Économie internationale 115 (2008), p. 65-108

ÉCONOMIE INTERNATIONALE
INTERNATIONAL ECONOMICS

The brain drain between knowledge-based economies: the European human capital outflow to the US

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Article received on May 5, 2008
Accepted on December 19, 2008

Abstract. This paper uses census data from 1980 to 2006 to study the new European emigration to the US. This emigration is about a small but rising number of individuals. Yet since 1990, emigrants are increasingly selected from the upper tail quality distribution of their source country workforce in terms of education, scientific knowledge and, unobservable skills. This nineties surge has been amplifed by the fact that returnees were fewer, older and, if anything, relatively less educated. As for the rationales, I provide preliminary evidence showing that the brain drain reflects the weakness of demand for skilled labor in Europe. Lately, I show that the technological changes triggered by human capital losses could make these outflows increasingly costly for Europe in terms of productivity.

JEL Classification: F22; J24; J31; O31.
Keywords: Brain Drain; Emigration; Human Capital; Europe-US.

Résumé. Cet article étudie la nouvelle émigration européenne vers les États-Unis en s'appuyant sur les données du Census américain disponibles pour la période 1980-2006. Cette vague d'émigration concerne un nombre réduit de personnes, mais est croissante. En effet, depuis 1990, les émigrants sont de plus en en plus sélectionnés dans la fraction de niveau le plus élevé de la population active des pays d'origine, que ce soit en termes d'éducation, de niveau scientifique ou de caractéristiques inobservables. La hausse des années quatre-vingt-dix s'est trouvée amplifiée du fait que ceux qui sont rentrés étaient moins nombreux, plus âgés, et relativement moins éduqués. Cet article apporte quelques premiers éléments d'explication qui montrent que la fuite des cerveaux est le reflet de la faible demande, en Europe, pour la main-d'œuvre qualifiée. L'article indique aussi que les changements technologiques déclenchés par des pertes en capital humain pourraient rendre ces départs de plus en plus coûteux pour l'Europe en termes de productivité.

Classification *JEL* : F22 ; J24 ; J31 ; O31.
Mots-clefs : fuite des cerveaux ; émigration ; capital humain ; Europe-États-Unis.

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1. Introduction

Like secondary education and physical capital investments were crucial to the post-war West-European economy to catch up, higher education and knowledge investments are crucial for Europe to take-off in the knowledge-based economy. In this context, many countries are seeking to increase their stock of "brainpower" by reducing mobility barriers for the highly skilled workers. Thus, following goods and capital, skills and talents are increasingly sought after in a global and competitive market. As a landmark, the European Commission proposed in October 2007 a "blue card" scheme, officially to rival the American Green Card, to significantly reduce immigration barriers for the highly skilled workers. Besides attracting worldwide brains, policymakers in Europe are also steadily concerned with retaining their human capital. For instance, The Third European Report on Science and Technology emphasizes that "Europe produces a large number of university graduates, doctorate recipients and postdoctoral students. But a significant share of them finds work in an occupation outside of European R&D. It may be one of Europe's biggest obstacles in its attempt to becoming the world's most competitive knowledge-based economy [...]." In its examination of the brain drain to the United States, the same report noticed that 73% of the 15000 Europeans who studied for their PhD in the United States between 1991 and 2000 plan to remain there.[2]

For various reasons, the US is a magnet for skilled workers coming from the developing world but also from the rich and relatively skill-abundant Europe.[3] Case studies also suggest that those workers are and have been important contributors to the American technological edge.[4] Despite high anxiety in the media and among policy makers, few studies brought the European brain drain to the scrutiny of the data to disentangle the "myth from the reality".[5] At issue is whether (i) emigrants are a significant share of their source country labor force; (ii) are they disproportionately skilled and educated compared to stayers; (iii) are they moving

2. In the US, 21% of all doctorates holder were foreign born in 1990, amongst them 1/5th are born in an EU15 country. By the year 2006, the foreign born represented 32% of US PhDs and approximately the same proportion as in 1990 were born in an EU15 country (sources: Author calculations from the US censuses).

3. The expatriates data of Dumont and Lemaître (2005) shows that the total number of Europeans in the US outweighs by a very large margin that of Americans in Europe. For instance, in 2000 there were 5 times more French and 15 times more Germans in the US than Americans in France and Germany. Hence, even if all US expatriates and only half of French and Germans expatriates were highly skilled, these countries would still be net exporter of skills to the US.

4. A study by Stephan and Levin (2001) over a sample of 4500 scientists concludes that "... individuals making exceptional contributions to S&E in the US are disproportionately drawn from the foreign born." On the same topic, *The Economist* (2006) reported that half the Americans who won Nobel prizes in physics in the past seven years were born abroad. Such success stories as Intel, Sun Microsystems, Yahoo, E-bay or Google were all founded or co-founded by immigrants.

5. Most existing studies are concerned about the brain drain from poor and human capital scarce countries toward rich and human capital abundant ones (Docquier *et al.*, 2007). Almost all studies on the brain drain between knowledge based economies consider the case of a single country. Ross Finnie (2001) showed that while the number of Canadian leavers is small, a disproportionate number of them can be found among particular groups of knowledge workers and high-income earners. Becker, Ichino and Peri (2003) investigated the brain drain of Italians to the rest of the world and found that a sizeable and increasing share of tertiary educated Italians are moving abroad.

permanently or temporary and (iv) what are the consequences for those that choose not to emigrate. The contribution of this paper is to exploit the unique strengths of US census data from 1980-2006, together with data on expatriates' origin countries characteristics, to answer these questions.

We owe to Saint-Paul (2004) the first empirical investigation of the first two issues. The author uses data on the stock of expatriates in the 1990 and 2000 US censuses. He shows that, compared to the year 1990, the expatriates in the 2000 census have a better schooling distribution than in the source countries and that they compare favorably to the US workers of similar educational levels. This paper begins by revising and extending these results in a number of directions. First, the brain drain is tracked on a broader sample of countries and over a larger time frame. I consider the period 1980-2006 over which the US experienced an unprecedented growth and for the first time since decades a fortune reversal with respect to Europe: the US productivity growth rate catched up and outpaced that of Europe after 1995 (Aghion, 2006). Throughout this period, the US followed by a number of European countries, have undergone a technological revolution with the onset of computers and the information and communication technologies. This process has shifted the demand toward highly educated workers and toward jobs with a greater content of "tacit" (non-codified) knowledge (Autor *et al.*, 1998, 2008). Second, in order to assess how observed changes are affected by different episodes of migrations, in each census a clear distinction is made between older emigrants and recent leavers. Third, from a methodological point of view, I assess the extent and nature of the brain drain using synthetic indices in which the magnitude of emigration (*emigration rate*) is weighted by its relative quality (*emigration selectivity*). There is a drain of a given type of skill only if expatriation decreases the average endowment of source countries' workers in that skill. Several dimensions of skill selectivity are considered. On top of schooling, I have tracked changes in occupational related skills, emphasizing occupations that are related to a country scientific human capital stock (engineers, researchers and academics). Lately, and following Saint-Paul (2004), I use information on expatriates' wage performance in the US labor market to shed light on the drain of talents; that is people endowed with skills which rise productivity but that are not measured by observable characteristics. Instead of looking at the average wage premium, I investigate changes in the position of successive cohorts of recent leavers at different point of the residual wage distribution. Moving gradually across skills with higher content of education and productivity reveals how the intensity of selection evolves over time along the ladder of labor quality.

