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BRAIN DRAIN AND HUMAN CAPITAL FORMATION IN DEVELOPING COUNTRIES: WINNERS AND LOSERS*

Michel Beine, Fréderic Docquier and Hillel Rapoport

Using new data on emigration rates by education level, we examine the impact of brain drain migration on human capital formation in developing countries. We find evidence of a positive effect of skilled migration prospects on gross human capital formation in a cross-section of 127 countries. For each country of the sample we then estimate the net effect of the brain drain using counterfactual simulations. Countries combining relatively low levels of human capital and low emigration rates are shown to experience a 'beneficial brain drain', and conversely, there are more losers than winners, and the former tend to lose relatively more than what the latter gain.

The term 'brain drain' designates the international transfer of resources in the form of human capital and mainly applies to the migration of relatively highly educated individuals from developing to developed countries. Recent comparative data reveal that by 2000 there were 20 million highly skilled immigrants (i.e., foreign-born workers with tertiary schooling) living in the OECD member countries, a 63.7% increase in ten years against only a 14.4% increase for unskilled immigrants (Docquier and Marfouk, 2006). The vast majority of these highly skilled immigrants come from developing countries and now represent more than a third of total immigration to the OECD. The causes of this growing brain drain are well known. On the supply-side, the globalisation of the world economy has strengthened the tendency for human capital to agglomerate where it is already abundant and contributed to increase positive self-selection among international migrants. And on the demand side, starting with Australia and Canada in the 1980s, host countries have gradually introduced quality-selective immigration policies and are now engaged in what appears as an international competition to attract global talent (ILO, 2006).

The consequences for source countries, on the other hand, are less obvious. Early contributions (Grubel and Scott, 1966; Bhagwati and Hamada, 1974; McCulloch and Yellen, 1977) identified a range of positive feedback effects (e.g., remittances, return migration with additional skills acquired abroad, creation of scientific and business networks) but concluded that the welfare of those left behind would still fall given that the social return to education exceeds its private return.[1]

In contrast, a series of recent papers (Mountford, 1997; Vidal, 1998; Beine *et al.*, 2001) suggested instead that in a context of probabilistic migration, the brain drain

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[1] The first papers investigating the effects of the brain drain in an endogenous growth framework also emphasised its negative impact. See Miyagiwa (1991), Haque and Kim (1995) or Wong and Yip (1999).

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may ultimately contribute to human capital formation in the sending countries. The essence of the argument is that since the return to education is higher abroad, migration prospects can raise the expected return to human capital and induce more people to invest in education at home.[2] Under certain theoretical conditions explored in these models, this incentive effect (or brain gain) can dominate that of actual emigration, in which case there is a net gain for the source country (i.e., a beneficial brain drain).[3]

In the absence of reliable comparative data on international migration by skill level, the debate on the consequences of the brain drain for developing countries has long remained purely theoretical.[4] This article takes advantage of a recent data set on emigration rates by education levels (Docquier and Marfouk, 2006) to investigate empirically how the positive and negative effects of the brain drain just described balance out. We first estimate the effect of skilled migration prospects on gross (or pre-migration or *ex ante*) human capital levels. We find that doubling the emigration rate of the highly skilled induces a 5% increase in human capital formation among the native population (residents and emigrants together). The coefficient is very stable across specifications and estimation methods. For each country of the sample we then use counterfactual simulations to estimate the net effect of the brain drain (i.e., once skilled emigration is netted out). We find that most countries combining low levels of human capital and low migration rates of skilled workers end up with a positive net effect. In contrast, the brain drain appears to have negative effects in countries where the migration rate of the highly educated is above 20% and/or the proportion of people with higher education is above 5%. There appears to be more losers than winners and, in addition, the former incur *relatively* high losses. However, the gains of the latter dominate in *absolute* terms, resulting in an overall gain for developing countries.

The remainder of this article is organised as follows. Section 1 presents the theoretical framework and derives the main testable implications of the analysis. Section 2 summarises the migration data. The empirical analysis is divided between Section 3, which discusses a number of econometric issues and then presents the cross-sectional results, and Section 4, dedicated to country-specific calculations. Section 5 concludes.

[2] For this incentive effect to operate, education must not only increase one's chances of migration but also allow for accessing to legal, high-skill jobs. In a context where immigration is illegal and migrants can only access unskilled jobs, the prospect of migration can instead reduce education investment. See McKenzie and Rapoport (2006) for Mexico and De Brauw and Giles (2006) for rural–urban migration in China.

[3] Using a slightly different perspective, Stark *et al.* (1997) also elaborated on the possibility of a brain gain associated with a brain drain in a context of imperfect information with return migration. See also Katz and Rapoport (2005) on migration imparting education with an option value, and McCormick and Wahba (2000), who obtain the result that more highly skilled migration may benefit those left behind in a model where migration, remittances and domestic labour-market outcomes are jointly determined and multiple equilibria arise, with the high-migration equilibrium Pareto-dominating the low-migration equilibrium. Commander *et al.* (2004) and Docquier and Rapoport (2008) survey the recent brain drain literature.

[4] An exception is Beine *et al.* (2001), who found a positive and significant effect of migration prospects on human capital formation in a cross-section of 37 developing countries. However, their study suffers from the fact that due to data constraints, they used gross migration rates as a proxy measure for the brain drain.

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1. Theoretical and Empirical Framework

1.1. *Theoretical Background*

Consider a stylised small open developing economy producing goods and human capital. The amount of goods produced is proportional to labour measured in efficiency units: $Y_t = w_t L_t$, where w_t is the equilibrium wage rate in this economy. At birth, individuals are endowed with a given level of human capital normalised to one. Individuals live for two periods and make two decisions: whether to invest in education during their youth, and whether to migrate in adulthood. In particular, increasing human capital requires private spending in education. There is a unique education programme e. For an individual opting for education, the number of efficiency units once adult is given by $h > 1$, while the cost of education, which is decreasing in personal ability, is denoted by c, a variable with cumulative distribution $F(c)$ and density function $f(c)$ defined on R^+.

Once adult, people can emigrate to a high-wage destination with probability p for skilled workers and $\underline{p}$ for unskilled workers. As explained in our introduction, selective immigration policies, together with the tendency for migrants to positively self-select out of the general population, explain why emigration rates are much higher among the highly educated and skilled.[5] We will therefore assume that $p > \underline{p}$. For analytical simplicity, we normalise $\underline{p}$ to zero. Also, in what follows, we treat p as exogenous, as if it were the result of a relative quota set by immigration authorities independently of the number of applicants. However, we could equally assume that a given number of visas is attributed, which can be translated into a probability of receiving an entry visa by agents with perfect (in which case the adjustment is immediate)[6] or adaptative (in which case the subjective and objective probabilities only coincide at the steady state) expectations with respect to others' education decisions.[7]

Individuals are assumed to be risk-neutral and maximise lifetime income. There is no intertemporal discounting of income. As explained, unskilled workers are assumed to remain in the home country and therefore earn the domestic wage w in both periods. In contrast, skilled workers have the possibility of migrating to a technologically more advanced country where the wage rate per efficiency unit of human capital is $w^* > w$. They earn $w - c$ in the first period and then either $w^* h$ if they migrate or wh if they do not. For a given migration probability p, the condition for investing in education is therefore:

$$w_t - c + (1 - p)w_{t+1}h + pw^*_{t+1}h > w_t + w_{t+1}$$

and individuals will opt for education if

$$c < c_{p,t} \equiv w_{t+1}(h - 1) + ph(w^*_{t+1} - w_{t+1}). \qquad (1)$$

Clearly, migration prospects raise the expected return to human capital in the developing country, thus inducing more people to invest in education. The critical threshold $c_{p,t}$ is increasing in the probability of migration and in the wage differential.

