Skilled migration, human capital inequality and convergence

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Abstract

In this paper, we analyze the evolution of human capital inequality across nations, and the impact of the mobility of talented workers on the international distribution of human capital. We derive testable predictions from an stylized theoretical model and then test them using an original panel data set on international migration by educational attainment. We obtain conditional convergence of schooling indicators over the period 1975-2000, with a relatively high speed of convergence. Hence, the current distribution of human capital is not far from the steady state distribution. Our findings also reveal that skilled migration fosters education in intermediate income countries. The brain drain thus increases human capital disparities between poorest and richest countries. However, skilled migration induces long-run beneficial effects in 23 intermediate 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 the industrialized nations in any meaningful way. Polarization in incomes and growth rates suggest that the world growth process departs from the predictions of the one-sector, convex model with complete markets (see Azariadis and Stachurski, 2005). Although a considerable amount of research has been devoted to the understanding of growth and development, economists have not yet discover how making poor countries richer. In this quest for growth, human capital has usually been considered as the right answer.

Although the literature of the 1990’s has fuelled a growing skepticism about the role of schooling\(^1\), recent empirical investigations of the contribution of human capital accumulation to long-run growth are quite optimistic. De la Fuente and Domenech (2002) provided evidence that these counterintuitive results can be attributed to deficiencies in the data. After correcting for substantial measurement errors, they estimate that human capital accounts for about 50 percent of the productivity differentials between OECD countries. Using direct measures of human capital based on literacy scores (which outperform measures based on years of schooling), Coulombe and Tremblay (2005) find a positive and highly significant effect of human capital on both transitory growth transition path and long-run levels of productivity and GDP per capita. In a sample including developed and developing countries, Cohen and Soto (2001) show that using ”good data” gives ”good results”. Improving human capital indicators, they obtain a macroeconomic return to schooling which is compatible with the microeconomic return derived from traditional survey data (i.e. 9 percent per year of schooling).

Benhabib and Spiegel (2002) and Aghion and Howitt (2005) provide another story. In a Schumpeterian model of innovation and technology adoption, they show that the world long-run growth rate is essentially determined in the leading economies. In these leading countries, human capital determines the pace of technological progress. In the rest of the world, human capital favors the country ability to innovate and to implement technological discoveries from the leaders. However, since the long-run growth rate is exclusively determined by the leaders, there is no long-run relationship between the followers’ level of human capital and long-run growth. Anyway, the country-specific level of schooling determines the distance to the technological frontier.

Our analysis builds on the fact that education is an important determinant of inequality across nations. We have two major objectives. First, we want to characterize the evolution of human capital disparities over the last decades. Second, we want to examine whether skilled migration has made the distribution of human capital more unequal. We address the latter issue in the framework of the new literature on the brain drain. This literature puts forward that high-skill migration entails beneficial feedback effects for the source countries. In particular, several authors such as Stark et al. (1998), Vidal 1998), Mountford (1999), Beine et al. (2001, 2003), Stark and Wang (2002) argued that migration prospects may foster education investments in developing countries, thus making it possible for a brain drain to be beneficial to the source country (i.e., the country may end up with a higher level of human capital after emigration is netted out). Their is a great deal of anecdotal evidence that migration prospects indeed impact on people’s decisions to invest in higher education. For example, in their survey on medical doctors working in the UK,

\(^1\)Human capital frequently turn out to be insignificant or to have the ”wrong” size. As a result, authors such as Pritchett (1999) were tempted to reconsider the role of education on productivity growth.
Kangasniemi et al. (2004) report that about 30% of Indian doctors surveyed acknowledge that the prospect of emigration affected their effort to put into studies; Commander et al. (2004) 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 shift in international demand.

Basically, we start from a stylized theoretical that which predicts persisting human capital disparities across countries. We distinguish the predictions on natives’ and residents’ human capital. In intermediate income countries, skilled migration has a positive impact on natives’ education choices (incentive effect) and an ambiguous impact on residents’ level of human capital. In very poor and high-income country, we demonstrate that the incentive effect is likely to small. We also show that our model is compatible with the fact that, despite considerable progress in educational attainment, the poorest countries of the world did not catch up with high-income nations in terms of GDP per capita.

Then, we use data on education attainment over the period 1975-2000 to test these predictions. To account for the potential “incentive effect” of migration prospects on human capital formation in the source countries, human capital is measured as the proportion of skilled among natives, rather than among residents. In a second step, the stock of human capital among residents can be predicted by dropping out emigrants from natives. Based on a cross-section β-convergence model, our results provide some support in favor of a convergence process. Nevertheless, the rate of convergence is quite low, slightly above 1 percent per year, meaning that almost a century is necessary for the human capital levels to converge to the same long run levels. As cross-section results are subject to important mispecification bias (see Islam, 1995), we then use panel models and control for unobserved heterogeneity. Our panel results reveal strong persistent disparities in the long-run level of human capital, and a convergence speed which reaches 14 percent a year suggesting that countries need on average 7 years to reach their long run human capital level.