As shown by Saint-Paul (2004), expatriates represent a small share of their source country labor force and they are clearly more educated. For all large European countries, this share is rising except for Italy. As for the dynamics, I show that it is only since 1990 that the rise is due to higher rates of departures. Moreover, while I also find that the share of tertiary educated among expatriates is rising, unlike Saint-Paul (2004) I do not find that the brain drain of tertiary educated has increased in the 1990s. On the contrary, by the year 2006, the tertiary educated expatriates were representing a slightly lower share of their source country tertiary educated than in 1990. However, a detailed look at occupational distribution of emigrants reveals an increasing concentration in the S&E occupations. This finding suggests that selectivity has shifted within the group of tertiary educated toward highly educated people. Using comparable international data on researchers, I show that the brain drain of researchers has increased from 2.7% in 1990 to 4.3% in 2006, and most of this growth has been due to the outflows during the 1990s. Regarding unobservable productive skills, we found a similar shift of quality: newer generations of movers are increasingly concentrated at the upper tail of the US residual wage distribution. This 1990s European brain drain surge has also been amplified by lower rates of returns. Moreover, the returnees are more likely to be older and, if anything, relatively less educated than in the 1980s. Overall, the educational, occupational and productivity related measures of brain drain computed over four successive censuses and generations of emigrants underscore a revival of the European brain drain in the 1990s. Relatively larger inflows, lower returns, and a higher selection of leavers at the upper end of the labor quality distribution have driven this revival.

What are the consequences for those that choose not to emigrate? This issue is addressed in the last part of the paper within a simple supply and demand framework similar to that used to investigate how changes in technology and the supply of human capital affect wage inequality (Katz and Murphy, 1992; Autor et Katz, 2002; Acemoglu, 2002; Autor *et al.*, 2008, 2006). The framework is used to develop productivity based brain drain indices that answer the following question: for each year of the census, by how much productivity in emigrants' source country would increase in the short and medium run if recent leavers were returning? I assume that technology is fixed in the short run, but in medium run it adjusts to changes in relative skilled labor supply. To motivate this process of technological adjustment, I construct a panel dataset on skilled labor wage premia and relative skilled labor supply and demand shifts, following the methodology of Caselli and Coleman (2006, 2002), but within a framework closer to Acemoglu (2003). I show that throughout the 1980s and 1990s changes in skilled labor wage premia are strongly correlated with changes in skilled labor demand shifts and are uncorrelated with changes in skilled labor supply. Interestingly, this framework turns also to provide a useful basis to make sense of differences across countries in the degree of migration selectivity. On this issue, my contribution evolves around the idea that skilled labor supply and demand differences across countries shape differences in returns to skills and, following the arguments of migration selection models (Borjas, 1987, 1994), determine differences of emigration selectivity. An excess supply or a lack of demand for skilled labor depresses the wage returns of tertiary educated workers compared to non-tertiary educated which increases the relative share of tertiary educated among leavers. Accordingly, I uncover a negative relationship between changes in the relative share of tertiary educated among leavers and changes in the relative demand for tertiary educated. Namely, countries that had a more dynamic supply of skilled labor experienced stronger skilled labor demand shifts that prevented the fall of skill premia and as a consequence the rise of skill selectivity among migrants. I interpret this, as preliminary evidence that the higher skill selectivity of European migration is a symptom of the weakness of demand for skilled labor.

The aforementioned relationship between skilled labor supply and skilled labor wage premia is consistent with recent theories of supply driven skill bias technological change (Acemoglu, 1998; Kiley, 1999; Nahuis and Smulders, 2002; Caselli and Coleman, 2006; Goldin and Katz, 2007). An important conclusion that is reached by this literature is that a higher supply of a factor can eventually trigger an endogenous response of firms' technological choices that could undo the negative impact of this higher supply on that factor productivity. This insight provides a straightforward way to disentangle the short and medium run productivity content of European emigration. In the short run lower expatriation of skilled workers increases human capital *per* workers and aggregate productivity. However, due to a dilution effect of technology, which in the short run is fixed, this higher supply of skilled labor decreases returns to skills. In a medium run, the higher supply of skilled labor triggers a skilled biased technical change that eventually undoes the negative impact on skilled labor productivity. In this context, I show that the medium run impact of the brain drain is much higher than the short run one. The technological adjustment that could be triggered by human capital losses could have large impact on source countries labor productivity. As the adoption of skill complementary technologies accelerated in the 1990s, the productivity costs of human capital outflows have also accelerated despite relatively lower rate of emigration of tertiary educated workers.

The remainder of the paper is organized as follows. The next section provides empirical evidence on trends in the magnitude and nature of European emigration to the US and on the importance of returns migration. Section 3 introduces a useful skilled labor supply and skilled labor demand framework to investigate the sources of differences in cross-country skilled labor wage premia which I relate to cross-country differences in emigration selectivity. Further, this framework is used to obtain a productivity based brain drain measure in which human capital outflows are weighted by their impact on source countries labor productivity. The last section concludes.

2. Inspecting the expatriates population

2.1. A useful index

The "brain drain" means that it is the best educated and the most qualified that leave their country to take up jobs in another one. Therefore its extent depends on two dimensions: the magnitude of emigration, i.e. the emigration rate, and how the quality of movers compares to that of stayers, i.e. the emigration selectivity. Throughout the paper, I consider the following generic brain drain index for the skill type *j* from country *c* at period *t* :

$$BD_{j,c,t} = 100 * \frac{M_{c,t}}{N_{c,t}} * \frac{s^m_{j,c,t}}{s^n_{j,c,t}} = 100 * em_{c,t} * S_{j,c,t} \tag{1}$$

where $M_{c,t}$ is the number of expatriates aged 25-64 years (therein defined as the working age) from country *c* living in the US in period *t*, and $N_{c,t}$ denotes the corresponding number of non-emigrants (also referred to as stayers) from that country. Since $em_{c,t}$ is a head-count ratio, it represents the raw labor conveyed from country *c* to the US by emigrants, as a share of the raw labor based in country *c*. The selectivity of emigrants is measured by the ratio of the share of expatriates with skill *j* ($s^{m}_{j,c,t}$) to the share of non-emigrants with that skill ($s^{n}_{j,c,t}$). The ratio measures the relative quantity of skill *j* conveyed by each emigrant from country *c* to the US. The selectivity index $S_{j,c,t}$ varies between 0 and ∞ and the larger it is above 1, the higher is the migration selectivity. Different measures of skills are considered: schooling related skills, occupation related skills focusing on S&E occupations (engineering, research and academia) and, productivity (wage) related skills. Therefore, the aggregate brain drain index $BD_{j,c,t}$ measures the quantity of skill *j* that is conveyed by emigrants from country *c* to the US as a share (%) of the total skill *j* left in country *c*. The index is computed over all expatriates and for the subgroup of recent emigrants, typically those that, at the year of the census, have less than 10 years of residence in the US. In that case, I will refer to $BD_{j,c,t}$ as the rate of departure of skill *j*. Unlike stocks, which are an amalgam of current and past mobility decisions, changes in the number of recent expatriates provide a "flow" measure which is less liable to initial demographic composition. This "flow" measure is useful to draw up trends in the size and quality of departures and to interpret observed changes.

2.2. The data

Data on source country workers. The main information that is needed on non-emigrants is their education. I use the data of Cohen and Soto (2006) that gives the share of the population aged 25-64 in 6 educational categories: primary non-completed, primary completed, secondary non-completed, secondary completed, tertiary non-completed and tertiary completed. Average years of schooling are computed by multiplying the population share in each category by the duration of schooling in that category, obtained from OECD Education at a Glance (1997,2007), and by summing up over categories.[6] Source countries' population size and their demographic characteristics are derived from the ILO Laborsta Data. Other source countries data are presented in the text.