[5] For example, Docquier and Marfouk (2006) find that emigration propensities are five to ten times higher for workers with more than twelve years of education than for workers with less than twelve years of education.

[6] Formally, p can be a decreasing function of $c_p(p)$ in (1), defining an implicit solution for p.

[7] In the empirical analysis, however, it will be important to assess the exogeneity of the migration probability.

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This suggests that the incentive effect of migration will be stronger in poor countries. However, credit constraints on education investment are likely to be more binding in poor countries. To take this into account, we introduce a minimum threshold of first-period consumption, μ_t, which must be financed out of first-period earnings. Hence, for an educated individual, it must be the case that $w_t - c > \mu_t$ or, equivalently, that:

$$c < c_{l,t} \equiv w_t - \mu_t. \tag{2}$$

Liquidity constraints are binding if $c_{l,t} < c_{p,t}$, that is, if $w_t - \mu_t < w_{t+1}(h - 1) + ph(w_t^* - w_t)$. At the steady state (i.e., for $w_t = w_{t+1}$), the binding liquidity constraints condition may be written as:

$$w(2 - h) - ph(w^* - w) < \mu.$$

We therefore impose the restriction that $h \in [1,2]$ to allow for the possibility of either binding or non-binding constraints,[8] depending on the value of w. It is clear from the last expression that liquidity constraints are more likely to be binding in poor countries (low w) facing high emigration rates (high p).

We denote by $H_{a,t}$ and $H_{p,t}$ respectively the gross or *ex ante* (i.e., before migration occurs) and the net or *ex post* (i.e., once emigration is netted out) proportions of educated in the population, which we take as a measure of the country's human capital level. The proportion of young agents opting for education is given by $H_{a,t} = F(c_t^*)$ where $c_t^* = \mathrm{Min}(c_{p,t}, c_{l,t})$ while the proportion of skilled adults remaining in the country is given by:

$$H_{p,t} = \frac{(1 - p)H_{a,t-1}}{1 - pH_{a,t-1}}. \tag{3}$$

At the steady state, we have

$$\frac{\partial H_p}{\partial p} = \frac{(1 - p)\partial H_a/\partial p - H_a(1 - H_a)}{(1 - pH_a)^2}.$$

Using the above expression, it appears that:

- There is a possibility of beneficial brain drain over some ranges of p providing that $\partial H_p/\partial p$ is positive at $p = 0$. This first requires that $\partial H_a/\partial p$ is positive (i.e., there is an incentive effect), which implies that liquidity constraints are not binding in the closed economy;
- At the margin, an increase in the rate of skilled emigration is good for human capital formation if $\partial H_p/\partial p$ is positive at the current emigration rate. Again, this first requires that liquidity constraint are not binding, but this time at the current level of p;
- Finally, the total or net effect of migration on human capital formation can be obtained by comparing the *ex post* (or net) level of human capital with its counterfactual level in the closed economy solution, $H_{p|p=0} = H_{a|p=0} \equiv \tilde{H}$. There is a beneficial brain drain if the net effect is positive, that is, if $H_p > \tilde{H}$.

[8] The hypothesis $h < 2$ is required to obtain internal solutions with non-binding constraints. Using a non-linear utility function with risk aversion would enable us to consider higher values for h.

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As explained, the realisation of these conditions depends on whether liquidity constraints are binding as well as on the ability distribution. For illustrative purposes, let us consider the case of a uniform distribution: $c \rightarrow U[0,1]$ and assume $\mu < w \leq 1$ to avoid corner solutions. With a uniform distribution, $H_a = c^* = \text{Min}(c_p, c_l)$. Starting from a closed economy equilibrium, three configurations arise.

The most pessimistic one occurs when liquidity constraints are binding in the closed economy. In this case, when $w(2 - h) < \mu$ (i.e., when the domestic wage rate is low), there can be no incentive effect: $\partial H_a/\partial p = 0$. Hence, any marginal increase in the skilled migration probability would generate a net loss:

$$\frac{\partial H_p}{\partial p} = \frac{-(w-\mu)(1-w+\mu)}{[1-p(w-\mu)]^2} < 0.$$

Obviously, in this case the brain drain can only be detrimental ($H_p < \tilde{H}$).

An intermediate configuration arises when liquidity constraints are not binding in the closed economy but become binding once migration prospects are introduced. In this case, when $w(2 - h) > \mu > w(2 - h) - ph(w^* - w)$ (i.e., when the domestic wage rate is not too low and the migration rate is relatively high), a sufficiently small degree of openness can foster *ex post* (or net) human capital if $\partial H_p/\partial p$ is positive at $p = 0$, that is if

$$h(w^* - w) > w(h-1)[1 - w(h-1)]. \qquad (4)$$

However, at the current migration rate, a marginal increase in p reduces the proportion of educated remaining in the economy as binding credit constraints do not allow for the incentive effect to operate further ($\partial H_a/\partial p = 0$). The net effect is positive ($H_p > \tilde{H}$) if the skilled emigration probability does not exceed the following critical value:

$$p < \frac{w(2-h) - \mu}{(w-\mu)(2-h)}.$$

The most optimistic case arises when liquidity constraints are never binding, thus allowing for the incentive effect to fully operate. In this case, obtained when $w(2 - h) - ph(w^* - w) > \mu$ (i.e., when the domestic wage rate is high enough and the skilled emigration rate is sufficiently low), the condition for a sufficiently small degree of openness to foster net human capital formation is the same as in (4) and the net effect is positive ($H_p > \tilde{H}$) when the skilled emigration rate does not exceed the following critical value:

$$p < \frac{h(w^* - w) - w(h-1)[1 - w(h-1)]}{h(w^* - w)[1 - w(h-1)]}.$$

Finally, the sign of $\partial H_p/\partial p$ evaluated at the current migration rate can be positive or negative depending on the wage differential and on the magnitude of emigration. When p tends to one, clearly, $\partial H_p/\partial p$ is more likely to become negative.

On the whole, our simple theoretical model predicts that migration prospects can stimulate the accumulation of human capital in developing countries under certain conditions: first, there must be an incentive effect (or brain gain) and, second, the latter

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must be greater than actual skilled emigration (or brain drain). The incentive effect would seem to be potentially stronger in poor countries but may be limited there if liquidity constraints are binding. It is therefore unclear *a priori* whether poor or intermediate income countries experience the strongest incentive effects and, consequently, it is also unclear which type of countries gain or lose more from the brain drain.

