y_{2,t+1}$ ). There is no saving. Utility is log-linear and there is no time-discount rate. We have

$$E[u_t] = \ln(y_{1,t} - \mu) + E[\ln(y_{2,t+1})] \quad (1)$$

where  $\mu$  is the level of subsistence (such that  $\mu \leq w(0)$ ). Such a parameter is important to model liquidity constraints. For mathematical tractability, we assume no

subsistence level in the second period of life.

Young individuals offer one unit of human capital and earn the low-skill wage  $w_t$ . They have the possibility to invest in education by spending a part of their income. There is a single education program and individuals are heterogeneous in their ability to learn. Agents are characterized by heterogeneous education costs (denoted by  $h$ ), with high-ability individuals incurring a lower cost. The cost of education is expressed as a proportion of the wage rate. For a type- $h$  agent, the cost is denoted by  $\alpha hw_t$  where  $\alpha$  is a parameter capturing the training technology and the fiscal policy (the more education is subsidized, the lower  $\alpha$ ). For simplicity, the variable  $h$  is distributed on  $[0, 1]$  according to a uniform density. In adulthood, individuals offer all their time on the labor market. Low-skill adults receive  $w_t$  whereas the highly skilled receive  $\sigma w_t$ .

With this stylized model, we first characterize the benchmark closed economy solution before investigating how skilled emigration affects welfare and economic activity. In a **no-migration economy** (subscripted  $n$ ), it is straightforward to show that education is optimal when

$$\ln(w_{n,t} - \alpha hw_{n,t} - \mu) + \ln(w_{n,t+1}\sigma) > \ln(w_{n,t} - \mu) + \ln(w_{n,t+1}) \quad (2)$$

Given the distribution of ability, the ex-ante proportion of educated in the young generation  $h_{n,t}$  is equal to the critical level of ability below which education is desirable:

$$h_{n,t} \equiv \frac{w_{n,t} - \mu}{\alpha w_{n,t}} \times \frac{\sigma - 1}{\sigma} \quad (3)$$

It is an increasing function of the skill premium  $\sigma$  and of the local wage rate  $w_{n,t}$ ; it is a decreasing function of  $\alpha$ . Our model thus reflects the fact that in poor countries the enrolment in education is low for two possible reasons: (i) only a few people can afford paying the education costs or (ii) domestic returns to education can be too small.. It is worth noticing that  $h_{n,t}$  is independent on the future wage rate  $w_{t+1}$ .

Without migration, the ex-ante proportion  $h_{n,t}$  is equal to the ex-post proportion of educated adults of the next period:  $H_{n,t+1} = h_{n,t}$ . As  $w_{n,t}$  is a function of  $H_{n,t}$  and given the possibility of technological increasing returns ( $w'' \leq 0$ ), our closed economy model is compatible with the existence of poverty traps (see Azariadis and Stachurski, 2005). Contrary to other models of the recent literature, the existence of a subsistence level and wage externalities can give rise to multiple steady states.

Consistently with micro-level evidence, let us now analyze how migration prospects may affect human capital accumulation. In a **probabilistic-migration economy** (subscripted  $m$ ),<sup>4</sup> we consider that young individuals anticipate a probability of migration  $m_{t+1}$  if they opt for education. We assume that low-skill adults have no access to migration. This simplifying assumption is reasonable since recent databases clearly show that low-skill emigration rates are immeasurably lower than those of the highly skilled. In a probabilistic migration framework where  $h_{m,t}$  denotes the proportion of young opting for education ex-ante, the ex-post proportion of highly skilled among remaining adults becomes:

$$H_{m,t+1} = \frac{(1 - m_{t+1})h_{m,t}}{1 - m_{t+1}h_{m,t}} \quad (4)$$

Ex-post (i.e. for a given investment in education ex-ante), it is obvious that the skilled emigration rate  $m_{t+1}$  reduces  $H_{m,t+1}$ . However, if correctly anticipated, migration prospects also affect the expected return to schooling and induce them to educate more, at least if migration results in higher income abroad. We denote by  $w^*$  the net-of-migration-costs wage rate in the potential host countries and, for simplicity, assume a constant skill premium across countries. In high-income or upper-middle-income countries where the domestic wage rate is equal or higher than  $w^*$ , migration prospects do not affect education choices: the closed economy model applies. In low-income and lower-middle-income countries, individuals engaging in education investments

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<sup>4</sup>Given quota systems and various types of restrictions imposed by immigration authorities to destination (such as the point systems), there is a probability that a migration project will have to be postponed or abandoned at all stages of the process. Following the recent literature, we consider the probabilistic migration framework as reasonable to model human capital accumulation.



may contemplate the prospect of emigration and take decisions under uncertainty. Ex-ante, the expectation of  $m_{t+1}$  increases the proportion of young agents engaging in education,  $h_{m,t}$ , creating the possibility of a net gain for the source country.