Expatriates sample. The data on European expatriates in the US are from the 1980, 1990, and 2000, 5% US censuses and from the 2006 1% US census, made available by the Minnesota Population Center (IPUMS). The primary advantages of these data are sample size and the possibility to identify precisely European expatriates. A second advantage is that US censuses include very detailed schooling variables that allow the matching with each of the six educational groups of Cohen and Soto (2006), such that I can compute average years of education of expatriates following the method used for source countries' populations. The sample of European expatriates is composed of individuals aged

6. For the non-completed educational categories, I assume that half of the curriculum is completed.

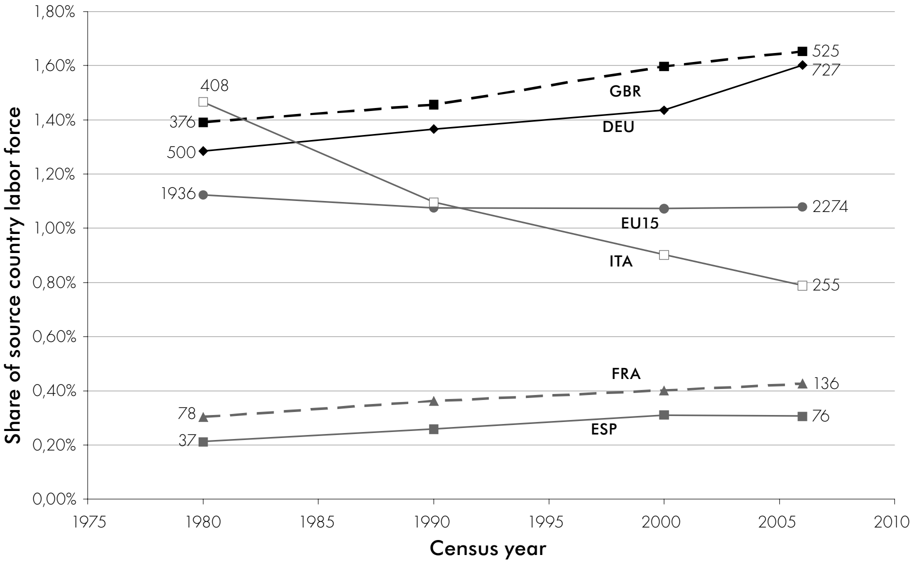
between 25 and 64 and born of non-American parents in a European country.[7] Thus, the 1980, 1990, 2000 and 2006 censuses include respectively 115316, 119116, 126111 and 23499 observations on European born workers aged 25-64. The number of observations for each European country and census is presented in TABLE A1.1 of the APPENDIX 1. The TABLE A1.2 of this appendix presents detailed characteristics of this working age population in each census. The demographic characteristics are fairly stable, though the average age of European expatriates and their number of years in the US are rising over time, reflecting the accumulating stock of previous immigrants. There is also a clear upward trend in average education. In average, European expatriates in 2006 have two more years of education than those in 1980. This difference is even more striking if we look at schooling distribution: the share of high school dropout in 2006 has been divided by 4 while the share with at least a bachelor degree has more than doubled. Geographic distribution of expatriates has also evolved away from the traditional northeast regions to the more dynamic south and west areas. The employment rate of European males has remained relatively stable whereas that of women has increased over time. The trend for women is probably reflecting that they are less likely to move as tied migrants over time. On average, Europeans are also more likely to be self-employed than US natives. Finally, average real wages show an upward trend for men and women, which is consistent with the observed upward trend in educational attainment. The hourly wage gap between European expatriates and the white US native workers has expanded rapidly between 1980 and 2006; the rise has been more impressive for women. Altogether, this data are suggesting that expatriates' labor quality has increased over time. However, to assess whether this is reflecting a higher brain drain from Europe, these characteristics need to be compared to those of non-emigrants in Europe.

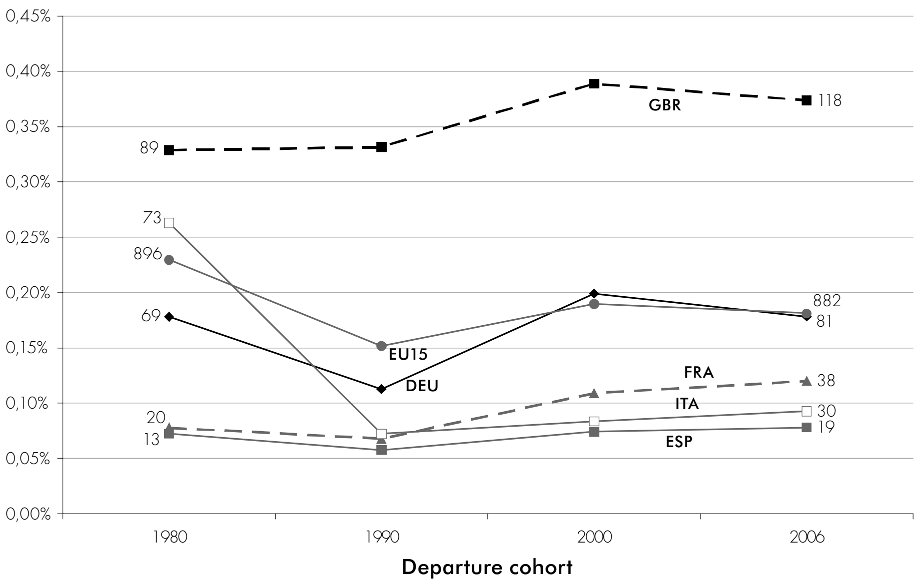
2.3. Trends in European brain drain: emigration rates and emigration selectivity

The top panel of FIGURE 1 portrays the total number of expatriates, and their share in the source country labor force (i.e. $em_{c,t}$), for the EU15 as a whole and for the largest countries. By the year 2006, the US based EU15 expatriates represent a little less than 1.1% of the EU15 working age population; this share has declined slightly during the 1980s and then plateaued. The five largest countries on the graph represent more than 3/4th of the total. The German and the British are by far the most numerous, accounting for more than half of the overall expatriates. The declining number of Italians working in the US drives heavily the trend at the EU15 level. If they were omitted, instead of a 17% increase, the number of expatriates would have grown by 33% between 1980 and 2006. The growth in absolute value and as a share of source country labor force has been above the EU15 average level for the other countries, in particular for France (+74%) and Spain whom the number of

7. These countries are Austria, Belgium, Denmark, France, Finland, Germany, Greece, Ireland, Italy, The Netherlands, Portugal, Spain, Sweden, Switzerland, and the Great Britain; due to small sample size, Luxembourg is omitted. In different part of the paper data on Canada, Switzerland and Norway are also included to increase the sample size.

Figure 1 – Trends in the magnitude of expatriates tocks and departures





Notes: Each point of the figure corresponds to a census year. The shares of expatriates are computed as $M_{c,t}/N_{c,t}$. On the top panel $M_{c,t}$ refers to all expatriates. Numbers are given (in thousands) for the 1980 and 2006 censuses. On the bottom panel, $M_{c,t}$ refers to expatriates with less than 10 years of residence in the US. Numbers are given (in thousands) for the 1980 and 2006 censuses.

expatriates has doubled. These evolutions of stocks are weighted by the history of the volume and character of past migration. The bottom panel of FIGURE 1 provides a more dynamic picture of European expatriation by showing the departure rates and the size of successive cohorts of recent emigrants in each census year. Departure rates are U shaped: after a steep decline or stagnation in the 1980s, the 1990s are marked by a clear recovery of European inflows into the US, albeit at a slower pace in the years 2000s.[8] The later deceleration should be interpreted in the light of the specific context, and switch in the US immigration policy and visa procedures that followed the September 11th events and the economic downturn of the early 2000s. These trends reveal that the growth of European emigrants in the 1980s on the top panel were merely an artifact due to favorable demographic differences between expatriates and sources countries' populations instead of a growing rate of expatriation. Instead, since the 1990s, the rising stocks are also pushed-up by higher rates of departures. Yet, and although these figures have to be put in the context of an aging European population,[9] taking the view of an homogenous labor, expatriates are still representing a small share of their home country's population, which is unlikely to have important impact. Thus, the economic significance of the brain drain, if any, should evolve around the selectivity margin.