1.2. *Related Empirical Model*

To evaluate the incentive hypothesis described theoretically in (1), we use a β-convergence empirical model and regress the growth rate of the *ex ante* stock of human capital (i.e., including emigrants) between 1990 and 2000, $\Delta \ln(H_a) \equiv \ln(H_{a,00}) - \ln(H_{a,90})$, on a set of explanatory variables. It is this human capital formation equation, (5), that we estimate econometrically in Section 3:

$$\begin{aligned}\Delta \ln(H_{a,90-00}) = a_0 + a_1 \ln(H_{a,90}) + a_2 \ln(p_{90}) + a_3 \ln(p_{90}) GNID_{90} \\ + a_4 DENS_{90} + a_5 SSAD + a_6 LATD + a_7 REM_{90} + \epsilon\end{aligned} \tag{5}$$

The following explanatory variables enter in the estimation of (5):[9]

- The log of the initial level of *ex ante* human capital, $\ln(H_{a,90})$, to capture potential catching-up effects. A negative sign for the coefficient a_1 would indicate convergence in natives' (residents plus emigrants) human capital among the countries sampled.
- The log of the skilled migration rate at the beginning of the period, $\ln(p_{90})$, as a proxy for the migration incentives faced by educated individuals. Ideally, the incentive effect of migration on human capital investment should be identified through the impact of migration prospects on expected returns to education. However, these cannot be computed directly as there are no comparative data on education premia in developing countries. Using differences in GNI *per capita*, on the other hand, raises endogeneity concerns as this variable is strongly correlated with human capital. In our benchmark model, we will thus let aside wage differentials and differences in GNI *per capita* and use instead $\ln(p_{90})$. A positive sign for the coefficient a_2 indicates that the incentive effect operates (i.e., there is a brain gain). Still, one may be concerned about possible non-linearities in the relationship between migration prospects and human capital formation at different income levels. In alternative specifications, we allow for this possibility by interacting this initial skilled emigration rate, $\ln(p_{90})$, with dummy variables for whether the country's income *per capita* was lower than a given threshold at the beginning of the period, $GNID_{90}$. A negative sign for the coefficient a_3 would suggest that the impact of higher liquidity constraints more than offsets that of higher wage differentials, resulting in a weaker incentive effect in poor countries. Obviously, robustness checks imply the use of different possible thresholds.
- The population density in 1990, $DENS_{90}$, as a proxy for the cost of acquiring education. Clearly, education costs depend on a host of factors such as public expenditures on general and higher education, distances to schools etc.

[9] The data sources are given in the Appendix.

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However, public expenditures on education at the beginning of the sample period (in 1990) are statistically very highly correlated in our sample with the initial level of human capital H_{90}. This certainly suggests that such expenditures are effective but the magnitude of the correlation (0.72) precludes any correct joint estimation of the impact of public expenditures and of possible convergence effects. Population density is likely to reduce distances to schools and, therefore, to decrease the opportunity cost of education.

- Workers' remittances as a share of GDP, REM_{90}, first because they can relax credit constraints on human capital investment, and second, because in the absence of statistics on return migration, they provide an indirect means of controlling for possible returns in subsequent periods.[10]
- Regional dummies for sub-Saharan Africa (*SSAD*) and Latin America (*LATD*).

2. Data on Human Capital and Migration Rates

Our empirical analysis is based on a new data set on international migration by educational attainment, namely, on the World Bank sponsored Docquier and Marfouk (2006) (henceforth DM) data set.[11] DM collected census, register and survey data reporting immigrants' educational levels and countries of birth from 27 OECD countries in 2000 (which accounts for 98% of the OECD immigration stock) and 24 countries in 1990 (91%). For the few remaining countries for which census data were not available, existing data by country of birth were split across educational levels on the basis of the regional structure or of the OECD average. They use these data to compute emigration rates by education level for 195 emigration countries in 2000 and 174 emigration countries in 1990. South–South migration is not taken into account but, on the basis of census data collected from selected non-OECD countries, DM estimate that about 90% of all highly skilled migrants live in the OECD area. Descriptive statistics (Docquier and Marfouk, 2006) show a clear decreasing relationship between emigration rates and country size, with average emigration rates being about 7 times higher for small countries (with population lower than 2.5 million) than for large countries (with population higher than 25 million). The highest emigration rates are observed in middle income countries where people have both the incentives and means to emigrate. High income countries (low incentives) and low income countries (where liquidity constraints are likely to be more binding) exhibit the lowest rates. This holds true for both total and skilled migration. Regarding the regional distribution of the brain drain, the most affected regions appear to be the Caribbean and the Pacific, which consist of relatively small islands, Sub-Saharan Africa, and Central America. The difference between skilled and total emigration rates is particularly striking in Africa.

The method used by DM is to rely on receiving country *r*'s census or population register to extract information on immigrants' country of birth, age, and skill level. Let

[10] Indeed, preparing one's return is known to be a central motivation for remitting and remittances tend to decline over time as migrants become better integrated in the host country. See Rapoport and Docquier (2006) for a comprehensive survey of migrants remittances.

[11] In an earlier version of this article we used the Carrington and Detragiache (1998) data and found very similar results. See Beine *et al.* (2003).

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$M^r_{t,s}$ denote the stock of working-age individuals born in a given country, of skill level s, $s = l,m,h$ (for low, medium and high skill)[12] and living in country r at time t. The stock of emigrants from a given country for a given education level, $M_{t,s} = \sum_r M^r_{t,s}$, is then obtained by summing over receiving countries. Emigration rates by education levels are then obtained by comparing the number of emigrants to the population at origin with similar characteristics, $N_{t,s}$. Emigration rates are given by

$$p_{t,h} = \frac{M_{t,h}}{N_{t,h} + M_{t,h}}; p_t = \frac{M_{t,l}}{N_{t,l} + M_{t,l}}$$

and the share of high skilled among the total native population (residents and emigrants included) by

$$H_{a,t} = \frac{N_{t,h} + M_{t,h}}{\sum_s (N_{t,s} + M_{t,s})}.$$

These steps require collecting data on the size and skill structure of the working-age population in the origin countries. Population data by age are provided by the United Nations.[13] Data are missing for a small number of countries but can be estimated using the CIA world factbook.[14] Population data are split across educational groups using international human capital indicators. The DM data set is based on the Barro and Lee (2001) estimates for most countries. For countries where the Barro and Lee measures are missing, DM transposed the skill structure of the neighbouring country with the closest human development index regarding education.

The variables $H_{p,t}$ and $H_{a,t}$ are two outputs of the data set. Implicitly, these two variables are connected in the following way:

$$H_{p,t} \equiv \frac{(1 - p_t)H_{a,t}}{1 - p_t H_{a,t} - \underline{p}_t(1 - H_{a,t})} \tag{6}$$

where $\underline{p}_t$ is the average emigration rate of workers without tertiary education.

This equation will be useful for our counterfactual experiments. Note that while we ignored unskilled migration in the theoretical model by setting unskilled migrants' probability to zero, this is clearly not satisfactory from an empirical perspective. We therefore include unskilled migration in our computation of the post-migration human capital stock in (6). This variable will play an important role when we will introduce counterfactual simulations to estimate the net effect of skilled migration on human capital formation in Section 5.

To conduct the empirical analysis, and given that we focus on the brain drain impact on developing countries, our sample excludes high-income countries as well as countries from the former USSR, Yugoslavia and Czechoslovakia (for consistency between the 1990 and the 2000 data points), which gives a total sample of 127 developing countries. We measure the emigration rate of skilled workers as the emigration rate among individuals with tertiary education: $p_t = p_{t,h}$. As emigration rates are strongly

[12] We define high-skill workers as those with tertiary (i.e., post-secondary) education, medium-skill workers as those with upper-secondary education and low-skill workers as those with less than upper-secondary education.
[13] See http://esa.un.org/unpp.
[14] See http://www.cia.gov/cia/publications/factbook.

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increasing in human capital, we also assume that the minimal or incompressible emigration rate is the one observed among people with primary education: $\underline{p}_t = p_{t,l}$.

3. Results

3.1. *Econometric Issues*

Before we carry out the estimation, we first address some specification issues. A first important question concerns the exogeneity of the migration rate. When trying to determine the impact of migration on education, one has to control for the reverse effect since, on average, the proportion of educated is likely to affect the rate of skilled migration. This is due to a number of reasons.[15] In an attempt to cope with this endogeneity issue, recent empirical growth analyses (Barro and Sala-I-Martin, 1995; Hall and Jones, 1999) have been concerned with the use of truly exogenous instruments. In these studies, the following variables have been suggested as candidate instruments for a first-stage migration equation:

- Life expectancy at birth (LE_{90}), as a proxy for general living conditions;
- The country's population size (POP_{90}), as small countries tend to be more open to migration (this is also very clear from the DM data);
- Racial tensions (*RAC*), a key traditional 'push' factor;
- The number of emigrants living in the *OECD* area at the beginning of the period (*MT*), to capture the size of the migration network on which prospective emigrants can count on;[16]
- The GDP *per capita* of the source country, as a proxy for wage differentials – clearly a driving force of migration.