Does the brain drain make the distribution more unequal? Empirically, cross-section empirical studies by Beine et al. (2001, 2003) confirm that migration prospects have a positive and significant impact on human capital formation between 1990 and 2000. Depending on the magnitude of the migration rate and initial human capital stock, the ex-post response (after migration is netted out) can be positive or negative. Mariani (2005) shows that the GDP growth rate is positively affected by the skilled migration rate in countries where the middle class is sufficiently large. The limit of these studies is that, due to data availability, they rely on cross-country regressions. They fail at capturing the strong heterogeneity between countries; the exact causality between human capital formation and skilled migration is not easy to detect. Here we extend these studies by using original panel data on skilled migration over the period 1975 to 2000. Focusing on six major destination countries (USA, Canada, Australia, Germany, UK and France), we compute skilled emigration stocks and rates from all the world countries (one observation every 5 years). Both cross-section and panel tests show that skilled migration affects the long-run levels of human capital among natives in intermediate income countries. As predicted by our theoretical model, the effect is not significant in poor and rich countries. Relying on counterfactual experiments, it

Our methodology builds on Docquier and Marfouk (2005) who focus on the 30 OECD receiving countries but provide 2 observations (1990 and 2000).
comes out that skilled migration has a positive global impact on human capital in a large number of countries. Among the 33 medium income countries, the brain drain stimulates residents’ human capital in 23 cases.

The structure of the paper is organized as follows. Section 2 describes a theoretical model characterizing human capital disparities across nations and explaining the effect of skilled migration. In section 3, we present the data and empirical results. In Section 4, we use counterfactual experiment to simulate the impact of skilled migration on the average years of schooling among residents. Finally, section 5 concludes.

2 Theory

In this section, we analyze the determinants of human capital in a model with heterogeneous agents. We consider a developing economy populated by two-period lived heterogeneous individuals. The proportion of individual opting for education is endogenous and determines the wage rate through an externality. Labor if the only factor of production and the production function is linear.

At each period $t$, a composite good is produced according linear production function. GDP per capita is given by

$$ y_t = w_t h_t $$

where $h_t$ is the total labor force in efficiency unit, and the wage rate per efficiency unit of labor, $w_t \geq 1$, is non decreasing function of the average level of human capital among adults, $b_t$. This spillover effect summarizes all the intergenerational externalities associated to human capital.

Young individuals offer one unit of human capital and earn a wage $w_t$. However, they have the possibility to spend a part of their income into education. There is a single education program and individuals are heterogenous in their ability to learn. Normalizing the number of efficiency units offered by an unskilled adult to one, an educated adult offers $\eta_t$ such units. Agents are characterized by different education costs, with high-ability individuals incurring a lower cost. The cost of education is expressed as a proportion of the wage rate of teachers (considered as skilled workers). For a type-$c$ agent, the cost is denoted by $\alpha c w_t \eta_t$ where $\alpha$ is the non subsidized proportion of education expenditure, $\eta_t$ is the skill premium at period $t$. The variable $c$ distributed on $[0,1]$ according to a uniform density.

When adult, individuals offer all their time on the labor market with heterogeneous abilities to produce. The economy-wide average level of human capital of the adults, $h_t$, is a function of the proportion of skilled workers in that generation, $\pi_t$. We have $h_t = 1 + \pi_t (\eta_t - 1)$. To model the effect of human capital on productivity, we assume a threshold externality:

$$ w_t = \begin{cases} \xi_t & \text{if } h_t < h^* \\ w(h_t) & \text{if } h_t \geq h^* \end{cases} $$

where $h^* < \eta_t$ is the threshold level of human capital above which the economy exit out the poverty trap; $\xi_t$ is a random iid process of unitary mean, constant variance and cumulative distribution $F(\xi)$. The random component $\xi_t$ has a double effect in our model. It first depicts the stonger volatility of output in poor countries. Second, it captures productivity shocks that can lead to growth miracles despite bad historical conditions.

3Typically, we can consider a lognormal process: $\ln(\xi_{t+1} + 1) \sim N(0, \sigma)$
Above the threshold $h^*$, the wage rate is an increasing and concave function of $h_t$ such that $w(h^*) \geq 1$. The expected future wage amounts to $w_{t+1}^e = E(\xi_{t+1}) = 1$ if $h_{t+1} < h^*$ and $w_{t+1}^e = w(h_{t+1})$ if $h_{t+1} \geq h^*$. Note that the condition $h_t \geq h^*$ can be rewritten as $\pi_t > \pi^* \equiv \frac{h^* - 1}{\eta_t - 1}$ ($\pi^*$ is lower than one).

There is no saving so that the utility depends on the first and expected second-period incomes. For simplicity, utility is log-linear and there is no time-discount rate. We have

$$u_{c,t}^e = \ln(y_{1,t} - \mu) + \ln(y_{2,t+1}^e)$$

where $\mu$ is the level of subsistence when young.

With this stylized model, we first characterize the closed economy equilibrium and then examine the effect of skilled emigration.

### 2.1 Closed economy disparities

Individuals choose their education so as to maximize their expected utility. The expected lifetime income for an uneducated agent is

$$u_{c,t}^e = \ln(w_t - \mu) + \ln(w_{t+1}^e).$$

By contrast, the lifetime income for an educated agent is

$$u_{c,t}^e = \ln(w_t - c\alpha w_t \eta_t - \mu) + \ln(w_{t+1}^e \eta_{t+1}^e).$$

Clearly, education is worthwhile for individuals whose education cost is lower than a critical value. The condition for investing in education in an economy with no migration (henceforth denoted using the subscript $n$) is:

$$c < c_{n,t} \equiv \frac{w_t - \mu}{\alpha_t w_t} \times \frac{\eta_{t+1}^e - 1}{\eta_t \eta_{t+1}^e}$$

which is an increasing function of the local wage rate $w_t$ and of the expected skill premium $\eta_{t+1}^e$, but a decreasing function of the current skill premium $\eta_t$ and of the share of education supported by individual $\alpha_t$ (one minus the subsidy rate). Note that in the steady state, $c_{n,t}$ increases in $\eta$ when $\eta$ is lower than 2. We then assume $\eta_t \in [1, 2]$ in what follows. Moreover, the proportion of educated is independent on the expected wage rate $w_{t+1}^e$.

