Migration, Human Capital Formation and Growth: an Empirical Investigation*

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Abstract

In this empirical investigation we study the effect of skilled emigration on human capital formation and growth in a sample of developing countries. We find that the migration rate exerts statistically significant effects on both the level and the skill composition of human capital. We also show that these migration-induced changes in the formation of human capital affect the growth performance of sending countries. The sign and the magnitude of these effects are shown to depend on the level of economic development of the sending country. Both the least and the most developed countries in our sample would suffer as a result of an increase in skilled migration, while countries at intermediate stages of development may benefit. Overall, the majority of sending countries are shown to lose from migration, and the losses that accrue to the least developed ones are larger than the benefits for the winners.

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1 Introduction

Over the last decades, a wide range of incentives and institutional mechanisms have been put in place by a growing number of developed countries to attract talented, skilled individuals from developing countries.[1] The direct consequence of such arrangements has been a dramatic modification of the composition of the pool of migrants moving from developing to developed countries. Recent data show that the ratio of international migrants to population in the most developed countries has more than tripled

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[1] A recent review of the debate, including a survey of existing and proposed policies, and of their consequences is offered by ILO (2006).

between 1960 and 2005, and more than doubled since the mid 1980's.[2] Over the last two decades, moreover, the share of highly skilled migrants in the total has raised dramatically. Docquier and Marfouk (2006), for example, estimate that between 1990 and 2000 the number of highly skilled immigrants (i.e., foreign-born workers with tertiary schooling) living in OECD member countries increased by 63.7%, while for unskilled migrants the increase was only 14.4%. Such accelerating *brain drain* is arguably one of the most striking features of globalization.

Whether the flow of skilled migrants from developing to developed countries is a curse or a blessing for sending countries has been a contentious issue among economists for several decades. Recent theoretical work hints at the possibility that migration, by increasing the returns to education, leads to an increase in the accumulation of human capital that may ultimately prove beneficial for sending countries. In support of this view, the International Organization for Migration has recently emphasized the interconnection between migration and education, claiming that *"prospects of working abroad have increased the expected return to additional years of education, and led many people to invest in more schooling"*, moreover – they add – the increase occurs *"especially in occupations in high demand overseas."*(IOM, 2003). Focussing on this last aspect, Di Maria and Stryszowski (2009) argue that since not only the *amount* of skills available to the economy matters, but also their *type*, the possibility of migration – by distorting the incentives to accumulate human capital among potential migrants – may actually slow down the process of economic development in source countries. In this paper, we use this theoretical insight as a stepping stone, and assess empirically the effect of migration on the formation of human capital – both on its level and composition – and on economic growth, in a sample of developing countries. Using a dataset of developing countries for 1990 and 2000, we find evidence that the possibility of migration does indeed affect both the *level* and the *type* of human capital accumulated in sending countries. Furthermore, our results show that both effects depend on the level of development of the sending country. Finally, we show that both the level and the composition of human capital significantly influence the growth rate. We conclude that migration, by affecting the process of skills accumulation has significant impacts on growth. Overall, our estimates imply that more than half the countries for which data are available for a complete assessment suffer because of skilled migration. Both the least and the most advanced countries in our sample show up as losers, while countries with an intermediate level of productivity benefit from skilled migration. The latter's gains, however, are dwarfed by the losses that accrue to some of the least developed countries in our dataset.

The present work relates to the vast literature on the brain drain, which dates back to the 1960's.[3] Early theoretical studies of the brain drain (e.g. Bhagwati and Hamada, 1974; Hamada and Bhagwati, 1975; Rodriguez, 1975; Kwok and Leland, 1982; Miyagiwa, 1991) almost unanimously concluded that the emigration of skilled workers is detri-

[2] In 1960 the ratio was 3.4%. By 1985 it was 4.6%, and reached 9.5% in 2005. Source: *Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, Trends in Total Migrant Stock: The 2005 Revision*, `http://esa.un.org/migration`, last accessed November 17, 2009.

[3] Commander et al. (2004) present an excellent review of this literature. See also the discussions in Beine et al. (2008) and Di Maria and Stryszowski (2009).

mental for sending countries.[4] More recent contributions (Mountford, 1997; Stark et al., 1997, 1998; Vidal, 1998; Beine et al., 2001, for example), instead, emphasize the potential for a *beneficial brain drain* (henceforth BBD), i.e. the possibility that the chance to emigrate may induce more skill creation than skill loss in sending countries.

Until recently, however, the lack of reliable comparative data on international migration by skill level prevented the type of empirical investigation that could test these opposing viewpoints. The seminal contribution of Beine et al. (2001), for example, uses gross migration rates as a proxy for the brain drain. Their findings supporting the BBD hypothesis, therefore, need to be taken with caution. Beine et al. (2003), instead, use the data on migration rates to the US by education levels published by Carrington and Detragiache (1998), and also find empirical support for the existence of a BBD in a cross-section of 50 developing countries. Their regressions, however, show that migration has a negative growth effect in most developing countries. The most accomplished empirical contribution in this field to date, Beine et al. (2008), uses the recent dataset by Docquier and Marfouk (2006) to test for the existence of 'incentive effects' in human capital accumulation, i.e. the positive effect of migration probabilities on human capital accumulation. They conclude that these effects are indeed positive. The authors go on to perform counterfactual simulations and compare the ex-post level of human capital in sending countries with and without migration. Also in this instance their conclusions are not clear-cut, as more than half the countries in their sample suffer from brain drain, rather than benefit from brain gain.

Di Maria and Stryszowski (2009) attempt to reconcile the theoretical literature with this mixed empirical evidence. They start from the observation that certain skills are relatively more valuable, and hence more rewarded, in countries closer to the technological frontier. This is due to the fact that in technologically advanced countries productivity advances are due to innovation, while in less developed ones imitation plays a major role. By allowing for the endogenous accumulation of skills on the part of workers, who base their decision on the relative rewards such skills entail, they show that the possibility of migration distorts the optimal formation of human capital, and hinders economic growth. As this effect is stronger the less developed the sending country, Di Maria and Stryszowski conclude that, when coupled with the evidence of Beine et al. (2008), this provides a potential explanation for the existence of both winners and losers among sending countries.

As an empirical investigation of the mechanism described above, our work is also closely related to the literature studying how the composition of human capital affects growth. While their main contribution focuses on the allocation of talent between entrepreneurship and rent-seeking, the empirical evidence found in Murphy et al. (1991) provides an early example of linking growth to the skill composition of the work force. Iyigun and Owen (1999) build on these findings and show that different ratios of entrepreneurs to professionals are optimal in different phases of economic development. The present paper, however, is closer in spirit to the work of Vandenbussche et al. (2006), who explicitly emphasize the interaction between the skill composition of the

[4]Note that, in contrast to this literature, the seminal work of Grubel and Scott (1966) maintained that skilled emigration would have no net effect on source countries, due to the existence of several positive effects counteracting the negative impacts of the brain drain.

work-force and the distance from the technological frontier in determining a country's growth performance. Their focus is however quite different from ours, given that they discuss secondary vs. tertiary education, do not deal with international migration, and concentrate their empirical efforts on OECD countries.