We retain only two out of these five candidate instruments in our first-stage migration equation as we have to eliminate the variables for which there is a strong presumption of a correlation with human capital. This is the case for wage differentials, for obvious reasons,[17] and for life expectancy, the exogeneity of which is questionable given the fact that longer-lived individuals can enjoy the benefits of education over a longer period of time. We also exclude racial tensions, for both technical and substantive reasons. Technically, their introduction would result in a significant drop in the size of the sample and would therefore lower the comparability with the OLS results.[18] More

[15] Standard neoclassical models would suggest that a larger stock of human capital may reduce the skill premium and thus increase skilled migration incentives through higher international wage differentials. On the other hand, a larger stock of human capital may also generate positive externalities on wages through a variety of channels emphasised in new growth and new economic geography models (Klenow and Rodriguez-Clare, 2005).

[16] As is well known, larger networks are associated with lower migration costs (especially information-related ones) and higher expected wages; all else equal, they should act to increase the number of future migrants. See for example Carrington *et al.* (1996), Munshi (2003) and Kanbur and Rapoport (2005).

[17] As a crude test, the correlation between wage differentials and human capital levels is indeed higher than 0.5.

[18] More precisely, the sample size falls to 59 countries when racial tensions are added to the set of instruments. We still obtain a positive incentive effect (of a higher magnitude) and conclude in favour of the exogeneity of the three instruments. The first-stage estimation also supports racial tensions as a strong instrument at the 10% significance level. The results with this specification are available from the authors upon request.

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substantially, it could well be that racial tensions impact on human capital formation, especially if ethnic discrimination is a serious issue.[19] We are therefore left with two instruments: total population size, and migration stocks at the beginning of the period. At a theoretical level, there is no obvious reason why the demographic size of a country should be correlated with its education level. Likewise, once we control for remittances, there is no *a priori* reason why migration networks at destination should impact on human capital formation beyond their effect on migration prospects and incentives (captured by our instrumentation equation). Since we have only one endogenous explanatory variable, the number of instruments is large enough to test for exogeneity of the retained instruments using a traditional overidentification test.

At an empirical level, the validity of our instruments rests on two conditions: the instruments should first be significantly correlated with the migration rate, and the exogeneity condition requires that they should be uncorrelated with the error term in (5).

Equation (7) reports the results of an OLS regression of the migration equation for the full sample on the two selected instruments (t-statistics in parenthesis):

$$\begin{aligned} p = \underset{(2.24)}{1.20} + \underset{(8.46)}{0.454}\ln(MT) - \underset{(-13.92)}{0.518}\ln(POP) \\ R^2 = 0.509; \text{Nobs} = 127; F = 97.14. \end{aligned} \tag{7}$$

The two instruments are significant at the 1% significance level and are therefore kept throughout the analysis. As expected, population size enters with a negative sign. The sign of $\ln(MT)$ is also in line with intuition: a higher initial stock of migrants stimulates future emigration. Together, the variables $\ln(MT)$ and $\ln(POP)$ account for more than 50% of the migration variability, which is quite satisfactory for a cross-section analysis. A more formal test relies on the value of the F statistics testing the null hypothesis that all coefficients in (7) jointly equal zero. The test reveals that this null hypothesis is clearly rejected, suggesting that the two instruments are strong. Finally, given that we have more instruments than endogenous variables, a J-test of overidentification was also run to assess the exogeneity property of the retained instruments, the p-values of which are reported in the result tables below. For the parsimonious specification, the test supports the exogeneity assumption of the two instruments, thus providing additional confidence that our instruments are indeed uncorrelated with the human capital variable.

3.2. *Testing for Incentive Effects*

We now turn to the estimation of (5). Table 1 reports the estimation results for the full specification and for a more parsimonious model from which insignificant variables such as *LATD*, *DENS*90 and *REM*90 were excluded. Exclusion of these variables leads to a significant increase in the number of countries included (from 103 to 127) as the variable *REM*90 displays many missing values. The results appear to be very robust across specifications and estimation techniques (OLS and IV). Skilled migration appears to increase gross (or *ex ante*, or pre-migration) human capital stocks

[19] See Tremblay (2001) and Docquier and Rapoport (2003).

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Table 1

Estimation Results: Benchmark Regressions

Dependent variable = gross investment in human capital.

Variable	(1)	(2)	(3)	(4)	(5)
constant	−0.0035	−0.0798	–	0.0214	−0.0798
	[−0.04]	[−1.12]	–	[0.20]	[−1.12]
ln(*p90*)	0.0487*	0.0421**	0.0481**	0.0573**	0.0499**
	[1.86]	[2.03]	[2.29]	[2.22]	[2.30]
ln(*H90*)	−0.2240***	−0.2211***	−0.1990***	−0.2238***	−0.2216***
	[−6.37]	[−6.30]	[−9.12]	[−6.38]	[−6.37]
SSAD	−0.382***	−0.325***	−0.299***	−0.386***	−0.323***
	[−3.98]	[−3.91]	[−4.36]	[−4.13]	[−3.90]
LATD	0.0258	–	–	−0.0351	–
	[−0.45]	–	–	[−0.59]	–
DENS90	−0.0998	–	–	−0.1085	–
	[−0.92]	–	–	[−0.99]	–
REM90	−0.0051	–	–	−0.0053	–
	[−1.12]	–	–	[−1.14]	–
R^2	0.410	0.353	0.763	0.409	0.352
Hausman	–	–	–	0.552	0.484
J test	–	–	–	0.056	0.163
Nobs	103	127	127	103	127

Variables: *p90* = skilled emigration rate in 1990. *H90* = lagged dependent variable (*ex ante* proportion of educated). *SSAD* = sub-Saharan African dummy.
LATD = dummy for Latin American countries. *DENS90* = population density in 1990. *REM90* = workers' remittances as % of GDP.
Notes. t-statistics in brackets. White corrections for heteroscedasticity.
Columns 1, 2 and 3: OLS regressions. Columns 4 and 5 : variable instrumental regressions; instruments: populatition size and stock of migrants in OECD countries.
Hausman and J test report the p-values for respectively the null of no endogeneity of migration rates and the null of valid instruments (no correlation with error term).
*, ** and *** denote significance at 10, 5 and 1% levels respectively.

significantly. The value of the migration coefficient lies between 0.042 and 0.050 for the OLS estimate (depending on whether the constant and the insignificant explanatory variables are included) and is slightly higher (0.050) after instrumenting.[20] Taken literally, this means that doubling the migration propensity of the highly skilled increases gross human capital formation by 5%. This is not negligible in countries where the proportion of highly educated typically lies in the 2–8% range and higher education significantly increases the chance of emigration (by a factor of 5 to 10).

Regarding the other control variables, we find evidence of convergence in human capital levels among the developing countries sampled. Indeed, the coefficient on the lagged human capital stock is negative and significant at the 1% threshold in all specifications. Moreover, in line with the findings of Easterly and Levine (1997), we find that Sub-Saharan countries display poor performances in terms of human capital formation. In contrast, population density and the dummy variable for Latin-America do not seem to exert any significant impact and are therefore omitted in the parsimonious specifications. Finally, workers' remittances are also insignificant in all

[20] The IV results obtained without a constant are not reported here to save space. In this regression, the estimated incentive effect amounts to 0.057. We obtain similar results with respect to the Hausman test and the over-identification test.

