Working Papers

Paper 75, October 2013

A Global Assessment of Human Capital Mobility

The Role of non-OECD Destinations

Erhan Artuç, Frédéric Docquier, Çaglar Özden and Christopher Parsons

This paper is published by the International Migration Institute (IMI), Oxford Department of International Development (QEH), University of Oxford, 3 Mansfield Road, Oxford OX1 3TB, UK (www.imi.ox.ac.uk).
IMI does not have an institutional view and does not aim to present one.
The views expressed in this document are those of its independent author.

The IMI Working Papers Series

The International Migration Institute (IMI) has been publishing working papers since its foundation in 2006. The series presents current research in the field of international migration. The papers in this series:

- analyse migration as part of broader global change
- contribute to new theoretical approaches
- advance understanding of the multi-level forces driving migration

Abstract

Discussions of high-skilled mobility typically evoke migration patterns from poorer to wealthier countries, the focus of which ignores movements to and between developing countries. This paper presents, for the first time, a global overview of human capital mobility, i.e. bilateral migration stocks by gender and education in 1990 and 2000 and nuanced brain drain indicators. Building upon newly collated data, we identify key determinants of international migration using a novel estimation procedure based upon a pseudo-gravity model, which we subsequently use to impute missing data. Non-OECD destinations account for one-third of skilled-migration, while OECD destinations are declining in relative importance.

Keywords: International migration, labour mobility, brain drain

Author: Erhan Artuç, World Bank; Frédéric Docquier, IRES-UCL, FNRS; Çaglar Özden, World Bank; and Christopher Parsons, International Migration Institute, University of Oxford, christopher.parsons@qeh.ox.ac.uk

We would like to extend our thanks to the Economic Research Forum for its financial support (contract #2009-057 on 'The efficiency and redistributive effects of international labor mobility: a bilateral approach with special focus on MENA migration'). Frédéric Docquier also gratefully acknowledges financial support from the Belgian French-speaking Community (convention ARC 09/14-019 on 'Geographical Mobility of Factors'). The findings, conclusions and views expressed are entirely those of the authors and should not be attributed to the World Bank, its executive directors or the countries they represent.

Contents

1 Introduction

Among the various dimensions of international migration, movements of the highly skilled people are arguably the most topical. On the one hand, governments of more developed countries are implementing policies to attract the best and the brightest in an increasingly competitive market for skills. On the other hand, many poorer countries, especially those already suffering from low levels of human capital, are deeply concerned about retaining their most skilled workers, whose absence would ultimately impinge upon their long-term economic growth and political development. Until now, the literature has almost exclusively examined high-skilled movements to OECD nations, often termed the 'Brain Drain.' Even a casual observation of basic migration patterns however, indicates that such a focus fails to capture the complete global picture.

The absence of detailed and high quality data is the main obstacle that prevents us from properly quantifying the extent of skill mobility across the world. These data shortcomings not only impede many important avenues of research, but in light of the wide absence of immigration and emigration flow data by skill level, also militate against countries' ability to assess their net human capital situation and thus the effectiveness of their immigration, education and labour market policies.[1] This paper is the first to seriously address this issue, by first developing a global overview of human capital mobility and then subsequently by introducing refined Brain Drain indicators, which, in comparison with the existing literature, provide superior estimates of gross and net human capital levels across the world.

There has been several efforts to analyze bilateral migration patterns. The Eurostat database[2] provides data on the size of migration flows, by age, gender and country of citizenship, but solely between EU member states and with numerous missing observations. More broadly, Ozden et al (2011) referred to OPSW henceforth, construct five 226x226 comprehensive matrices of origin-destination stocks that correspond to the last five com-

[1]In the absence of immigration and emigration flow data by skill level, the best nations are able to do in terms of assessing their net human capital situation and thus the effectiveness of their policies, is to compare the total level of human capital at a single point in time (i.e. at the time of census) with the total number of domestic nationals abroad. To be able to do this accurately, bilateral data are required for all potential destinations worldwide.

[2]See http://epp.eurostat.ec.europa.eu/portal/page/portal/population/publications/migration_asylum

pleted census rounds, thereby extending the work of Parsons et al. (2007). However, while OPSW significantly broadens the time, gender and geographical coverage of the available data, different skills or education levels are not distinguished.

Another set of studies investigates the education structure of migration, but only for a limited set of destination countries for which data are more easily available. Docquier and Marfouk (2004, 2006) and Dumont and Lemaitre (2004) collect detailed census and register data on immigration from all the host countries of the Organization for Economic Co-operation and Development (referred to as OECD henceforth). Aggregating these numbers allows them to characterize the size and structure of low-skilled and high-skilled emigration stocks to the OECD from all the countries of the world. Docquier, Lowell and Marfouk (2009 - referred to as DLM henceforth) and Dumont, Martin and Spielvogel (2007) introduce the gender breakdown in the above analyzes.

Existing analyses of bilateral migrant stocks disaggregated by education level only capture the size and structure of migration to a large subset of OECD destinations. This is an important limitation, since migration to non-OECD nations is significant. Figure 1 shows that the share of non-OECD destination countries in the world immigration stock has gradually decreased since the sixties (from 57 to 49 percent). Nevertheless, non-OECD nations still host about half of all current international migrants. This share is not homogenous across gender; it is larger for men (51 percent in 2000) than for women (48 percent). Countries such as Russia, Ukraine, India and Pakistan attract large numbers of migrants, mostly from neighboring countries and as a result of political events that changed national boundaries. As far as high-skilled migration is concerned, countries such as South Africa, the member states of the Gulf Cooperation Council (referred to as GCC henceforth) and some East Asian countries (e.g. Singapore or Hong Kong) are among the most important non-OECD destinations. Omitting these destinations from any analysis results in an important piece of the global puzzle remaining missing, thereby limiting our understanding of the full nature of international human capital mobility.

[INSERT FIGURE 1 AROUND HERE]

In this paper, we perform, for the first time, a global analysis of bilateral migration patterns by gender and for two education levels, i.e. for four labor types. Compared to previous analyses, we account for migration to all non-OECD country destinations by introducing new data and utilizing appropriate estimation methods where actual bilateral data are missing. Furthermore, we are able to refine existing measures of immigration and emigration rates by expressing immigrant and emigrant stocks relative to a more appropriate measure of labor force, the *natural* labour force, i.e. the number of workers from a particular origin country regardless of where they currently reside

Our analysis shows that migration to non-OECD countries increased at a slower pace (+23 percent) than migration to the OECD (+39 percent) between 1990 and 2000. Nevertheless, these former groups constitute about 47 percent of the world adult migration stock, and are characterized by both lower shares of college graduates (approximately half the level of migration to OECD countries) and women. The selection on skills is particularly pronounced in the case of least developed countries, increasing with regional income levels and for most global regions between 1990 and 2000. These patterns demonstrate the continued and increasing attractiveness of OECD destinations for high-skilled and female workers. Conversely however, we find the opposite pattern in terms of the international emigration of females. In other words, although OECD destinations are still broadly favoured by female migrants, the extent of this selection on gender decreased between 1990 and 2000, which highlights the rising appeal of non-OECD destinations for female migrants. Emigration to non-OECD countries accounts for about one third of the total brain drain from low-income and the least developed countries and adding non-OECD destinations increases the high-skilled emigration rate of 32 countries by more than 50 percent. These nations are predominantly those close to South Africa, members of the former Soviet Union or else those that send large numbers of workers to oil producing Persian Gulf countries. The influence of additional countries on female high-skilled emigration, however, is less pronounced given the continued tendency for female migrants to migrate to OECD nations.

High-income and OECD countries exhibit negative net brain drain rates that show that the incoming pool of educated talent to these regions more than compensates for any skill loss suffered as a consequence of their high-skilled nationals emigrating abroad. The converse is true of developing regions since, although gross and net rates are strongly correlated, their net rates are broadly lower. Finally we compare the proportions of educated natives and country residents, the results from which show that globally countries' natural work force is more highly educated than the workforce that resides in that country. In other words, high-skilled immigration to these nations fails to compensate for the skill losses endured when college-educated natives move abroad.

Before delving into the details of the empirical exercise and the analysis of our data, we first present summary statistics of the numbers of high-skilled migrants in the database in Table 1. We distinguish between migration to OECD and non-OECD countries and between raw data and estimated/imputed data. For each year, the migrant stock in the 34 OECD countries is shown in the second column. There are 59.3 million migrants above age 25 in 2000, of which 20.9 million (35 percent) have college education, and 30.2 million (51 percent) are women. For 1990, we identify 42.5 million migrants to OECD countries of which 30 percent are highly educated and 51 percent are women.

The third and fourth columns show the data obtained or estimated for non-OECD countries. There are 52.6 million migrants, of which 7.9 million (15 percent) are highly educated and 24.3 million (46 percent) are female. For 1990, we identify 42.7 million migrants, including 8.7 percent highly educated and 45 percent women. In comparison with OECD destinations, the shares of both the high-skilled and female migrants in non-OECD countries are lower.

Finally, for completeness, the fifth and sixth rows present the numbers and the proportions of migrants imputed across unobserved corridors. For 2000, imputed values represent 16.7 million migrants in the 90 destination countries for which actual data are not available. Although imputed values account for 15 percent of the total migration stock in 2000, the share is around 8.7 percent for college-educated migrants. In other words, over 90% of college-educated migrants are captured by our raw data and we believe that our imputation strategy should therefore not adversely effect our overall measurement of high-skilled emigration and dilute our conclusions.

Overall, the resulting migration matrices identify 111.9 million migrants (age 25+) in 2000 which represents about 63 percent of the 177.4 million migrants (age 0+) recorded in the United Nations database and 70 percent of the 160.1 million migrants (again age 0+)

recorded in OPSW for those 190 countries that appear in our matrices.[3] 28.8 million of this migrant stock have college education and 54.5 million are women. For 1990, we identify 85.3 million migrants (aged 25+), including 16.3 million high-skilled migrants and 40.9 million women. Our data show that the overall migrant stock increased by 31 percent between 1990 and 2000, while the stock of high-skilled migrants increased by 77 percent. As a result, the share of high-skilled in the overall migrant stock increased from 19 percent to 26 percent. The share of women increased from 48 percent to 49 percent, a result mainly driven by the increased feminization of migration to non-OECD countries.

[INSERT TABLE 1 AROUND HERE]

The remainder of this paper is organized as follows. Section 2 describes our data collection, while our econometric strategy and the accompanying results are presented in Section 3. In the following section we introduce our nuanced Brain Drain indicators before we present our global assessment of human capital mobility in Section 5. Finally, we conclude.

2 Data Compilation

The first contribution of the paper is in compiling a more complete global data set of bilateral migrant stocks, disaggregated by education level and gender for the years 1990 and 2000, by including as many developing destination countries in our sample for which data are available. Our data collection builds upon the previous database of DLM, which documents migrant stocks disaggregated by education levels to 30 OECD destination countries, our methodology in this section is a direct extension to this earlier work. We add 4 new OECD members (for both 1990 and 2000), 66 non-OECD destinations in 2000 and 27 non-OECD countries in 1990 for which comparable data could be found. The data are disaggregated by gender and two separate education levels. We distinguish males and females, $g = (m, f)$, and two skill types $s = (h, l)$ with $s = h$ for individuals with post-secondary or college education (referred to as the highly skilled), and $s = l$ for less educated individuals (referred to as the

[3] There are differences between OPSW and the United Nations database. For example, OPSW remove refugees wherever possible from their data since their primary focus is upon economic migration.

low-skilled). In each decade, we thus have migrant stocks of high-skilled males, low-skilled males, high-skilled females and low-skilled females for each bilateral corridor.

Subsequently, we use the primary data from these 190x100 and 190x61 matrices, for 2000 and 1990 respectively, to make out-of-sample predictions for those destination countries for which data are missing. Taken together the raw and imputed data comprise 190 countries in 1990 and 2000 (denoted by $j = 1, ..., J$) and include stocks of migrants aged 25 and above. This cutoff is chosen so as to omit students and children since our focus is upon the labor market impact. The full data set in turn facilitates, for the first time, a global analysis of human capital mobility over time using nuanced and improved Brain Drain indicators as described in Section 4.

2.1 Migration Data for OECD Countries

Our starting point in the construction of our matrices is the Docquier, Lowell, Marfouk (DLM) data set, that comprises a collection of census and register data by country of birth, education level and gender for OECD countries in 1990 and 2000. The original DLM data set omitted data for member states that subsequently joined the OECD in 2010 however (namely Chile, Estonia, Israel and Slovenia), so in this paper we augment the original OECD data from the DLM data set with census data pertaining to these newer members. As a result, our set of OECD countries includes all 34 current members for both 1990 and 2000.

DLM enumerates stocks of migrants living in a destination country at the time of census as opposed to flows that are observed between two points in time. For reasons of consistency and comparability, the four methodological choices made in DLM guide our current work:
(i) 190 origin countries in both 1990 and 2000 are distinguished. Starting with the 192 UN member states we: aggregate South Korea and the Democratic People's Republic of Korea since some destination countries only provide the total number of Koreans, Serbia and Montenegro are treated as a single entity and the Taiwan, Hong Kong, Macao and the Palestinian Territories are added as individual entries to the country list. We drop 5 countries (Nauru, Palau, Tuvalu, Belize and the Holy See) due to their small size and their absence in the data of some destination countries.

(ii) Migration is predominantly measured on the basis of country of birth as opposed to citizenship, since our goal is to have a consistent definition over time. Whereas individuals' country of birth is predominantly time invariant and independent of the variation in laws regarding citizenship within and across countries, the concept of citizenship conversely changes with naturalizations. Furthermore, many destination countries grant citizenship selectively to migrants from certain countries, significantly biasing the overall migration data based on citizenship status.