If  $w^* > w_{m,t+1}$ , education is optimal when it maximizes expected utility:

$$\begin{aligned} & \ln(w_{m,t} - \alpha h w_{m,t} - \mu) + m_{t+1} \ln(w^* \sigma) + (1 - m_{t+1}) \ln(w_{m,t+1} \sigma) \\ > & \ln(w_{m,t} - \mu) + \ln(w_{m,t+1}). \end{aligned} \quad (5)$$

The ex-ante proportion of educated in the young generation is now given by

$$h_{m,t} \equiv \frac{w_{m,t} - \mu}{\alpha w_{m,t}} \cdot \frac{\sigma \left( \frac{w^*}{w_{m,t+1}} \right)^{m_{t+1}} - 1}{\sigma \left( \frac{w^*}{w_{m,t+1}} \right)^{m_{t+1}}} \quad (6)$$

Clearly, if  $m_{t+1} = 0$ , we obtain the same proportion as in the closed economy ( $h_{m,t} = h_{n,t}$ ). Otherwise, when  $\left( \frac{w^*}{w_{m,t+1}} \right)^{m_{t+1}} > 1$ , the critical level of ability increases with  $m_{t+1}$  and more individuals engage in education. Formally, for  $w^* > w_{m,t+1}$ , the incentive mechanism is characterized by the following derivative

$$\frac{\partial h_{m,t}}{\partial m_{t+1}} = \frac{w_{m,t} - \mu}{\alpha w_{m,t}} \cdot \frac{\ln \left( \frac{w^*}{w_{m,t+1}} \right)}{\sigma \left( \frac{w^*}{w_{m,t+1}} \right)^{m_{t+1}}} > 0 \quad (7)$$

There is a close link between the size of the incentive effect and the level of development at origin. On the one hand, in least developed countries where the average wage rate is close to the subsistence level, liquidity constraints limit the capacity of people to respond to incentives. On the other hand, the lower the level of development, the stronger are the expected migration premium and the impact of migration prospects on the expected return to schooling.

Finally, although skilled individuals form expectations on the future probability to emigrate, this **migration probability must be considered as potentially endogenous** since there are risks of reverse causation from human capital accumulation to migration rates.

A first risk of reverse causality comes from the fact that countries with a long tradition of human capital investments may have invested more in the quality of education. The higher the proportion of educated among adults (including teachers), the higher the quality of education and the probability to overcome immigration and labor market restrictions in developed destinations. Formally, this means that  $m_{t+1}$  can be seen as an increasing function of  $H_{m,t+1}$ .

A second risk of reverse causality is due to immigration policies at destinations. Suppose that the receiving country is willing to accept an absolute number  $Q_t$  of educated immigrants at time  $t$ . The anticipated immigration quota  $Q_{t+1}$  can be expressed as a fraction  $q_{t+1}$  of the adult native population at time  $t + 1$ . Hence, the higher the proportion of educated adults, the lower the probability that each of them will leave the country. Under perfect foresights, individuals anticipate  $m_{t+1} = q_{t+1}/h_{m,t}$  which is clearly a negative function of the ex-ante proportion of educated. Although explicit origin-based-quota systems are rarely observed in OECD countries, this prediction is compatible with the stylized facts and empirical findings presented in Docquier, Lohest and Marfouk (2007): *ceteris paribus*, an increase in natives' average level of schooling reduces the skilled emigration rate.

To sum up, the four main **testable predictions** of our model are the following:

1. In a framework with Lucas-type externalities and a minimal subsistence level of consumption, human capital accumulation is governed by a dynamic process which can give rise to multiple long-run equilibria. A realistic empirical model of human capital accumulation should allow for long-run disparities between countries.
2. Skilled migration prospects positively impact human capital formation in the sending countries where expected local wages are sufficiently low compared to the wage rate observed in industrialized destinations. This can be the case in middle-income and low-income countries.

3. The size of this incentive mechanism ambiguously depends on the country level of development. Interacting skilled migration prospects and country-development dummies is necessary to identify the link.
4. An appropriate empirical model of human capital accumulation with migration-induced incentives should account for the potential endogeneity of the skilled emigration rate. Instrumental techniques are required.

Predictions 1 and 2 were investigated in previous studies (see Beine et al, 2008, 2009). Prediction 3 will be rigorously tested in this paper. Prediction 4 is implicit in many previous works and is theoretically founded here.

### **3 Human capital and migration data**

The model predictions can be tested by regressing an indicator of ex-ante human capital formation of natives (i.e. residents + emigrants) on the skilled emigration rate and other country-specific characteristics. Our dependent variable will be the log-change in the proportion of highly skilled (individuals with post-secondary education) among natives. This requires collecting data on human capital of residents and emigrants. This work was done by Docquier and Marfouk (2006) and Docquier, Lowell and Marfouk (2009) who provide emigration rates by education attainment and human capital indicators for all countries in 1990 and 2000. These estimates were used in cross-country regressions supporting the incentive mechanism. We follow here the work of Defoort (2008) who generalizes the Docquier-Marfouk's methodology and, in order to overcome the limitations of cross-section approaches, builds a similar database covering the period 1975-2000 with data sampled at a five-year frequency.

The skilled migration rate (capturing  $m_t$ ) is defined as the ratio of the stock of high-skill natives living in OECD (i.e. emigrants) countries to all high-skill natives born in the country (i.e. residents + emigrants). To compute this ratio, it is necessary

to quantify the proportion of high-skill within the emigrant and resident populations. The proportion computed for residents is a good proxy for the ex-post stock of human capital  $H_t$  defined in (4); the proportion computed for the sum of residents and emigrants is a good proxy for the ex-ante stock of human capital  $h_t$  defined in (6). The high-skill group corresponds to workers with post-secondary education.

Regarding the residents' proportion of post-secondary educated people, several data sources are available for different samples of countries and periods. Defoort (2008) mostly uses data from Barro and Lee (2001) for developing countries, and from De La Fuente and Domenech (2002) for OECD countries. For countries where Barro and Lee measures are missing, she uses Cohen and Soto (2007) or transpose the proportion observed in the neighboring country with the closest domestic enrolment rates in tertiary education.