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Table 2

Estimation Results: Conditional Effects

Dependent variable = gross investment in human capital.

Variable	(1)	(2)	(3)
constant	−0.128*	−0.089	−0.100
	[−1.69]	[−1.08]	[−1.33]
ln (*p90*)	0.031*	0.040**	0.036**
	[1.86]	[2.74]	[2.53]
ln (*p90*) × *GNID*	0.037	0.005	0.012
	[1.09]	[0.17]	[0.47]
ln (*H90*)	−0.237***	−0.224***	−0.228***
	[−6.08]	[−5.34]	[−5.83]
SSAD	−0.322***	−0.327***	−0.326***
	[−3.93]	[−3.96]	[−3.95]
R^2	0.370	0.353	0.355
Nobs	127	127	127

Variables: *p90* = skilled emigration rate in 1990. *H90* = lagged dependent variable (*ex ante* proportion of educated).
SSAD = sub-Saharan African dummy. *GNID* = low-income dummy.
Notes. t-statistics in brackets. White Corrections for heteroscedasticity.
In columns (1) (2) and (3), the low income dummies are defined using thresholds of income per head in 1990 equal respectively to 500, 750 and 900 US$.
*, ** and *** denote significance at respectively 10, 5 and 1% levels.

regressions and are therefore left aside throughout the rest of the empirical analysis. While the overidenfication test supports the exogeneity of the two instruments in the parsimonious specification, the Hausman test does not support the need for accounting for reverse causality. The p-values associated with this test for the two specifications considered are indeed above the usual significance levels.

Regardless of the retained specification and the estimation method, we always find a positive incentive effect in the sense that the coefficient of the rate of skilled migration is significantly positive at a 5% level (10% in column (1)). The benchmark elasticity of human capital formation to skilled migration is obtained in column (3) of Table 2. In this best parsimonious specification, we have $a_2 = 4.81\%$. Using the standard error of the coefficient, we can also provide an interval of confidence at 90% for the elasticity. The lower bound for a_2 is equal to 1.37% and the upper bound to 8.25%. Hence, the incentive effect is definitely positive.

3.3. *Testing for Non-linearities*

To test for possible non-linearities in (5), we interact skilled migration rates with a dummy variable for low-income status. To define a 'poor country' we use three alternative threshold values of the 1990 GNI per head (500, 750 and 900 US$). We augment the benchmark specification by adding the interaction term $\ln(p_{90}) \times GNID$ to the set of explanatory variables in (5), where *GNID* is a dummy variable equal to 1 if country i is a low income country. The advantage of this specification is that the correlation between the raw migration rate and the interaction term remains modest, which moderates the statistical effects of collinearity. Table 2 reports the results with this specification. As the Hausman test conducted above confirmed the exogeneity of the

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migration rate, we only present the OLS results for the specification with interaction terms.[21]

On the whole, the results do not provide any evidence of a different impact for the poorest countries. In all regressions, the interaction term $\ln(p_{90}) \times GNID$ is insignificant at usual significance levels. Interestingly, the value of the migration coefficient, $\ln(p_{90})$, seems unaffected by the inclusion of interaction terms. However, one may be concerned that in the absence of information on income distribution, average income levels may only imperfectly capture the extent of liquidity constraints. In unreported regressions, we also interacted skilled migration with a dummy variable *POOR* for whether more than 40% of the country's population live on less than one dollar per day. As with the previous definition, no significant differences were found between poor and richer countries, leading us to conclude to the absence of non-linearities in the skilled migration–human capital formation relationship.

4. Country-specific Results

The cross-sectional results just derived show that migration prospects have a significant positive impact on gross human capital formation. From the perspective of source countries however, what matters is not the number of people who acquire education but the number of educated who remain in the country after education is acquired. To evaluate whether the country has experienced a beneficial or a detrimental brain drain, one must compare its observed human capital level to some relevant counterfactual. Since the incentive effect emphasised above relies on skill-biased migration prospects, a natural counterfactual experiment to make is to compare current human capital levels to their erstwhile value had skilled workers been allowed to emigrate at the same rate as unskilled workers in 1990 and 2000, i.e. $p_{90} = \underline{p}_{90}$ and $p_{00} = \underline{p}_{00}$.[22] We consider the initial stock of human capital, $H_{a,1990}$, as given. In other words, people who were educated prior to 1990 are considered as having done so independently of their chances of migration. It is important to emphasise that this assumption increases the likelihood of our counterfactual experiment yielding a negative (detrimental) outcome.

Our simulations are based on the coefficient obtained in the best parsimonious specification presented in column 3 of Table 1 (i.e., $a_2 = 0.0481$). Since $\underline{p}_{90} < p_{90}$, the counterfactual proportion of tertiary educated natives, $H^{cf}_{a,2000}$, is always lower than the actual proportion, $H_{a,2000}$. Assuming $p_{00} = \underline{p}_{00}$, (8) is directly derived from (6). Using (6), it clearly appears that the *ex post* and *ex ante* human capital stocks are equal when skilled workers are allowed to emigrate at the same rate as unskilled workers: this gives (9). The simulation system is given by the following equations:

$$H^{cf}_{a,2000} = H_{a,2000} - a_2 \ln(p_{90}/\underline{p}_{90}) \tag{8}$$

[21] Using the values of p_{90} predicted by the first stage migration regression leads to similar estimates. These results are available upon request.

[22] For a small number of countries where the unskilled emigration rate is close to zero and, given that we use a log specification, we impose a lower bound equal to 10% of the skilled emigration rate.

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$$H^{cf}_{p,2000} = H^{cf}_{a,2000}. \tag{9}$$

Consequently, for each country in the sample, we measure the human capital gain/loss associated to the brain drain as the difference between the current and counterfactual proportions of skilled, that is, by $H_{p,2000} - H^{cf}_{p,2000}$. The results of this counterfactual experiment are apparent from Table 3 which gives the net effect of the brain drain on the labour force, on the number of skilled workers and on the proportion of high skill workers residing in their home country. As the latter variable is the cornerstone of our analysis, we provide a confidence interval evaluated at the 90% rate (i.e., using the lower and upper bounds of the coefficient a_2 from the previous Section).

The countries are ranked in Table 3 by decreasing gain. As may be seen from the Table, there are slightly more losers than winners. More importantly, the gains of the winners are relatively small and exceed 1% of the country's skilled labour force only in a handful of cases. In contrast, the losses of the losers can be substantial and exceed 10% in many small Caribbean and Pacific countries.

A more general pattern emerges when the gains and losses in terms of human capital formation are plotted against two key characteristics: the skilled emigration rate in 1990 and the observed proportion of educated natives in 1990. It appears that the countries experiencing a beneficial brain drain (the 'winners') generally combine low levels of human capital and low skilled migration rates, whereas the 'losers' are typically characterised by high skilled migration rates (above 20%) and/or high proportions of highly educated in the adult population (above 5%). Figures 1 and 2 give the reduced-form relationship between the human capital impact of the brain drain and these two variables. For each relationship, we estimate a quadratic reduced-form adjustment. The relationships are very significant and exhibit high R^2 (respectively 61% and 37%).