(iii) Only adult migrants aged 25 and above are recorded. This measure therefore excludes both students, who temporarily relocate to complete their education and children who accompany their parents abroad. This is a superior measure when wishing to examine the economic and labour market effects of migration.

(iv) Along with the gender dimension, two separate levels of education are distinguished. High-skill migrants include those with at least one year of college or post-secondary education. Low-skill migrants include all of those with a level of schooling up to and including an upper-secondary education.[4]

As shown in Table 1, the OECD data allow us to characterize the education level, origin and destination of about 59.3 million migrants in 2000 and 42.5 million migrants in 1990. About 16.9 million of the 20.9 million high-skill migrants in the OECD countries are concentrated in only 5 destination countries: the U.S. (10.3 million), Canada (2.7 million), Australia (1.6 million), the United Kingdom (1.2 million) and Germany (1.2 million).

2.2 Migration data for non-OECD countries

We further supplement our expanded data collection of our 34 OECD destinations with 66 non-OECD countries in 2000 and 27 countries in 1990, adhering to the same methodological principles and definitions as in DLM. The data sources for these destination countries, together with the total number of migrants and the total number of highly skilled migrants for both 1990 and 2000 are presented in Table A.1. In 16 cases, data are obtained directly from

[4] Note that DLM disaggregated low-skill migrants into two categories, those with upper-secondary education and those with less (including low-secondary, primary or no schooling). In this paper, we aggregate these two categories for estimation purposes.

the relevant destination countries' national statistical offices. In 24 cases, data are taken from IPUMS-International or the United Nations' Economic Commission for Latin America and the Caribbean (ECLAC) databases, two of the largest archives of publicly available census samples. They are based on samples of at least 5 percent to the whole population. Data for the 6 Gulf Cooperation Council (GCC) countries are estimated on the basis of their Labor Force Surveys. Usually, primary data only provide limited details on the country of origin and education level of migrant workers. For example, Saudi Arabia's Labor Force Survey distinguishes a dozen main origin countries while reporting an important residual category. In addition, it only provides the aggregate proportion of post-secondary educated guest workers. We rely on the database provided in OPSW to split residuals by country of origin and assume that educational structures are homogenous across source countries. The same methodology is applied to the other GCC countries and Saudi Arabia's education breakdown is applied if observations are otherwise missing.

In comparison with DLM, adding 66 destination countries increases the overall migrant stock by 35.9 million in 2000, including 5.4 high-skilled migrants and 16.3 million women (see Table 1). The proportion of college graduates among the observed non-OECD nations is 15 percent and the share of women is 45 percent, far below the ratios observed in OECD destination countries in both of these dimensions (35 percent and 51 percent, respectively). These ratios vary considerably across countries and this heterogeneity is explored in more detail in Section 5. Six of these 66 additional destination countries are home to more than one million foreign-born adults in 2000. These are Ivory Coast (3.9 million), Saudi Arabia (3.1 million), Hong Kong (1.9 million), Israel (1.5 million), the United Arab Emirates (1.2 million) and Malaysia (1.0 million).

3 Econometric Strategy for Imputing Missing Data

Despite the additional data for 66 non-OECD destinations in 2000 and 27 non-OECD destinations in 1990, our bilateral migration matrices remain incomplete. It is important to emphasize that despite lacking data for a fairly large number of destination countries, the raw data that we have collected nevertheless comprise around 85% of the total in 2000 and two-thirds of the total in 1990. The second major contribution of our paper is in imputing, to the greatest extent possible, those cells for which data are still missing, along both the gender and education dimensions. To this end, we develop a three-step estimation procedure, based upon the most up-to-date theoretical and empirical advances in the literature. We subsequently use these parameter values to predict the bilateral migrant stocks for cells for which we lack data. While no doubt second-best, given the wider paucity of migration data, we deem our methodology worthwhile in the sense that our results, especially when aggregated over regions, still provide superior estimates of the global winners and losers in the global contest for high-skilled migrants (in a static sense) as when compared to their total absence.[5] A fair comparison to our intuitive approach, which is widely accepted in the literature are global GDP figures, balance of payments components and international capital flow estimates which for many countries are computed in light of the paucity of better quality data.

The data set of OPSW plays a key role in our imputation strategy. While not providing data disaggregated by skill level and additionally comprising migrants of all ages (as opposed to only those aged 25 and above), OPSW embodies significant informational content about the composition of overall bilateral migration stocks globally; arguably far more than any estimation procedure alone could be reasonably expected to capture. These data, which span 1960-2000, prove useful on two counts. First, they provide information on past (pre-1990) migrant stocks, i.e. migrant networks, that we use in our estimations. Second, since the data that we are imputing are a sub-sample of these overall migrant stocks, the OPSW data importantly provide upper-bounds to our estimates that can then be subsequently disaggregated according to this paper's main focus, migrants' level of human capital.

In the next section, we first outline the pseudo-gravity model, the ideal econometric specification that one would use and highlight the need for our three-step econometric procedure.

[5] In other words, given migrant inflow and outflow data disaggregated by skill level are not available for the vast majority of nations globally, the best available (static) estimates, (thus ignoring dynamic, brain gain effects for example), of the winners of losers of the global battle for talent can be made by comparing the total high-skilled stock in a particular country with the total number of skilled emigrants from that country for which global data on potentially all destinations are required. Even if our imputation methods are imperfect, a sensible allocation of these migrants is still superior for informing one as to the overall global situation, in comparison with the total absence of such data.

Next, we discuss a number of issues in estimation that further need be considered, before continuing to an analysis of the accuracy of our results.

3.1 The Three-step Econometric Model

The econometric model that we use to construct our out-of-sample predictions is an extension of the recent developments in the literature. Our theoretical foundation is the income (utility) maximization model, which has been used extensively in the literature, for example Borjas (1987). The main premise is that individuals with different levels of human capital i.e. education, are assumed to choose between staying at home or moving to alternate destinations; with their decisions based upon the utility or income they are expected to receive in competing destinations as when compared to remaining sedentary. Recent examples in this literature include Anderson (2011), Beine et al. (2011) and Hanson and Grogger (2011), Ortega and Peri (2012), Beine and Salamone (2013) and Bertoli and Fernandez-Huertas Moraga (2013). Our model most closely follows that of approach of Beine et al (2011) and Hanson and Grogger (2011) however. Each gender and education specific country-pair or potential migration corridor, is characterized by dyadic migration costs in addition to origin and destination specific push and pull factors, leading to the following specification:

$$M_{g,s,t}^{jk} = \exp\left(\alpha_{0,g,s,t} + \alpha_{1,g,s,t} d_{g,t}^{jk} + \alpha_{2,g,s,t} b^{jk} + \gamma_{g,s,t}^{j} + \lambda_{g,s,t}^{k}\right) + \epsilon_{1,g,s,t}^{jk}, \quad (1)$$

The variables are defined as following.[6] The dependent variable $M_{g,s,t}^{jk}$ is the bilateral stock of migrants from country j in country k in year t (either 1990 or 2000), of gender g and skill (education) s. The explanatory variables comprise an historical bilateral time-varying diaspora variable, $d_{g,t}^{jk}$, which is a key determinant of future migration levels (Beine et al 2011). In addition, we have various time-invariant bilateral variables, denoted by b^{jk}, such as geographic distance, common language, contiguous borders and shared colonial heritage that account for cultural, political and geographic linkages including geographic distance, common language, contiguous borders and shared colonial heritage that account for cultural,

[6] Table A.2 in the Appendix describes the data sources as well as the way we construct and measure these explanatory variables that influence migrant stocks.

political and geographic linkages. In this ideal set-up, origin country characteristics (such as economic, political and social push factors) are captured by a set of origin fixed effects introduced through the vector $\gamma^{j}_{g,s,t}$. Similarly comparable (pull) factors at destination would be accounted for by the inclusion of vector $\lambda^{k}_{g,s,t}$ of destination fixed effects. Since our goal is to impute migration data for those cells for which destination data are missing, it is not possible to include vector $\lambda^{k}_{g,s,t}$ in our regressions. This gives rise to our *prediction problem*, which our three-step estimation seeks to address.[7]

Our preliminary step is to run a first-stage gravity regression with education-aggregated migration data disaggregated by gender (but not skill level), obtained from OPSW on the left hand side, to recover estimates of the gender specific pull variable $\lambda^{k}_{g,t}$ (i.e. destination fixed effects aggregated over the education dimension) for all countries in our sample. This takes the form:

$$M^{jk}_{g,t} = \exp\left(\alpha_{5,g,t} + \alpha_{6,g,t} d^{jk}_{g,t} + \alpha_{7,g,t} b^{jk} + \lambda^{k}_{g,t} + \theta^{j}_{g,t}\right) + \epsilon^{jk}_{2,g,t}. \tag{2}$$

In this equation, $M^{jk}_{g,t}$ is observed for all origins and destinations in OPSW and it is equal to the sum of all education-specific bilateral migrant stocks for a given gender and time period. In line with Equation (1) we include a comprehensive set of dyadic variables to capture migration costs as well as origin and destination fixed effects in each regression. The estimation of Equation (2) thus furnishes us with estimates of the time and gender-specific destination pull variables, $\hat{\lambda}^{k}_{g,t}$.

Since the goal of our initial econometric procedure is to compute estimates of gender and education specific destination fixed effects, we further parameterize the gender-education destination pull factor as:

$$\lambda^{k}_{g,s,t} = \alpha_{3,g,s} A^{k}_{t} + \alpha_{4,g,s} \lambda^{k}_{g,t} \tag{3}$$

In this expression, $\lambda^{k}_{g,t}$ is the gender specific pull variable and A^{k}_{t} is a vector of destination specific parameters, included in estimation to further distinguish across skill groups. These include (for the destination country) whether people speak English, the size of the total

[7] A second issue is that the sample of countries for which data are missing is likely a non-random sample. Addressing this second issue is beyond the scope of the current work.

labour force (in logs), GDP per capita (in logs), the total fertility rate (in logs), the ratio of the number of highly skilled to the total labour force and the labour force participation rate of men and women. A number of dummy variables are also included that capture whether a destination country belongs to the GCC, whether military service is compulsory and whether polygamy is legally practiced

Putting everything together, we substitute Equation (3) into Equation (1), which yields our second-stage regression:

$$M^{jk}_{g,s,t} = \exp\left(\alpha_{0,g,s,t} + \alpha_{1,g,s,t} d^{jk}_{g,t} + \alpha_{2,g,s,t} b^{jk} + \alpha_{3,g,s} A^k_t + \alpha_{4,g,s} \hat{\lambda}^k_{g,t} + \gamma^j_{g,s,t}\right) + \epsilon^{jk}_{1,g,s,t}. \quad (4)$$

When compared with Equation (1), A^k_t is the vector of destination specific parameters from Equation (3) and the gender-specific destination pull variables, $\hat{\lambda}^k_{g,t}$ are those estimates obtained from our first-stage regression, Equation (2). Our two-step procedure up until this point, which aims to maximize the accuracy of our predictions, comes at a cost; our gender-specific destination pull variables, $\hat{\lambda}^k_{g,t}$, will be correlated with the vector A^k_t of destination specific variables. In turn, this means that it is impossible to meaningfully interpret A^k_t and as such these results are not reported. Given that more data exist in 2000, when compared to 1990 and again, so as to maximize the accuracy of our predictions, for each gender-education pair we run regressions for both 1990 and 2000 simultaneously, allowing our explanatory variables to vary over time, but additionally forcing the coefficients on these variables to be constant in both years.

Until this point, we have four separate gender-education pairs: high-skilled men, high-skilled women, low-skilled men and low-skilled women. In our final step, we take our predictions for the missing cells from Equation (4) and apply the resulting shares to the totals detailed in OPSW. Since these data provide the most accurate estimates of global migrant stocks, we are, in effect, splitting the OPSW data into the relevant education-gender bilateral migrant stocks. Herein lies the final econometric issue that needs addressing, namely that OPSW refers to migrants of all ages, while DLM instead only refers to those in the labour force. The difference are those aged 24 and below, which for the sake of simplicity we term *youth*. To surmount this final issue, we run estimate Equation (4) twice more, for male youth and female youth.[8] Finally, putting together all of our estimates, for those destination countries without raw migration we further use the following restriction to split the total gender specific migrant stock provided by OPSW into the gender-skill specific migrant stock:

$$\tilde{M}^{jk}_{g,s,t} = \frac{\hat{M}^{jk}_{g,s,t}}{\sum_s \hat{M}^{jk}_{g,s,t}} M^{jk}_{g,t}. \tag{5}$$

Our final matrices are composed of the original gender-education specific data for those destination countries for which we have original raw data and the predicted migrants stocks, $\tilde{M}^{jk}_{g,s,t}$, for those without data.

3.2 Econometric Issues

The presence of a large number of zero or undefined observations in the dependent variable (gender and education specific bilateral migrant stocks) gives rise to econometric concerns that would yield inconsistent OLS estimates. Zero observations appear in large numbers in many other bilateral contexts such as international trade, official aid, military conflict and political alliances. This phenomenon is especially prevalent in migration data sets, since there is no observed or recorded migration between many country pairs, for example, between Rwanda and Mongolia, due to high geographic, cultural and economic barriers. Furthermore, censuses or alternative surveying instruments are unlikely to capture small migration corridors should any sampling strategy be followed. As a result, we have zero values for about 48.5 percent of the 14,820 observations (195 destination x 76 origin countries) in the aggregate migration matrix from OPSW for 2000. The ratio of zero observations is 52.6 percent for low-skilled males, 52.9 percent for high-skilled males, 52.8 percent for low-skilled females and 54.0 percent for high-skilled females.[9]

Two main reasons explain why a high proportion of zero observations in the dependent variable typically results in inconsistent parameter estimates. The first is selection bias.

[8]Youth (for each gender group) is defined as the difference between total migrant stock from OPSW minus low-skilled and high-skilled migrant stock.