Regarding the education structure of emigrants, she collects immigration data by country of birth and education level from various OECD countries. Such details can be found in host countries' census and register. For each origin country, emigration stocks by education level are then computed by aggregating the numbers sent to all destinations. Compared to previous works, Defoort (2008) extends the time series dimension by collecting census data from 1975 to 2000. Unfortunately, census and register data cannot be obtained from all OECD countries on such a long horizon. Consequently, she has to focus on a more limited number of host countries. She collects census data on immigration by country of birth and by education attainment from the 6 major receiving OECD countries, i.e. Canada, Australia, the US, the UK, France and Germany. Compared to Docquier and Marfouk (2006), these 6 countries represent 77 percent of the OECD skilled immigration stock in 2000. However, for particular countries sending a small proportion of their migrants to the 6 major destinations, the estimates can be much less reliable<sup>5</sup>. For each origin country, we

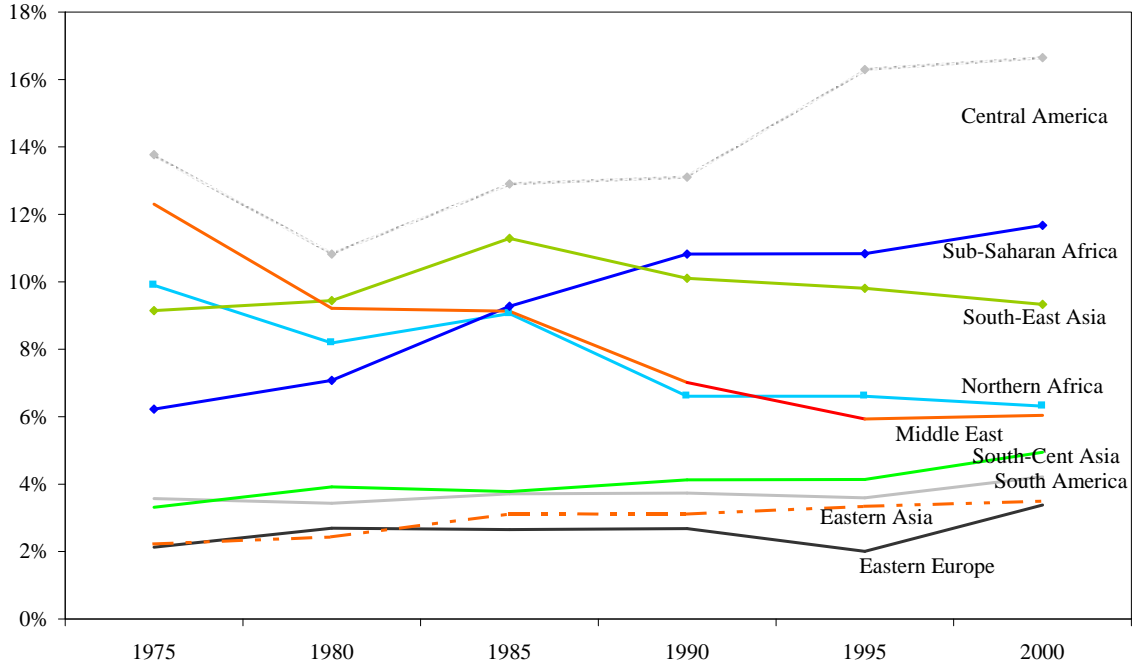
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<sup>5</sup>For example, this is typically the case of Suriname sending most of their migrants to the Netherlands.

construct a reliability rate equal to the 2000 share of the 6 host nations in the skilled emigration stock in the OECD. In our regressions, we either exclude observations characterized by a reliability rate lower than 70 percent or use reliability rates in weighted least squares models.

The data set reveals interesting features. Although globalization and selective immigration policies have undoubtedly increased the number of skilled emigrants to the OECD, the intensity of the brain drain has been extremely stable at the world level or at the level of developing countries as a whole. This can be explained by two important supply changes at origin: (i) the population size in developing countries has increased hugely and (ii) all countries (even the poorest ones) experienced a remarkable rise in education attainment. As shown on Figure 1, some regions experienced an increase in the intensity of the brain drain (Central America, Eastern Europe, South Central Asia and Sub Saharan Africa) while significant decreases were observed in other regions (notably the Middle East and Northern Africa). Regions where the brain drain increased significantly are those where education progresses were small and conversely. This comforts our choice to endogenize the probability of migration in regressions.

Figure 1. Long-run trends in skilled emigration rates



## 4 Panel data analysis

Our empirical investigation relies on the standard framework of convergence models. In particular, we will analyze the dynamics of human capital accumulation in all countries and evaluate the role of migration of skilled workers. To account for the potential incentive effect of migration prospects on human capital formation, we measure human capital as the proportion of high-skill natives, rather than high-skill residents. We disregard the country where education was acquired. This assumption is primarily guided by the data: international migrants are defined on the basis of their country of birth, wherever they were trained. This contrasts with Rosenzweig (2007) who emphasizes the effect of migration prospects on student migration. The outsourcing of education is followed by subsequent returns, which are potentially beneficial for poor countries.