Finally, it is striking from Table 3 that the most populated countries (China, India, Indonesia, Brazil, Egypt, Bangladesh) are all among the winners. Once translated into absolute numbers, their relatively modest gains more than offset the losses of the many small countries hard hit by the brain drain. This is more apparent from Table 4, which gives the results for country groups defined according to demographic size, income level, and region. In aggregate, there were 116.5 million skilled workers living in the 127 developing countries of our sample in 2000 (representing about 5% of the sample's labour force). This number would fall to 113.2 million under the counterfactual scenario, meaning that according to our computations the brain drain generates a 3% increase in the total number of skilled workers *living* in the developing world.

Desegregating by demographic size, income level and region, it is noteworthy that large countries (with population higher than 25 million) form the only group to experience a net gain while losses are concentrated on the relatively small countries (with a population lower than 10 million). For the smallest countries (with a population lower than 1 million), the losses are substantial once expressed in relative terms as they represent a 33% net loss. In contrast, there is no clear pattern for the decomposition by income levels (2000 classification). Finally, at a regional level, the brain drain appears to be extremely detrimental in Central America (especially in the Caribbean), the Pacific region, and to a lower extent in Sub-Saharan Africa, while Asia and South America experience significant gains.

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Table 3

Country-specific Impact of Skilled Migration on Human Capital Counterfactual experiment: skilled emigration rate = unskilled emigration rate

Countries experiencing a beneficial brain drain	Effect on the labour force: ΔLF	Effect on the skilled labour force: ΔSLF	Effect on the proportion of skilled: *BG*	Confidence interval on *BG* (90%)
Argentina	−89827	292215	1.5%	(0.3%–2.8%)
Venezuela	−64675	131002	1.3%	(0.1%–2.4%)
Saudi Arabia	−9720	113487	1.2%	(0.4%–2.1%)
Mongolia	−2225	12668	1.2%	(0.3%–2.1%)
Maldives	−128	1102	1.1%	(0.3%–1.9%)
Libya	−9186	22575	1.1%	(0.2%–2.0%)
Costa Rica	−24903	15304	1.0%	− (0.3%–2.4%)
Thailand	−83572	318506	1.0%	(0.2%–1.8%)
Bolivia	−27614	26067	0.9%	−(0.1%–1.9%)
Albania	955	14390	0.9%	(0.3%–1.4%)
Oman	−713	9331	0.8%	(0.3%–1.5%)
Chile	−76311	59461	0.8%	−(0.2%–1.9%)
Bahrain	−2095	2589	0.8%	(0.0%–1.6%)
Egypt	−135204	202416	0.7%	(0.0%–1.5%)
Brazil	−152218	625298	0.7%	(0.2%–1.3%)
Jordan	−28054	7439	0.7%	−(0.5%–1.8%)
Paraguay	−6788	13063	0.6%	(0.0%–1.2%)
Syria	−44301	31541	0.6%	−(0.2%–1.4%)
Ecuador	−79255	17925	0.6%	−(0.5%–1.7%)
South Africa	−152228	74385	0.4%	−(0.3%–1.2%)
Indonesia	−99302	451452	0.4%	(0.1%–0.8%)
Swaziland	−955	21987	0.4%	(0.1%–0.7%)
Bulgaria	28998	28998	0.4%	(0.4%–0.4%)
Uruguay	−19474	5619	0.4%	−(0.4%–1.2%)
Solomon Islands	−692	531	0.4%	−(0.1%–0.9%)
India	−942212	1513624	0.3%	(0.0%–0.7%)
Namibia	−930	2118	0.3%	(0.0%–0.6%)
Botswana	−853	1812	0.3%	(0.0%–0.6%)
Bhutan	−104	1933	0.2%	(0.1%–0.4%)
Burma (Myanmar)	−28033	49958	0.2%	(0.0%–0.5%)
Bangladesh	−75739	122289	0.2%	(0.0%–0.5%)
Cote d'Ivoire	−10916	10775	0.2%	(0.0%–0.4%)
China	−741293	1440794	0.2%	(0.0%–0.4%)
Colombia	−211071	15774	0.2%	−(0.5%–0.9%)
Turkey	−3522	58858	0.2%	(0.1%–0.3%)
Burkina Faso	−1744	6032	0.2%	(0.0%–0.3%)
Chad	−1200	4371	0.2%	(0.0%–0.3%)
Philippines	−1008357	−176017	0.1%	−(1.5%–1.8%)
Nepal	−11906	13083	0.1%	(0.0%–0.3%)
Iraq	−83960	4330	0.1%	−(0.5%–0.8%)
Yemen	−6554	5472	0.1%	(0.0%–0.2%)
Madagascar	−10964	4998	0.1%	−(0.1%–0.3%)
Sudan	−17086	9840	0.1%	−(0.1%–0.2%)
Central African Republic	−1720	949	0.1%	−(0.1%–0.2%)
Lesotho	−269	423	0.1%	(0.0%–0.1%)
Malaysia	−92619	−815	0.1%	−(0.5%–0.6%)
Burundi	−3234	869	0.0%	−(0.1%–0.2%)
Niger	−949	797	0.0%	(0.0%–0.1%)
Vanuatu	−657	−30	0.0%	−(0.5%–0.6%)
Ethiopia	−46732	2765	0.0%	−(0.1%–0.2%)
Nigeria	−135982	−1811	0.0%	−(0.2%–0.2%)
Djibouti	−558	−8	0.0%	−(0.1%–0.2%)
Guinea	−3331	−175	0.0%	−(0.1%–0.1%)

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Table 3

Continued

Countries experiencing a beneficial brain drain	Effect on the labour force: ΔLF	Effect on the skilled labour force: ΔSLF	Effect on the proportion of skilled: BG	Confidence interval on BG (90%)
Equatorial Guinea	−851	−50	0.0%	−(0.3%–0.3%)
Benin	−4351	−292	0.0%	−(0.1%–0.1%)
Mali	−3487	−973	0.0%	−(0.1%–0.0%)
Tanzania	−29329	−4517	0.0%	−(0.2%–0.1%)
Pakistan	−201568	−28980	0.0%	−(0.3%–0.2%)
Congo, Dem. Rep.	−30061	−7170	0.0%	−(0.1%–0.1%)