[9]Similarly, in 1990, we have zero values for 43.2 percent of the 11,895 observations (195x61 countries) in the aggregate matrix. Similar ratio is 46.9 percent for low-skilled males, 49.0 percent for high-skilled males, 47.2 percent for low-skilled females and 50.9 percent for high-skilled females.

Since observations including a zero value in the dependent variable will be dropped from estimation, an inherent selection bias will be introduced since the occurrence of zero observed flows are non-random. In a double log regression model, the norm therefore is to add ”one” to the value of the dependent variable and then take the log. The second bias has been well documented by Santos Silva and Tenreyro (2006) who demonstrate in their influential paper, in the presence of numerous zeroes in the dependent variable, that the expected value of the error term will be correlated with some of the independent variables should the variance of the error term also be correlated with the independent variables. In other words, in the presence of numerous zero observations in the dependent variable and heteroscedasticity, that one of the key assumptions of the OLS model will be violated, namely that the expectation of the error term will be non-zero. In order to surmount both of these issues, Santos Silva and Tenreyro (2006) advocate the use of Pseudo-Poisson Maximum Likelihood (PPML) estimator that yields consistent parameter estimates even in the presence of numerous zero observations in the dependent variable. We therefore deem the PPML estimator as the most appropriate technique for obtaining our parameter estimates. Actually, our discrete choice specification is a special case of Artuc, Chaudhuri and McLaren's (2010) self selection model. Artuc (2013) provides a detailed comparison of PPML and its alternatives for estimating relevant discrete choice models, which includes migration estimations. Observations are weighted by the log of the aggregate migrant stock and robust standard errors are always implemented.

3.3 Estimation Results

The results of our estimation are presented in Tables 2a and 2b. The first table is for the first stage, Equation (2), which generates the estimates of the time and gender-specific destination pull variables, $\hat{\lambda}^k_{g,t}$. In addition, the estimation generates coefficients for the bilateral variables that are gender specific but are not skill specific. These coefficients all have the expected signs and are consistent with the results from the literature.

The more interesting results are those of the determinants of our four gender-education specific migration pairs estimated simultaneously for 2000 and 1990, which are presented in

Table 2b. As noted in the previous section, we only report our estimates of the bilateral variables since the parametrization of our gender-specific destination (pull) fixed effect $\lambda_{g,t}^{k}$ means that the coefficients on our destination specific variables, A_t^k are not numerically interpretable. All the bilateral variables that capture various aspects of migration costs are highly significant at the 1% level, with sensible orders of magnitude relative to previous findings in the literature, which moreover vary sensibly over both skill groups. Geographical distance deters international migration and has a stronger impact upon the low-skilled., since typically high-skilled migrants are better able to overcome higher international migration costs. Similarly, while migrants from both skill groups on average migrate more to bordering countries, this effect is much stronger for the low-skilled., for similar reasons previously outlined. Furthermore, both of these effects are similar in magnitude in both 1990 and 2000. Sharing a common language is more important for the high-skilled since language requirements are generally more relevant for this group. Diaspora networks conversely encourage the migration of low-skilled. migrants more than their high-skilled counterparts, since this latter grouping typically has additional resources in order to migrate internationally. An alternative explanation is that networks will likely play a more important role in South-South migration, which comprises higher volumes of low-skilled. migrants. Similarly, colonial links, which may be considered to also comprise an historical diaspora component are more relevant for the low-skilled., but across both skill groups the influence of colonial links declines between 2000 and 1990, a result in line with Head, Mayer and Ries (2010). All of these results on the role of the bilateral variables are consistent with other papers in the literature, such as Beine et al. (2011) and Grogger and Hanson (2011). The differences in the magnitudes of the parameter estimates are likely to be driven by the fact that previous papers had to use data from OECD destinations whereas we are able to include many non-OECD destinations.

[INSERT TABLES 2a AND 2b AROUND HERE]

Once the estimation is complete, we use the estimated parameter values from the equations above to predict the missing values in the bilateral migration matrices for both years, genders and educations levels. Before analyzing the predictions and their implications for the global migration patterns by skill level, we evaluate out-of-sample performance of our predictions. In order to do this, we first randomly drop low-skilled and high-skilled migrant stock data for 5 countries from the sample for which we have actual data. We then estimate the gravity model as explained in the previous section as if these five destination countries also had missing data. We impute the missing low-skilled and high-skilled migrant stocks for these five countries and calculate the log-ratios of these imputed data to the actual migrant data. We repeat these four steps 100 times and check their performance.

Figure 2 presents the density functions of these log-ratios for female migrants for 2000. The first three graphs are for low-skilled migrants and last three are for high-skilled migrants, using different size cutoffs to assess the predictions of corridors of different sizes. More specifically, the first graphs capture all corridors; the second set of graphs are for corridors larger than 1,000 migrants and the third graphs are for corridors with more than 10,000 migrants. In each case, the densities are bell-shaped and the median is around zero.[10] Yet there are inherent idiosyncratic factors that exist in the estimation of small migration corridors. As clearly seen in the comparison of Figures 2a, 2b and 2c or 2d, 2e and 2f, the distribution of small corridors (2a and 2d) cover a wider range indicating a large standard deviation. On the other hand, as the corridors get larger, the distribution of the log ratio becomes more concentrated around zero indicating higher precision. Since these large corridors cover the vast majority of the migrant stocks, higher precision of larger corridors increases our confidence in our results and their implications for the global migration patterns.

[INSERT FIGURE 2 AROUND HERE]

4 A Refinement of Global Brain Drain Indicators

Our raw data in combination with our imputed data allow us to improve upon existing high-skilled migration indicators (e.g. Docquier and Marfouk, 2006, Dumont and Lemaitre, 2004, Docquier, Lowell and Marfouk, 2009 and Dumont, Martin and Spielvogel, 2008). Previous studies provide cross-country data on the relative intensity of emigration (referred to as

[10]The results are similar for other types and the year 1990.

emigration rates), controlling for the population size and the skill structure in the origin country, while focusing upon the subset of OECD destinations.[11] Such measures necessarily omit emigrants that reside in non-OECD destinations therefore, which in turn leads to biases that are especially severe for countries that send a large proportion of their emigrants to non-OECD nations.

First we define the following key variables:

$M^{jk}_{g,s,t}$: the stock of bilateral migrants from country j to country k of gender g and skill s at time t,

$I^{i}_{g,s,t}$: the stock of total immigrants of type (g, s) to country i in year t,

$E^{i}_{g,s,t}$: the stock of total emigrants of type (g, s) from country i in year t,

$L^{i}_{g,s,t}$: the (observed) resident labor force of type (g, s) in country i in year t and

$N^{i}_{g,s,t}$: the natural labor force of type (g, s) in country i in year t. This is the number of workers from a given country i regardless of their current location.

For each labor type, the aggregation of bilateral migration stocks yields total emigration and immigration for each country:

$$I^{i}_{g,s,t} \equiv \sum_{j} M^{ji}_{g,s,t} \tag{6a}$$

$$E^{i}_{g,s,t} \equiv \sum_{k} M^{ik}_{g,s,t}. \tag{6b}$$

We then use data on both the educational and gender structure of the labor force to identify the vectors of $L^{i}_{g,s,t}$ and $N^{i}_{g,s,t}$ for all i, g, s, t. By definition, the observed resident labor force of type (g, s) in country i, $L^{i}_{g,s,t}$, is equal to the *non-migrant* labor force (natives residing in their country of birth) plus immigrants. Similarly, the natural labor force of type (g, s) in country i , $N^{i}_{g,s,t}$, is equal to the *non-migrant* labor force plus emigrants. We can therefore state that the non-migrant labor force can be expressed as either of the following expressions (residents minus immigrants or naturals minus emigrants):

$$L^{i}_{g,s,t} - I^{i}_{g,s,t} = N^{i}_{g,s,t} - E^{i}_{g,s,t} \tag{7}$$

[11] Data on selected non-OECD destination countries were included in Docquier and Rapoport (2011) and in the latest version of the OECD database.

The ability to recover our measure of the natural labour force $N^i_{g,s,t}$, a prerequisite for which is to have measures of immigrant/emigrant stocks for all nations in the world, is a key contribution of the current work since it allows a more nuanced understanding of the mobility of human capital internationally. Given our estimates of immigration and emigration globally, before we can construct $N^i_{g,s,t}$ using Equation (7), we first need to construct a consistent measure of $L^i_{g,s,t}$, i.e. the resident labour force.

We begin with a measure of the total working-age population (i.e. aged 25 and over) by gender as provided by the United Nations.[12] Data are missing for a few countries and these are instead obtained from the CIA world factbook.[13] These data are then split across skill (i.e. education) groups using international indicators of educational attainment. Here, we follow Docquier and Marfouk (2006) or Docquier, Lowell and Marfouk (2009) and combine different data sets documenting the proportion of post-secondary educated workers in the population aged 25 and over (i.e. De La Fuente and Domenech, 2006, Barro and Lee, 2001, and Cohen and Soto, 2007). The post-secondary concept corresponds to a broad definition of high-skill labor as it includes workers with at least one year of college or university. This definition is relevant for developing countries, where the share of college graduates in the labor force is lower than one percent in some cases. Given the construction of $L^i_{g,s,t}$, Equation (7) is then used to identify the size and structure of the natural labor force, $N^i_{g,s,t}$, for each labor type, country and period.

With all the constituent components in hand we now define: gross emigration rates ($e^i_{k,s,t}$) and net emigration rates ($b^i_{k,s,t}$) for a given country i are defined as follows :

$$e^i_{g,s,t} \equiv \frac{E^i_{g,s,t}}{N^i_{g,s,t}}, \quad b^i_{g,s,t} \equiv \frac{E^i_{g,s,t} - I^i_{g,s,t}}{N^i_{g,s,t}} \tag{8}$$

so that (7) can be written as $L^i_{g,s,t} \equiv N^i_{g,s,t}(1 - b^i_{g,s,t})$.

In comparison to the existing literature, the current paper contributes three major improvements to the measurement of international human capital mobility:

Comprehensiveness – Existing studies record immigrants in a limited set of destina-

[12]Population data by age and gender are provided by the United Nations Population Division and can be found at http://esa.un.org/unpp.

[13]See http://www.cia.gov/cia/publications/factbook.

tion countries (OECD countries in addition to a few selected non-OECD destinations). By expanding the number of destinations to cover all countries in the world, we provide a comprehensive picture of international human capital mobility. Furthermore, we are able to quantify total emigrant stocks, $E_{g,s,t}$ for all the countries of the world, since we present comprehensive migration matrices. For example, compared to the set of OECD destinations, the total number of adult migrants identified in 2000 increases from 59.3 to 100.5 million.

Natural-based – We are able to refine our definition of emigration rates. Instead of dividing the number of migrants by the corresponding labor force at origin (which includes immigrants), we divide it by the natural labor force, i.e. the number of individuals born in the origin country (which excludes immigrants). Our emigration rates thus differ from those computed in previous studies, $E_{g,s,t}/(L_{g,s,t} + E_{g,s,t})$ as we do not need to proxy the natural labor force $N_{g,s,t}$ at the denominator with $L_{g,s,t} + E_{g,s,t}$. This makes a substantial difference in countries with large levels of immigration, especially for high skill levels.

Net vs Gross – We are also able to identify the size and skill structure of adult immigration and emigration in all host countries, including the developing world. Those immigration data were only available for OECD member states and selected non-OECD countries in previous works and complete emigration data were not available. Furthermore, data were only gross immigration. Since we have both immigration and emigration numbers for all countries, we can compare entries and exits of workers and compute comparable net migration balances for college graduates and less educated workers for all nation states.

Given the scope of our data set, we are also able to characterize the skill levels of the natural population. Given (7) and (8), average skill levels of naturals and residents are linked by the following equation, where the subscripts h and l stands for the high and low skilled, respectively:

$$\frac{L^i_{k,h,t}}{L^i_{k,l,t}} \equiv \frac{1 - b^i_{k,h,t}}{1 - b^i_{k,l,t}} \cdot \frac{N^i_{k,h,t}}{N^i_{k,l,t}}.$$

International migration affects average human capital levels if emigrants and immigrants differ from non-migrants in terms of their skill composition or if net emigration rates differ across skill groups ($b^i_{k,h,t} \neq b^i_{k,l,t}$). Many studies have documented and explained the pattern of positive selection in international migration ($e^i_{h,s,t} > e^i_{l,s,t}$). However, what matters is the net emigration rates of high-skilled and low-skilled workers: international migration reinforces human capital inequalities across nations if $b^i_{k,h,t} > b^i_{k,l,t}$. We will illustrate this phenomenon by comparing the concepts of human capital per natural and per resident, measured by the following indicators:

$$H^i_{g,t} = \frac{N^i_{g,h,t}}{N^i_{g,l,t} + N^i_{g,h,t}}; \quad h^i_{g,t} = \frac{L^i_{g,h,t}}{L^i_{g,l,t} + L^i_{g,h,t}} \quad \forall g, t$$

where $H^i_{g,t}$ is the proportion of college graduates among naturals of gender g, and $h^i_{g,t}$ is the same proportion computed on the resident labor force.

5 A Global Assessment of Human Capital Mobility

In this section, we provide some general statistics and highlight the global patterns of international migration in 1990 and 2000 (Section 5.1). We then study country-specific characteristics and identify the main source countries, focusing on college-graduate migrants (Section 5.2), and college-graduate female migrants (Section 5.3). Finally, we will compare the concepts of human capital per resident and per natural (Section 5.4).