Without migration, the proportion of educated adults is given by the lagged proportion of the young opting for education, $\pi_t = c_{n,t-1}$ and the average level of human capital is given by

$$h_t = 1 + \frac{w_t - 1}{\alpha_t w_t} \times \frac{\eta_{t-1}^e - 1}{\eta_{t-1} \eta_t^e} \times (\eta_t - 1)$$

Since $w_{t-1}$ is determined by $h_{t-1}$ at least in countries where the lagged level of human capital exceeds $h^*$, the previous equation determines the dynamics of human capital. For constant skill premia and subsidy rates, we have:

$$h_t = \begin{cases} 1 + \frac{\xi_{t-1} - \mu}{\alpha_t w_t} \times \left(\frac{w - 1}{\eta_t}\right)^2 & \text{if } h_{t-1} < h^* \\ 1 + \frac{w(h_{t-1} - 1)}{\alpha_t w(h_{t-1})} \times \left(\frac{\eta_{t-1}^e - 1}{\eta_t^e}\right)^2 & \text{if } h_{t-1} \geq h^* \end{cases}$$

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**Multiple steady states.** This dynamic function is likely to give rise to multiple steady states. Two steady states can be observed: a poverty trap with \( h_t \rightarrow h_{ss} \) (South equilibrium) and a high steady state with \( h_t \rightarrow \bar{h}_{ss} \) (North equilibrium). If \( w(h^*) = 1 \) and if South and North countries exhibit the same education policies and skill premia, then the threshold \( h^* \) determines the basins of attraction of both equilibria (see Case 1 on the left panel). If \( w(h^*) > 1 \) or if South and North countries exhibit different characteristics, there can be a jump in the dynamic function so that the basin of attraction of the South equilibrium (under \( w(h^*) = 1 \), we had \( h' = h^* \))

**Growth miracles.** Given the random shock \( \xi_t \), countries are not deterministically stuck into the poverty trap. Even when \( h_{t-1} < h^* \), a poor country can exit out a poverty trap by experiencing a large productivity shock such that \( 1 + \frac{\bar{w}-\mu}{\alpha\xi_t} \times \left( \frac{\eta-1}{\eta \eta} \right)^2 > h' \). Such a take-off (growth miracle) occurs with a probability

\[
1 - F \left[ \frac{\mu \left( \frac{\eta-1}{\eta \eta} \right)^2}{\left( \frac{\eta-1}{\eta} \right)^2 - \alpha (h' - 1)} \right]
\]

which is increasing in \( \eta \) but decreasing in \( h' \), \( \alpha \) and \( \mu \).

Except for large random shocks, there are self-reinforcing mechanisms which cause poverty to persist. Realistically, poverty traps in human capital formation are likely to be the rule and one should not expect human capital disparities to vanish in the long-run.

**Inequality across nations.** Although long-run disparities are clearly predicted by our model, the magnitude of these disparities is clearly endogenous and can vary over time. Let us denote the leading countries by an upper bar and suppose that their wage rate \( \bar{w}_{ss} \) is much larger than \( \mu \) so that we can write \( \frac{\bar{w}_{ss} - \mu}{\alpha E \xi_t} \approx \frac{1}{\alpha} \) (the minimum of subsistence does not matter in the North). In the long run, i.e. without random shock and under constant policy and skill premia, the North-South ratio in the proportion of educated are given by:

\[
E \left( \frac{\bar{h}_{ss}}{h_{ss}} \right) \equiv \frac{1 + \frac{1}{\bar{\pi}} \times \left( \frac{\eta-1}{\eta \eta} \right)^2}{1 + \frac{1-\mu}{\alpha} \times \left( \frac{\eta-1}{\eta} \right)^2} < 1
\]

Long-run partial convergence in human capital occurs when \( \eta \) and \( \bar{\pi} \) increase or when \( \eta \) and \( \alpha \) decrease. In other words, partial convergence is obtained when the education policy becomes more generous and when the skill premium increases in the South (relatively to the North).
Inequality in GDP per capita depends on the magnitude of the wage externality. Despite considerable progress in educational attainment, the poorest countries of the world may not catch up with high-income nations. The long-run ratio of GDP per capita is given by

$$E \left( \frac{\bar{y}_{ss}}{y_{ss}} \right) = w(\bar{h}_{ss}) E \left( \frac{\bar{h}_{ss}}{h_{ss}} \right) > E \left( \frac{\bar{y}_{ss}}{h_{ss}} \right) \quad (11)$$

Clearly, the ratio of GDP per capita can increase despite a decrease in the ratio of human capital. We have $d \ln E \left( \frac{\bar{y}_{ss}}{y_{ss}} \right) = d \ln w(\bar{h}_{ss}) + d \ln E \left( \frac{\bar{h}_{ss}}{h_{ss}} \right)$. Suppose a rise in both levels of human capital but a stronger rise in the South. Then $d \ln E \left( \frac{\bar{h}_{ss}}{h_{ss}} \right)$ is negative but $d \ln w(\bar{h}_{ss})$ is positive. If the wage externality $d \ln w(\bar{h}_{ss})$ is sufficiently strong in high-income countries, the ratio of GDP per capita increases.