2.3.1. Schooling related brain drain indices

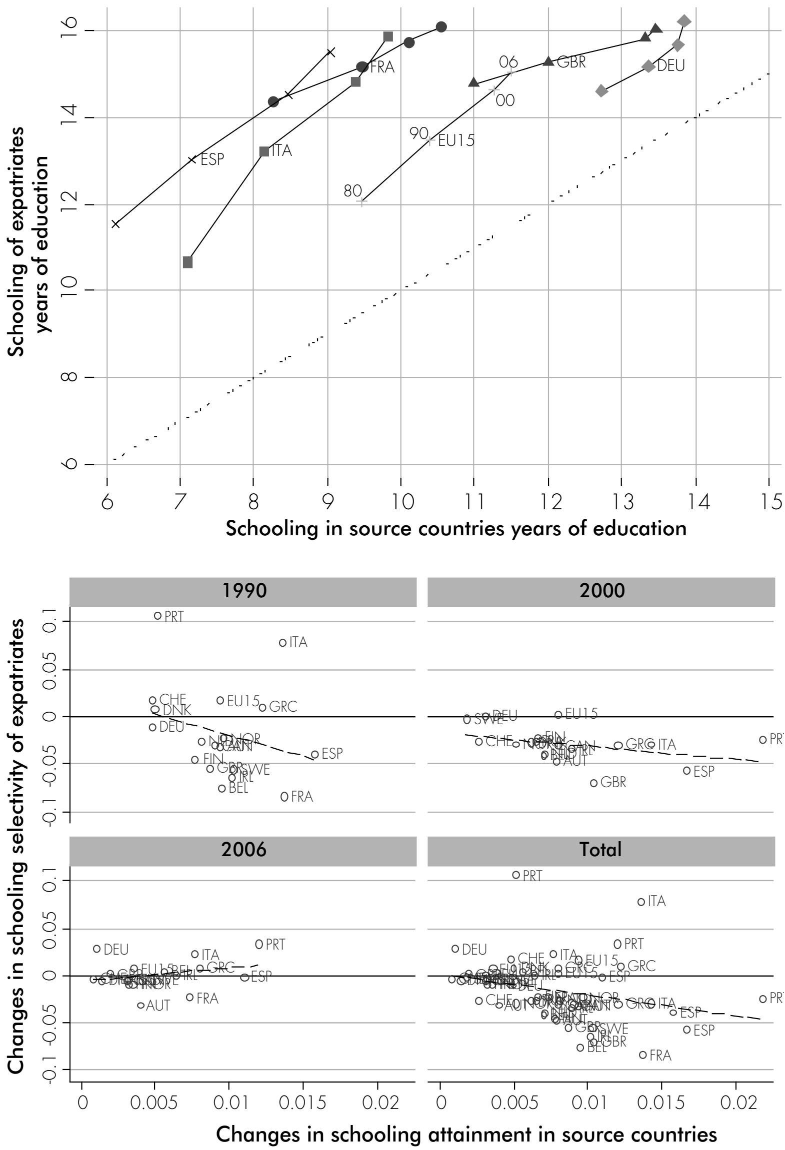
European emigrants may take a lot with them. In any case, a primary component of their human capital is their education. How much schooling they have compared to stayers is an essential indicator of human capital selectivity and is a key determinant of their occupations and productivity. The top panel of FIGURE 2 draws up trends on the educational selectivity of movers by representing the schooling attainment of stayers (x-axis) and that of successive cohorts of recent expatriates (y-axis).[10] Movers are clearly positively selected. Moreover, and not surprisingly, expatriates from countries with highly educated populations are more educated (Germany and UK for instance), but not that much educated as compared to stayers than are those from countries with less educated populations. The latter remark suggests that as countries are making progress in educational attainment, the selectivity may decrease and eventually vanish. This possibility is checked on the bottom panel of FIGURE 2 which shows the relation between educational progress and changes in the selectivity of departures. Indeed, the selectivity of departures has decreased during the 1980s and 1990s as most countries lie below the abscise line (except for Portugal and Italy in the 1980s). However, looking at the distribution of countries across the abscise line at each census reveals that the decline has decelerated in the 1990s and even halted for the last departure cohort for most countries,

8. During the 1990s departures have decreased only in Greece and Portugal; France and Germany have the highest departures in this period.

9. For instance, between 1995 and 2005, the working age population in Germany has decreased by 3% while it has increased by 6% during the 1990s; most European countries are experiencing a similar aging process.

10. Therein, the term cohort refers to expatriates that enter the US at the same time period.

Figure 2 – Emigrants educational selectivity



Notes: Years of education of expatriates are computed for the recent departures. Reading of top panel: each point on the graph represents an observation for the years of schooling of recent expatriates (y-axis) and in source country (x-axis) in a given census year. Along a country plot, a shift to the north-east away from the diagonal indicates an increasing selectivity of departures in terms of years of education. Reading of bottom panel: schooling selectivity is the ratio of the average years of education of expatriates to theaverage years of education of stayers. The selectivity ratio on the y-axis is expressed in log first difference with respect to the last census. Changes in schooling on the x-axis are in log difference with respect to the previous census on a yearly basis. The regression line on the pooled data (bottom right graph) has a coefficient of −2.2 which is not statistically significantly different from zero if dummies for years are included in the regression.

except in France and Austria.[11] There is also some evidence of a weak negative relation between educational progress and selectivity. Overall, higher schooling does not guarantee a lower selectivity which suggests that other differences in push factors across countries are at work. I will return on this issue in the last section of the paper.