Table 3 details total emigrant stocks and their education/gender composition in 2000 and 1990 for key regions or income categories of the world. The top portion of Table 3 isolates the group of OECD countries and divides the world into high-income and developing countries. We then distinguish between low income, least developed and small island developing states (SIDS) which have unique migration patterns. The second section of the table divides the world into twelve geographical regions: (1) the United States, (2) Canada, Australia and New Zealand as a single entity, which is referred to as CANZ, (3) the twenty-seven nations of the European Union (EU27), (4) the oil rich Gulf Cooperation Council (GCC) countries, (5) Latin America and the Caribbean (LAC), (6) Sub-Saharan Africa (SSA), (7) the countries of the Commonwealth of Independent States (CIS), (8) India, (9) China, and (10) countries in the Middle East and North Africa excluding the GCC (MENA). We do not report results for the heterogeneous set of remaining countries.

Beginning in the top-most panel, the numbers reveal that as income levels increase so do the percentages of high-skilled emigrants and female emigrants abroad. Comparing emigrations from these regional groupings to OECD and non-OECD destinations further reveals the strong selection inherent in world migration patterns. Across all regional groups, a far higher proportion of both college educated and women emigrate to OECD destinations. This selection on skills is most pronounced in the cases of low income and least developed countries from which only 4.1% and 3.5% of emigrants to non-OECD nations have college education as opposed to 38.0% and 34.6% in OECD nations respectively. These patterns are also reflected strongly in the data for 1990.

The second sections of the top and bottom panels of Table 3, again reveal strong patterns of selection. The proportions of both the high-skilled and women emigrants are far larger in OECD destinations when compared to non-OECD destinations in 2000; with the exception of women from Latin America and the Caribbean who have a greater tendency to emigrate to non-OECD destinations. This almost certainly reflects intra-regional migration in that part of the world. Examining how this selection between OECD and non-OECD destinations has changed over time - in other words the difference of the differences - also yields interesting results. The selection of emigrants from all regions to OECD nations, in terms of high-skill composition increased between 1990 and 2000, with the exception of those from the GCC and the Commonwealth of Independent States, which over time both sent more highly skilled migrants to other non-OECD destinations. Similarly, although many regions send larger numbers of female migrants abroad in both 1990 and 2000 e.g. the GCC, Latin America and the Caribbean, sub-Saharan Africa, the Commonwealth of Independent States, India and China, the selection on females increasingly favoured the OECD from all these regions with the exception of the GCC and the Commonwealth of Independent States.

[INSERT TABLE 3 AROUND HERE]

Columns 1 and 4 in Table 4 provide gross and net emigration rates, calculated according to Eq. (4). For gross rates, we further distinguish between emigration to OECD and non-OECD countries (columns 2 and 3). Net rates are provided for men and women with college education (columns 5 and 6). Globally, gross high-skilled emigration rates decrease with country size and income level, which is a finding in accordance with the previous literature. The groups of small developing islands and least developed countries are most affected, with high-skilled emigration rates of 40.9 and 19.9 percent, respectively. The most affected geographic regions are the MENA (17.5 percent), CIS (16.1%), sub-Saharan Africa (15.6 percent) and the GCC (14.3%). The role of non-OECD destinations varies across groups. High-skilled emigration to non-OECD countries is negligible for high-income and small islands developing states. Conversely however, high-skilled emigration to non-OECD countries accounts for about one third of the brain drain from lower-income countries and is of particular significance for the countries of the ex-Soviet block, the GCC and MENA regions.

A comparison of gross and net emigration rates proves highly instructive. High-income and OECD countries exhibit negative net high skilled migration rates; the incoming pool of educated people to those regions more than compensates for any human capital loss suffered as a consequence of their high-skilled nationals emigrating abroad. Consequently, international high-skilled mobility increases the number of college graduate workers in the labor force by over 10 percent in the United States, around 30 percent in other settlement countries (Canada, Australia and New Zealand) and remarkably more than doubles this proportion in oil producing countries. With regards developing regions, gross and net rates are strongly correlated although net rates are sensibly lower. Another advantage of calculating net migration rates at the regional level is that they remove intra-regional movements. This explains why net brain drain rates are much lower than gross rates in the MENA and CIS regions, two regions characterized by large internal migration flows. Turning finally to gender differences, the final columns of Table 4, demonstrate that in all regions net emigration rates are lower for males than for females, with the exception of the EU27 and MENA.

[INSERT TABLE 4 AROUND HERE]

5.1 Country-specific results

Our exploration of the impact of skill transfer around the globe highlights the importance of our introducing non-OECD destinations into our analysis. Collectively their introduction serves to highlight significant heterogeneity across countries and within regions. The aim of this section is to present some important and insightful country-specific stylized facts. Figure 3 illustrates the effect of introducing non-OECD countries into our analysis upon the distribution of high-skilled emigration rates. Although the average share of non-OECD destination in high-skilled migration is around 20 percent (7.9 million over 28.8 in 2000 and 3.7 over 16.3 in 1990, as shown in Table 1), the variance of this share is large. Figure 3.a plots the distribution of the ratio of non-OECD to total gross emigration rates in 2000 for college graduates.[14] The peak of this kernel density corresponds to a ratio of just 0.065 and in the majority of cases (123 out of 195), the ratio does not exceed 0.20. However the distribution is heavily right-skewed such that this ratio exceeds 0.50 in 32 countries, i.e. in not less than a sixth of the sample. The individual countries that comprise the thick right-hand tail of the distribution include nations of the Middle-East (that predominantly send emigrants to oil producing countries), Southern African nations (that principally send migrants to the Republic of South Africa) and ex-Soviet-block members, which are characterized by significant and voluminous migrations between one another.

Unsurprisingly, for many countries, a significant disparity exists when comparing high-skilled emigration rates to all destinations and to the OECD alone, which until now has been the focal group in the literature. These marked differences are illustrated in Figure 3.b, which plots the gross emigration rates of college graduates to OECD destinations on the x-axis, against those to all destinations on the y-axis, for each country. In doing so, the figure highlights the importance of our comprehensive global approach. Each bubble in Figure 3.b represents an origin country and the size of the bubble is proportional to the high-skilled emigration stock from that country.

Overall there exists a strong correlation between our (OECD-) restricted and our global measures; but in many cases, the inclusion of non-OECD destinations has a dramatic impact on the magnitude of our estimates of high-skilled emigration rates, i.e. the gross brain drain, for many poorer developing countries. Examples of these differences include a 53 percentage point difference for West Bank and Gaza, 37 for Yemen, 27 for Namibia and 25 for Jordan, which tend to send emigrants to other countries in their regions. Changes are significantly

[14] We use the gaussian kernel density estimator implemented in Stata.

lower for the small islands of the Pacific and the Caribbean where the largest emigration rates are observed since these countries predominantly send emigrants to North America, Australia and New Zealand.

Figure 3.c compares the gross and net emigration rates of college graduates on the horizontal and vertical axes, respectively, shows the advantage of using net rather than gross rates. Obviously, net rates (exits minus entries) are by definition lower than gross rates (exits) so that the whole scatterplot lies beneath the 45 degree line. Net rates are high and similar to gross rates in small island developing states, but they are negative in high-income countries and, especially, in the GCC countries.

[INSERT FIGURE 3 AROUND HERE]

Table 5 lists the 25 countries with the highest (left panel) and lowest (right panel) net emigration rates of college graduates, excluding small states with less than one million workers (population aged 25+). Eight sub-Saharan African countries belong to the top-25. Other remarkable cases are Jamaica (84.6 percent) and Haiti (80.9 percent), Laos (45.5 percent), Afghanistan (44.2 percent) and seven other countries that lose more than 30 percent of their college educated labor force (Bosnia and Herzegovina, Lebanon, Yemen, Macedonia, Sri-Lanka, El Salvador and Nicaragua). Among the main net receivers, we find many high-income OECD and oil producing countries but also countries such as Kazakhstan, Paraguay and the Ivory Coast where relatively few natives have college education.

[INSERT TABLE 5 AROUND HERE]

5.2 The Female High-Skilled Migration

Migration of the highly skilled women is a matter of deep concern, not least since it is recognized that women's human capital is an important determinant of labor productivity, children's education and economic growth (see for instance Knowles et al., 2002, Coulombe and Tremblay, 2006, Klasen 2000, Dollar and Gatti, 1999, Blackden et al., 2006). Societies that are characterized by a failure to invest in female education or else those that lose a high proportion of educated women through emigration are therefore likely to exhibit slower growth rates and lower income levels. Conversely, societies that experience a net female skill gain may experience higher growth rates. This issue becomes even more relevant as many developing countries devote significant resources to the education of women in key skill areas and manage to close the gaps with men. However, retention is necessary to bear the fruits of these efforts.

Figure 4 illustrates graphically the impact of our introducing non-OECD destinations into our analysis of female high-skilled emigration rates. In Figure 4.a, we compare the high-skilled emigration of men (x-axis) and women (y-axis). Most observations (136 out of 195) lie above the 45 degree line, indicating that brain drain is more pronounced in the case of females (when compared to males). On average, the brain drain for females is 15 percent higher than for males, as illustrated on Figure 4.a by the linear trend estimated for the whole sample.[15] Such gender disparities are particularly apparent from sub-Saharan African countries and more broadly in cases in which women have poorer access to human capital. The intensity of college-educated women emigration is greater to OECD destinations however, such that the inclusion of non-OECD destinations has less bearing on our analysis of female brain drain in comparison with the impact on total high-skilled emigration rates, as demonstrated by comparing Figure 4.b and Figure 3.b. Nevertheless, the ratio of non-OECD to total female gross emigration rates in 2000 exceeds 0.50 in 33 countries (as opposed to the 36 cases taking men and women together). Similarly to Figure 3.c, Figure 4.c plots gross and net emigration rates of college graduates only this time focusing solely upon female migration. Although as previously noted, the impact upon our analysis of high skilled female migration is less pronounced when we introduce non-OECD destinations, Figure 4.c nevertheless highlights the fact that wealthier countries gain relative to poorer nations since they are more successful in attracting higher numbers of college educated females.

[INSERT FIGURE 4 AROUND HERE]

Table 6 lists the 25 countries with the highest (left panel) and lowest (right panel) net emigration rates of female college graduates, excluding small states with less than one million workers (population aged 25+). By and large the entries are similar to those in Table

[15] Focusing on OECD destination countries, the gap increases to 18 percent (see Docquier, Lowell and Marfouk, 2009).

5 although the magnitude of the net losses are broadly larger for the most affected countries. New entries in the left panel include Mongolia and several African nations, namely, Cameroon, Congo, the Democratic Republic of Congo, Rwanda Nigeria, Malawi and Togo; meaning that for these countries the magnitude of high-skilled emigration rates are particularly skewed in favour of women. The only new entries in the right panel in Table 6 (as when compared to Table 5), include Burkina Faso, Norway, Moldova, Japan and Turkey, meaning that these destinations are particularly attractive to college-educated female migrants relatively to their natural female population of college graduates.

[INSERT TABLE 6 AROUND HERE]

5.3 Brain drain and Human Capital

Our final piece of analysis draws upon the recent contribution of Clemens and Pritchett (2008), who provide comparable measures of income based upon the concept of the natural population. They argue "If economic development is that which raises human well-being, then crossing international borders is not an alternative to economic development; it is a form of economic development". They estimate income per natural, the mean annual income of persons born in a given country regardless of where that person resides and compare it with the standard indicator of income per capita, based upon a specific geographic area. Since human capital mobility affects both incomes per natural and the more usual measure of income per capita, it is instructive to compare measurements of human capital for both the resident and the natural population.

In line with our earlier expression for the average skill levels of naturals and residents, Figure 5.a graphically compares the high-skilled emigration rates of natives (i.e. naturals) on the x-axis and of residents on the y-axis. Since most countries that deviate from the 45 degree line lie beneath it, this shows that in general, countries' natural work force is more highly educated than the workforce that resides in that country ($h^i_{w+m,t} < H^i_{w+m,t}$). In other words, high-skilled immigration to these nations fails to compensate for the skill losses endured when college-educated natives move abroad or else that those countries characterized by net entries of college graduates also experience greater net inflows of less educated workers.

For the year 2000, we identify 41 cases with negative net high-skilled emigration rates, but globally migration only increases human capital in 26 of them. In the remaining 23 countries, net entries of college graduates fail to compensate for net inflows of less educated workers; this group includes developing countries such as Cote d'Ivoire, Gabon and Russia, but also wealthier countries such as Belgium, France, Luxembourg, the Netherlands, New Zealand, Norway and the United States among others. Similarly, Figure 5.b repeats the previous exercise only this time restricting the analysis to females, the results from which are broadly similar. For the year 2000, we identify 39 cases with negative net high-skilled emigration rates, but global migration only increases women's human capital in 26 of them.

[INSERT FIGURE 5 AROUND HERE]

6 Conclusion

This paper is the first to conduct a comprehensive examination of global human capital mobility, an analysis that rests upon three key contributions, 1) a significant collection of primary data sources, 2) an innovative estimation procedure used to impute data where they are otherwise missing and 3) a reformulation of existing high-killed migration measures, which in turn form the basis of our global analysis. Broadening our analysis from the more orthodox approach of focusing solely upon OECD destination countries, yields many important insights that have previously been overlooked. Perhaps most pertinently, migration to non-OECD countries accounts for 20% of all high-skilled migration and these movements comprise relatively large numbers of individuals from low income and least-developed nations in many regions of the world. In the wake of the recent global financial crisis and the shifting balance of power in the global economy, no doubt these migratory patterns will become more pronounced in the years to come. We hope our analysis and the data we provide will pave the way for further analytical and empirical work.

7 References

Anderson, J., (2011). "The Gravity Model,"The Annual Review of Economics, 3(1).

Artuc, E., S. Chaudhuri and J. McLaren (2010). "Trade Shocks and Labor Adjustment: A Structural Empirical Approach," American Economic Review, 100(3).

Artuc, E., (2013). "PPML estimation of dynamic discrete choice models with aggregate shocks,", World Bank Policy Research Working Paper Series #6480.

Barro, R., J and J-W., Lee (2001), "International Data on Educational Attainment: Updates and Implications," Oxford Economic Papers, vol. 53(3), pages 541-63.