### 2.2 Skilled migration and human capital convergence

It is usually argued that the brain drain (from poor to rich countries) makes rich countries richer at the expense of the poor. Although skilled migration is likely to generate multiple effects on the sending economy, we focus here on the impact of the brain drain on human capital disparities.

In poor countries, the incentives to educate are low. The main reason is that, due to technological and institutional characteristics, the cost of education is high and/or domestic returns to education are small. However, given the recent evolution of immigration policies in rich countries, education is more and more considered as a passport for emigration. As candidates leave nothing to chance, migration prospects may affect the expected return to education and induce them to educate more. Then, given quota systems and various types of requirements and restrictions imposed by immigration authorities (such as the point systems), there is a probability that the migration project will have to be postponed or abandoned at all stages of the immigration process.

Individuals engaging in education investments with the prospect of migration must therefore factor in this uncertainty, creating the possibility of a net gain for the source country.

Let us now examine the impact of skilled migration on poor economies. Indeed, if the economy is at the good equilibrium, nobody wants to emigrate. Suppose the sending country is stuck in the poverty trap but agents have now the possibility to emigrate to a rich economy where $w = \bar{w}$. The sending country is small and cannot affect the wage rate in the North.

Due to immigration restrictions, the receiving country is willing to accept a number $Q_t$ of educated immigrants at time $t$. Every educated adult is a candidate to emigration. The immigration quota $Q_t$ represents a fraction $q_t$ of the adult population at time $t$. For simplicity, we assume a constant skill premium across countries and periods. Young agents now educate by anticipating a probability $p^e_{t+1}$ of emigrating to the rich country. The expected lifetime income for an uneducated agent is

$$w^e_{t+1} = \ln(\xi_t - \mu) + \ln(1). \quad (12)$$

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4The total impact of the brain drain depends (i) on the fiscal impact of emigration (skilled emigrants are likely to be the net contributors to the government budget), (ii) on the likelihood of future return migration, (iii) on the magnitude of remittances, (iv) on the network impact on FDI inflows and trade with receiving countries, (v) on the complementarity/substitutability between skilled and unskilled workers on the labor market, (vi) on the consequences on wage bargaining and income sharing in the home country, etc. The only difference is that the convergence is slower than with rational expectations (under rational expectations, the convergence is instantaneous).
The lifetime income for an educated agent now becomes
\[ u_c^t = \ln(\xi_t - \alpha \xi_q \eta - \mu) + (1 - p_{t+1}^e) \ln(\eta) + p_{t+1}^e \ln(\bar{w}) \].
(13)

Clearly, education is worthwhile for individuals whose education cost is lower than a critical value. The condition for investing in education in an economy with migration (henceforth denoted using the subscript \( q \)) is:
\[ c < c_{q,t}^* = \frac{\xi_t - \mu}{\alpha \xi_t w_{q,t}} \times \frac{\bar{w}^{\pi}_{t+1} \eta - 1}{\bar{w}^{\pi}_{t+1} \eta^2} \]
(14)
which is an increasing function of the local wage rate \( \xi_t \), of the expected skill premium \( \eta \), of the foreign wage \( \bar{w} \) and of the probability of emigration \( p_{t+1}^e \). Clearly, we have \( c_{q,t} = c_{n,t} \), if \( p_{t+1}^e = 0 \).

Suppose individuals form rational expectations on \( p_{t+1}^e \), i.e. they anticipate \( p_{t+1}^e = q_{t+1}^e/c_{q,t}^* \). Endogenizing the probability of emigration, the equilibrium proportion of educated among natives is determined by the following implicit equation
\[ c_{q,t}^* = \frac{\xi_t - \mu}{\alpha \xi_t w_{q,t}} \times \frac{\bar{w}^{\pi}_{t+1} \eta - 1}{\bar{w}^{\pi}_{t+1} \eta^2} \equiv g(\bar{w}, \xi_t, \eta, q_{t+1}^e, c_{q,t}) \]
(15)
Using the implicit function theorem, it can easily be shown that the equilibrium value for \( c_{q,t}^* \) is increasing in the expected quota \( q_{t+1}^e \) (brain gain), in the skill premium \( \eta \) and the expected migration premium \( \bar{w} \).

The proportion of educated among remaining adults is now given by
\[ \pi_t = \frac{c_{q,t-1}^* (1 - p_t)}{1 - p_t c_{q,t-1}^*} = \frac{c_{q,t-1} - q_t}{1 - q_t} = \pi(q_t; c_{q,t-1}) \]
(16)
Clearly, for a given \( c_{q,t-1}^* \), the remaining proportion of educated decreases in \( q_t \) (brain drain). However, \( c_{q,t-1}^* \) increases in \( q_t \). Consequently, the global impact of skilled migration on human capital is ambiguous. In the long-run, we have \( q_t = q_t \), \( c_{q,t} = c_{q,t} \) and \( p_t = \frac{q_{t+1}^e}{c_{q,t}} \). It follows that the steady state proportion of educated residents amounts to \( \pi_{ss} = \frac{c_{q,t} - q_{t+1}^e}{1 - q_{t+1}^e} \). The marginal impact of \( q \) on \( \pi_{ss} \) is given by
\[ \frac{d\pi_{ss}}{dq} = (1 - q)^2 \left[ c_{q,t} + c_{q,t}^* (1 - q) - 1 \right] \]
(17)
where \( c_{q,t}^* \) is the positive derivative of \( c_{q,t} \) with respect to \( q \).

A limited degree of openness is desirable when \( \frac{d\pi_{ss}}{dq} > 0 \) at \( q = 0 \). This requires that \( \ln \bar{w} \) is sufficiently high. Otherwise, migration decreases the average level of human capital among adults.