Finally, the present paper also contributes to the large body of empirical literature on the determinants of economic growth reviewed by Barro and Sala-i-Martin (2004) and Durlauf et al. (2005).

In the next section we describe the conceptual framework underlying our empirical analysis, and detail our empirical specification. We then make use of the data described in Section 3 to obtain the results discussed in Section 4. The significance of these results for the developing countries in the sample are discussed in Section 5. Finally, Section 6 concludes the paper with a summary of the results and some implications for migration policy.

2 Empirical Specification

In this section we present the conceptual framework that underlies our empirical strategy. The analysis involves estimating three equations. The first two refer to the impact of migration on the formation of human capital, and account for both its level and composition. The third equation links human capital to the growth performance of developing countries, specifically allowing for the role played by each country's level of technological sophistication.

Our empirical investigation builds on a rich theoretical literature discussing the consequences of the international migration of skilled individuals for their country of origin. A long theoretical and empirical tradition maintains that human capital, being instrumental to technological change, is good for growth (Nelson and Phelps, 1966; Romer, 1990; Grossman and Helpman, 1991; Barro and Sala-i-Martin, 2004, just to name a few). Skilled emigration, which reduces the level of human capital in sending countries, is thus thought to be detrimental for growth. As mentioned in the introduction, however, a recent strand of research stresses that human capital accumulation – like any other investment decision – hinges upon the incentives faced by the agents. When the possibility of working and earning higher wages abroad increases the expected returns to skills accumulation, a larger share of the population invests in education and contributes to the accumulation of human capital. Since migration is uncertain some of this skills remain in the country of origin and may lead to a *brain gain*. Under appropriate conditions (See, for example, Stark et al., 1998, p. 365) such *gain* more than compensates for the *drain* and migration is good for growth.

On the basis of this literature, our first equation studies the effect of migration on human capital accumulation. The relevant definition of human capital in this case is one that considers not only the residents in the sending country, but also skilled natives who eventually work abroad. We denote this pre-migration, or *ex-ante*, measure of human capital as H_a, where the subscript indicates its gross nature. Our empirical specification builds on Beine et al. (2008), and is given by

$$\begin{aligned}\Delta \ln(H_{a,00-90}) = \alpha_0 + \alpha_1 \ln(H_{a,90}) + \alpha_2 \ln(mig_{h,90}) + \alpha_3 \ln(proxim_{90}) * \ln(mig_{h,90}) \\ + \alpha_4 dens_{90} + \alpha_5 \ln(pub\_edu_{90}) + \alpha_6 rem_{90} + \alpha_7 SSA + \alpha_8 LAT + \varepsilon. \qquad (1)\end{aligned}$$

The dependent variable, $\Delta \ln H_a = \ln(H_{a,00}) - \ln(H_{a,90})$, is the growth rate of the *ex-ante* stock of human capital between 1990 and 2000. We use the stock of human capital at the beginning of the period, $H_{a,90}$, to control for possible catching-up effects across countries in the proportion of tertiary educated workers out of total working age population before migration. The migration rate of tertiary educated individuals in 1990, $mig_{h,90}$, captures the incentive effects discussed above. To control for potential non-linear effects of migration at different level of economic development of the source country, we include the interaction term $\ln(proxim_{90}) * \ln(mig_{h,90})$ in some of our regressions, where $proxim_{90}$ is the proximity of the country to the world technological frontier, which we use to proxy for the country's level of development.[5] Population density in 1990, $dens_{90}$, is used as a proxy for the cost of acquiring education; *a priori* one would expect that the higher the population density, the smaller the average distance from schools, the lower the cost of education. Additionally, we introduce public spending on education in 1990, pub_edu_{90}, to better proxy for the cost of acquiring education, and to control for the quality of higher education.[6] rem_{90} is workers' remittances in 1990, a control for return migration and alleviated credit constraints on human capital investment. Finally, SSA and LAT are regional dummies for Sub-Saharan Africa and Latin America, respectively, as defined by the World Bank.

The analysis of this level effect, however, is only part of the story. As mentioned in the introduction, the possibility that certain skills are more demanded – and more rewarded – in destination countries adds another layer of complexity to the analysis of human capital formation under migration. Our second equation is thus an empirical test of the theoretical prediction that the possibility for migration distorts the composition of human capital in the source country, and that this distortional effect depends on its distance from the technological frontier.

Ideally, we would like to use data on migration rates of tertiary educated natives by field of study. Such data are unfortunately unavailable, and we can only use migration rates by educational level. We thus have to assume that all tertiary educated workers face the same migration rate.[7] This implies that the *ex-ante* and *ex-post* skill composition of human capital is the same; it also simplifies notation as we don't need to introduce subscripts to distinguish between gross and net variables. Furthermore, due to lack of data we use the proportion of *enrollment* in tertiary education with scientific and

[5] Details on how this variable is constructed can be found in Section 3.

[6] Beine et al. (2008) do not include this variable because of its high correlation with the initial level of human capital in their sample. In our sample, however, the pairwise correlation between the log of initial human capital and the log of the public expenditure on education as a percentage of GDP is fairly small (0.288), and we include both variables. The exclusion of this expenditure on education indicator, however, doesn't change our qualitative results.

[7] Note that the main conclusion of Di Maria and Stryszowski (2009) – that the distortional effect of migration possibilities slows down growth in sending countries – doesn't hinge upon the migration rates being different across skill types. It is, however, true that the distortions are strongest when the migration probabilities differ for different types of skills. As a consequence, our analysis might underestimate the distortionary effect of migration.

technical major, $S\&T$, as a proxy for the proportion of science and technology graduates in the stock of skilled workers. While this is a limitation for our growth regressions below, it is clear that enrollment is indeed the correct point of analysis to identify the incentive effects of migration on the composition of human capital, since enrollment reacts to work prospects much faster than the stock of university graduates.

We model the empirical relation linking the composition of human capital (before migration) to the migration rate of skilled workers as

$$\begin{aligned} S\&T_t =& \beta_0 + \beta_1 mig_{h,t} + \beta_2 \ln(proxim_t) + \beta_3 \ln(proxim_t) * mig_{h,t} \\ &+ \beta_3 SSA + \beta_5 LAT + \upsilon_t, \end{aligned} \tag{2}$$

where the variables $S\&T_t$, $mig_{h,t}$, $proxim_t$, SSA, and LAT have all been defined above and are measured at time t. Notice that, once again, to capture the impact of the distance to frontier we include an interaction term, $proxim_t * mig_{h,t}$, which allows for different effects of migration on the composition of human capital at different stages of development.

The last step in our empirical endeavor is to gauge the significance that changes in human capital formation due to migration may have on economic growth. To this end, we study the effect of both the level and composition of human capital on the growth rate of GDP per capita. Here we build upon the empirical growth model of Vandenbussche et al. (2006) who study the effect of human capital on growth as a function of the country's technological development. While the aim of Vandenbussche et al. (2006) is rather different from ours, their model is well suited to study the hypothesis that different compositions of human capital are better for growth at different stages of development.