Beine, M., F. Docquier and C. Ozden (2011), "Diasporas", Journal of Development Economics, 95(1), pages 30-41.

Beine, M., and Salomone S., (2013), "Network Effects in International Migration: Education versus Gender," Scandinavian Journal of Economics, 115(2), pages 354-380.

Bertoli, S., and FernÃ¡ndez-Huertas Moraga, J., (2013), "Multilateral resistance to migration," Journal of Development Economics, 102(C), pages 79-100.

Blackden, M., Canagarajah, S., Klasen, S., Lawson, D., (2006), "Gender and growth in Sub-Saharan Africa: Issues and evidence", UNU-WIDER Research Paper no. 2006/37, UNUWIDER: Helsinki.

Borjas, G. J., (1987), "Self-Selection and the Earnings of Immigrants", American Economic Review, vol. 77(4), pages 531-53.

Clair, G., G. Gaullier, Th. Mayer and S. Zignago (2004): A note on CEPII's distances measures. Explanatory note, CEPII, Paris.

Clemens M. A., and L. Pritchett, (2008), "Income per Natural: Measuring Development for People Rather Than Places," Population and Development Review, vol. 34(3), pages 395-434.

Cohen, D. and M., Soto, (2007), "Growth and human capital: good data, good results," Journal of Economic Growth, vol. 12(1), pages 51-76.

Coulombe, S. and J-F. Tremblay (2006), "Literacy and Growth", Topics in Macroeconomics, vol. 6 (2).

Docquier, F., and A. Marfouk (2004): Measuring the International Mobility of Skilled Workers - Release 1.0. Policy Research Working Paper, no. 3382.World Bank,Washington, DC.

Docquier, F., and A. Marfouk (2006): International migration by educational attainment

(1990-2000). In C. Ozden and M. Schiff (eds): International Migration, Remittances and Development. Palgrave Macmillan: New York.

Docquier, F., B.L. Lowell and A. Marfouk (2009): A gendered assessment of highly skilled emigration. Population and Development Review, vol. 35 (2), pages 297-321.

Dollar D and R., Gatti (1999), "Gender inequality, income, and growth: are good times good for women?", World Bank Policy Research Report on Gender and Development, Working Paper Series No. 1.

Doménech R. and A., de la Fuente (2006), "Human Capital in Growth Regressions: How much difference does data quality make?", Journal of the European Economic Association, vol. 4(1), pages 1–36.

Dumont, J.C., and G. Lemaître (2004): Counting immigrants and expatriates in OECD countries: a new perspective. Mimeo: OECD.

Dumont, J.C., J.P. Martin and G. Spielvogel (2007): Women on the move: the neglected gender dimension of the brain drain. IZA Discussion Paper 2920.

Grogger, J., and G.H. Hanson (2011): Income maximisation and the selection and sorting of international migrants. Journal of Development Economics, vol. 95(1), pages 42-57.

Head, K., T. Mayer, T. and J. Ries (2010), "The erosion of colonial trade linkages after independence," Journal of International Economics, Elsevier, 81(1), pages 1-14.

Klasen, S., (2000), "Does Gender Inequality Reduce Growth and Development? Evidence from Cross-Country Regressions", Collaborative Research Center 386, Discussion Paper 212.

Knowles, S., P. K., Lorgelly and P. D. Owen (2002), "Are educational gender gaps a brake on economic development? Some cross-country empirical evidence", Oxford Economic Papers, vol. 54(1), pages 118-149.

Ozden, C., C.R. Parsons, M. Schiff and T. Walmsley (2011): Where on earth is everybody? The evolution of global bilateral migration 1960-2000? World Bank Economic Review vol. 25(1), pages 12-56.

Parsons, C.R., R. Skeldon, T.L. Walmsley and L.A. Winters (2007): Quantifying international migration : a database of bilateral migrant stocks. Policy Research Working Paper 4165: World Bank.

Ortega F. and Peri, G. (2012), The Effect of Income and Immigration Policies on International Migration, NBER Working Paper No. 18322

Santos Silva, J.M.C., and S. Tenreyro (2006): The log of gravity. Review of Economics and Statistics, vol. 88(4), pages 641–658.

8 Appendix

8.1 Data sources

The statistical appendix in DLM (2009, p. 317) describes the data sources for the 30 OECD countries in their sample. Table A1 below describes the various data sources used for the 46 additional countries covered in this study. It provides the total number of migrants together with the number of high-skill immigrants recorded in 1990 and 2000, by destination country. Country order is governed by the size of the total immigration stock in 2000.

[INSERT TABLE A1 ABOUT HERE]

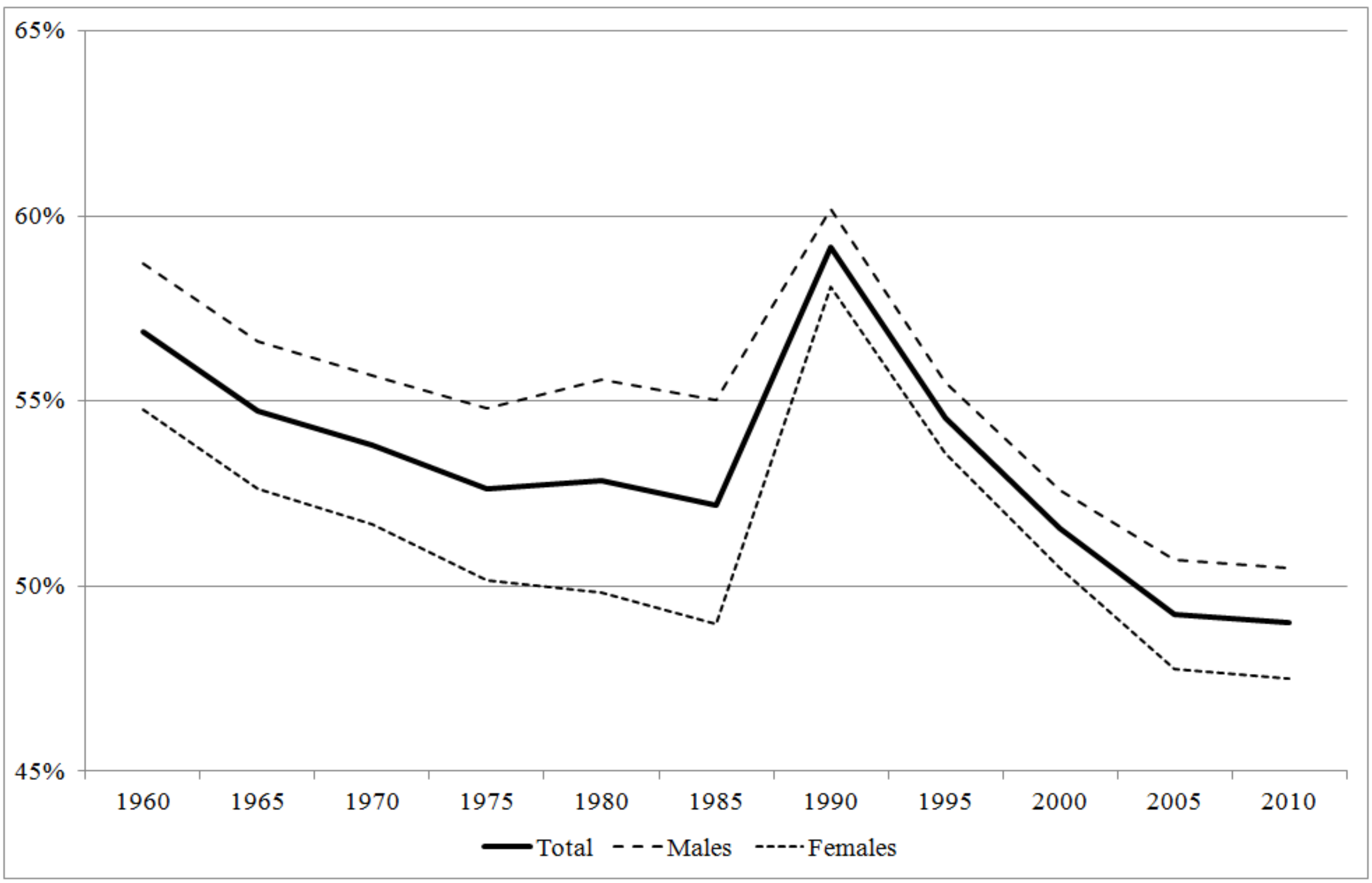
8.2 Explanatory variables

Table A2 describes the data sources for the explanatory variables used in regressions of Section 2.3.

[INSERT TABLE A2 ABOUT HERE]

TABLES AND FIGURES

Figure 1. Share of non-OECD destinations in the world migration stock (data by gender, 1960-2010)



Source: United Nations Population Division (2007, 2012)

Table 1. Migration stocks 25+ in 1990 and 2000 (in millions)

	Total (million)	To OECD[a] (million)	To non-OECD[a] (million)	(%)[b]	Including imputed stocks (milion)	(%)[b]
Year 2000						
Total	111.9	59.3	52.6	47.0	16.7	14.9
College graduates	28.8	20.9	7.9	27.4	2.5	8.7
Less educated	83.1	38.3	44.7	53.9	14.2	17.1
Males	57.4	29.0	28.4	49.4	8.7	15.1
College graduates	15.1	10.6	4.5	30.0	1.4	9.0
Less educated	42.3	18.4	23.8	56.4	7.3	17.3
Females	54.5	30.2	24.3	44.5	8.0	14.7
College graduates	13.7	10.3	3.3	24.4	1.1	8.3
Less educated	40.8	19.9	20.9	51.3	6.9	16.8
Year 1990						
Total	85.3	42.5	42.7	50.1	30.5	35.7
College graduates	16.3	12.6	3.7	22.8	2.4	14.9
Less educated	69.0	30.0	39.0	56.6	28.1	40.7
Males	44.4	21.0	23.4	52.7	15.6	35.2
College graduates	9.0	6.7	2.3	25.2	1.4	15.1
Less educated	35.4	14.3	21.2	59.7	14.3	40.3
Females	40.9	21.6	19.3	47.3	14.8	36.3
College graduates	7.3	5.9	1.4	19.8	1.1	14.6
Less educated	33.6	15.7	17.9	53.3	13.8	41.0

Notes. [a] 34 OECD destination countries; [b] Share of migrants to non-OECD countries, and imputed migration stock, in total migration.

Table 2a. First stage regression results

	Female		Male	
	Year 2000	***Year 1990***	***Year 2000***	***Year 1990***
Language	0.483	0.407	0.373	0.279
	(0.042)	*(0.035)*	*(0.038)*	*(0.033)*
Border	0.401	0.393	0.407	0.425
	(0.045)	*(0.037)*	*(0.043)*	*(0.036)*
Distance	-0.488	-0.334	-0.492	-0.344
	(0.021)	*(0.018)*	*(0.021)*	*(0.018)*
Colonial link	0.660	0.029	0.627	0.058
	(0.045)	*(0.041)*	*(0.045)*	*(0.041)*
Diaspora	0.457	0.550	0.467	0.553
	(0.007)	*(0.007)*	*(0.006)*	*(0.006)*
OBS	35,910	35,910	35,910	35,910
RSQR	0.908	0.915	0.847	0.885

Notes: All estimates are significant at 99% level.

Table 2b. Second stage regression results

	Female				Male			
	High-skill		**Low-skill**		**High-skill**		**Low-skill**	
	Year 2000	***Year 1990***	***Year 2000***	***Year 1990***	***Year 2000***	***Year 1990***	***Year 2000***	***Year 1990***
Language	0.663	0.553	0.484	0.454	0.577	0.518	0.153	0.258
	(0.030)	*(0.045)*	*(0.040)*	*(0.049)*	*(0.030)*	*(0.042)*	*(0.042)*	*(0.051)*
Border	0.281	0.223	0.808	0.606	0.515	0.222	0.844	0.488
	(0.036)	*(0.056)*	*(0.043)*	*(0.057)*	*(0.040)*	*(0.059)*	*(0.047)*	*(0.062)*
Distance	-0.247	-0.348	-0.381	-0.524	-0.163	-0.280	-0.395	-0.585
	(0.013)	*(0.017)*	*(0.019)*	*(0.021)*	*(0.014)*	*(0.017)*	*(0.021)*	*(0.023)*
Colonial link	0.496	0.708	0.211	0.644	0.498	0.588	0.349	0.653
	(0.030)	*(0.044)*	*(0.041)*	*(0.051)*	*(0.034)*	*(0.049)*	*(0.047)*	*(0.058)*
Diaspora	0.394	0.342	0.537	0.463	0.419	0.387	0.542	0.495
	(0.005)	*(0.006)*	*(0.007)*	*(0.008)*	*(0.005)*	*(0.007)*	*(0.007)*	*(0.008)*
Destination fixed effect	0.911	0.911	1.084	1.084	0.989	0.989	1.148	1.148
	(0.016)	*(0.016)*	*(0.020)*	*(0.020)*	*(0.018)*	*(0.018)*	*(0.022)*	*(0.022)*
OBS	30,419		30,419		30,419		30,419	
RSQR	0.893		0.898		0.871		0.871	

Notes: All estimates are significant at 99% level.