When \( \frac{d\pi_{ss}}{dq} \) is positive at \( q = 0 \), there is an optimal level of quota maximizing \( \pi_t \). Increasing skilled migration is desirable if \( c_{q,t}^* > \frac{1 - \pi_{ss}}{1 - q} \), i.e. when the brain gain effect dominates the brain drain. This condition is more restrictive as \( q \) increases. Hence, the higher the brain drain, the lower is the probability of obtaining a beneficial effect on human capital.

Case 1 on Figure 2 illustrate the effect of skilled emigration on the long-run level of human capital when the country is not too poor, i.e. when the local wage is far above the subsistence level \( \mu \).

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Note that in the case of myopic expectation (i.e. \( p_{t+1}^e = p_t = q_t/c_{q,t-1} \)), we would have the same long-run equilibrium. The only difference is that the convergence is slower than with rational expectations (under rational expectations, the convergence is instantaneous).

When \( p_t \) tends to one (or \( c_{q,t-1} = q_t \)), the equilibrium proportion of educated among remaining adults tends to zero.
• the right panel illustrates the long-run impact of skilled emigration on the native proportion of educated, $c_q$. The equilibrium proportion of educated is the intersection between $c_q$ and $g(\bar{w}, x_i, \eta, q_{t+1}, c_q)$. We distinguish two possible values for the quota $q$: when the quota increases, the $g(\bar{w}, x_i, \eta, q_{t+1}, c_q)$ function shifts upwards. The equilibrium moves from A to B then fostering the proportion of educated among natives;

• the left panel illustrates the long-run impact on the residents’ proportion of educated. We have $\pi(c_q, q) = c_q - q_1 - q_2$. Note that when $q = 0$, we have $\pi(c_q, q) = c$ (45° line). When $q$ is positive, we have $\pi' > 1$, $\pi(0, q) < 0$ and $\pi(1, q) = 1$.

Let us now use the graphical representation. In a closed economy, we have $g(\bar{w}, \eta, q, c_q) = \xi_t - \mu \alpha + \eta - 1 \eta^2$ and $\pi = c$. Hence, point N describes the closed economy "poverty trap" equilibrium. The good equilibrium is obtained when $\pi > \pi^*$ and $c > c^*$. In that case, no individual wants to emigrate. The point TK describes the frontier above with a takeoff is observed. Suppose the economy starts at the "bad" equilibrium and let us introduce skilled migration prospects. Between N and TK, educated adults choose to emigrate and the equilibrium proportion of educated residents may increase or decrease in the relative quota, $q$. Under positive emigration quotas, the function $g(\bar{w}, \eta, q, c_q)$ is decreasing in $c$ and convex; as $q$ increases, $g(\bar{w}, \eta, q, c_q)$ shifts upwards. On the right panel, the function $\pi(c_q, q)$ is linear but shifts upwards as well. Point A describes the case of a beneficial brain drain. If the quota is rather small, the proportions of educated natives and residents reaches $c_1$ and $\pi_1$. Point B describes the case of a beneficial brain drain. When the quota is large, the proportions of educated natives and residents reaches $c_2$ and $\pi_2$. Hence, $c_q$ is unambiguously increasing in $q$ a while the effect of $q$ on $\pi$ is clearly ambiguous.

On Case 2, we represent an economy where the local wage rate is not far above the minimum of subsistence. On the right panel, the incentive effect of skilled migration is small (from A to N). If the proportion of educated natives is below the quota that can be accepted by the receiving country, all the educated are leaving and the proportion of educated among remaining residents falls to zero. When random shocks are introduced, the probability to exit out the poverty trap depends on the effect of the brain drain on the proportion of educated. When skilled emigration increases $\pi_{ss}$, it also increases the probability to exit out the trap. When skilled migration reduces $\pi_{ss}$, it also reduces the probability of a growth miracle.

3 Empirical tests

Our empirical investigation relies on the standard framework of convergence models. In particular, we will assess to which extent human capital levels have converged across countries and we will evaluate the role of migration flows of skilled workers in the convergence process. 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. In a second step, the residents’ level of schooling will be predicted by dropping out emigrants from natives. Before discussing the various convergence processes and their related econometric specifications, we first expose how the crucial variables at stake here, namely human capital levels and migration flows, are measured.
Case 1. Intermediate country (I is large)  

\[ c_q \theta (n, \theta, \alpha, n_0) \]

Figure 2: Skilled migration and human capital: intermediate country case.

Case 2. Poor country (I is small)  

Figure 3: Skilled migration and human capital: intermediate country case.
3.1 Data issues

Our dependant variable, namely the human capital level, is captured by the resident’s proportion of tertiary educated people in each country. The tertiary education level corresponds to the one obtained after more than 13 years of education. The data are mostly based on the well-known dataset built by Barro and Lee (2000) for developing countries, and De La Fuente and Domenech (2002) for OECD countries. For countries where Barro and Lee measures are missing, we either use Cohen and Soto (2001) indicators, or transpose the skill sharing of the neighboring country with the closest domestic enrollment in tertiary education. This method is used in Docquier and Marfouk (2005). These data are built on a period ranging from 1975 to 2000 and span periods of five years.