The empirical relation between the level and composition of human capital and growth is given by the following equation:

$$\begin{aligned} \Delta GDP_{pc,00-05} =& \gamma_0 + \gamma_1 \ln(GDP_{pc,80}) + \gamma_2 H_{p,00} + \gamma_3 proxim_{00} * H_{p,00} + \gamma_4 \ln S\&T_{90} \\ &+ \gamma_5 proxim_{00} * \ln(S\&T_{90}) + \gamma_6 SSA + \gamma_7 LAT + \nu. \end{aligned} \tag{3}$$

The dependent variable, $GDP_{pc,00-05}$ is the average annual growth rate of GDP per capita between 2000 and 2005.[8] $GDP_{pc,80}$ is GDP per capita in 1980; this control is added to capture convergence effects. $H_{p,00}$ is the level of human capital after migration (*ex-post*) in 2000. $S\&T$, the proportion of enrollment in tertiary education with technical and science specialty, is used here to proxy for the proportion of the stock of workers in the labor market with the same characteristics. Since changes in enrollment only gradually manifest themselves as corresponding changes in the stock, in this equation we use a 10-year-lag for this variable. $proxim_{00} * H_{p,00}$ and $proxim_{00} * \ln(S\&T_{90})$ are interaction terms that are included to allow for the possibility that the level and composition of human capital have different effects on growth, depending on the country's distance from the technological frontier. Finally, SSA and LAT are the country group dummies described above.

[8] As customary in the literature, we use five-year-period averages for the growth rate, as this reduces the risk of capturing business cycle effects.

3 Data description

The data set needed to estimate equations (1)-(3) is constructed from three different sources. Data on the level of human capital and migration is taken from the data set on international migration by educational attainment constructed by Docquier and Marfouk (2006) and used by Beine et al. (2008).[9] The data set contains the following information for 203 source countries: the emigration rate of working-age individuals towards the 27 OECD countries, by educational level; the stock of working-age emigrants in OECD countries, by educational level; the stock of working-age residents, by educational level. We define mig_h as the emigration rate of working-age individuals with tertiary education to OECD countries. Focusing the attention only to the OECD countries is clearly a limitation of the data, however, since about 90% of all high-skilled emigration is towards the OECD, the emigration rate in the Docquier and Marfouk (2006) data is a good proxy for the overall high-skilled emigration rate.[10] Following Beine et al. (2008), we define the level of human capital before migration, H_a, as the ratio of working-age nationals with tertiary education (i.e working-age residents with tertiary education plus the working-age stock of emigrants with tertiary education) to the total working-age nationals (that is the total number of working-age residents plus working-age emigrants). The corresponding *ex-post* variable, H_p, is instead defined as the proportion of working-age residents with tertiary education divided by the total number of working-age residents. In our estimations we will also use the total stock of working-age emigrants from a country to the OECD, ms_{tot}, and the stock of working-age emigrants with secondary education, ms_{sec}, to instrument for the skilled migration rate. These data are available for all countries in the dataset, with a few exceptions, for 1990 and 2000.

We exclude from our analysis twenty-nine countries which are considered 'immigration-receiving'.[11] We further remove from the sample the former socialist countries since human capital formation in these countries in the early 1990's was severely affected by the transition from a centrally-planned to a market-driven economy.

Data on the composition of human capital is taken from the UNESCO Education Statistics. We define $S\&T$ to be the proportion of students enrolled in science and technology out of total enrollment in tertiary education. Data are available for 1970, 1980, 1985, 1990, 1995, 1996, and 1997. Due to the great number of missing values in the series, however, we take values in 1985 and 1980 to represent the values in 1990 when these are missing. To match the composition of human capital data with the Docquier and Marfouk data, we take the most recent values (1997) to represent $S\&T$ in 2000. If missing, we use the 1996 or 1995 values as available. In this way we

[9] We refer the interested reader to these sources for a comprehensive description of the data and for discussions of the data collection techniques.

[10] See Docquier and Marfouk (2006) and Beine et al. (2008) for more detailed discussions on this issue.

[11] This traditional immigration countries are: Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, the Republic of Korea, Luxembourg, Malta, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Our choice mirrors a similar strategy pursued by Ivlevs and de Melo (2008).

construct data on $S\&T$ for 83 countries in 1990, and 46 countries in 2000.

The remainder of the variables are taken from the World Development Indicators (World Bank, 2009). We take GDP in constant 2000 US dollars and divide it by total population to construct GDP per capita, GDP_{pc}. The dependent variable of the growth regression, $\Delta GDP_{pc,00-05}$, is constructed as the average annual growth rate of GDP per capita between 2000 and 2005. From this database we also use as controls remittances as a percentage of GDP, *rem*, population density, *dens*, and total public spending on education as a percentage of GDP, *pub_edu*. In addition, as instruments for migration and proximity to the technological frontier, we use total population, *pop*, the percentage of paved roads in the total, *roads*, and the difference in GDP per capita between each country and the US, *GDP_diff*.

We construct the indicator of proximity to the frontier, *proxim*, as the ratio of the total factor productivity (TFP) of country i to that of the US. We calculate TFP as the log of output per worker, minus the log of capital per worker times the capital share which we take to be constant and equal to 0.3.[12] To construct the capital stock series, we follow Vandenbussche et al. (2006), and use a perpetual inventory method with a 6% depreciation rate. As capital investment, we take gross capital formation in constant 2000 US dollar, $I_{i,t}$. Thus, the initial level of capital for country i, $K_{i,0}$ is given by:

$$K_{i,0} = \frac{I_{i,1}}{g_i + 0.06},$$

where $I_{i,1}$ is the earliest available data on gross capital formation for country i; and g_i is the growth rate of GDP of country i in the period from the earliest till the latest date of available data on gross capital formation.[13]

Table 1: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Max
H_a	262	0.0770	0.0648	0.0014	0.2781
H_p	262	0.0589	0.0529	0	0.2240
$S\&T$	129	0.3716	0.1640	0	0.7581
mig_h	262	0.2383	0.2515	0.0017	0.9673
$proxim$	239	0.7030	0.1134	0.4700	0.9674
$\Delta GDP_{pc,00-05}$	239	0.0143	0.0371	-0.2556	0.2045

Table 1 shows summary statistics for the main variables used in the empirical analysis. One can see that the average percentage of tertiary educated working age residents is 7.8% prior to migration, 5.9% after it, and that both variables have a relatively high dispersion around the mean. Among the countries with the highest level of human capital before migration are Antigua and Barbuda, and St. Kitts and Nevis. After migration, the highest level of tertiary educated workers are in Peru and the Philippines.

[12]This assumption is quite common in the literature given the lack of appropriate data on labour shares. Vandenbussche et al. (2006) make a similar assumption, as does Topel (1999).

[13]Our series on gross capital formation starts in 1960. Due to missing observations, however, the earliest available data for some countries can be as late as the 1980's.

The lowest level of human capital before migration is found in Mozambique, while after migration the countries with the lowest level of human capital are the Gambia, Kiribati, and Samoa. In our dataset, Dominica has the highest $S\&T$ share. Djiboouti, Seychelles, Lao, and Brunei have the lowest percentage of science and technology students. The mean percentage of science and technology enrollment in tertiary education is 37%. Countries also vary greatly in terms of the migration rate of the highly skilled: the average value is 23.8%, the maximum 96.7% (Samoa), and the minimum 0.17% (Swaziland). The average proximity to the technological frontier of 0.70, where value 1 indicates that a country is at the frontier. The country which is closest to the frontier in our sample is Brunei, the one furthest away from it is Malawi. The average annual growth rate for 2000-2005 was 1.4%, but the sample reflects a wide range of experiences.