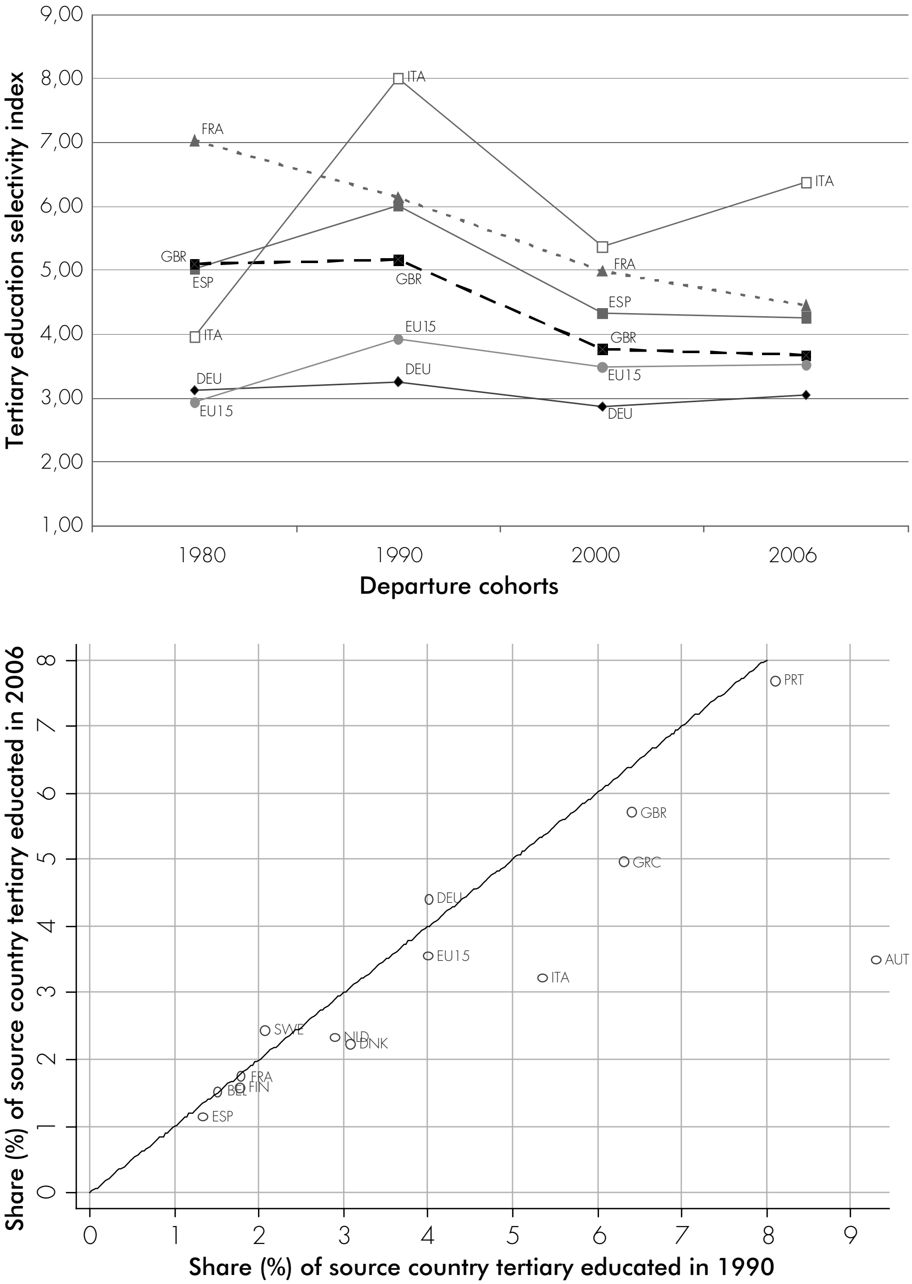
Given the strong positive relation between average years of education and labor market productivity at the microeconomic level, the relative years of education of expatriates is a direct evidence of their relative quality. However, through a macroeconomic lens it may not be the most relevant margin to assess the significance of outflows. In their survey of education and economic growth for instance, Krueger and Lindhal (2001) found that "education is statistically significantly and positively associated with subsequent growth only for the countries with the lowest level of education". Recently, Vandenbussche, Aghion and Meghir (2006) provided a rational for the puzzling effect of education on growth. Technological progress results not only from the adoption of existing technologies, but also from pure innovation. Highly educated workers are the more important factor for innovation. Using panel data on 19 OECD countries, they show that non-tertiary education has contributed little to technological improvement, that the relevant margin is *tertiary education,* and that the latter has been an important source of growth divergence in OECD. In this context, FIGURE 3 shows for the main source countries on the top panel the trends in the selectivity of departures in terms of tertiary education. The bottom panel of the figure displays the aggregate brain drain index (1) for the tertiary educated workers in 1990 and 2006.

The top panel of FIGURE 3 makes clear that movers are much more likely to be tertiary educated than stayers, by a factor ranging from 3 (Germany) up to 6 (Italy) for the most recent cohorts. However, there is no evidence of higher selectivity over time. There is instead a clear declining selectivity among French movers, for the other countries and the EU15 as whole the selectivity has slightly increased in the 1980s and has decreased (Spain, UK) or plateaued (Germany and EU15) afterward. This lower selectivity has to be related to the progress of education in Europe that accelerated in the 1990s as shown in FIGURE 2. The slowdown in the pace of educational progress could also explain the halt and sometime the reversal of the declining selectivity that was observed in the early 2000s. For instance, the yearly growth rate of the share of tertiary educated workers in the EU15 was 2.4% in the 1980s, 3.8% throughout the 1990s but only 1.4 % between 2000 and 2006.[12] Lastly, the bottom panel of FIGURE 3 confirms the importance of selectivity: while expatriates represent around 1.1% of the EU15 working age population in 1990 and 2006, they represent respectively 4% and 3.5% of its

11. To account for schooling disparities due to age differences between expatriates and stayers, I have computed the average years of education assuming that expatriates have the same age distribution as stayers. I found that higher share of young among expatriates account for a very small part of schooling disparities. This is an indication that the emigrants-stayers schooling gap concerns all age groups. Results are available from the author upon request.

12. Interestingly, the yearly growth rate of tertiary educated workers has been high in the US in the 1980s at 3.7% per year against 1.2% in the 1990s and only 0.9% during the first half of the 2000s. Assuming that the growth college educated labor supply is related to its demand; the years 1980s were a period of high demand for skills in the US compared to periods afterward as witnessed by the surge of college educated wage premium observed in the 1980s.

Figure 3 – Emigrants educational selectivity



Notes: The selectivity index in the top panel refers to the ratio of the share of tertiary educated among expatriates to that share among source country workers, that is the index $S_{tertiary,c,t}$ of Equation 1. It is computed over successive cohorts of recent emigrants. The bottom panel is the brain drain index of Equation 1 for tertiary educated, computed in 1990 and 2006 over the whole stock of tertiary educated expatriates.

tertiary educated workers. The brain drain of Germans tertiary educated has slightly increased since 1990, from 4 to 4.4%, mostly due to higher rates of departures (see FIGURE 1). However, and unlike the claim made by Saint-Paul (2004), overall the drain of tertiary educated workers has slightly decreased since 1990 in most countries. Saint-Paul (2004) compares educational progress in gross percentage point (and not rate) which is misleading. Namely, the brain drain is a relative measure whose changes depend on changes in the *relative quality* and the *relative size* of expatriates.[13] The index (1) makes this distinction clear. In terms of tertiary education, the relative quality of expatriates has not increased since 1990 which is why the tertiary educated expatriates are representing a lower share of their source country peers in 2006.

2.3.2. Occupation related brain drain indices

Worries about a European brain drain are very often centered on individuals that adopt, and create knowledge (engineers and researchers), and that transmit this knowledge to future generations (academics). Those are the key players in the global competition in education, research and innovation. As a landmark, these are the specific skills and people targeted by the EU15 "blue card" proposal.[14] As a matter of fact, FIGURE 4 confirms that these skills are increasingly represented among movers. The proportion of recent EU15 expatriates working in these occupations has increased from 6.7% in 1980 to 19.7% in 2006, which represents an almost threefold increase and a much higher growth than the share of expatriates with tertiary education. The higher concentration of movers into S&E occupations translated into higher concentration in the overall population of expatriates for which the share of S&E has increased from 5.6% in 1980 to 10.2% in 2006. Looking at specific countries, among recent French, German, Italian and Spanish emigrants the share working in these occupations has been multiplied respectively by 2.7, 3.5, 7.9 and 6; within the whole population of expatriates the share has been multiplied by respectively 2.4, 2.6, 4.2 and 4.1. Given that over the same period the share of tertiary educated expatriates has increased at a much lower rate, the highly-skilled and highly-educated owe to be increasingly represented among tertiary educated emigrants. A closer look by occupation in FIGURE 4 reveals an even more rapid shift of selectivity toward the upper tail of the educational distribution as the proportion of researchers and academics expanded at a more rapid pace than that of engineers. Interestingly, unlike that of engineers, demand for these skills, and especially for academics, does not seem to have been affected by the 2000s

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13. To see this, assume that the share of college educated among stayers has increased from 5% in period t to 15% in period $t+1$ and that over the same period, this share has increased from 40% to 60% among expatriates. In percentage points tertiary education has increased more among expatriates (20 percentage points). Yet, in relative term, the share of educated has increased by half among expatriates while it has been multiplied by 3 for the stayers. Thus, while in 1990 an expatriate was 8 times more likely to be a tertiary educated than a stayer, in 2000 she is 4 times more likely. As a consequence, with a constant emigration rate, the brain drain of tertiary educated in 2000 is half that of 1990.