An important objective of this paper is to measure the impact of the emigration of skilled workers on the long run level of the human capital level of the countries. For 1990 and 2000, emigration rates by education attainment are provided by Docquier and Marfouk (2005). This data set relies on two steps. First, emigration stocks by education level are computed using census data collected in all OECD countries. Second, these stocks are expressed in percentage of the total labor force born in the sending country (including migrants themselves) with the same education attainment. Basically, Docquier and Marfouk (2005) provide estimates of the brain drain phenomenon for 175 countries in 1990 and 195 countries in 2000. They attempt to improve the previous estimates provided by Carrington and Detragiache (1998) that were used in previous empirical evaluation of the incentive hypothesis (Beine et al., 2003 for instance).

Here we follow the same methodology. However, in order to overcome the limitations of the cross-section approaches, we extend the time series dimension of the data set to cover the period 1975-2000 with data sampled at a five-year frequency. Unfortunately, we have to focus on a more limited number of host countries. We collect census data on immigration by country of birth and by education attainment from the 6 major receiving OECD countries, i.e. Canada, Australia, US, UK, France and Germany. In some cases, reasonable interpolations are required to evaluate the structure of immigration between two censuses. In order to ensure a high degree of reliability of the migration data, we keep in the sample only countries which send at least 70% of their skilled migrants to OECD countries. For instance, this leads to the exclusion of countries which send most of their migrants to Gulf countries. The skill levels considered are fully consistent with the one used for capturing the human capital level.

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 (called classification 1), we include in the rich group the countries considered rich 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. Table 1 provides the definition of the classifications.

3.2 Panel data analysis

In this paper, we combine 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 to overcome
Table 1: Definitions of country classifications results

<table>
<thead>
<tr>
<th>Classif</th>
<th>Our groups</th>
<th>World Bank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rich</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>*</td>
</tr>
<tr>
<td>2</td>
<td>Rich</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Interm</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>*</td>
</tr>
<tr>
<td>3</td>
<td>Rich</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Interm</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>*</td>
</tr>
<tr>
<td>4</td>
<td>Rich</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Interm</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>*</td>
</tr>
<tr>
<td>5</td>
<td>Rich</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Interm Upper</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Interm Lower</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>*</td>
</tr>
</tbody>
</table>

The table gives the correspondence between our 5 classifications and those used by the World Bank.

The limitations of a pure cross section analysis.

First, as well documented by Islam (1995) for income levels, cross section results are subject to important mispecification bias. Failure to control for the factors that influence the human capital accumulation process leads to some omission variable bias 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. Assuming that these factors are constant over time, a panel data analysis can take that into account through the introduction of country specific effects. We will show that the introduction of these effects results in an estimated equation that behaves particularly well in an in-sample forecasting exercise.

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.

We estimate the following equation:

\[ \ln(h_{i,t}) - \ln(h_{i,t-1}) = \alpha + \alpha_i + \delta_t + \gamma_r m_{r,t} + \gamma_p m_{p,t} + \beta \ln(h_{i,t-1}) + \epsilon_{i,t}; t = 1, \ldots, 6. \]  

As for the effect of education expenditures, it is not possible to introduce them in the panel data analysis due to the highly missing information in most countries for a lot of years. The influence documented in the cross section could therefore be well captured by the \( \alpha_i \).
where \( h_{i,t} \) denote the level of human capital level for country \( i \) at time \( t \) (similar notations hold for the migration rates), \( \alpha_i \) is the country specific effect capturing the influence on the long-run level of country specific factors that are constant over time, \( \delta_t \) captures the impact of common shocks across countries specific to year \( t \).\(^8\) \( m^r_{i,t} \) and \( m^d_{i,t} \) are the migration rate of skilled workers coming from respectively rich and developing countries.

As a benchmark, this equation is estimated using fixed time and individual effects on our selected sub-sample.\(^9\) For the sake of robustness, we also consider alternative techniques our approaches that account for specific methodological issues at stake here.

First, equation 18 is dynamic in the sense that \( \ln(h_{i,t-1}) \) enters as an explanatory variable. The use of fixed effects and AR terms leads to inconsistency of estimates, especially when the number of periods is increasing (Nickell, 1981). While 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. Therefore, we estimate the model using Arellano-Bond GMM estimation (Arrelano and Bond, 1991) to assess the robustness of the results.

A second problem concerns the endogeneity of migrations rates of skilled workers (\( m^r_{i,t} \) and \( m^d_{i,t} \)) with respect of the change in the human capital level. Basically, one can expect that migration rates will be higher 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, we use instrumental variable estimation to estimate equation 18. Moe precisely, we use lagged values of \( m^r_{i,t} \) and \( m^d_{i,t} \) as instruments of the migration rates. First stage regressions show that \( m^r_{i,t-1} \) and \( m^d_{i,t-1} \) are strong predictors of current migration rates with \( t - stats \) above 9 and 10 respectively.

Finally, we also address the issue of the reliability of the sample. Basically, choosing a reliability criterion for the migration rates might be somewhat arbitrary. Countries sending less than 70% of their skilled migrants to OECD countries are completely excluded from the sample, which leads to a significant loss of information. On the other hand, the lower the proportion of migrants to OECD countries, the lower is the degree of reliability of the migration data. To solve this problem, we also use weighted FE estimation in which the regression weights are given by the proportion of skilled migrants to OECD countries. This allows to include more than 20 additional countries in the sample.

Table 2 provides the estimation results of equation 18 using the four different approaches explained above. Column (1) reports the estimates with the fixed effect estimation. Column (2) gives the results using the Arellano-Bond GMM estimation procedure. Columns (3) and (4) provide the instrumental variable estimation results, for the full model and the parsimonious one. Finally, column (5) gives the parameters estimates with the weighted fixed effect estimation procedure.