4 Results

In this section we discuss the econometric estimation of the regression models specified in Section 2. We begin with the human capital accumulation equation in (1).

4.1 Migration and the level of human capital

Equation (1) is intended to gauge whether the possibility of migration – proxied by the historical propensity of tertiary educated workers to migrate – has an impact on the *level* of human capital accumulated in the economy.

As a benchmark we take the model studied by Beine et al. (2008). In columns [1] and [2] of Table 2 we present the results from an OLS and IV estimations of this model, respectively. As the accumulation of human capital and the migration rate may be simultaneously determined – a higher level of human capital may induce higher migration rate due to a reduction in the skill premium on the local labor market compared to foreign ones, for example – we are concerned with the endogeneity of the migration rate in equation (1). Of the various instruments suggested in the literature (Barro and Sala-i-Martin, 2004; Hall and Jones, 1999) such as the country's population size, the initial stock of emigrants, life expectancy at birth, various indices of social unrest and racial tensions, and the per capita GDP, Beine et al. (2008) advocate the use of only the first two, either because the others are very highly correlated with the initial level of human capital or because of the insufficient number of observations. In our analysis, in addition to these two instruments, we also use the difference between the country's GDP per capita and the corresponding US level to proxy for wage differentials. These three instruments pass the Stock and Yogo test for weak instruments (Stock and Yogo, 2005) with an F-statistics equal to 196.32, which is much higher than the critical value of 22.3 for one endogenous variable and three instruments. As reported in Table 2, the instruments also pass the J test for over-identifying restrictions as the p-value of the J-test is higher than 0.1.

The estimate of the effect of the migration rate on skill formation that we obtain has comparable magnitude to the results in Beine et al. (2008): a 1 percent increase in the migration rate of high-skilled workers increases the growth rate of the share of high-skilled workers by about 0.05 percentage points in both specifications. We also find evidence of convergence in human capital levels among countries in the sample, as the initial level of human capital has a statistically significant negative coefficient. According to our estimates, neither public spending on education (*pub_edu*) nor workers' remittances (*remit*) has a statistically significant effect in either regression. The same holds for the Latin America dummy variable (*LAT*). In fact, a test on the joint significance of these variables indicates that they can be excluded from the model as a group (p-value of 0.5245 in the OLS, and 0.7406 in the IV regression). The coefficient of population density (*dens*), which is insignificant in the OLS regression, becomes significant at the 5% in the IV estimation. The sign of the coefficient, however, is negative. This is contrary to what one would expect assuming that this variable captures accessibility to higher education. The negative sign, instead, is consistent with a Malthusian interpretation of *dens* as a proxy for social conflict and environmental pressure (see Malthus, 1798, and more recently Urdal, 2005).

A comparison of the OLS and IV results reveals that the two estimates are quite similar: with the exception of the significance of $dens_{90}$ all regressors have comparable size of coefficients and the same level of significance under both OLS and IV. In fact the Durbin-Wu-Hausman (DWH) test for the endogeneity of the migration rate indicates that we cannot reject the null hypothesis that it is exogenous.

Next we extend the benchmark model to add an interaction term between the migration rate and the proximity to technological frontier of a country. In this way we want to assess whether the possibility for migration affects the accumulation of human capital differently at different stages of technological development. Column [3] in Table 2 presents the result of the OLS regression for this model.[14]

The empirical findings lend support to the proposition that the effect of the possibility for migration on the level of human capital does depend on the country's proximity to the technological frontier. In particular, our results show that the positive effect[15] of migration on human capital accumulation only works via the interaction term, and that this effect is stronger the further countries are from the technological frontier.[16] This effect fades as the frontier is approached, and eventually vanishes once the frontier is reached.

Compared to the benchmark model, the estimates of the coefficient of *remit* is now significant, larger in magnitude, and with the expected positive sign. The statistically

[14] Given the results of the DHW test above, and the robustness of the results across specifications, and for the sake of brevity we only present the OLS estimates. We also ran an IV specification for this extended model using as instruments for the migration rate and the interaction term the logarithm of the difference between the country's GDP per capita and the US level, the logarithm of the population size and the interaction terms between the logarithm of population and GDP, and the proportion of paved roads with the initial stock of emigrants. The results discussed below are once again robust across models. The full output of this procedure is available from the authors upon request.

[15] Notice that as *proxim* is a variable between 0 and 1, its natural logarithm, $\ln(proxim)$, is negative.

[16] To ensure that the lack of significance of the coefficient of $\ln(mig_h)$ is not due to the reduced sample in [3] relative to [1] and [2], we estimate both the OLS and IV regressions of the benchmark models in [1] and [2] using the same sample with which model [3] is estimated. In both cases $\ln(mig_h)$ retains significance at the 5% level. We can thus conclude that the results are robust.

Table 2: Level of Human Capital – dependent variable $\Delta \ln H_{a,00-90}$

Variable	[1]	[2]	[3]	[4]
$\ln(H_{a,90})$	-0.2462	-0.2456	-0.2095	-0.1985
	(0.0596)***	(0.0609)***	(0.0291)***	(0.0271)***
$\ln(mig_{h,90})$	0.0478	0.0537	-0.0352	–
	(0.0193)**	(0.0214)**	(0.0426)	–
$\ln(proxim_{90}) * \ln(mig_{h,90})$	–	–	-0.2471	-0.1795
	–	–	(0.0958)**	(0.4594)***
$dens_{90}$	-0.0002	-0.0005	-0.0004	-0.0005
	(0.0002)	(0.0002)**	(0.0002)**	(0.0002)**
$\ln(pub\_edu_{90})$	0.0595	0.0552	-0.0498	-0.0375
	(0.0416)	(0.0524)	(0.0636)	(0.0635)
$remit_{90}$	0.0007	0.0038	0.0294	0.0292
	(0.0020)	(0.0062)	(0.0154)*	(0.0157)*
SSA	-0.3423	-0.3608	-0.2339	-0.2348
	(0.1258)***	(0.1262)***	(0.0697)***	(0.0675)***
LAT	0.0066	0.0125	-0.0710	-0.0611
	(0.0465)	(0.0508)	(0.0656)	(0.0654)
Constant	-0.2052	-0.1751	-0.0068	0.0449
	(0.1484)	(0.1840)	(0.1572)	(0.1493)
Obs.	82	76	55	55
R^2	0.4926	–	0.6182	0.6112
J-test	–	0.4868	–	–
DWH-test	–	0.654	–	–

Notes: Columns [1], [3], and [4] present OLS estimates, while column [2] presents IV estimates. Heteroskedasticity-robust standard errors are reported in parenthesis. ***, **, and *, indicate significance at 1%, 5%, and 10%, respectively. For the J and DWH tests, p-values are reported.

significant effect of population density found in the IV estimate of the benchmark model carries over to the OLS estimate of the extended model.