Countries experiencing a detrimental brain drain	Effect on the labour force: ΔLF	Effect on the skilled labour force: ΔSLF	Effect on the proportion of skilled: BG	Confidence interval on BG (90%)
Malawi	−4981	−2383	−0.1%	−(0.1%–0.0%)
Mauritania	−2306	−883	−0.1%	−(0.2%–0.0%)
Zimbabwe	−29708	−5280	−0.1%	−(0.5%–0.3%)
Rwanda	−4121	−2685	−0.1%	−(0.1%–0.1%)
Gabon	−1971	−569	−0.1%	−(0.3%–0.1%)
Mozambique	−9725	−8087	−0.1%	−(0.1%–0.1%)
Zambia	−12489	−4958	−0.1%	−(0.3%–0.0%)
Cameroon	−19833	−8158	−0.1%	−(0.3%–0.0%)
Tunisia	−23298	−8637	−0.2%	−(0.4%–0.1%)
Guinea-Bissau	−1377	−777	−0.2%	−(0.2%–0.1%)
Senegal	−13889	−5724	−0.2%	−(0.3%–0.0%)
Togo	−7143	−3230	−0.2%	−(0.4%–0.0%)
Hungary	−98959	−25187	−0.2%	−(0.9%–0.5%)
Iran	−280075	−74908	−0.2%	−(0.7%–0.3%)
Algeria	−43766	−31182	−0.2%	−(0.3%–−0.1%)
Morocco	−84703	−40772	−0.3%	−(0.5%–−0.0%)
Comoros	−1130	−769	−0.3%	−(0.4%–−0.2%)
Mexico	−302138	−179516	−0.3%	−(0.5%–−0.1%)
Afghanistan	−48244	−27984	−0.3%	−(0.5%–−0.1%)
Papua New Guinea	−10581	−7277	−0.3%	−(0.5%–−0.2%)
Uganda	−31811	−24376	−0.3%	−(0.4%–−0.2%)
Panama	−49890	−15899	−0.4%	−(1.9%–−1.2%)
Angola	−18426	−17753	−0.4%	−(0.4%–−0.4%)
Cambodia	−45513	−23192	−0.4%	−(0.7%–−0.1%)
Congo, Rep.	−13246	−6755	−0.5%	−(0.9%–−0.1%)
Kenya	−70493	−55544	−0.5%	−(0.7%–−0.4%)
Gambia	−3310	−2942	−0.6%	−(0.6%–−0.5%)
Somalia	−25277	−17720	−0.6%	−(0.8%–−0.4%)
Sri Lanka	−105462	−69618	−0.6%	−(0.9%–−0.4%)
Ghana	−64804	−54217	−0.7%	−(0.9%–−0.6%)
Vietnam	−458807	−289465	−0.7%	−(1.1%–−0.4%)
Honduras	−43364	−22237	−0.8%	−(1.3%–−0.2%)
Guatemala	−59056	−36179	−0.8%	−(1.1%–−0.4%)
Sierra Leone	−16382	−14255	−0.9%	−(1.0%–−0.7%)
Kiribati	−972	−516	−0.9%	−(1.5%–−0.3%)
Sao Tome and Principe	−452	−537	−1.0%	−(0.9%–−1.1%)
Dominican Republic	−111922	−65695	−1.2%	−(2.0%–−0.4%)
Palau	−290	−188	−1.3%	−(1.9%–−0.6%)
Liberia	−18950	−15693	−1.5%	−(1.8%–−1.2%)
Laos	−48145	−37361	−1.7%	−(2.0%–−1.4%)
El Salvador	−81164	−56829	−1.7%	−(2.3%–−1.1%)
Nicaragua	−61669	−38884	−1.8%	−(2.6%–−0.9%)
Cuba	−273935	−187232	−2.1%	−(2.8%–−1.3%)

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Table 3

Continued

Countries experiencing a detrimental brain drain	Effect on the labour force: ΔLF	Effect on the skilled labour force: ΔSLF	Effect on the proportion of skilled: *BG*	Confidence interval on *BG* (90%)
Suriname	−6144	−5711	−2.2%	−(2.4%−−2.1%)
Mauritius	−19957	−16512	−2.3%	−(2.6%−−2.0%)
Micronesia, Fed. States	−1595	−1136	−2.4%	−(3.1%−−1.7%)
Marshall Islands	−1216	−967	−2.9%	−(3.7%−−2.1%)
Cape Verde	−5880	−5456	−3.2%	−(3.4%−−3.0%)
Lebanon	−104570	−83527	−3.8%	−(4.5%−−3.0%)
Haiti	−138488	−128385	−4.0%	−(4.4%−−3.7%)
Seychelles	−1951	−1667	−5.3%	−(5.9%−−4.6%)
Fiji	−36598	−30356	−6.7%	−(7.7%−−5.7%)
St Lucia	−6420	−5701	−7.1%	−(7.7%−−6.4%)
Samoa	−6361	−5763	−7.4%	−(8.0%−−6.9%)
Tonga	−4825	−4242	−8.3%	−(9.1%−−7.5%)
Belize	−14090	−12004	−9.9%	−(11.2%−−8.7%)
Barbados	−25201	−22986	−10.3%	−(11.0%−−9.5%)
Trinidad and Tobago	−108326	−93869	−11.0%	−(12.2%−−9.8%)
Dominica	−5954	−5560	−12.3%	−(13.0%−−11.6%)
Jamaica	−238038	−217245	−14.0%	−(14.9%−−13.0%)
St Vincent & Grenadines	−10403	−9522	−14.1%	−(14.9%−−13.1%)
Antigua and Barbuda	−8881	−7816	−14.7%	−(16.2%−−13.1%)
St Kitts & Nevis	−4728	−4481	−16.9%	−(17.6%−−16.1%)
Guyana	−94604	−85811	−17.8%	−(19.0%−−16.5%)
Grenada	−11309	−10583	−21.5%	−(22.6%−−20.4%)

Effect on the labour force (population aged 25 and more): observed labour force minus counterfactual labour force
Effect on the skilled labour force (with post-secondary education): observed skilled labour force minus counterfactual skilled labour force
Effect on the proportion of skilled (*BG*): observed proportion minus counterfactual proportion (brain gain)
Source: Own calculations

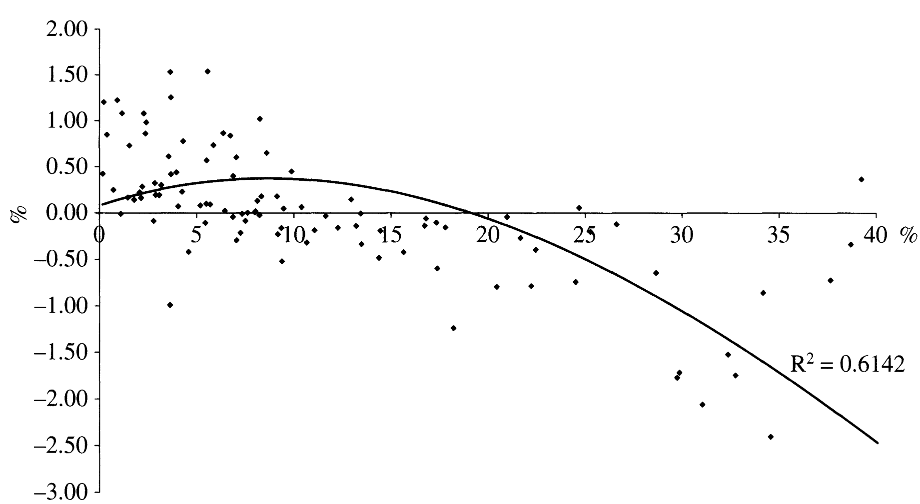

Fig. 1. *Brain Drain Effect and Skilled Migration Rate*

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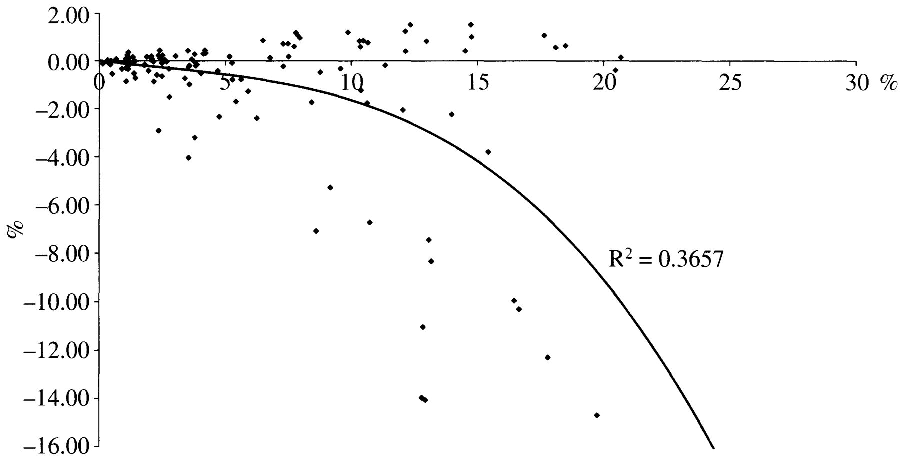

Fig. 2. *Brain Drain Effect and Residents' Human Capital*

5. Conclusion

The brain drain has long been viewed as a serious constraint on poor countries' development. However, recent theoretical literature suggests that migration prospects can raise the expected return to human capital and foster investment in education at home. This article investigates how these positive and negative effects balance out. Using recent data on emigration rates by education levels (Docquier and Marfouk, 2006), we find evidence of a positive effect of skilled migration prospects on gross (pre-migration) human capital levels in a cross-section of 127 developing countries. More precisely we find that the elasticity of human capital formation to skilled migration is equal to about 5% and is very stable across specifications and estimation methods. For each country we then estimate the net effect of the brain drain using counterfactual simulations. We find that countries combining relatively low levels of human capital and low skilled emigration rates are more likely to experience a beneficial brain drain (net positive effect) and conversely. There appear to be slightly more losers than winners and, more importantly the former tend to lose *relatively* more than what the latter gain. The situation of many small countries in Sub-Saharan Africa and Central America, in particular, is extremely worrisome. In contrast, the main globalisers (China, India, Brazil) all seem to experience non-negligible gains. Once translated into numbers, these gains outweigh the losers' losses, resulting in an overall gain for developing countries as a whole.