Results of Table 2 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

\(^8\)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.

\(^9\)Hausman tests (not reported here to safe space) strongly reject the inclusion of random effects.
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 is quite homogeneous across regressions. It ranges from 16% to 20%, suggesting that on average, it takes about 25 to 30 years for the countries to reach their long-run levels in terms of education.

Second, the results suggest that migration of skilled workers coming from less developed countries tended to exert a positive impact on the long-run level of human capital of these countries. The coefficient of $m_{dt}$ is always significantly positive in all regressions. Note that the decrease in the significance level of $\gamma_d$ in columns (3) and (4) is due to a bow-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. Interestingly, the coefficient of migration rate for rich countries ($\gamma_r$) is never significant at usual confidence levels. All in all, these results are consistent with the incentive story of skilled migration for less developed countries explained in a couple of theoretical and empirical papers (Beine et al., 2001 and 2003, Stark et al., 2001).

### 3.3 Country classification: robustness check

The results provided in Table 2 highly depend on the chosen classification of sending countries. Therefore, it is desirable to check the robustness of the results to alternative classification schemes. Also, a further breakdown of the group of the less developed countries might be interesting. Such a breakdown could show which countries tend to drive the positive impact of migration of skilled workers in terms of education.
Table 3: Convergence of human capital: panel data results

<table>
<thead>
<tr>
<th>Var</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\text{Constant}$</td>
<td>$-0.0625^a$</td>
<td>$-0.0659^a$</td>
<td>$-0.0641^a$</td>
<td>$-0.0636^a$</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$-0.1175^a$</td>
<td>$-0.1218^a$</td>
<td>$-0.1181^a$</td>
<td>$-1.177^a$</td>
<td>$-0.1183^a$</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>$\gamma_r$</td>
<td>0.1728</td>
<td>0.1593</td>
<td>0.1471</td>
<td>$-0.0115$</td>
<td>$-0.1468$</td>
</tr>
<tr>
<td></td>
<td>(0.321)</td>
<td>(0.320)</td>
<td>(0.328)</td>
<td>(0.190)</td>
<td>(0.329)</td>
</tr>
<tr>
<td>$\gamma_d$</td>
<td>0.1487$^c$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_i$</td>
<td>-</td>
<td>-0.0664</td>
<td>-0.0543</td>
<td>-0.0490</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.217)</td>
<td>(0.129)</td>
<td>(0.150)</td>
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</tr>
<tr>
<td>$\gamma_{iu}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0619</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.223)</td>
<td></td>
</tr>
<tr>
<td>$\gamma_{il}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0497</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.150)</td>
<td></td>
</tr>
<tr>
<td>$\gamma_p$</td>
<td>-</td>
<td>0.1871$^c$</td>
<td>0.3043$^a$</td>
<td>0.3050$^a$</td>
<td>0.3041$^a$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.081)</td>
<td>(0.098)</td>
<td>(0.099)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.1771</td>
<td>0.1878</td>
<td>0.1786</td>
<td>0.1776</td>
<td>0.1791</td>
</tr>
<tr>
<td>$\text{Nobs}$</td>
<td>588</td>
<td>588</td>
<td>588</td>
<td>588</td>
<td>588</td>
</tr>
<tr>
<td>$\text{Ncountries}$</td>
<td>147</td>
<td>147</td>
<td>147</td>
<td>147</td>
<td>147</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.5552</td>
<td>0.5592</td>
<td>0.5388</td>
<td>0.5382</td>
<td>0.5390</td>
</tr>
</tbody>
</table>

Note: Estimated equation: $\ln(h_{i,t}) - \ln(h_{i,t-1}) = \alpha + \alpha_i + \delta_i + \sum_{j=1}^{5} \gamma_j m_{i,t}^{j} + \beta \ln(h_{i,t-1}) + \epsilon_{i,t}, j = \{r, d, u, il, p\}$. $\alpha_i$ and $\delta_i$ not reported here to save space.

$a, b, c$ mean significance of coefficients at respectively 1, 5 et 10% significance levels.

$\lambda$ is the implied rate of annual convergence computed as $\frac{\ln(1+(5\beta))}{5}$. Estimates of $\alpha_i$ and $\delta_i$ not reported to save space.

All regressions estimated with instrumental variables. Lagged values of migration rates used as instruments of current migrations rates. Columns (1), (2), (3), (4) and (5) report results obtained with classification of sending countries 1, 2, 3, 4 and 5 respectively.

To this aim, we run the same regression procedure as the one conducted in Table 2 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 report the initial results with the benchmark classification. Columns (2) to (5) report the results obtained with classifications 2, 3, 4 and 5 which are defined in Table 1.

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 are driven by the effects peculiar to the poorest countries. Results obtained with classification (5) which follows the decomposition of the World Bank show that migration rates of poor countries exert strong and positive effects in terms of human capital accumulation. These results still hold when intermediate lower income countries are included in the same group. Nevertheless, the impact is much less strong, both in terms of value and in terms of statistical significance.
4 Counterfactual experiments

Our empirical analysis reveals that skilled migration fosters natives’ human capital formation in intermediate income countries. In poor and high income countries, migration prospects do no affect education choices. In this section, we use counterfactual experiments to evaluate the effect of skilled migration on the average level of schooling remaining in the origin country (i.e. the average level of schooling among residents). Our experiments consists in setting the skilled emigration rate to the unskilled emigration rate. Indeed, the unskilled rate captures the minimal level of mobility of workers, given the country size, distances with the main receiving countries, country-specific push factors...