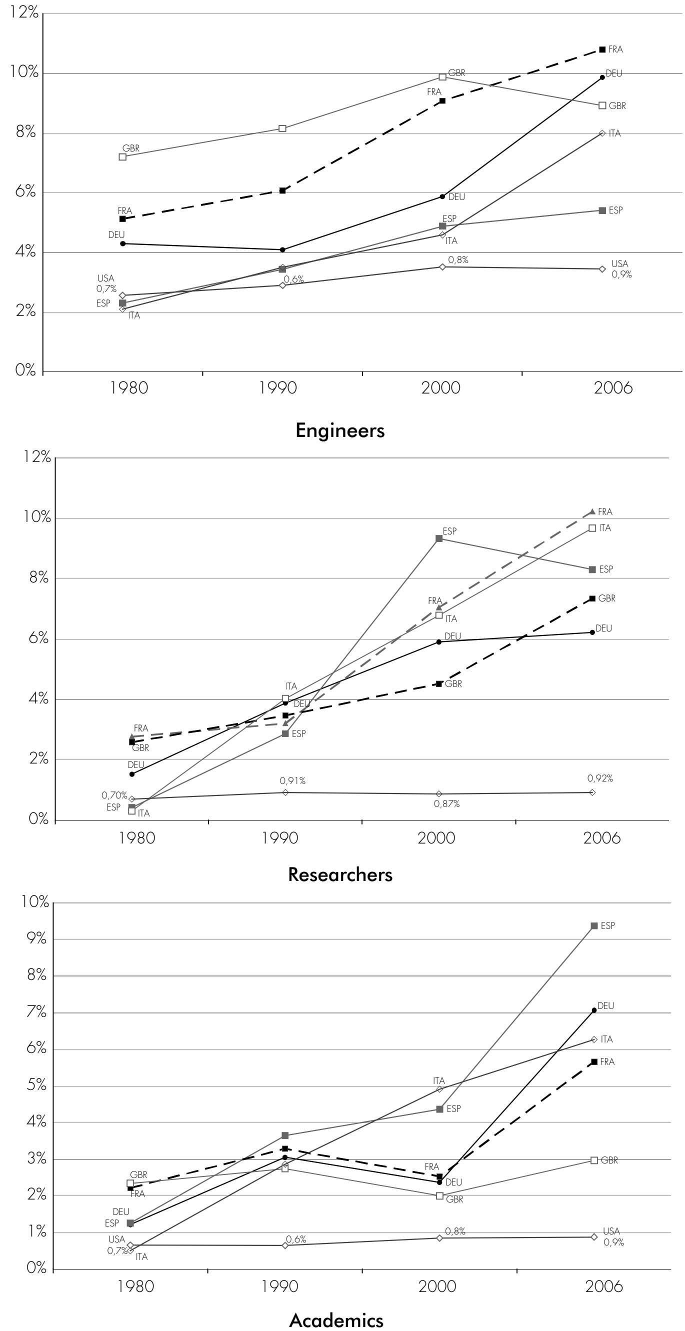
14. For a long time, this has been the case in countries with point-based migration systems (Australia, Canada, New Zealand). The US is increasingly filling its scientific human capital shortage using its H1B visa. More recently, the traditionally non selective European countries have also adopted special entry gateways for these occupations. They have been introduced in France in its "wanted" list of occupations and in Germany that has introduced a "green card" for scientific and technical occupations.

dot-com burst. Unfortunately, the lack of comparable data from origin countries precludes the computation of the brain drain index (1) for engineers and academics. Nevertheless, it can be gauged by noting that the shares of expatriates in these three occupations have increased at a faster rate than those shares in the overall US labor force. For instance, in 1980 the ratios of the share of engineers, researchers and academics among expatriates and in the US labor force were respectively, 1.3, 1.4 and 1.8; by the year 2006 the ratio for engineers is 1.6, and for researchers and academics it jumps respectively to 2.5 and 2.7. This trend in the occupational composition of movers has also translated into a similar shift within the whole population of expatriates.

This can be given a more precise evaluation for researchers. I use internationally comparable data on the number of researchers in the labor force gathered from OECD *Science, Technology and R&D Statistics* database to compute the brain drain index (1).[15] The top panel of FIGURE 5 displays the selectivity of departures for the researchers in the last three censuses, as a benchmark the selectivity in terms of tertiary education is also presented. These graphs make clear the fact that selectivity is rising along the skill ladder and that these rising selectivity has intensified for the most recent cohorts. This increasing selectivity can be evaluated by the widening gap between the two curves. For instance, in 1990 the EU15 expatriates were almost 4 times more likely to be tertiary educated than stayers and already 5.1 times more likely to work as researchers. In the year 2006 movers are relatively less likely to be college educated than their 1980s peers, but 10 times more likely to be researchers. Thus, the intensity of selection among tertiary educated emigrants is twice higher for the most recent departure cohort than it was for the 1980s cohort. An important question is whether these trends have contributed to a higher aggregate brain drain of European researchers. The answer is given in the bottom panel of FIGURE 5 and is clearly affirmative. The share of EU15 based researchers represented by US based European researchers has increased from 2.7% in 1990 to 4.2% in 2006. Over the same period, the share of tertiary educated expatriates in their source country tertiary educated workforce has decreased from 4% to 3.5%. It is important to note that in 2006, 44% of European researchers in the US have less than 10 years of residence, while in 1990 this share was 28%. This shows that the researchers brain drain surge is a rising but also a recent phenomenon.

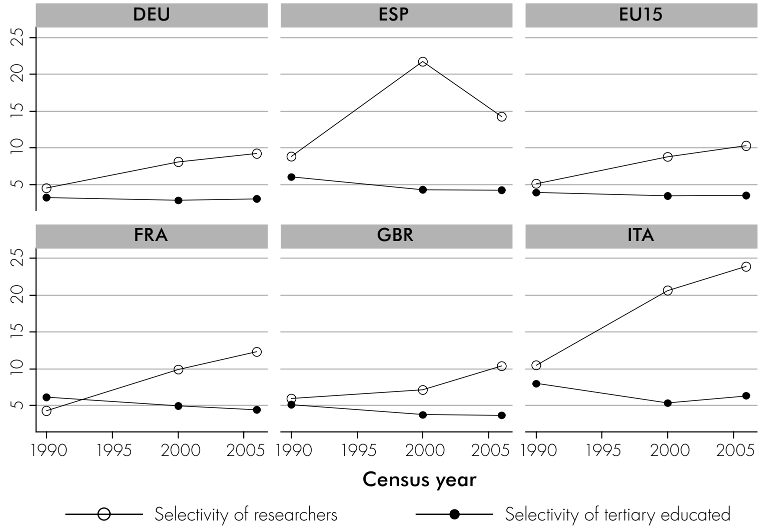
15. The numbers of researchers in the OECD data are given in Full Time Equivalent. As a consequence, the number of researchers in the US censuses is higher than that found in this data. To correct for this, the expatriates' data for researchers have been deflated by a conversion factor equal to the ratio of the number of US researchers in the US census to the number of researchers in the OECD data.