Our model combines the time series dimension and the cross section variation

of the data. Beyond the mere advantage of using much more observations, there are a set of reasons that justify the use of a panel data approach rather than a pure cross-section analysis. First, as well documented by Islam (1995) for income levels, cross section results are subject to important misspecification biases. Failure to control for the factors that influence the human capital accumulation process leads to omitted-variable biases as these factors are likely to be correlated with the initial level of human capital. While the migration rates of skilled workers might be one of these factors, a number of unobservable factors are likely to influence human capital accumulation.<sup>6</sup> Assuming that these factors are constant over time, a panel data analysis can take that into account through the introduction of country specific effects capturing part of the unobserved heterogeneity. The fact that the introduction of fixed effects accounts only for the time-invariant unobservable factors is much less limitative that it seems at first glance. First, a lot of factors such as ethnic diversity or degree of urbanization are relatively stable over time. Second, other factors such as the cost of education or the quality of institutions exhibit a lot of inertia over time. It is thus unclear whether their explicit inclusion (should we have observations for these factors) in the regression model would improve significantly the quality of fit and would reduce the degree of misspecification bias.

Second, extending the analysis to a panel dimension allows to account for the effect of shocks to human capital accumulation common to all countries. This is indeed important for human capital levels since education levels have obviously improved around the world along with increased globalization. Third, as for the role of migration, a pure cross section analysis would implicitly assume a constant rate of emigration of skilled workers for each country. This is obviously a strong assumption.

**The regression model.** Our regression model is based on a conventional convergence equation with migration rates of skilled workers influencing the long-run

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<sup>6</sup>For instance, it is not possible to introduce education expenditures in the panel data analysis due to the high number of missing information in most countries for a lot of years.

levels of human capital among natives. We regress the average annual growth rate of natives' human capital on the skilled migration rate and on the initial level of human capital, first allowing heterogenous responses for developing and rich countries:

$$\frac{1}{5} \ln \left( \frac{h_{i,t+5}}{h_{i,t}} \right) = \alpha_0 + \alpha_i + \delta_t + \gamma_r m_{i,t}^r + \gamma_d m_{i,t}^d + \beta \ln(h_{i,t}) + \epsilon_{i,t} \quad (8)$$

where  $h_{i,t}$  denotes the level of human capital of natives for country  $i$  at time  $t$  (similar notations hold for the migration rates),  $\alpha_0$  is the intercept,  $\alpha_i$  is the country-specific effect capturing the influence on the long-run level of human capital of country-specific factors that are constant over time,  $\delta_t$  captures the impact of common shocks across countries specific to year  $t$ <sup>7</sup>,  $m_{i,t}^r$  and  $m_{i,t}^d$  are the migration rate of skilled workers coming from respectively rich and developing countries (following the World Bank classification),  $\beta$  is a parameter measuring the speed of convergence to the long-run level of human capital.

As a benchmark, this equation is estimated using time and individual effects on our samples.<sup>8</sup> As discussed by Islam (2003), there is no optimal estimation method for convergence equations in a panel data set-up. therefore, we consider alternative techniques that account for specific methodological issues at stake here. It is important to understand that there are two separate econometric problems related to equation (8). The first one is related to the dynamic structure of equation (8) and is well discussed in the recent econometric literature such as Islam (2003). The second one is related to the possible endogeneity of  $m_{i,t}^d$  and  $m_{i,t}^r$ .

Let us first look at the first econometric problem. Equation (8) is dynamic in the sense that  $\ln(h_{i,t})$  enters as an explanatory variable. This leads to potential econometric problems. The use of fixed effects and AR terms leads to inconsistency of estimates, especially when the number of periods is increasing (Nickell, 1981).

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<sup>7</sup>It should be emphasized that the estimates of  $\delta_t$  are all highly significant at the 1% level. They suggest that the growth rate of human capital was on average increasing over time.

<sup>8</sup>Hausman tests (not reported here to save space) strongly reject the inclusion of random effects. Furthermore, from a conceptual point of view, the use of random effects does not make much sense since we include almost all the countries of the world.



Although the ratio of the cross-section dimension to the time dimension suggests that the Nickell bias should be limited in our regressions, it is interesting to look at alternative approaches. This is especially important here given the seemingly high rate of convergence we get with the fixed effects specification. One way to overcome this problem is to use instrumental variable estimation. To this aim, we estimate the model using GMM regressions<sup>9</sup> to assess the robustness of the results. Nevertheless, as reminded by Islam (2003), GMM methods are also subject to significant small sample bias, as demonstrated by several Monte Carlo studies. Therefore, as stated by Islam (2003), it is unclear whether GMM approaches dominate traditional fixed effects estimates. This implies that the use of different estimators are desirable to ensure the robustness of the estimates. To this aim, we estimate equation (8) using standard techniques such as FGLS and GMM and compare the results across the estimation methods.

As abundantly discussed in the theoretical framework, a second problem concerns the endogeneity of migrations rates of skilled workers ( $m_{i,t}^r$  and  $m_{i,t}^d$ ) with respect to the change in the human capital level. Basically, one can expect that migration rates will be lower in countries in which the increase in the level of education has been relatively stronger. Failure to account for some potential reverse causality is likely to result in biased estimates of the parameters in general, and of  $\gamma_r$  and  $\gamma_d$  in particular. To account for that, as an alternative to fixed effect estimates (FGLS), we use instrumental variable estimation to estimate equation (8). More precisely, we use lagged values of  $m_{i,t}^r$  and  $m_{i,t}^d$  as instruments of the migration rates. First stage regressions show that  $m_{i,t-1}^r$  and  $m_{i,t-1}^d$  are strong predictors of current migration rates with  $t$ -statistics above 9 and 10 respectively.<sup>10</sup>

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<sup>9</sup>See Arrelano and Bond (1991), Arellano and Bover (1995), or Blundel and Bond (1992). We use the Arellano and Bover (1995) technique.

<sup>10</sup>Actually, it is important to notice that the use of IV estimation requires the choice of instruments that both vary across countries and across time. This is due to the fact that the impact of time-invariant variables cannot be jointly estimated with fixed individual effects. As a result, variables such as colonial links or island cannot be considered as valid instruments.