Starting from the human capital level observed in 1975, we sequentially use the estimated equation (21) and compute the dynamics of natives’ human capital between 1975 and 2000:

$$\ln h_{i,t}' = \alpha + (1 + \beta) \ln h_{i,t-1}' + \delta m_{i,t-1} I_i + a_i + b_t + \varepsilon_{i,t}$$

where $h_{i,t}'$ is the counterfactual proportion of tertiary skilled among natives, $m_{i,t-5}$ is the lagged skilled emigration rate (observed or counterfactual), $I_i$ is the dummy capturing intermediate income countries ($\alpha, \beta, a_i, b_t$) are estimated coefficients and fixed effects, and $\varepsilon_{i,t}$ is the residual obtained in our regression. By intergrating $\varepsilon_{i,t}$, the simulation with the skilled emigration rate $m_{i,t-1} = m_{i,t-1}^s$ would exactly match observations.

Note that our estimated equation also allow us to simulate the steady state level of human capital for any skilled emigration rate. We have:

$$\ln h_{i,ss}' = \alpha + \delta m_{i,2000} I_i + a_i + b_{2000} + \varepsilon_{i,2000}$$

In 2000 or at the steady state, residents’ human capital is then obtained by dropping out the (observed or counterfactual) proportion $m_{i,2000}$ of emigrants from the native labor force.

Results are presented in Table 5. We distinguish high-income, intermediate-income and low-income countries. In each group, the first two columns compare observed and steady state levels of human capital. It is noteworthy that the steady state level of human capital is usually close to the observed level in 2000. Some countries will experience a modest rise in human capital while other will experience a slight decrease. The relative increase is important in some African countries (Mozambique, Gambia, Burundi, Rwanda, Comoros) or in Solomon islands and Iran. An important relative decrease is expected in Angola, Somalia, Central Africa or Namibia. However, in most cases, we should not expect to observe a strong convergence in human capital for the coming decades.

The last two columns give the results of our counterfactual experiments, i.e. setting the skilled emigration rate to the unskilled rate.

• In low-income and high-income countries, migration does not induce any incentive effect on human capital formation. Hence, slowing skilled migration does not affect natives’ choice and reduces human capital losses. These countries would clearly gain from reducing the human capital flight. The gains are relatively small in the large majority of cases. However, strong improvement would be obtained in countries where skilled migration rates reach international records such as Somalia, Guyana, Haiti, Trinidad and Tobago, Grenada, St...
Lucia, Rwanda, Gambia, Sierra Leone etc. In some of the latter cases, the proportion of tertiary educated would rise by more than 10 points of percentage. In the largest emigration countries such as China, India, Mexico or Pakistan, the effect is very small.

In intermediate-income countries, migration prospects stimulate human capital accumulation. The global effect is then ambiguous. Among the 33 medium income countries, reducing skilled migration would increase the average level of schooling in 10 cases (the detrimental brain drain cases). On the contrary, it would reduce residents’ human capital in 23 cases (the beneficial brain drain cases). As shown in previous studies (Beine et al, 2004), the detrimental cases are small islands in which the skilled emigration rates is particularly high (on average, 45 percent), or countries in which the brain drain is low but the general level of education is relatively high (Bulgaria, Romania, Algeria). In the other countries, the skilled emigration rates is lower (on average, 17 percent). These countries would clearly loose from reducing the brain drain. The loss would be important in Lebanon, El Salvador, Iran, Cuba, Belize, Vanuatu or Tunisia. Note that Turkey and Thailand would also belong the beneficial brain drain group.

Finally, the impact of skilled migration on the international distribution of human capital is illustrated on the gaussian densities in figure Y. Both 2000 and steady state densities are right skewed, globally unimodal with mode around 5 percent. Clearly, reducing skilled emigration would affect two specific segments of the human capital density. First, it would improve the situation of the poorest countries: we observe a downward shift at very low human capital levels. The
### Table: Residents' proportion of tertiary educated in 2000 and in the steady state

<table>
<thead>
<tr>
<th>Country</th>
<th>h(2000)</th>
<th>h(ss)</th>
<th>h'(2000)</th>
<th>h'(ss)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>12.4%</td>
<td>12.5%</td>
<td>12.4%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Belgium</td>
<td>12.5%</td>
<td>12.6%</td>
<td>12.5%</td>
<td>12.6%</td>
</tr>
<tr>
<td>Canada</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Cyprus</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Denmark</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Estonia</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Finland</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>France</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Germany</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Greece</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Iceland</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Ireland</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Israel</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Japan</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>South Korea</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Malta</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Netherlands</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>New Zealand</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Norway</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Portugal</td>
<td>12.5%</td>
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<td>12.5%</td>
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</tr>
<tr>
<td>Spain</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Sweden</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Switzerland</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
<td>12.5%</td>
</tr>
</tbody>
</table>

Note: h(2000) = residents' proportion observed in 2000; h'(2000) = residents' proportion observed in 2000 with counterfactual emigration rates; h(ss) = steady state residents' proportion with observed skilled emigration rates; h'(ss) = steady state residents' proportion with counterfactual emigration rates.

Figure 5: Residents' proportion of tertiary educated in 2000 and in the steady state.
proportion of countries characterized by a proportion of tertiary educated below 7 percent would then decrease. On the other hand, the proportion of countries characterized by a proportion of tertiary educated between 17 and 31 percent would increase. Although the tails of the distribution would be rather unaffected, reducing the brain drain would make the distribution more bimodal. The same conclusion is obtained at the steady state.
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