Figure 2. Histograms of Out-of-sample log ratios, Female migrants, 2000

Figure 2a. Low-skilled, cutoff=0

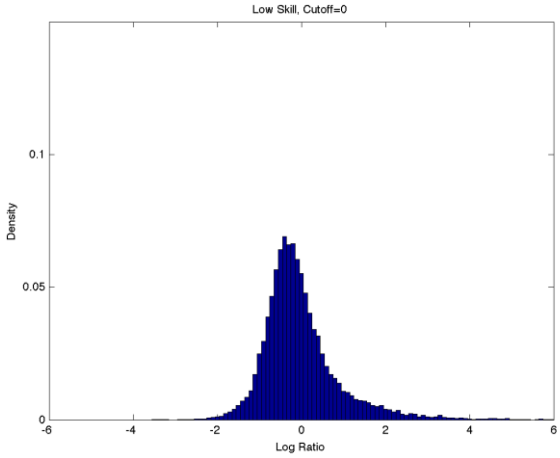


Figure 2d. High-skilled, cutoff=0

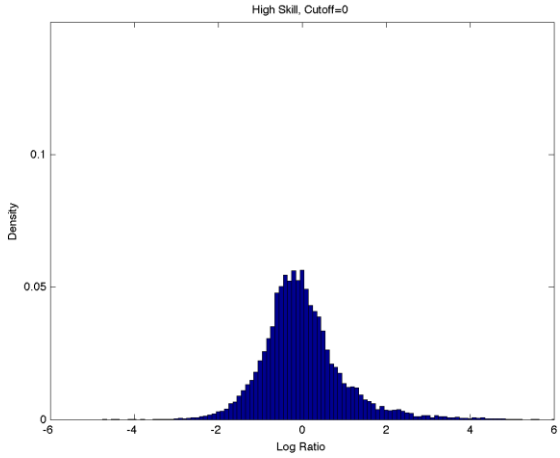


Figure 2b. Low-skilled, cutoff=1,000

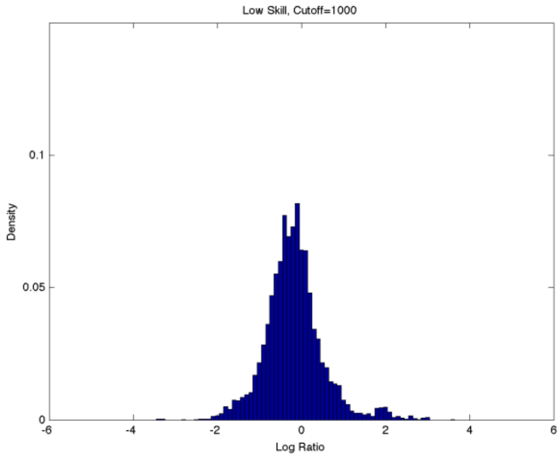


Figure 2e. High-skilled, cutoff=1,000

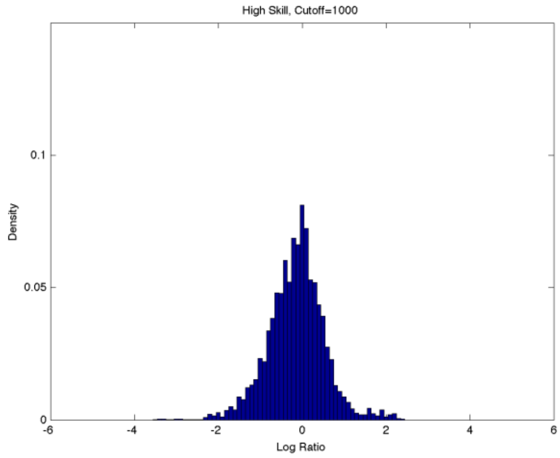


Figure 2c. Low-skilled, cutoff=10,000

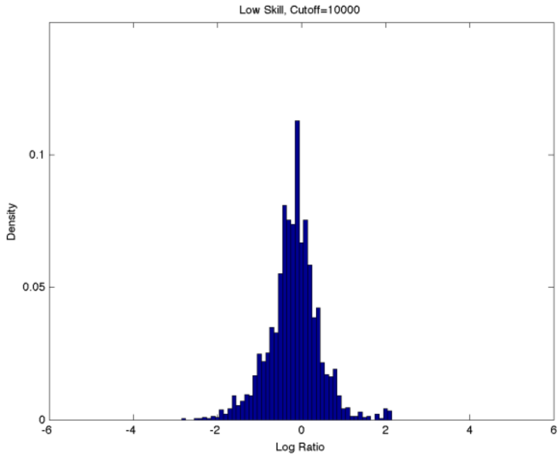


Figure 2f. High-skilled, cutoff=10,000

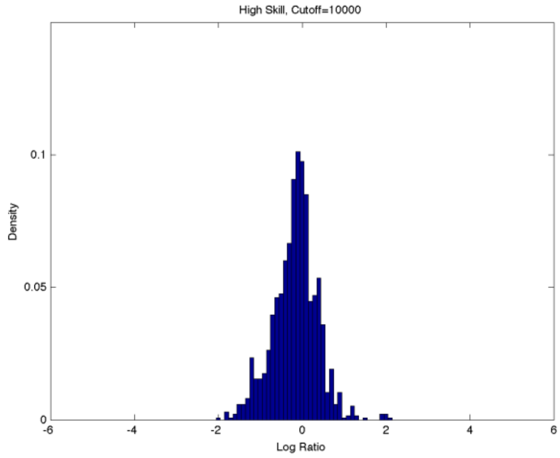


Table 3. Emigration patterns by country group. 1990 and 2000

	Total emigration			Emigration to OECD			Emigration to non-OECD		
	Stock (million)	College (%)	Women (%)	Stock (million)	College (%)	Women (%)	Stock (milion)	College (%)	Women (%)
Year 2000									
WORLD	111.9	25.7	48.7	59.3	35.3	51.0	52.6	15.0	46.1
OECD	32.2	30.4	50.4	29.1	31.0	50.8	3.1	24.4	46.6
HIGH	26.3	36.0	52.0	22.3	38.4	53.0	4.0	22.6	46.6
DEV	85.6	22.6	47.7	37.0	33.4	49.8	48.6	14.3	46.1
LOW	15.5	9.6	45.0	2.5	38.0	48.5	13.0	4.1	44.3
LDC	15.1	8.5	43.6	2.4	34.6	47.7	12.7	3.5	42.8
SIDS	4.3	35.6	54.6	4.0	37.0	54.9	0.3	17.7	51.7
USA	0.9	58.7	50.0	0.7	62.9	52.6	0.2	45.0	41.4
CANZ	1.5	57.1	54.0	1.4	57.6	54.3	0.1	46.9	47.9
EU27	20.0	32.3	52.0	17.7	33.1	52.4	2.3	25.6	48.8
GCC	0.6	20.3	37.3	0.0	65.2	39.7	0.6	16.5	37.0
LAC	15.6	25.1	50.2	14.0	26.4	50.1	1.6	13.9	51.6
SSA	10.5	11.5	45.2	2.2	43.1	47.5	8.3	3.1	44.6
CIS	19.2	26.3	54.6	2.4	42.1	58.2	16.8	24.0	54.1
INDIA	6.1	23.7	36.9	1.7	60.5	47.2	4.4	9.4	32.9
CHINA	3.9	27.9	51.8	1.7	46.7	53.0	2.3	14.0	51.0
MENA	9.1	21.8	37.9	4.2	29.9	43.0	4.9	14.7	33.5
Year 1990									
WORLD	85.3	19.1	47.9	42.5	29.5	50.7	42.7	8.7	45.2
OECD	25.7	26.2	51.1	23.3	26.9	51.6	2.4	19.4	46.3
HIGH	23.4	29.1	52.0	20.5	30.5	52.8	2.9	18.9	46.4
DEV	61.9	15.3	46.4	22.1	28.6	48.7	39.8	7.9	45.1
LOW	13.1	7.2	42.9	1.4	33.7	45.6	11.7	4.0	42.6
LDC	13.0	6.5	41.4	1.4	30.2	45.1	11.6	3.7	40.9
SIDS	3.0	31.0	52.6	2.6	34.6	53.6	0.4	7.8	46.5
USA	0.8	51.4	50.4	0.6	53.8	53.0	0.2	43.3	41.3
CANZ	1.3	46.0	56.1	1.2	46.4	56.3	0.1	38.2	52.6
EU27	18.8	25.3	51.9	16.9	26.0	52.2	1.9	19.4	49.2
GCC	0.4	17.7	34.2	0.0	64.8	35.6	0.4	14.3	34.1
LAC	8.2	24.7	50.4	7.0	27.4	50.7	1.2	9.3	48.2
SSA	8.5	7.5	44.1	1.2	39.6	44.3	7.3	2.1	44.1
CIS	14.1	12.7	57.4	1.8	20.8	56.3	12.2	11.5	57.6
INDIA	5.5	12.4	35.1	1.0	45.5	47.0	4.5	5.2	32.5
CHINA	3.3	16.5	50.7	0.9	40.0	50.2	2.4	7.8	50.9
MENA	6.8	17.3	36.1	3.2	23.8	41.5	3.6	11.6	31.3

Notes. Colomn ‘Stock’ gives the aggregate stock of emigrants in millions ; ‘College’ gives the percentage of high-skilled emigrants ; ‘Women’ gives the percentage of female emigrants.. For high-income (HIGH). developing (DEV) and low-income countries (LOW). we use the World Bank classification. Least developed countries (LDC) and small island developing states (SIDS) are defined by the United Nations. EU27: 27 countries of the European Union. USA: United States of America. CANZ: Canada + Australia + New Zealand; CIS: Commonwealth of independent States of the former USSR. MENA: Middle East and Northern Africa. SSA: Sub-Saharan Africa. Each country only belongs to one geographical group.

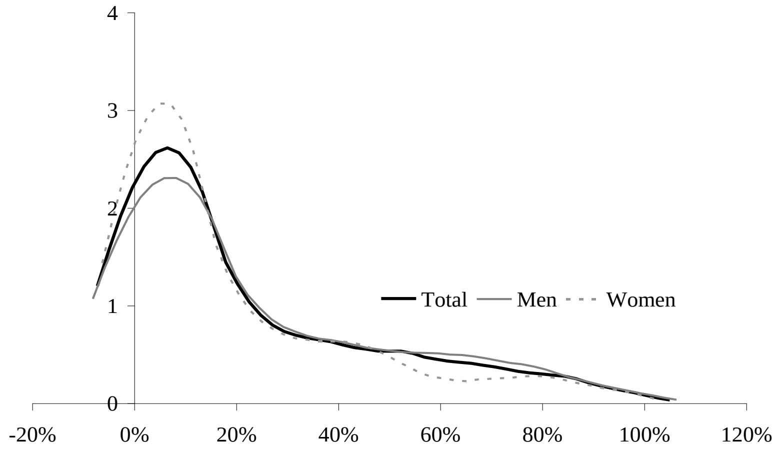
Table 4. High-skilled emigration rates. 1990 and 2000

	Gross high-skilled emigration rate			Net high-skilled emigration rates		
	To all	To OECD	To non-OECD	Total	Men	Women
Year 2000						
WORLD	8.1	5.9	2.2	0.0	0.0	0.0
OECD	4.8	4.4	0.4	-5.5	-5.4	-5.7
HIGH	4.8	4.4	0.5	-6.6	-6.8	-6.4
DEV	12.0	7.7	4.3	8.0	7.0	9.6
LOW	20.3	13.0	7.3	16.0	13.7	21.2
LDC	19.9	12.9	7.0	16.6	14.9	21.0
SIDS	40.9	39.3	1.6	34.8	29.3	40.8
USA	0.6	0.5	0.1	-11.6	-12.0	-11.2
CANZ	7.2	6.9	0.2	-30.9	-32.4	-29.5
EU27	9.7	8.8	0.9	2.4	2.4	2.3
GCC	14.3	3.6	10.7	-104.9	-230.7	-32.2
LAC	12.2	11.5	0.7	10.8	9.8	11.9
SSA	15.6	12.3	3.3	10.2	8.6	13.7
CIS	16.1	3.2	12.9	2.8	2.2	3.6
INDIA	6.0	4.3	1.7	5.4	4.7	7.0
CHINA	5.2	3.7	1.5	5.2	3.7	9.2
MENA	17.5	11.2	6.4	9.0	10.3	6.6
Year 1990						
WORLD	6.8	5.2	1.5	0.0	0.0	0.0
OECD	4.6	4.3	0.3	-4.0	-3.8	-4.3
HIGH	4.8	4.4	0.4	-4.7	-4.7	-4.7
DEV	9.6	6.4	3.2	6.8	6.0	8.1
LOW	23.2	11.8	11.4	18.9	17.7	21.8
LDC	23.2	11.7	11.6	20.4	19.2	24.1
SIDS	42.2	40.7	1.4	38.0	33.0	43.8
USA	0.7	0.5	0.1	-10.0	-9.4	-10.8
CANZ	6.6	6.3	0.3	-28.8	-30.5	-27.0
EU27	9.2	8.5	0.7	3.9	3.8	4.1
GCC	12.9	3.1	9.8	-104.1	-188.2	-36.4
LAC	10.7	10.1	0.6	9.3	8.3	10.5
SSA	17.2	13.1	4.1	10.6	9.0	15.2
CIS	7.6	1.6	6.0	1.8	1.6	2.1
INDIA	4.3	2.8	1.5	2.6	2.1	3.9
CHINA	4.5	3.0	1.6	4.5	3.2	10.5
MENA	19.9	12.9	7.0	13.7	13.9	13.2

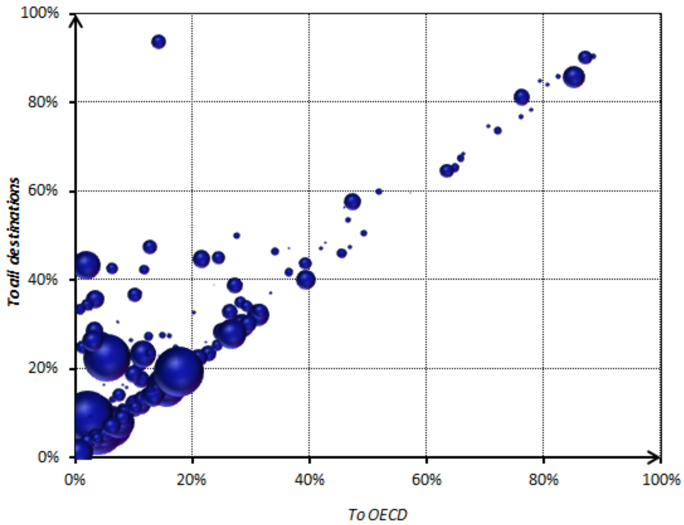
Notes. Colomn ‘Stock’ gives the aggregate stock of emigrants in millions ; ‘College’ gives the percentage of high-skilled emigrants ; ‘Women’ gives the percentage of female emigrants.. For high-income (HIGH). developing (DEV) and low-income countries (LOW). we use the World Bank classification. Least developed countries (LDC) and small island developing states (SIDS) are defined by the United Nations. EU27: 27 countries of the European Union. USA: United States of America. CANZ: Canada + Australia + New Zealand; CIS: Commonwealth of independent States of the former USSR. MENA: Middle East and Northern Africa. SSA: Sub-Saharan Africa. Each country only belongs to one geographical group.