Finally, we also address the issue of the reliability of the sample. As discussed above, our panel data set is based on migration data collected in 6 major receiving countries. Our data capture a fraction of the skilled emigration to the OECD. Basically, the lower the proportion of migrants to OECD countries, the lower is the degree of reliability of the migration data. In a first step, we eliminate countries sending less than 70% of their skilled migrants to the 6 main destinations, which leads to a significant loss of information. In a second step, we also use weighted FE estimation in which the regression weights are given by the 2000 proportion of skilled migrants captured in our sample. This allows to include more than 20 additional countries in the regression sample.

Table 1 provides the estimation results of equation (8) using the four different approaches explained above. Column (1) reports the estimates with the fixed effect estimation. Column (2) gives the results using the GMM estimation procedure. Columns (3) and (4) provide the instrumental variable estimation results, for the full model and the parsimonious one. Column (5) gives the parameter estimates with the weighted fixed effect estimation procedure. Finally, Column (6) gives estimates for the random-effects (RE) model.<sup>11</sup>

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<sup>11</sup>Note that the use of RE estimates is provided here only for the sake of information only. As explained by Islam (2003) RE estimates might be invalid since variables defining the country-specific steady states such as the migration rates are correlated with the country specific effect. This is also likely to be case here.

**Table 1: Human capital and migration prospects: panel data results**

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$\beta$	-0.111*** (0.009)	-0.074*** (0.007)	-0.117*** (0.007)	-0.118*** (0.007)	-0.110*** (0.009)	-0.013*** (0.001)
$\gamma_r$	0.071 (0.073)	0.079 (0.068)	0.172 (0.276)	- -	0.070 (0.056)	0.018 (0.019)
$\gamma_d$	0.060** (0.027)	0.108** (0.044)	0.148** (0.068)	0.147* (0.068)	0.058** (0.027)	0.015* (0.009)
Nb. obs.	735	735	588	588	855	735
Nb. countries	147	147	147	147	171	147
R <sup>2</sup>	0.6145	-	0.5552	0.5561	0.6064	0.0943

Note: Estimated equation (8). Fixed effects  $\alpha_i$  and  $\delta_t$  not reported. P-value: \*p<0.1, \*\*p<0.05, \*\*\*p<0.01. In column (1), fixed-effects (FE) estimates are included. In column (2), the GMM procedure is used to account for the endogeneity of the lagged dependent variable. Column (3) reports the instrumental variable estimation with emigration rates instrumented by their lagged values. Column (4) gives the parsimonious version of column (3). Column (5) gives the FE estimates with regression weighted by the proportion of OECD migrants captured in the data set. Column (6) gives estimates for the random-effects (RE) model. Note that the Hausman test strongly rejects the RE specification. The Hansen/Sargan J test (not reported here) supports the validity of the instruments in GMM regressions. Note that since we have no overidentification degree in IV regressions, the Hansen/Sargan J test is not conducted for IV estimates. Nevertheless, the Anderson test supports the relevance of lagged migration rates as instruments in IV regressions.

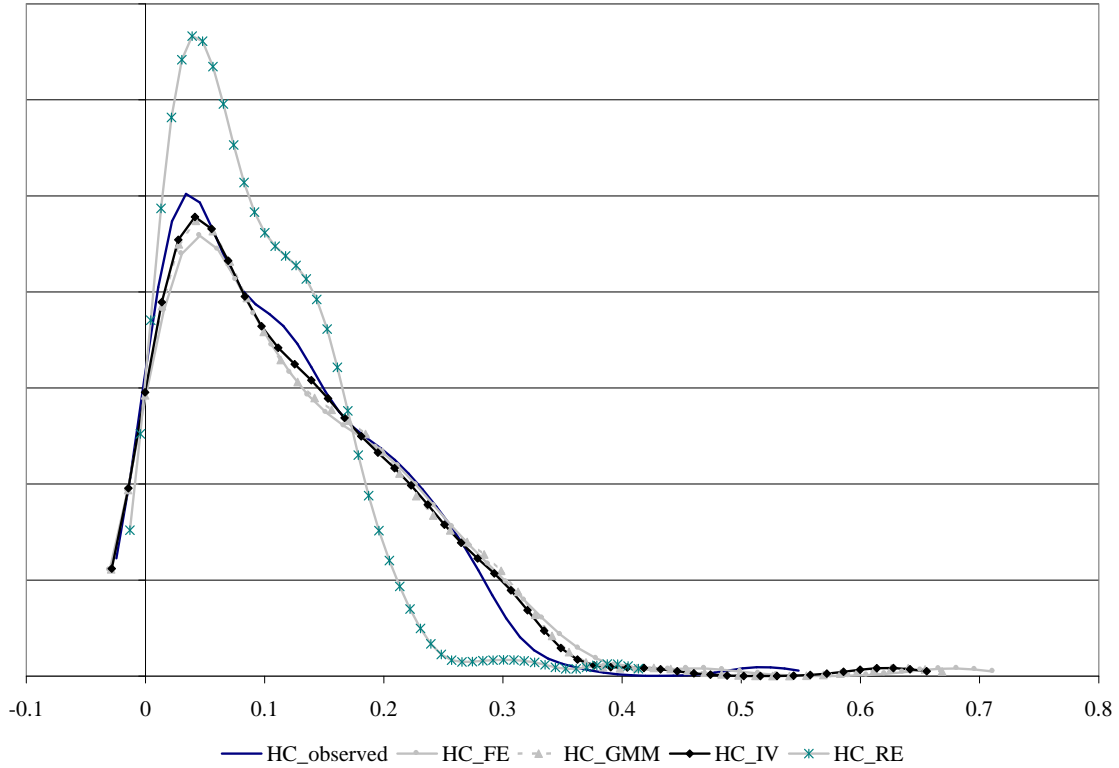
Results of Table 1 suggest that our findings are robust to the use of alternative methods and approaches. These findings can be summarized as follows. First, our results suggest that a catching-up process in terms of education level has taken place over the investigation period. The coefficient relative to the initial value of human capital is always highly significant. Furthermore, the implied speed of convergence (towards the country-specific steady state) is quite homogeneous across regressions. It ranges from 8% to 12% per year. In other terms, it takes about 10 years for each country to converge to its own long-run level of human capital.