Column [4] of Table 2 presents a version of the extended model where the skilled migration rate has been dropped from the estimation. We will use these estimates in Section 5 below, when we discuss the effect of migration on growth via its effect on the accumulation of human capital.

4.2 Migration and the composition of human capital

Estimating equation (2) we find evidence that the possibility of migration has a statistically significant impact on the *composition* of human capital (See Table 3). In particular, our results show that a higher rate of skilled migration affects the proportion of students in tertiary education who enroll in science and technology majors. Furthermore, we find evidence that the sign of this effect depends on the country's level of development. In countries further away from the technological frontier, for which *proxim* is lower than 0.57, the effect is negative, while for those above this threshold the effect is positive.[17] Thus, in countries at relatively low levels of development the possibility of migration reduces the enrollment in science and technology specialties, compared to a situation in which no emigration is allowed. The opposite occurs in relatively more developed countries. The result complies with our intuition: science and technology skills are arguably more prone to obsolescence than other types of skills, and may be deemed less marketable abroad if acquired in countries that lag far away from the frontier; thus, students in the least developed countries would be more inclined to acquire other skills, studying arts and humanities, for example, in view of migration. On the other hand, emigration is generally believed to be easier for science and technology graduates, provided of course that their skills are current, hence our result for relatively more developed countries.[18]

Table 3: Composition of Human Capital – dependent variable: $S\&T$

Variable	**OLS**		**IV**	
	Coeff.	**Std. Error**	**Coeff.**	**Std. Error**
$mig_{h,90}$	0.3783	(0.1387)***	0.8895	(0.2701)***
$\ln(proxim_{90})$	-0.2627	(0.1284)**	-0.6169	(0.3011)**
$\ln(proxim_{90}) * mig_{h,90}$	0.6753	(0.3699)*	2.4334	(1.1831)**
SSA	-0.0607	(0.0383)	-0.0548	(0.0557)
LAT	0.0779	(0.0368)**	0.1032	(0.0432)**
Constant	0.2726	(0.0495)***	0.1481	(0.0833)*
Obs.	98		76	
R^2	0.1463		–	
J-test	–		0.3206	
DWH-test	–		0.2671	

Notes: Heteroskedasticity-robust standard errors are reported. ***, **, and *, indicate significance at 1%, 5%, and 10%, respectively. For the J and DWH-tests, the p-values are reported.

Proximity to the technological frontier also directly affects the composition of enrollment in tertiary education in a statistically significant way. The direction of this effect depends on the migration rate: for countries with a migration rate higher than 39%, approaching the frontier has a positive effect on the share of enrollment in $S\&T$; for countries with a migration rate below that threshold, being closer to the frontier has the opposite effect. We believe these results to be consistent with an interpretation focussed on two mechanisms. First, as countries move closer to the frontier, workers'

[17] In our sample there are sixteen countries which fall below this threshold, including Burkina Faso, Central African Republic, Ethiopia, and Madagascar.

[18] Abella (2006) discusses policies implemented by several OECD countries involved in the on-going international "competition for global talent". Point systems, temporary admissions under skill-based categories (e.g. H-1B visas), and facilitation of family migration for specific categories of workers have all been used to favour workers in the field of science and technology, markedly health professionals, geneticists and IT specialists.

incentives to acquire $S\&T$ skills may decrease if complementarities across skills become more pronounced, and a broader variety of skills are demanded. It has been suggested that this is indeed what happens when countries complete the transition from being mere imitators of foreign technologies, a phase in which a high share of technically inclined graduates is preferable, to being properly innovative, when a wider range of skills become necessary (Feinstein, 2006; Yusuf, 2007). This view implies that the $S\&T$ share should decline as proximity increases. Second, as migration becomes easier, a larger proportion of workers actively seek jobs abroad. Since most destination countries favour technically skilled immigrants, investing in $S\&T$ skills equips potential migrants with competencies that are in high demand overseas (provided that the country is advanced enough). This latter mechanism is more prominent in high emigration countries. The interplay between these two mechanisms explains our results above: at low levels of migration the former effect dominates, while for higher levels of migration it is the latter effect that has the stronger impact.

Once again we are concerned with the endogeneity of the migration rate and the proximity to the technological frontier due to simultaneous causality. With respect to the migration rate, we have already argued that the possibility for migration might motivate individuals to acquire certain types of skills that would make them more employable abroad. The reverse causality then implies that the high migration rate is driven by more workers having acquired skills which are in high demand abroad. Similarly, proximity to the technological frontier determines $S\&T$ as different types of human capital are demanded at different stages of development, e.g. imitation-facilitating versus innovation-facilitating. On the other hand, the composition of human capital determines the proximity to the frontier as development depends on the suitability of the acquired skills by workers for the current stage of development. Barro and Sala-i-Martin (2004) and Temple (1999) discuss the merits of using past values of the endogenous variables as instruments in growth regressions. Such instruments, however, are not available in our case due to the large number of missing observations.[19] Instead, to instrument for proximity, we use the logarithm of GDP per capita as a proxy for wealth, and the logarithm of the percentage of paved roads as a proxy for the quality of infrastructures. The migration rate, similarly to what we have done in the previous section, is instrumented by the difference between the logarithm of GDP per capita between each country and the US, the logarithm of the population size, and the logarithm of the stock of emigrants in the OECD countries with secondary education. The interaction term between the migration rate and proximity is instrumented by the interactions between the logarithm of stock of emigrant with secondary education and GDP per capita, and the logarithm of the population size and GDP per capita. Using these instruments we obtain the results presented in the last two columns of Table 3. The number of observations drops from 98 to 76 compared to the OLS due to missing values.[20] The set of instruments passes the tests for validity. In terms of the tests for relevance, the F-statistics equal to 11.62, 287.44, and 59.81 for the $mig_{h,90}$, $\ln(proxim_{90})$, and $\ln(proxim_{90}) * mig_{h,90}$ equations, respectively. As the critical values

[19]If we were to use lagged values as instruments, the regression model would have to be estimated with only 35 observations.

[20]Note that the OLS results are robust to estimation with the reduced sample used to obtain the IV estimates.

for three endogenous variables are not tabulated by Stock and Yogo (2005), we use those for two endogenous variables and seven instruments.[21] All the statistics exceed the critical value of 9.77 for 5% significance level and 20% maximal size. Furthermore, the instruments pass the test for exogeneity given a p-value for the J-test higher than 0.1.

Comparing the IV estimates with the OLS ones, we do not observe significant differences in terms of statistical significance: only the interaction term and the constant change their level of significance; with the former now significant at the 5%, while the latter's significance level is somewhat reduced. The differences in magnitude of the coefficients between the two estimators are more notable. According to the IV regression, the threshold for the reversal in the sign of the effect of migration is now 0.69 as compared to 0.57 obtained by OLS. The migration rate threshold above which the proximity to the frontier has a positive effect on $S\&T$ falls from 0.39 to 0.25. These differences, however, are not statistically significant as the DWH-test for endogeneity indicates that we cannot reject the null hypothesis that the three variables taken as a group are exogenous. Due to the relatively higher statistical significance of the coefficients in the IV regression, we will use these results in Section 5 when assessing how emigration affects growth via its distorting effect on the composition of human capital.