Two central conclusions emerge from the above analysis. First, brain drain migration contributes to an increase in the number of skilled workers living in the developing countries. This suggests that the traditionally pessimistic view of the brain drain has no empirical justification *at an aggregate level*. Second, the brain drain has important *distributional* effects among developing countries, a dimension that has so far been absent from policy debates.

This article offers initial insights on the general circumstances under which a beneficial or a detrimental brain drain is obtained. However, further empirical

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Table 4

Results by Country Group

Counterfactual experiment: skilled emigration rate = unskilled emigration rate

	Observations in 2000			Counterfactual experiment			Brain drain effect		
	Labour Force ($LF \times 1000$)	Number of skilled workers ($Y \times 1000$)	In % of the labour force ($y = Y/LF$)	Labour Force ($LF' \times 1000$)	Number of skilled workers ($Y' \times 1000$)	In % of the labour force ($y' = Y'/LF'$)	Change in the number of skilled ($Y - Y'$)	Change in % (Y')	Change in the proportion of skilled ($y - y'$)
By country size (in 2000)									
Large (>25 million)	2,001,110	97,370	4.9	2,006,533	93,081	4.6	4,288	4.6	0.2
Upper-Middle (from 10 to 25)	181,152	11,968	6.6	182,472	12,066	6.6	−97	−0.8	0.0
Lower-Middle (from 2.5 to 10)	80,638	6,525	8.1	81,752	7,104	8.7	−578	−8.1	−0.6
Small (<2.5 million)	10,026	632	6.3	10,419	946	9.1	−313	−33.1	−2.8
By Income Group (in 2000)									
Upper-Middle	244,175	26,917	11.0	245,441	26,064	10.6	853	3.3	0.4
Lower-Middle	274,867	29,990	10.9	278,272	30,356	10.9	−367	−1.2	0.0
Low-Income	1,753,884	59,589	3.4	1,757,464	56,776	3.2	2,813	5.0	0.2
Least Developed	278,320	6,801	2.4	279,192	6,939	2.5	−137	−2.0	0.0
By region									
China	759,550	20,508	2.7	760,291	19,067	2.5	1,441	7.6	0.2
India	480,422	23,060	4.8	481,364	21,547	4.5	1,514	7.0	0.3
Indonesia	103,980	5,199	5.0	104,079	4,748	4.6	451	9.5	0.4
Turkey	33,130	2,816	8.5	33,134	2,757	8.3	59	2.1	0.2
Other Middle East	62,404	5,494	8.8	62,964	5,478	8.7	16	0.3	0.1
Other Asia	344,538	23,927	6.9	347,308	24,045	6.9	−118	−0.5	0.0
Asia	1,721,620	75,510	4.4	1,726,177	72,163	4.2	3,347	4.6	0.2
Egypt	29,266	3,131	10.7	29,401	2,929	10.0	202	6.9	0.7
Other Northern Africa	33,560	2,264	6.7	33,722	2,322	6.9	−58	−2.5	−0.1
Nigeria	40,174	1,245	3.1	40,310	1,247	3.1	−2	−0.1	0.0
South Africa	19,914	2,071	10.4	20,066	1,997	10.0	74	3.7	0.4
Other sub-Saharan Africa	174,178	3,164	1.8	174,747	3,387	1.9	−222	−6.6	−0.1
Sub-Saharan Africa	234,266	6,480	2.8	235,123	6,630	2.8	−150	−2.3	−0.1
Africa	296,842	11,870	4.0	297,995	11,876	4.0	−5	0.0	0.0
Pacific Islands	849	60	7.1	903	103	11.4	−43	−41.4	−4.3
Mexico	45,226	5,111	11.3	45,528	5,290	11.6	−180	−3.4	−0.3
Carribbean	16,577	1,545	9.3	17,520	2,304	13.1	−759	−32.9	−3.8
Other Central America	14,499	1,498	10.3	14,833	1,665	11.2	−167	−10.0	−0.9
Central America	76,302	8,154	10.7	77,882	9,259	11.9	−1105	−11.9	−1.2

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Table 4

(Continued)

	Observations in 2000			Counterfactual experiment			Brain drain effect		
	Labour Force ($LF \times 1000$)	Number of skilled workers ($Y \times 1000$)	In % of the labour force ($y = Y/LF$)	Labour Force ($LF' \times 1000$)	Number of skilled workers ($Y' \times 1000$)	In % of the labour force ($y' = Y'/LF'$)	Change in the number of skilled ($Y - Y'$)	Change in % (Y')	Change in the proportion of skilled ($y - y'$)
Brazil	87,063	7,313	8.4	87,215	6,688	7.7	625	9.3	0.7
Argentina	20,151	3,970	19.7	20,241	3,678	18.2	292	7.9	1.5
Other South America	53,887	7,410	13.8	54,473	7,232	13.3	177	2.5	0.5
South America	161,101	18,693	11.6	161,929	17,598	10.9	1,095	6.2	0.7
Latin America	237,403	26,846	11.3	239,811	26,856	11.2	−10	0.0	0.1
Total	2,272,926	116,495	5.1	2,281,177	113,196	5.0	3,299	2.9	0.2

Source: Own calculations.

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research is needed before policy conclusions can be derived with more confidence. We see three main directions for future empirical research. First and most obviously, panel data over longer time periods are needed to confirm the evidence. Second, it is also important to control for immigrants' age of entry since only people who acquired education in their home country can truly be defined as 'highly skilled emigrants'. And third, the sectorial composition of emigration can be of interest, especially if the brain drain disproportionately affects specific professions (e.g., health professionals, engineers) whose presence at home strongly conditions the productive potential of others.

Appendix: Data Sources

- Data on human capital levels ($H_{a,t}$ and $H_{p,t}$), emigration rates (p_t and $\underline{p}_t$) and total stocks of emigrants (MT_t) are taken from Docquier and Marfouk (2006).
- Data on *GNI* and *GDP per capita,* population size (POP_t) and population density ($DENS_t$), life expectancy at birth (LE_t) and workers' remittances (REM_t) are taken from the World Development Indicators (World Bank, 2005). The *GNI per capita* is measured in US$, using the Atlas method. The *GDP per capita* is measured in constant 2000 US$.
- Data on racial tensions (*RAC*) come from the International Country Risk Guide (1984)
- Regional dummies *SSAD* and *LATD* are according to the commonly used World Bank classification
- Dummies based on poverty rates (*POOR*) are taken from the United Nations. We use the 1900–2003 average proportion of the population living with less than $1 a day.

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