Second, the results suggest that the emigration of skilled workers from developing to rich countries tends to exert a positive impact on the long-run level of human capital of these countries. The coefficient of  $m_{i,t}^d$  is always significantly positive in

all regressions. This means that the obtained incentive effect is robust to the use of alternative regression methods. The IV method is nevertheless the only one coping explicitly with the possible endogeneity of migration rates. Therefore, we will use the IV method in subsequent regressions allowing for various schemes of country classification.

Although Table 1 suggests that the results are qualitatively similar across regression techniques, the value of the estimated coefficient of  $m_{i,t}^d$  does vary quite significantly. The size of the incentive effect is found to be quite higher with IV estimates compared to fixed effect or GMM estimates. This suggests that accounting for the endogeneity of migration rates is important for the assessment of the incentive effect in poor countries. The differences between the estimated coefficients of  $m_{i,t}^d$  raises the question of the predictability of the models. To address this issue, we proceed for all estimated models to in-sample simulations of the human capital level. Using estimates of Table 1 and on the basis of the initial value of the human capital level (observed in 1975), we start from the observations for  $h_{i,1975}$  (human capital levels in 1975) and use (8) to forecast the values in 2000. Figure 2 plots the observed human capital distribution in 2000 with the simulated one for the four alternative regression techniques (FE, GMM, IV and RE). The first three regression techniques that rely on fixed effects lead to extremely similar forecasts which are relatively close to the observations. This contrasts with the RE effects model that leads to poor forecast of the HK distribution. This is consistent with the results of the Hausman test which tends to favour the use of fixed rather than random effects.

**Figure 2: In-sample simulation of the human capital distribution in 2000**



HC\_observed = observed distribution of human capital in 2000; HC\_FE = simulated distribution with fixed effects; HC\_GMM = simulation with GMM; HC\_IV = simulation with IV method; ; HC\_RE = simulation with random effects.

Note that the decrease in the significance level of  $\gamma_d$  in columns (3)-(4) is due to a blow-up of the standard error of the parameter rather than a decrease in the value of the coefficient. This is a well-known effect due to the use of two-stage procedures like the instrumental variable method used in this regression. Unsurprisingly, the coefficient of migration rate for rich countries ( $\gamma_r$ ) is never significant at usual confidence levels. These results are consistent with the incentive hypothesis of skilled migration for developing countries explained in a couple of theoretical and empirical papers (Beine et al., 2001 and 2008, Stark et al., 1997, 1998, Stark and Wang, 2002).

**Analysis by country group.** Our theoretical model clearly shows that the size of the incentive effect depends on the level of development. Although the cross-

section results in Beine et al (2008) do not provide any evidence of a different impact for the poorest countries, it is worth allowing for such differentials in a panel setting. In order to allow for different incentive impacts across types of countries, we make explicit distinction between rich, intermediate and poor countries. In this respect, we use some combination of the classifications provided by the World Bank. In the benchmark classification used in the general model (called classification 1), we include in the rich group nations defined as high-income countries by the World Bank. The remaining countries are included in the group of developing countries. The other classifications are generated by combining the 4 initial groups defined by the World Bank into sub-groups, i.e. high-income, upper-middle-income, lower-middle-income and low-income countries. Distinguishing groups instead of interacting the emigration rate with the GDP per capita level avoids strong problems of endogeneity but also implausible assumptions on the conditional effect of migration. Table 2 provides the definition of the classifications.

**Table 2: Definition of country groups**

Classification	Our groups	High-income	Upper-mid	Lower-mid	Low-income
<b>1</b>	Rich	*			
	Poor		*	*	*
<b>2</b>	Rich	*			
	Intermediate		*		
	Poor			*	*
<b>3</b>	Rich	*			
	Intermediate		*	*	
	Poor				*
<b>4</b>	Rich	*	*		
	Intermediate			*	
	Poor				*
<b>5</b>	Rich	*			
	Intermediate+		*		
	Intermediate-			*	
	Poor				*

Correspondence between our groups and the World Bank 2000 classification.

The results provided in Table 3 highly depend on the chosen classification of sending countries. Therefore, it is desirable to check the robustness of the results to alternative classification schemes. A further breakdown of the group of the less developed countries might also be interesting. Such a breakdown could show which type(s) of countries tend to drive the positive impact of migration of skilled workers in terms of education. To this aim, we run the same regression procedure as the one conducted in Table 1 but with alternative classifications. We use IV estimation in order to rule out any bias due to reverse causality. All first-stage regression results (not reported here to save space) show that the lagged values of skilled migration rates are strong instruments of the current rates. Column (1) of Table 3 reports the initial results with the benchmark classification. Columns (2) to (5) report the results obtained with classifications 2, 3, 4 and 5 as defined in Table 2.