4.3 Human capital and growth

Last, we turn to the empirical evidence on the effect of human capital on growth summarized in Table 4. Our first regression, marked by [1] in Table 4, estimates equation (3) excluding $S\&T$ and its interaction with our measure of proximity. This benchmark replicates for a sample of developing countries the regressions in Vandenbussche et al. (2006) who perform similar regressions for OECD countries. Vandenbussche et al. (2006) estimate a threshold in terms of the country's proximity to frontier above which the level of human capital has a positive effect on total factor productivity growth. Below that threshold the effect is instead negative. In the various specifications of their model, the threshold ranges from 0.67 to 0.85. As shown in the first two columns of Table 4, we find that for countries close to the frontier (i.e. such that $proxim > 0.76$) an increase in the level of human capital has a positive effect on growth, while for those further away from the frontier a marginal increase in the level of human capital has a negative effect on growth.[22] We further test whether this threshold is statistically smaller than 1, and our test leads us to reject the null that instead the sign reversal occur at the frontier at the 10% (F-test=2.18, p-value=0.078). Due to the limitations of the data on capital investment, we cannot capture convergence by using the initial level of proximity as done by Vandenbussche et al. (2006), instead we control for initial conditions, using the logarithm of GDP per capita in 1980. We obtain the expected

[21] Since the critical values tabulated by Stock and Yogo (2005) decrease with the number of endogenous variables, by taking the critical values for two endogenous variables to represent those for three, we impose a more stringent requirement on our instruments.

[22] As a robustness check we also estimate the model using the interaction between the logarithm of proximity and the level of human capital. The threshold value using that model is a bit higher and equals 0.81. We prefer the specification presented in Table 4 because of the higher level of statistical significance of most regressors.

negative and statistically significant coefficient.

To assess the overall impact of human capital on growth, we next add the composition of human capital and its interaction with the proximity variable to the benchmark regression discussed above. The results of the extended regression model are presented in the last two columns of Table 4. Both the direct and indirect effect (through the interaction term) of $S\&T$ are statistically significant at the 1% level. The results indicate that a threshold exists in terms of proximity in the effect of skills composition on growth: countries with severe TFP lags would benefit from an increase in the relative number of graduates enrolling in science and technology specialties, while the opposite holds for countries whose technological gaps are smaller. Out of the 57 countries on which our estimation is based, 49 have proximity level below 0.84 – the estimated threshold level – and would hence benefit from an increase in $S\&T$. The countries in the sample above this threshold level are Argentina, Chile, Kuwait, Mexico, Saudi Arabia, Trinidad and Tobago, United Arab Emirates, and Uruguay. Admittedly, the estimated threshold level is just a point estimate to which we can attach a confidence interval. Our results show that we cannot reject the hypothesis that the threshold equals 1 (i.e. the point at the technological frontier).[23] These findings seem to support the claims discussed above that closer to the technological frontier too high a concentration on science and technology skills may be suboptimal, as opposed to the early stages of development where technology is improved by imitation only, rather than by *bona fide* innovation.

In the extended regression, the effect of the level of human capital becomes statistically insignificant at conventional levels (the p-values are 0.26 and 0.29 for the level and the interaction term, respectively), but several reasons seem to indicate that this effect should still be taken into account. In the first place, the coefficients differ little between regressions [1] and [2], and the estimated threshold for the level of human capital increases only slightly from 0.76 to 0.79, adding to our feeling that this result is rather robust across specifications. Moreover, using the sub-sample of countries for which we can estimate the second regression to estimate the model in [1], we obtain coefficients very close to those in [2], and the statistical significants improves only slightly (p-values of 0.21 and 0.26, respectively). Based on this evidence, we believe that the limited sample size due to the lack of data for $S\&T$ (only 57 data points for 1990) explains the low significance of the level effect, while the fact that the coefficients change little across specifications gives us some confidence as to the economic significance of the level effect.

5 Migration, human capital formation and growth

The results derived in the preceding section allow us to discuss the impact of skilled migration on growth in sending countries. We have identified two channels through which this effect takes shape, on the one hand the *level effect* operates via changes in the level of human capital accumulated due to migration; on the other, changes in the

[23] The test that the coefficient of $\ln(S\&T)$ plus the coefficient of $proxim * \ln(S\&T)$ equal 0 yields a p-value of 0.2922.

Table 4: Growth regression – dependent variable: $\Delta GDP_{pc,00-05}$

	[1]		[2]	
Variable	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
$\ln GDP_{pc,80}$	-0.0070	(0.0032)**	-0.0159	(0.0081)**
$H_{p,00}$	-0.5461	(0.3150)*	-0.5186	(0.4512)
$proxim_{00} * H_{p,00}$	0.7116	(0.4160)*	0.6543	(0.6118)
$\ln S\&T_{90}$	–	–	0.0999	(0.0288)***
$proxim_{00} * \ln S\&T_{90}$	–	–	-0.1186	(0.0444)*
SSA	-0.0252	(0.0103)**	-0.0166	(0.0084)**
Constant	-0.1495	(0.0451)***	0.1547	(0.0503)***
Obs.	141		57	
R^2	0.2114		0.3828	

Notes: Heteroskedasticity-robust standard errors are reported. ***, **, and *, indicate significance at 1%, 5%, and 10%, respectively.

composition of skills affect growth performances in economically significant ways via the *composition effect*. The sign and the magnitude of both effects also depend on the relative level of development of the sending country, as proxied by its TFP relative to that of the US.

Formally, differentiating (3) we can write:

$$\frac{\partial \Delta GDP_{pc,00-05}}{\partial mig_{h,90}} = \underbrace{(\gamma_2 + \gamma_3 proxim_{00})\frac{\partial H_{p,00}}{\partial mig_{h,90}}}_{\textit{level effect}} + \underbrace{\frac{1}{S\&T_{90}}(\gamma_4 + \gamma_5 proxim_{00})\frac{\partial S\&T_{90}}{\partial mig_{h,90}}}_{\textit{composition effect}}. \tag{4}$$

Using the parameter estimates obtained from the extended model of Table 4, the term in parenthesis in the level effect component is positive if the proximity indicator exceeds 0.79, negative otherwise. This indicates that countries close to the frontier would benefit from more tertiary educated workers. Whether (*ex-post*) human capital accumulation is encouraged by migration, however, depends on the impact of the migration rate on the *ex-ante* accumulation, the skilled migration rate, and the migration rate for 'unskilled' workers (i.e. those without tertiary education). To see this, we need to rewrite the partial derivative of H_p with respect to the skilled migration rate in a more informative way. First, notice that the *ex-ante* and *ex-post* measures of human capital are linked by the following relationship:

$$H_{p,t} \equiv \frac{(1 - mig_{h,t})H_{a,t}}{1 - mig_{h,t}H_a - mig_{o,t}(1 - H_{a,t})}, \tag{5}$$

where mig_o is the migration rate of unskilled workers. Using (5), we can write the partial derivative of ex-post human capital with respect to the skilled migration rate as follows[24]

$$\frac{\partial H_{p,00}}{\partial mig_{h,90}} = \frac{(1-mig_{h,00})(1-mig_{o,00})}{[1-mig_{h,00}H_a - mig_{o,00}(1-H_{a,00})]^2}\frac{\partial H_{a,00}}{\partial mig_{h,90}} - \frac{H_{a,00}(1-H_{a,00}(1-mig_{o,00})}{[1-mig_{h,00}H_{a,00} - mig_{o,00}(1-H_{a,00})]^2}. \quad (6)$$