Figure 3. Distribution of high-skilled emigration rates

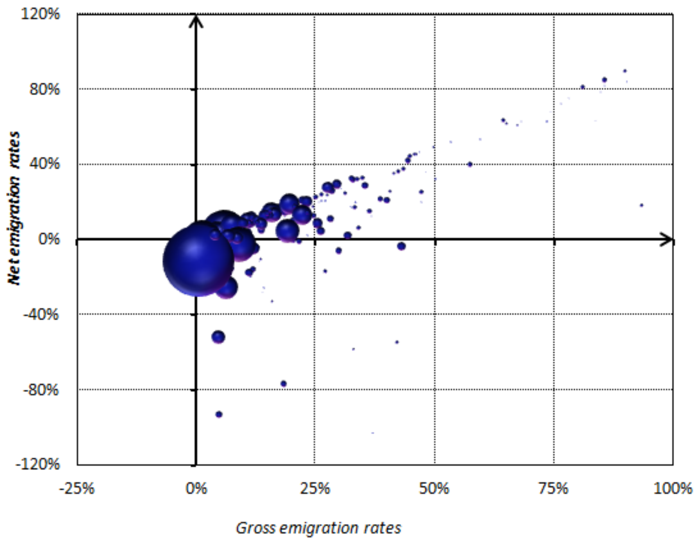
3.a. Density of "non-OECD to total" ratio of emigration rates



3.b. High-skilled emigration rates to OECD and to all destinations in 2000



3.c. Net versus gross emigration rates in 2000



Notes. On Figures 2.b and 2.c. each country is a represented by a bubble, the size of which is proportional to the high-skilled emigration stock.

.

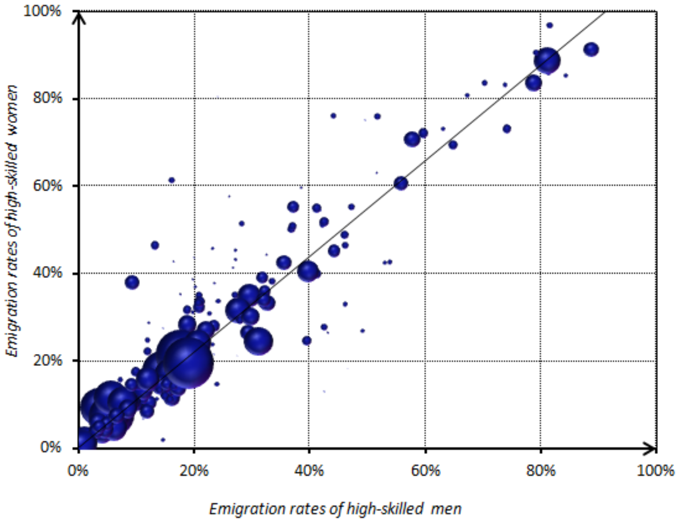
Table 5. Brain drain: most and least affected countries

Largest high-skilled net emigration rates							Lowest high-skilled net emigration rates						
	2000			1990				2000			1990		
Country	Net (%)	Gross (%)	non-OECD (%)	Net (%)	Gross (%)	non-OECD (%)	*Country*	Net (%)	Gross (%)	non-OECD (%)	Net (%)	Gross (%)	non-OECD (%)
Jamaica	84.6	85.6	0.6	85.5	86.5	0.9	United Arab Emirates	-309.4	9.0	70.6	-103.5	3.0	77.1
Haiti	80.9	81.0	5.9	73.5	73.7	7.9	Saudi Arabia	-93.3	5.0	63.5	-132.4	5.6	61.8
Liberia	53.3	59.8	13.0	55.0	62.9	13.7	Israel	-77.1	18.4	18.2	-19.4	13.2	14.6
Sierra Leone	51.9	53.4	12.7	46.7	48.5	14.0	Oman	-58.7	33.1	98.2	-55.0	29.2	98.4
Eritrea	49.2	49.9	44.6	48.1	49.7	48.6	Kuwait	-54.6	42.2	71.8	-39.4	37.9	75.6
Laos	45.5	45.8	0.5	40.3	42.0	1.8	Australia	-51.9	4.7	8.9	-47.9	3.4	8.0
Somalia	45.1	46.2	26.0	32.2	34.0	30.8	Canada	-25.8	6.4	2.8	-22.9	6.5	3.5
Afghanistan	44.1	45.0	45.5	25.8	26.9	59.4	Switzerland	-17.7	11.2	8.0	-12.4	8.2	11.0
Bosnia and Herzegovina	41.7	44.6	51.5	29.7	33.8	29.0	Singapore	-16.0	12.0	19.6	1.0	11.1	13.4
Lebanon	39.8	57.5	17.6	52.3	65.4	16.9	Libya	-15.8	7.7	19.7	-22.0	9.3	14.7
Kenya	37.2	43.5	9.5	48.7	50.5	11.4	United States	-11.6	0.6	18.1	-10.0	0.7	18.9
Yemen	36.0	42.5	84.8	55.4	59.8	73.0	Sweden	-6.8	5.2	2.7	-3.9	4.3	3.9
Uganda	34.9	41.6	12.0	42.5	43.9	19.7	New Zealand	-6.4	30.0	1.3	-19.9	25.1	2.9
Macedonia	32.6	34.9	18.7	26.1	30.3	6.5	Netherlands	-4.9	12.0	6.7	-2.4	12.1	6.4
Sri Lanka	32.4	32.8	19.2	34.0	37.0	33.9	Paraguay	-4.2	6.2	33.8	-4.7	4.6	8.1
Congo, Rep. of the	32.3	33.6	21.0	14.2	22.0	25.6	Cote d'Ivoire	-4.1	12.9	49.8	-16.5	7.5	25.1
El Salvador	31.9	32.9	3.7	32.9	33.7	5.1	Kazakhstan	-3.8	43.2	95.1	-8.8	9.6	90.1
Nicaragua	31.8	33.9	13.1	28.6	30.0	8.1	Russia	-2.7	9.0	75.3	1.0	4.7	75.9
Cuba	29.4	29.5	3.4	31.6	31.8	2.9	Belgium	-2.6	6.7	9.2	-0.8	5.3	6.2
Azerbaijan	28.5	35.5	90.1	-4.0	5.3	75.6	France	-2.5	4.0	13.8	-1.1	3.1	12.1
Vietnam	27.4	27.7	3.1	23.9	24.0	1.1	Spain	-2.4	4.3	15.9	-0.8	3.4	11.6
Chad	26.8	30.4	75.8	25.3	27.3	77.6	Nepal	-1.7	5.9	27.5	21.1	23.6	79.3
Georgia	25.6	28.5	88.1	11.3	16.1	90.6	Latvia	-0.8	20.5	45.5	-34.8	27.1	63.9
Armenia	24.9	47.2	72.7	24.5	29.4	66.2	Germany	0.2	6.8	9.2	2.4	6.8	4.6
Cambodia	24.6	31.4	0.6	26.9	27.8	1.9	Costa Rica	0.2	8.4	8.8	-6.0	10.5	8.5

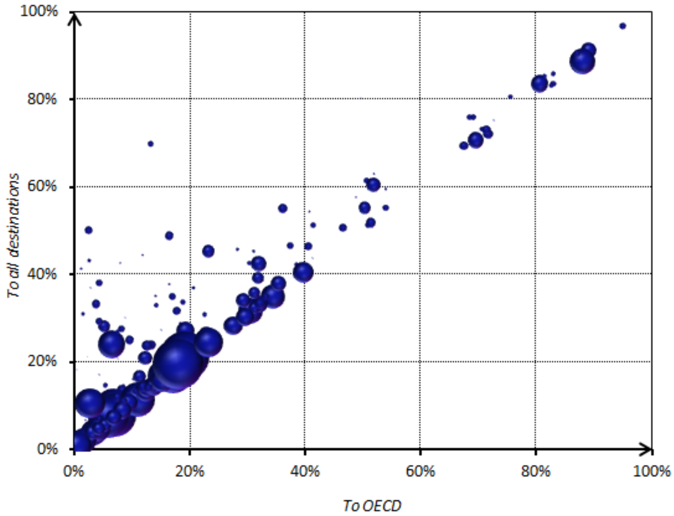
Notes. Only countries with labor force above one million are included. Countries' ranking is based on net emigration rates in 2000. The non-OECD share measures the share of non-OECD countries in gross emigration of college graduates.

Figure 4. Distribution of emigration rates of high-skilled women

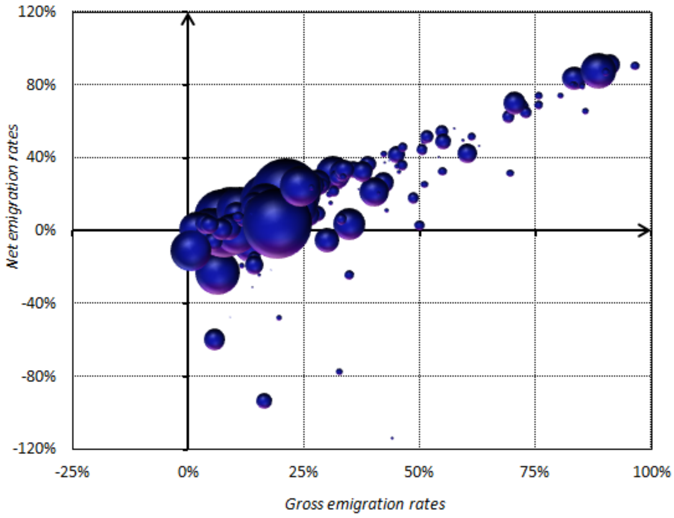
4.a. Emigration rates of high-skilled women and men



4.b. Emigration rates of high-skilled women to OECD and to all destinations in 2000



4.c. Net versus gross emigration rates of high-skilled women in 2000



Notes. On Figures 3.b and 3.c. each country is a represented by a bubble. the size of which is proportional to the emigration stock of high-skilled women in 2000.

.

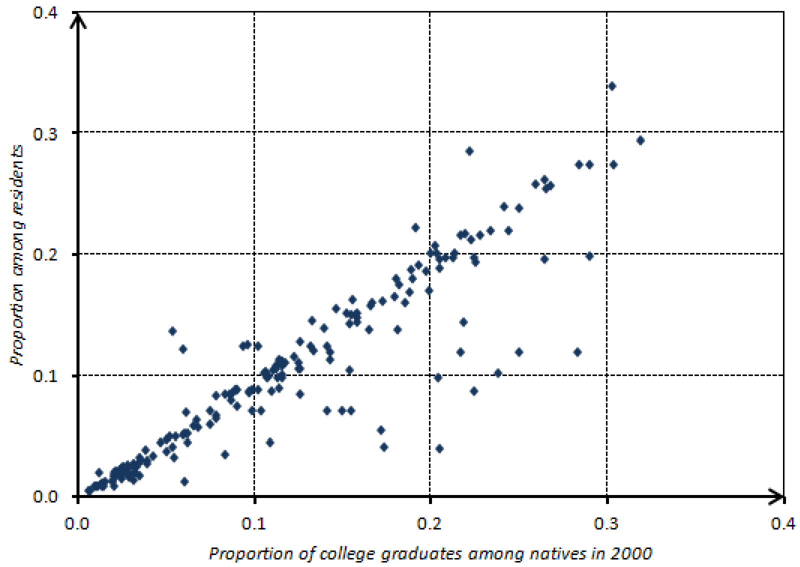
Table 6. Women's brain drain: most and least affected countries