**Table 3: Differentiating the effects by country group**

Variables	(1)	(2)	(3)	(4)	(5)
$\beta$	-.117*** (0.008)	-.122*** (0.009)	-.118*** (0.008)	-.118*** (0.008)	-.118*** (0.010)
$\gamma_r$	0.172 (0.321)	0.159 (0.320)	0.147 (0.328)	-0.011 (0.190)	-0.146 (0.329)
$\gamma_d$	0.148** (0.079)	-	-	-	-
$\gamma_i$	-	-.066 (0.217)	-.054 (0.129)	-.049 (0.150)	
$\gamma_{i+}$	-	-	-	-	-.062 (0.223)
$\gamma_{i-}$	-	-	-	-	-.050 (0.150)
$\gamma_p$	-	0.187** (0.081)	0.304*** (0.098)	0.305*** (0.099)	0.304*** (0.099)
Nb. obs.	588	588	588	588	588
Nb. countries	147	147	147	147	147
R <sup>2</sup>	0.5552	0.5592	0.5388	0.5382	0.5390

Note: Estimated equation (8) in which developing countries are split according to Table 2. Fixed effects  $\alpha_i$  and  $\delta_t$  not reported. P-value: \*p<0.1, \*\*p<0.05, \*\*\*p<0.01. All regressions are estimated with instrumental variables. Lagged values of emigration rates are used as instruments of current values

Results reported in Table 3 provide a strikingly similar picture as the one given before. The results support the catching-up hypothesis and deliver similar speeds of convergence. Concerning the influence of migration rates on long-run levels of human capital, the results allow to refine the previous interpretation. It is seen that the positive incentive impact of migration rates of skilled workers is driven by the effects peculiar to the poorest countries. Results obtained with classifications (3) to (5) in which low-income countries (defined as in the World Bank classification) are isolated, show that migration rates of poor countries exert strong, robust and positive effects in terms of human capital accumulation. In column (2), this result still holds when lower-middle-income countries are associated to low-income countries, but the coefficient is much lower and less significant. Once again, this is consistent with the



idea that the incentive effect concerns mainly the poorest countries.

We conclude that a strong incentive effect is at work in low-income countries. By increasing the expected return to education, migration prospects foster the number of natives investing in human capital. In poor countries, such an incentive effect makes the global impact of the brain drain on human capital ambiguous. In the middle-income and rich countries, we find no evidence of a positive incentive effect. The brain drain then unambiguously reduces the stock of human capital in these countries.

## 5 The case for a brain gain

In this section, we turn our attention to low-income countries and investigate whether the incentive mechanism is strong enough to generate a brain gain (i.e. a positive net/global effect on human capital accumulation). We use the estimated model to simulate the net impact of the brain drain on the level human capital in low-income countries. It is worth reminding that our in-sample simulations of the human capital level indicated that our empirical model with fixed effects generates predictions which are extremely close to observations. On Figure 2, the proportion of educated of each country can be accurately predicted once two country characteristics are known: the observed high-skill emigration rate ( $m_i$ ) and the country fixed effect ( $\alpha_i$ ) estimated in (8). This suggests that our numerical exercises can be reasonably trusted.

Our numerical experiment is simple. For each possible value of the country fixed effect (in low-income countries,  $\alpha_i$  ranges from -0.6 to -0.3), our simulation consists in letting the skilled emigration rate ( $m_i$ ) vary between 0 and 100 percent and using the empirical model to compute the ex-post proportion of educated remaining in the country. As the empirical model is dynamic, human capital adjustments take several periods. Hence, to capture the full scale of the brain drain impact on human capital, our numerical experiments are conducted at the steady state.

Clearly, our empirical and theoretical models suggest that the human capital response to changes in skilled emigration is ambiguous. We have shown that ex-ante,

skilled migration prospects foster human capital formation of natives originating from low-income countries. Ex-post, skilled migration reduces the number of remaining educated adults. Our simulations combine these two effects. Simulations are based on the two following equations (9) and (10). Equation (9) is the long-run expression of (8), which characterizes the size of the ex-ante incentive mechanism. If  $\beta$  is negative (a result always obtained in our regressions), the ex-ante level of human capital (i.e. proportion of educated among natives) converges toward a country-specific equilibrium. Imposing  $\ln(h_{i,t+5}) = \ln(h_{i,t})$  in (8), we can easily derive the expression of the steady state proportion of educated among natives:

$$h_{i,ss} = \exp \left[ \frac{\alpha_0 + \alpha_i + \delta_{ss} + \gamma m_i}{-\beta} \right] \quad (9)$$

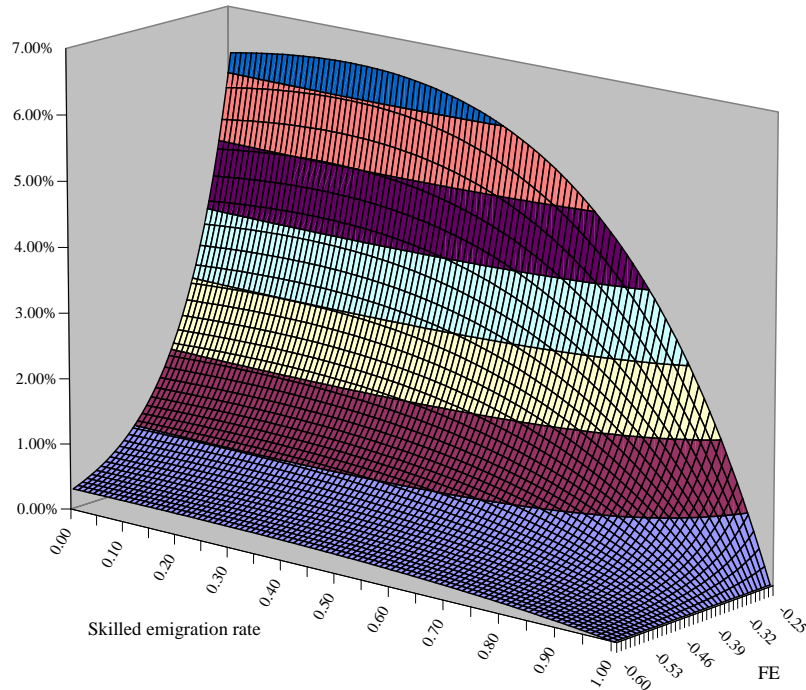
where  $\delta_{ss}$  is the long-run value of the time fixed effect.