This expression informs us that, even if the level effect on the *ex-ante* human capital is positive, the final – post migration – effect might well be negative. From our discussion in Section 4.1, we know that the rate at which (gross) skills are accumulated increases with the rate of migration, and that this effect vanishes as the frontier is approached. Thus, $\partial H_a/\partial mig_h$ tends to zero for the relatively more developed countries. Accordingly, equation (6) implies that a higher migration rate leads to a lower level of *ex-post* human capital for the most developed among the sending countries. While it is in general not possible to identify a threshold in terms of proximity above which the contribution of skilled migration to growth via the level effect becomes negative, it is clear that the sign of the level effect impinges on the relative sizes of the migration rates. In particular, the higher the skilled migration rate, and the lower the migration rate of unskilled workers, the more likely it is that positive changes in H_a lead to reductions in the level of human capital available post migration.

Using (1), it is straightforward to derive a computable expression for $\partial H_{a,00}/\partial mig_{h,90}$ in (6):

$$\frac{\partial H_{a,00}}{\partial mig_{h,90}} = e^{\alpha_0+(1+\alpha_1)\ln(H_{a,90})+\ldots+\alpha_8 LAT}\left(\frac{\alpha_2+\alpha_3\ln(proxim)}{mig_{h,90}}\right).$$

The estimates from Table 2, column [4], and from Table 4, column [2], allow us to compute the level effect for some of the countries in our dataset. Given data limitations, however, we can estimate this effect for only 40 countries. The second column of Table 5 reports our estimates of the level effect, and Figure 1 provides a visual overview of the results.[25] Out of the 40 countries in the sample, 22 would benefit from a marginal increase in the migration rate via the level effect.

Figure 1 confirms that countries closer to the technological frontier suffer as a result of additional migration via this channel. Argentina, Mexico, Chile, Trinidad and Tobago, and Turkey would all lose from an increase in the migration rate. This is in line with the theoretical literature in that the incentives to increase the accumulation of skills are smaller in countries whose productivity levels (and hence wages) are close to those of the technological leaders. In this case, with little to show in terms of a *brain gain*, increased migration cannot but lead to the most obvious of the drain effects. Most of the severely lagging countries benefit from the level effect, with the exception of Ethiopia and Madagascar. Among the countries with an intermediate

[24] In the derivation of the expression that follows we make two simplifying assumptions. First, we let $\partial mig_{h,00}/\partial mig_{h,90} = 1$, assuming that mig_h exhibits perfect persistence. This leads to overestimating the magnitude of the effect of changes in the rate of skilled migration on the *ex-post* level of human capital, but it doesn't affect the sign of the derivative. Second, in the interest of simplicity and for lack of a better alternative, we assume that the migration rate of unskilled workers doesn't change as mig_h increases.

[25] Notice that, for the sake of graphical clarity we have excluded Swaziland from the graph.

Table 5: Effects of a marginal increase in skilled migration on growth

Country	**Level**	**Comp.**	**Total**
Colombia	0.0014	0.0083	0.0097
Honduras	0.0037	0.0035	0.0073
Egypt	0.0002	0.0069	0.0070
El Salvador	0.0017	0.0052	0.0070
Philippines	0.0058	0.0009	0.0067
Morocco	0.0022	0.0042	0.0065
Mauritius	-0.0004	0.0067	0.0064
Brazil	0.0008	0.0054	0.0062
Dominican Republic	0.0014	0.0046	0.0059
Algeria	0.0011	0.0046	0.0057
Botswana	0.0007	0.0047	0.0054
Iran	0.0026	0.0025	0.0050
Tunisia	0.0009	0.0040	0.0049
Peru	0.0003	0.0041	0.0044
Panama	-0.0017	0.0052	0.0035
Malaysia	-0.0008	0.0041	0.0033
Ecuador	-0.0022	0.0042	0.0020
Costa Rica	-0.0018	0.0029	0.0011
Turkey	-0.0013	0.0006	-0.0007
Chile	-0.0019	-0.0003	-0.0022
Cameroon	0.0013	-0.0045	-0.0032
Sri Lanka	0.0023	-0.0070	-0.0046
Mexico	-0.0034	-0.0014	-0.0048
Argentina	-0.0024	-0.0044	-0.0068
Trinidad and Tobago	-0.0068	-0.0001	-0.0070
Indonesia	-0.0026	-0.0099	-0.0125
Zimbabwe	0.0003	-0.0144	-0.0141
Sudan	-0.0006	-0.0160	-0.0166
China	-0.0064	-0.0180	-0.0244
Guinea	0.0007	-0.0276	-0.0269
Madagascar	-0.0040	-0.0283	-0.0323
Togo	0.0010	-0.0375	-0.0366
Mozambique	0.0004	-0.0388	-0.0383
India	-0.0116	-0.0322	-0.0439
Mali	-0.0001	-0.0546	-0.0547
Lesotho	0.0003	-0.0608	-0.0605
Swaziland	-0.0709	0.0030	-0.0679
Uganda	0.0016	-0.0783	-0.0767
Ethiopia	-0.0028	-0.0840	-0.0868
Malawi	0.0004	-0.2843	-0.2838

level of development our results are more mixed. The largest countries in this group (China, India and Indonesia) would all lose out from a marginal increase in migration. Conversely, in the Philippines an increase in migration would boost growth.

The contribution of migration to growth via the composition effect is more straightforward to analyze. Using the estimates obtained from the extended model in Table 4, we can immediately conclude that the sign of the parenthesis in the composition-effect term in (4) is positive for values of proximity to the frontier below 0.84, negative otherwise. Moreover, it is easy to sign the partial derivative of the composition of enrollment with respect to the skilled migration rate using equation (2), and the results in Table 3. As discussed in Section 4.2, an increase in the rate of skilled migration leads to an increase in the *S&T* ratio in countries that are relatively close to the frontier (i.e. such that *proxim*>0.69), and to a decrease elsewhere. Combining these two observations, we conclude that the composition effect is *negative* both for countries with a proximity value below 0.69, and for those with a value exceeding the 0.84 threshold; the effect