Highest net high-skilled emigration rates							Lowest net high-skilled emigration rates						
	2000			1990				2000			1990		
Country	Net (%)	Gross (%)	non-OECD (%)	Net (%)	Gross (%)	non-OECD (%)	***Country***	Net (%)	Gross (%)	non-OECD (%)	Net (%)	Gross (%)	non-OECD (%)
Jamaica	87.7	88.6	0.7	87.5	88.5	1.0	United Arab Emirates	-202.9	6.6	69.4	-123.4	2.4	69.1
Haiti	83.3	83.5	3.4	78.8	79.0	5.8	Israel	-93.5	16.5	14.2	-20.5	11.2	12.2
Sierra Leone	73.7	75.9	9.6	72.1	74.4	13.5	Kuwait	-77.7	32.9	56.6	-73.3	26.8	64.0
Liberia	68.7	75.8	8.8	64.3	72.5	11.5	Australia	-59.9	5.8	7.6	-66.7	5.2	6.7
Afghanistan	54.3	54.8	34.0	45.8	47.1	51.8	Canada	-23.0	6.4	2.3	-18.8	6.8	3.0
Laos	51.4	51.7	0.5	42.9	45.4	2.1	Oman	-21.7	18.1	97.2	-18.3	15.9	97.9
Cameroon	51.1	61.3	17.3	30.0	35.1	26.9	Switzerland	-19.1	14.4	6.3	-10.6	11.2	8.6
Congo, Rep. of the	49.3	51.2	18.9	27.4	39.4	26.2	Singapore	-15.2	14.3	16.3	6.1	14.7	13.5
Kenya	48.6	55.1	8.5	59.7	61.3	10.2	Saudi Arabia	-12.7	1.8	56.7	-18.4	2.2	57.2
Somalia	45.5	46.4	19.3	34.4	36.2	25.3	United States	-11.2	0.6	14.3	-10.8	0.8	14.5
Uganda	44.3	50.7	8.0	57.7	59.2	13.2	Netherlands	-8.8	13.2	5.4	-6.7	14.1	4.9
Lebanon	42.1	60.4	14.2	57.4	70.7	14.6	Burkina Faso	-8.7	22.0	76.2	11.4	20.7	84.9
Eritrea	41.8	42.4	28.3	46.8	48.4	35.9	Cote d'Ivoire	-7.4	11.2	45.5	-21.8	4.8	19.6
Bosnia and Herzegovina	41.6	45.0	48.2	29.7	34.3	24.2	Libya	-6.5	9.2	18.3	-9.5	12.8	12.5
Mongolia	37.2	42.5	81.2	22.3	25.9	9.8	Sweden	-6.2	5.5	2.4	-3.5	4.8	3.5
Macedonia	36.5	39.0	18.1	30.9	34.9	5.2	New Zealand	-5.4	30.1	1.1	-14.4	24.8	3.1
Congo, Dem. Rep. of the	35.6	46.3	12.4	45.8	55.4	18.9	Norway	-3.0	7.1	2.4	0.6	8.2	1.7
Rwanda	35.1	45.2	31.1	-68.8	70.7	38.0	Spain	-2.6	4.2	13.0	-1.5	3.3	8.5
Sri Lanka	33.5	33.9	13.5	33.0	35.7	30.4	Paraguay	-2.4	7.1	37.0	-2.3	4.7	5.9
Nicaragua	33.3	35.7	12.5	31.3	32.5	7.3	Moldova	-2.2	24.9	61.3	-6.4	8.4	69.1
Nigeria	32.2	37.8	6.4	13.1	15.8	12.3	Belgium	-2.1	7.2	7.2	-0.8	5.9	4.4
El Salvador	32.2	33.1	2.8	33.9	34.6	3.0	Russia	-1.8	10.4	73.7	1.0	5.4	75.5
Malawi	32.0	36.8	43.6	41.9	50.8	30.8	Latvia	-1.7	23.8	43.8	-32.1	31.8	66.9
Togo	31.9	45.6	37.9	19.9	33.9	45.6	Japan	0.4	1.9	7.7	0.9	1.8	4.5
Cuba	31.2	31.5	2.7	32.8	32.9	2.5	Turkey	0.5	7.2	3.9	6.6	12.2	2.8

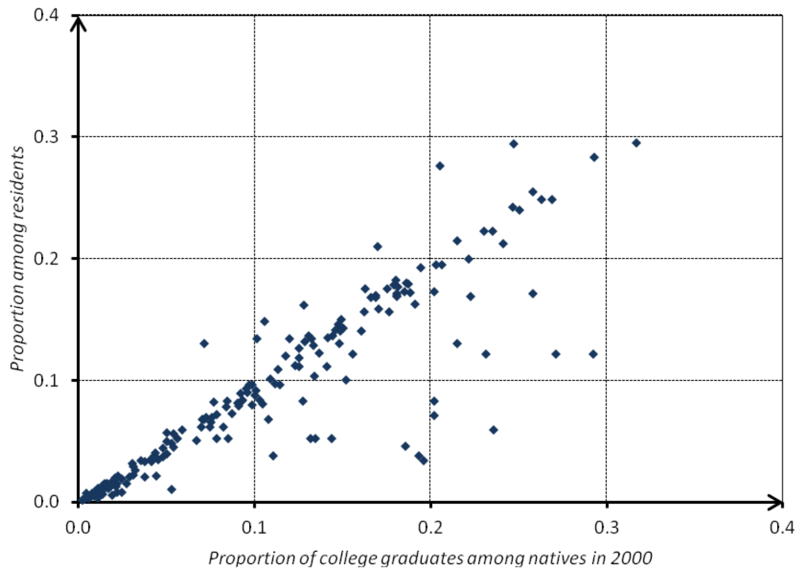
Notes. Only countries with labor force above one million are included. Countries' ranking is based on net emigration rates in 2000. The non-OECD share measures the share of non-OECD countries in gross emigration of college graduates.

Figure 5. Human capital among natives and residents in 2000

5.a. Women and men together



5.b. Women only



Note: Human capital is measured by the proportion of college graduates in the population aged 25 and more.

Table A1. Migration data for non-OECD destinations (1990-2000 census rounds)

Country	Source	1990 Round		2000 Round	
		Total	High-skilled	Total	High-skilled
Argentina (1991-2001)	IPUMS International[b]	54,743	1,512	680,583	60,056
Armenia (n.a.-2001)	DIOC-E database (OECD)[d]	-	-	240,839	55,081
Bahrain (1990-2000)	Labor Force Survey[c]	115,735	18,295	153,544	31,876
Belarus (1991-1999)	IPUMS International[b]	50,931	10,392	946,933	248,826
Benin (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	129,015	1,447
Bolivia (n.a.-2001)	IPUMS International[b]	-	-	45,200	14,560
Brazil (1991-2000)	IPUMS International[b]	341,985	67,229	298,257	67,356
Bulgaria (n.a.-2001)	National Statistical Institute	16,388	4,772	76,951	26,362
Burkina Faso (n.a.-2006)	DIOC-E database (OECD)[d]	-	-	189,188	15,680
Chile (1992-2002)	IPUMS International[b]	15,980	1,930	25,040	4,080
Ch - Hong Kong (n.a.-2000)	Census and Statistics Dep.	-	-	1,854,892	279,965
Colombia (1993-2005)	IPUMS International[b]	41,100	3,400	48,280	5,718
Costa Rica (1984-2000)	I.N. Estadistica y Censos	235,652	29,927	175,454	29,273
Cote d'Ivoire (1987-1999)	Institut National de Stat.	3,262,289	30,020	3,906,629	35,916
Croatia (1991-2001)	Central Bureau of Statistics	399,679	58,040	498,153	68,794
Cuba (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	8,770	1,780
Cyprus (1991-2001)	Cyprus Statistics	23,157	8,672	42,315	17,095
Dominican Rep (n.a.-2002)	United Nations CEPAL[a]	-	-	37,847	17,681
Ecuador (n.a.-2001)	DIOC-E database (OECD)[d]	-	-	69,134	21,495
El Salvador (n.a.-2007)	DIOC-E database (OECD)[d]	-	-	20,910	4,201
Estonia (1994-2000)	Statistics Estonia	402,958	113,181	233,112	72,594
Gambia (n.a.-2003)	DIOC-E database (OECD)[d]	-	-	59,199	3,307
Georgia (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	75,773	19,927
Guatemala (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	25,096	7,583
Guinea (n.a.-1996)	IPUMS International[b]	-	-	126,370	4,920
Honduras (n.a.-2001)	United Nations CEPAL[a]	-	-	17,478	5,635
India (n.a.-2000)	DIOC-E database (OECD)[d]	-	-	5,165,258	147,085
Indonesia (n.a.-2000)	DIOC-E database (OECD)[d]	-	-	6,156	4,708
Iraq (n.a.-1997)	IPUMS International[b]	-	-	50,670	8,450
Israel (1995-2008)	Central Bureau of Statistics	1,178,590	159,800	1,510,067	511,562
Jamaica (n.a.-2001)	DIOC-E database (OECD)[d]	-	-	7,541	3,487
Kenya (1989-1999)	IPUMS International[b]	39,300	2,080	193,820	12,900
Kuwait (1990-2000)	Labor Force Survey[c]	489,735	74,780	668,885	128,738
Kyrgyztan (n.a.-1999)	IPUMS International[b]	-	-	312,740	46,200
Laos (n.a.-1995)	DIOC-E database (OECD)[d]	-	-	5,558	468
Latvia (n.a.-2001)	Latvia Statistics	675,602	108,305	401,471	66,019
Lithuania (1991-2001)	Statistics Lithuania	271,824	41,355	203,374	42,417
Macedonia (1991-2001)	State Statistical Office	43,230	6,198	29,947	5,754
Malaysia (n.a.-2000)	IPUMS International[b]	-	-	769,700	39,400
Mali (n.a.-1998)	DIOC-E database (OECD)[d]	-	-	56,549	2,477
Malta (1995-2005)	National Statistics Office	12,613	5,279	19,009	8,524
Mauritius (n.a.-2000)	DIOC-E database (OECD)[d]	-	-	11,067	972
Mongolia (1989-2000)	IPUMS International[b]	-	-	4,410	1,440
Morocco (n.a.-2004)	Haut Commissariat au Plan	-	-	34,555	15,247
Nepal (n.a.-2001)	DIOC-E database (OECD)[d]	-	-	391,000	17,665
Nicaragua (n.a.-2005)	United Nations CEPAL[a]	-	-	41,903	4,858
Oman (1990-2000)	Labor Force Survey[c]	279,630	40,093	411,640	75,477
Panama (1990-2000)	IPUMS International[b]	-	-	59,290	11,930
Paraguay (n.a.-2002)	United Nations CEPAL[a]	-	-	105,022	18,408
Peru (n.a.-2007)	DIOC-E database (OECD)[d]	-	-	50,626	29,493
Philippines (1990-2000)	IPUMS International[b]	176,364	69,134	208,517	63,433
Qatar (1990-2000)	Labor Force Survey[c]	194,233	27,183	247,201	45,331
Romania (1992-2002)	IPUMS International[b]	81,397	24,781	76,519	27,408
Russia (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	9,009,859	2,207,429
Rwanda (1991-2002)	IPUMS International[b]	101,652	9,296	124,550	4,210

Saudi Arabia (1990-2000)	Labor Force Survey[c]	2,842,783	397,989	3,078,548	577,867
Senegal (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	35,285	6,909
Serbia/Montenegro (n.a.-2001)	DIOC-E database (OECD)[d]	-	-	713,596	114,268
Seychelles (n.a.-2000)	DIOC-E database (OECD)[d]	-	-	3,858	728
Singapore (1990-2000)	Statistics Singapore	397,189	30,191	512,515	137,705
Slovenia (1991-2002)	Statistical Office Slovenia	153,953	16,128	152,890	17,819
South Africa (1991-2001)	Statistics South Africa	635,110	101,876	795,066	174,873
Sri Lanka (n.a.-2001)	DIOC-E database (OECD)[d]	-	-	14,135	1,729
Tanzania (n.a.-2002)	DIOC-E database (OECD)[d]	-	-	161,390	4,185
Thailand (n.a.-2000)	DIOC-E database (OECD)[d]	-	-	158,445	14,081
Trinidad & Tobago (n.a.-2000)	United Nations CEPAL[a]	-	-	28,225	2,004
Uganda (1991-2002)	IPUMS International[b]	274,198	835	189,700	6,620
Un Arab Emirates (1990-2000)	Labor Force Survey[c]	675,549	98,565	1,160,658	213,445
Uruguay (n.a.-2006)	DIOC-E database (OECD)[d]	-	-	68,062	10,773
Venezuela (1990-2001)	IPUMS International[b]	493,935	18,243	489,636	37,159

Notes. Between parentheses and after the country name, n.a. means non available. [a] United Nations' Economic Commission for Latin America and the Caribbean (http://www.cepal.org). [b] See Minnesota Population Center (2010) and https://international.ipums.org. [c] Data for GCC countries: for Saudi Arabia. see *Population and Social Statistics* at http://www.cdsi.gov.sa; for the United Arab Emirates. see *Statistic Reports-Census 2005* at http://www.economy.ae; for Qatar. see *Labour Force Sample Survey* at http://www.qsa.gov.qa; for Bahrain. see *Labour Market Indicators* at http://blmi.lmra.bh; for Oman. see Periodic *Labour Force Survey* at http://www.moneoman.gov.om; and for Kuwait. see *Microdata of the Labor Force Survey* at http://scs.mop.gov.kw. [d] See "Dumont, Jean-Christophe & Gilles Spielvogel & Sarah Widmaier (2010). Les migrants internationaux dans les pays développés, émergents et en développement : élargissement du profil, Questions sociales, emplois et migrations, n. 114.

Table A2. Description of Explanatory Variables

Variable	Source	Description
Common border	CEPII[a]	Dummy equal to 1 if a country pair share a land border
Distance	CEPII[a]	Measure of geodesic distance between country pair's main cities
Common language	CEPII[a]	Dummy equal to 1 if a country pair shares a common official language
Former colony	CEPII[a]	Dummy equal to 1 if a country pair share a colonial history
OPSW bilateral stock	OPSW (2010)	Total migrant stock recorded between origin i and destination j
Some English	CIA World Factbook[b]	Dummy equal to 1 if a destination country speaks some English
GDP per capita	Penn World Tables[c]	Per capita income of the destination country in PPP
Total fertility	World Development Indicators	Total fertility rate (in log) in the destination country
Skill destination workforce	DLM (2009)	Share of the destination country workforce that are tertiary educated (by gender)
Total labor force	DLM (2009)	Population aged 25 and over in the destination country (by gender)
Labor force participation	World Development Indicators	Labor force participation rate in the destination country (by gender)
Military service dummy	Own calculation	Dummy equal to 1 if military service is compulsory in the destination country
Polygamy dummy	Own calculation	Dummy equal to 1 if polygamy is legally or socially accepted in the destination country
GCC dummy	Own calculation	Dummy equal to 1 if a destination country belongs to GCC

Notes: a See: http://www.cepii.fr/anglaisgraph/bdd/distances.htm. see Clair et al. (2004).
[b] See: https://www.cia.gov/library/publications/the-world-factbook.
[c] See: http://pwt.econ.upenn.edu.