Then, following (4), the ex-post effect is governed by:

$$H_{i,ss} = \frac{(1 - m_i)h_{i,ss}}{1 - m_i h_{i,ss}}. \quad (10)$$

Figure 3 gives a three-dimension representation of the simulation results. Country characteristics are represented on the horizontal axes. The skilled emigration rate  $m_i$  varies between 0 and 100 percent; the country fixed effect  $\alpha_i$  varies from -0.6 to -0.3. The long-run proportion of remaining high-skill workers  $H_{i,ss}$  is represented on the vertical axis. The numerical experiment is based on the parameter set  $(\beta, \alpha_0, \alpha_i, \gamma)$  estimated in Column 3 of Table 3; we assume that  $\delta_{ss}$  is the time fixed effect estimated for the year 2000. Under the latter assumption, it is worth noticing that this simple simulation model (9)-(10) generates a steady state distribution of human capital which is extremely close to the distribution observed in 2000 (results are unreported but available upon request).

**Figure 3: Brain drain and human capital accumulation in low-income countries**



FE stands for fixed effect; in poor countries, fixed effects range from -0.6 to -0.3. Simulation are based on classification 3 in Table 2, and column (3) in Table 3.

It clearly appears that the fixed effect has a strong impact on the long-run level of human capital, especially at low skilled emigration rates. This result is not surprising as fixed effects captures many determinants of human capital formation such as education policies, returns to skills, governance, ethnic discrimination, etc. More importantly, the link between human capital and high-skill emigration rate is characterized by an inverted U-shaped relationship. The latter result confirms the theoretical model and predictions from cross-country analyzes (see Beine et al, 2008, 2009). We observe that, a low levels of emigration, the brain drain has a small but positive net impact on human capital accumulation. The "optimal" migration rate (i.e. maximizing residents' human capital) varies between 20 and 30 percent: it is around 20 percent in countries where the fixed effect is low and around 30 percent in

countries where the fixed effect is higher. However, when the emigration rate exceeds its "optimal" value, the human capital loss increases exponentially compared to the closed economy benchmark. Obviously, when the high-skill emigration rate is 100 percent, the proportion of educated among educated adults is equal to 0.

Data reveals that brain drain rates are lower than 20-30 percent in the vast majority of low-income countries, except in a couple of very small states. Consequently, our results suggest that most low-income countries experience a net brain gain of small size. On the contrary, in the absence of significant incentive effect ex-ante, middle-income and high-income countries are likely to suffer from the brain drain.

## 6 Conclusion

The new growth literature has stressed the role of human capital for economic development. Hence, the emigration of skilled workers is usually blamed for depriving developing countries of their most talented workers. This view has been challenged by a new literature putting forward multiple positive feedback effects for sending countries. However, the empirical literature on the consequences of the brain drain remains quite limited. In particular, several contributions demonstrate that skilled migration prospects can increase human capital accumulation ex-ante, possibly turning the brain drain into a brain gain. Due to data limitations, existing empirical studies are based on cross-sectional regressions and suffer from the bias of omitted variables/unobserved heterogeneity, and the difficulty to solve potential endogeneity problems.

Taking advantage of a new panel data set of emigration rates by education level, this paper confirms the existence of a strong incentive mechanism when unobserved heterogeneity and endogeneity issues are seriously addressed. In addition, it comes out that such an incentive effect is only perceptible among low-income countries for which migration premia are high. In middle-income and rich countries, migration prospects have no significant impact on education decisions so that skilled emigration

rates directly reflect their loss of human capital. In poor countries, the net effect of the brain drain on human capital is positive when the brain drain is not too high (say lower than 20 to 30 percent depending on country characteristics). This is the case of many countries, except very small states. When the emigration rate exceeds that threshold, the human capital loss induced by the brain drain increases exponentially.

Many questions and sources of uncertainty remain in the literature on the consequences of the brain drain. Where did migrants acquire education? Can the outsourcing of education explain the positive correlation between emigration rates and human capital investments? Does the outsourcing of education lead to important return flows of educated migrants? Is the incentive effect depending on the destination? Does the brain drain induce severe occupational shortage? In our regressions, many of these factors (outsourcing of education, return migration, etc.) are likely to be assimilated to pure incentive mechanisms. It would be helpful to build new micro surveys explicitly conducted to capture the relationship between emigrants and their country of origin, to collect more data and case-studies on the sectoral impact of the brain drain, to improve the quality of human capital indicators of residents. However, within the limits of a macroeconomic approach, our analysis provides an additional argument in favor of the incentive mechanism. A global research agenda based on multi-level studies (combining country cases, micro and macro studies) would be needed to refine the nature of the effect captured in our regressions.

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