Figure 4 – Share of S&E among recent expatriates

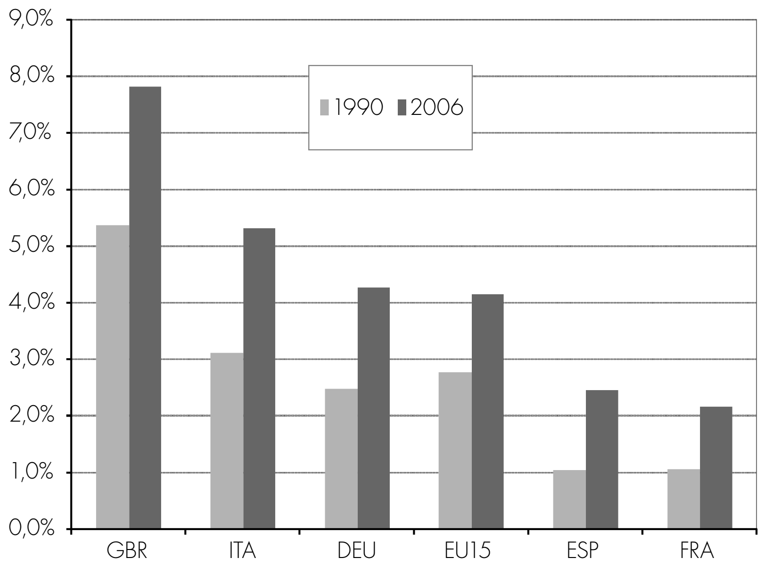


Notes: These shares are computed as the ratio of the total number of recent expatriates working in one occupation over the total number of recent expatriates.

Figure 5 – Brain drain of European researchers



Selectivity along the skill ladder



Brain drain of researchers

Notes: On the top panel, the selectivity of tertiary educated is computed as the ratio of the share of recent expatriates with tertiary education to that share in the source country labor force. The selectivity of researchers is the ratio of the share of recent expatriates that work as researchers to that share in the source country labor force.

On the bottom panel, the brain drain corresponds to the index (1) computed over the stock of researchers.

2.3.3. Are exceptional European talents moving away?

"[…], consider biotechnology in 1973 and suppose that six people in two laboratories knew how to do genetic engineering (recombinant DNA). Suppose one knowledgeable person can transfer the knowledge to at most one person per year. Then the maximum number of potential practitioners of the art in year t (t = 0 in 1973) is $6*2^t$. Even if this rapid rate of diffusion were possible, there would only be $6*2^{10} = 6{,}144$ potential practitioners of genetic in 1983, each of whom would still be earning a very large shadow wage."

From Michael R. Darby and Lynne G. Zucker, *Growing by leaps & inches: creative destruction, real costs reduction and inching up.*

This quote emphasizes what is at stake in knowledge economies: the brain drain threat is much more serious if people with scarce skills and exceptional talents are more likely to leave and more so for countries competing at the technological frontier.[16] Up to now, expatriates and stayers have been compared with respect to their observable characteristics. However, expatriates may be selected along dimensions of skills that are not observable. One way to look at this issue is to estimate wage premia by emigrants' country of origin. Using this technique, Saint-Paul (2004) found a positive European wage premium that has increased between 1990 and 2000 for the tertiary educated workers. This tells us that on average expatriates perform better than similar US workers. However being above average is not enough to define the magnitude of talents lost since a positive wage premium says little about the proportion of exceptional people.[17] One way to tackle this issue is, following Acemoglu (2002), to think about observable skills (education and experience) as one index of skill and unobservable skills (cognitive ability, personality, school quality) as another one. Assume that for any set of observable skills, expatriates have higher endowments of the second type of skills than US natives. Accordingly, expatriates should be more represented in the upper tail of the residual wage distribution (i.e. wages adjusted for differences in observable characteristics) than US natives. Assume next that the supply of talent within each skill group is invariant across time and countries.[18] Then, the relative share of expatriates above any threshold of the residual wage distribution is a potentially useful index to assess differences across countries and changes over time in the drain of talents.

To proceed, I form a sample of wage workers aged 25 to 64. In each census the sample comprises recent European expatriates (less than 10 years of residence) and US white natives. From this sample I exclude those working for less than 40 weeks a year and less than 20 hours a week. It is well known since Murphy, Pierce and Juhn (1993) that within

16. On the importance of talents in a fast evolving technological environment see Hassler, J. and Rodriguez, Sevi Mora (2000) and Acemoglu, Aghion and Zilliboti (2002).

17. Another concern about using wage premium computed over the stock of expatriates across two censuses is that it confounds changes in the composition of stocks due for instance to selective return migration and assimilation, with changes due to the arrival of new cohorts of emigrants.

18. This amount to assume for instance that the share of exceptional researchers among American and Italian researchers is the same. Still the US have more exceptional researchers than Italy because it produces more researchers. A similar argument is used by Acemoglu (2002) who argue that the relative supply of unobserved skills within each observable skill group is constant over time. Here the same argument is extended across countries.

group inequality in the US, i.e. residual inequality, has dramatically increased over the period covered by the censuses and more so among college educated workers.[19] To control for spurious measure of changes in the relative distribution of residual wages due to the mechanical effect attributable to higher schooling (relative to the US natives) of successive cohorts of expatriates, I consider only the post college educated workers (those with graduate and professional degrees). This group is also particularly interesting since we know from previous results that selectivity has increased at the upper end of the schooling distribution. For each year census, residual distribution is obtained after running the following standard Mincerian type human capital regression:

$$\ln w_{it} = \beta' x_{it} + \varepsilon_{it} \qquad (2)$$

where w_{ijt} is the gross hourly wage rate; expressed in 2000 dollar using the CPI obtained from the US bureau of labor statistics, of a worker *i* observed in year *t*; x_{it} is a vector of socioeconomic characteristics. Specifically, x_{it} includes a full set of potential experience dummies; measured as age minus years of education minus 6, dummies for years of education, a quartic term for experience which is crossed with education dummies and additional controls for marital status, gender and English proficiency. TABLE A1.3 (APPENDIX 1) provides summary statistics of the variables and the number of observations for each regression. Work by Lemieux (2006) shows that this specification of the Mincer-type equation provides a better fit of recent US wage data. The individual specific error term ε_{it} is assumed to be uncorrelated with the other regressors. Due to possible unobserved components of variance for individuals born in the same country (Moulton, 1986), standard errors are computed using a country of birth clustering of observations.

FIGURE 6 plots, for recent cohorts of expatriates and each census, the ratio of the share of expatriates above the 50^{th} and 90^{th} percentiles of the residual wage distribution to that share among US natives. The plots show that expatriates are more likely than natives to be in the upper median residual wage distribution.[20] This confirms, for recent expatriates, the results of Saint-Paul (2004) that emigrants are earning a wage premium relatively to US workers with the same observable characteristics. Moreover, these premia have a positive trend reflecting the increasing quality of movers. More subtle, the disparity with the US natives is increasing as we move from the 5^{th} to the last decile of the residual wage distribution. This is a mark that Europeans are more likely to hold scarcer and more productive unobservable skills than US born workers. For instance, in 2006 the French expatriates are 1.4 time more likely to be above the median residual wage than a US natives, but 2.7 times more likely to be above the 9^{th} decile. A second trend worth emphasizing is the rising gap between the selectivity at the 50^{th} and 90^{th} percentiles, which underscores a higher intensity of selection over time.