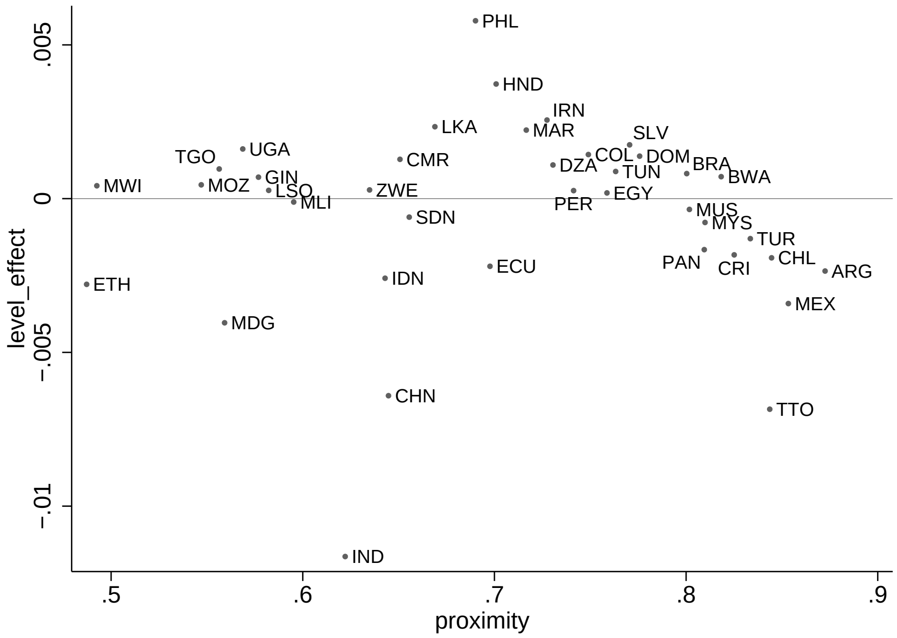

Figure 1: *The level effect*

is positive for countries whose proximity indicator falls between these values (See the third column of Table 5). Thus, a marginal increase in migration is growth reducing for two different groups of countries and for opposite reasons: in the least developed countries, where more $S\&T$ skills would be beneficial for growth (the term in parenthesis is positive), the prospect of easier migration leads to the accumulation of those skills that are more marketable abroad: given the low level of technological sophistication, such skills tend to be of a more humanistic nature. Thus, $S\&T$ falls and the growth performance worsens. In the most developed countries, instead, where a broader range of skills are necessary for innovation and growth, the prospects of migration (and the tendency of destination countries to favour technically skilled migrants – via point systems, for example) induce a stronger specialization of the workforce in technical skills. Once again the direction of skills accumulation is wrong, and growth rates decline as a result.

Our computation of the composition effect in Table 5 underscores two issues: first, the composition effect is larger in magnitude than the level one, for most countries; second, the only countries who benefit from this channel are those with an intermediate distance from the frontier of technology, while least developed countries are shown to suffer greatly from the distortionary impact of migration on the composition of human capital. Several African economies seem to be particularly vulnerable to this mechanism: Ethiopia, Uganda, Lesotho and Mali stand out in this respect. India, China and Indonesia once again show up among the losers. By contrast the gains reaped by the 20 winners are smaller in magnitude.

Figure 2 plots the results of our computations for the total effect of migration on eco-

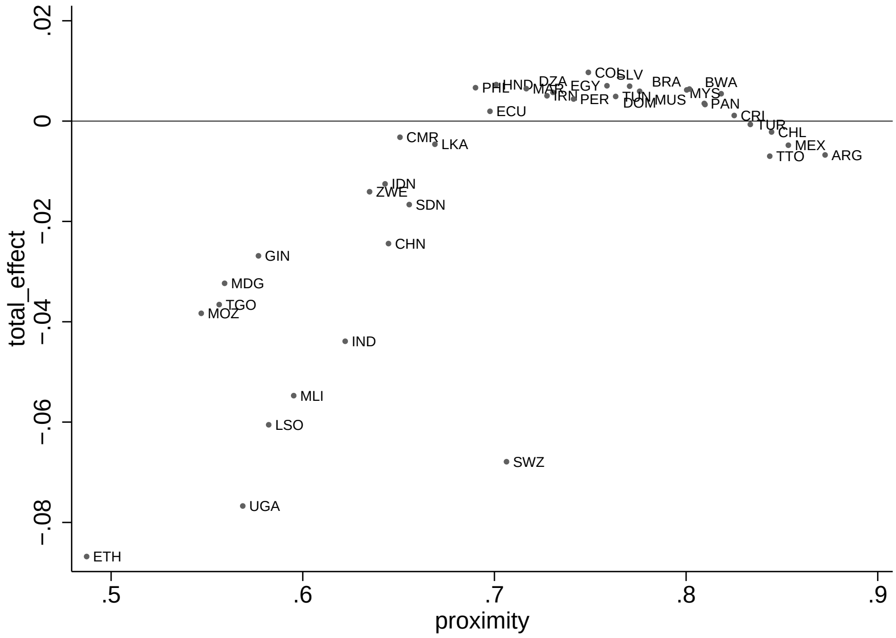

Figure 2: *Effects of migration on growth vs. proximity*

nomic growth (see the last column of Table 5). Three things are worth noticing. First, overall more countries are likely to suffer from an increase in the rate of skilled migration than to benefit from it (22 against 18). These losers include the most populous countries and, as a group, account for 84% of the total population represented in our sample; second, the magnitude of the negative impacts is far larger than that of the positive ones; finally, the largest losses accrue to the least developed countries, but also the most developed countries in our sample seem vulnerable to increases in migration rates (Argentina, Mexico, Chile and Turkey are all among the net losers).[26]

6 Conclusion

By bridging two strands of literature, that on the economic consequences of brain drain, and the growth one focussing on the role of human capital formation, we provide several new insights. First, besides confirming the existence of an incentive effect on the level of (*ex-ante*) human capital accumulation (as in Beine et al., 2008), we present evidence that the possibility of migration also affects the types of skills that agents choose to acquire. This underscores that the level effect exists alongside a composition effect. Second, we show that both these effects depend on the level of development of the sending country (its proximity to the frontier). Differences in wages and the degree of marketability of migrants' skills depend on the level of technological development,

[26]In terms of welfare, our results have even stronger implications. Not only is over 80% of the population affected by losses, but also, given the decreasing marginal utility of income, losses among the poorest countries should be weighted much more than gains to more developed ones.

thus the effect of migration needs to be discussed taking explicitly into account the technological gap of each sending country. Third, our growth regression allows us to quantify the relative size of the level and composition effects. The latter is shown to be much larger in magnitude than the former. Hence, the existing literature, by focussing on the level effect, might have underestimated the overall impact of migration on per capita GDP growth. Fourth, more than half the countries in our dataset, representing 84% of the total population, are shown to suffer as a result of a marginal increase in migration. The losers are to be found both among the most lagging and the most developed countries in our sample; only the countries in the middle of the pack seem to benefit from skilled emigration. Fifth, the losses are much larger in size than the gains, and they are concentrated among the least developed countries.

Like for any empirical endeavour, our results are highly influenced by the quality of the data used. In this respect, data on educational attainment by field of study leave much to be desired, especially when focusing on non-OECD countries as we do. The need to invest resources in the generation of better data to help empirical research cannot be overstated in this field. Despite this caveat, our analysis provides clear empirical support to the claim by developing countries that recent immigration policies of OECD countries may have dire consequences for the migrants' countries of origin. While selecting the most talented individuals from developing countries has a clear economic rationale for destination countries, our work sheds more light on its implications for sending countries: by changing both the level and the composition of human capital, an increase in the possibility of migration for (certain types of) skilled workers reduces the growth rate of GDP per capita in sending countries. The need for a more concerted approach to migration policy among developed and developing countries in an increasingly globalized world emerges very starkly from our analysis.

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