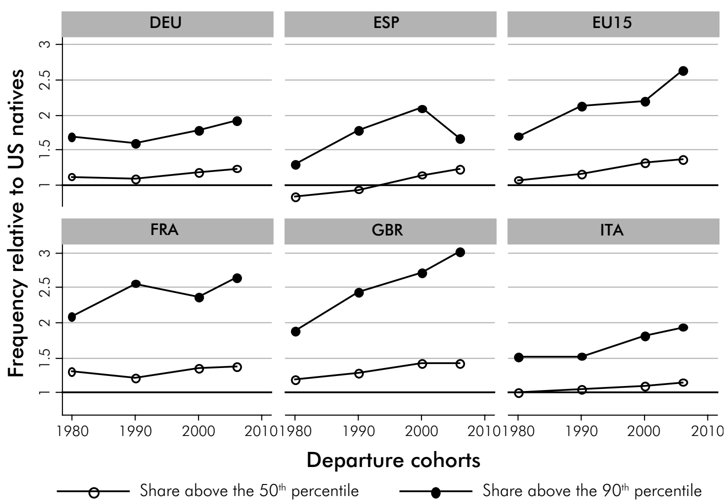
19. In this case changes in labor force composition of different cohorts can raise the share of expatriates in the tails of the wage distribution by altering the employment shares of groups that have more dispersed earnings, relatively to US natives. The recent contribution of Autor, Katz and Kearney (2008) shows a convexification in the returns to education, which is a further justification for restricting the estimation of (2) to highly educated workers.

20. The curve is above 1, except for Spain in 1980.

Interestingly, this pattern parallels and reinforces the selectivity observed on occupational distribution of tertiary educated in FIGURE 5.

Few notes of cautions related to the meaning of unobservable skills are needed to interpret these results. First, this may reflect that Europeans select into occupations and industries that pay large premium to non observable characteristics. Indeed, the rise in within group wage premia observed in the US since 1980 has partly been attributed to the "new-economy" and technological frontier industries which value embodied intangible assets.[21] Zucker *et al.* (1998, 2002) documented this for instance during the birth of the semi-conductor and biotechnology sectors in the US. Given that the share of industries at the technological frontier is lower in Europe, the proposed measure could overestimate the drain of talents. Second, the trend may also reflect a secular increase of labor quality in emigrants' source country due to higher average quality of education, which will raise the price of these countries specific skills. However, at least for the large continental European countries, this assumption does not find support in international ranking of universities that places most European universities behind the US ones. Moreover, there is no pattern of higher achievement of European students compared to American ones over time (Jacobs and van der Ploeg, 2005). A more convincing argument could be that, within the schooling quality ladder of their source countries, expatriates are pulled from the few that graduate from the top engineering schools or PhD programs and from the most productive and rewarding fields.

Figure 6 – Relative residual wage distribution of expatriates



Notes: The residuals are obtained from regression (2) as it is described in the text. The relative distribution is computed as the ratio of the share of expatriates above each percentile to that share in the US labor force. Summary statistics of the variables used in the regressions and the number of observations are provided in TABLE A1.3 of the APPENDIX 1.

21. According to Acemoglu (2002) this explains that not only inequality has increased between well defined groups of education but also within those groups since the 1980s.

2.4. Brain drain or brain-circulation: how important is return-migration?

An important issue in labor flows is whether migration is permanent or temporary. European countries can clearly benefit from the brain circulation of emigrants as they could apply and transmit their valuable skills upon their return at home. The question is how large are these returns and how the quality of returnees compares to that of non-returnees. Answering this question is not an easy task with our data since return migrants are not observed. However, an assessment can be given by tracking a migration cohort (less than 5 years after its arrival) and changes in its size and its characteristics across subsequent censuses. This is done with the cohort of recent expatriates aged 25 to 54 years old in the 1980 and 1990 censuses. From these two cohorts, the non-returnees, observed in 1990 and 2000, are those aged 35 to 64 years old that emigrated respectively in the second half of the 1970s and the 1980s. A limit of this exercise is that "missing" expatriates, instead of returning back home, may have moved to another country or passed away.[22] Despite these shortcomings, the cohort analysis is still a useful tool to detect some time pattern and for this reason it is common in migration studies (Smith, 2006).

Figure 7 shows a plot of the share of expatriates aged 25-54 that emigrate between 1975-1980 and that are still working in the US by the year 1990 against the shares of 1985-1990 expatriates that are still in the US by the year 2000. Return migration is more frequent among Scandinavian whom 50% of 1980s emigrants returned back home by the year 2000, while it is comparatively much lower for Southern European countries, whom less than 20% of 1980s emigrants returned back home by the year 2000. For all large European countries, rates of return migration have decreased during the 1990s compared to the 1980s, except for the UK where it has remained stable at below 40%.

Gains from return migration to the source country depend on the age of returnees. Benefits are lower if returnees are older as they have less time left on the labor market and that on average they are less educated. Given an initial cohort, without age-bias in return migration, this cohort should be on average 10 years older in the next census, if it happens to be younger then this may be an indication that older emigrants are more likely to return home.[23] The top panel of figure 8 shows clearly that in most countries returnees are more likely to be older, and more so in the 1990s than in the 1980s. A life cycle human capital interpretation of this pattern suggests that young expatriates invest more heavily in US specific assets such as housing, language or social ties, whose returns are recouped over a longer period of stay.

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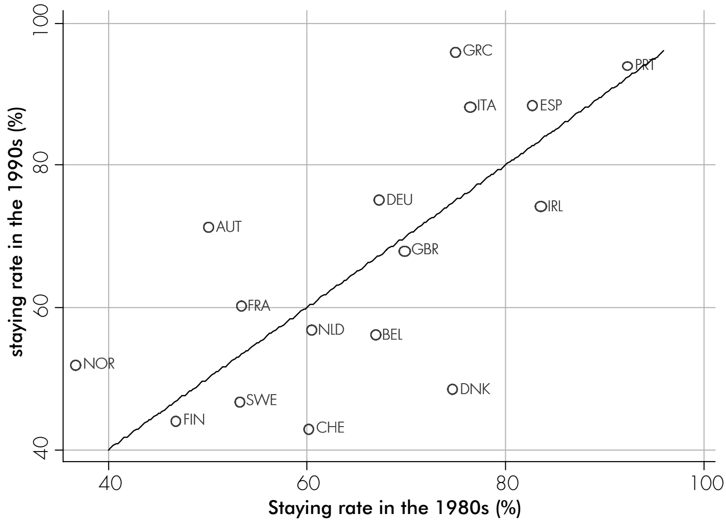
22. The last point should be a minor concern. Indeed, most of recent expatriates belong to the group with probably the lowest mortality rate: the youth and educated.

23. I have try controlling for differences in mortality rates across ages by assuming that European expatriates have the same age-gender specific mortality rates as US white natives. The results are very close to those obtained without control.

Figure 7 – Emigrants staying rates in the 1980s and the 1990s



Lastly the bottom panel of figure considers the schooling disparities of returnees and non-returnees. Among the large European countries, only the French appear slightly more educated than the non-returnees in both periods. Instead, the British returnees are less educated and there is no significant pattern for the Germans. During the 1990s, Italian and Spanish returnees were relatively less educated than non-returnees, which is a strong reversal compared to the situation in the 1980s. This finding is consistent with the data on the top panel which shows for instance that Spanish returnees in the 1980s were the youth, while in the 1990s they were older, and the fact that old expatriates are on average less educated. At the EU15 level, there is some evidence that the 1990s returnees were slightly less educated than non-returnees in the 1990s.

Results obtained so far underscore a brain drain surge in the 1990s. The number of migrants leaving Europe for the US has increased in absolute term and relatively to source countries' workforce.[24] These movers are positively and increasingly selected along the educational distribution and ladder of occupations that matter the most in the knowledge economy. A similar positive and rising selectivity is observed for unobservable skills in the US labor market. For all large European countries, return-migration represents no more than 40% of recent inflows and return rates have declined in the 1990s compared to the 1980s. On average, the returnees are also more likely to be older and if anything relatively less educated.

In light of US economic performance of the last three decades, these movements are probably to be excepted. Migration theories teach us that the magnitude of emigration results from the economic performance in the destination and source countries, and its skill composition (selectivity) from differences in returns to skills (Borjas, 1987, 1999). On the determinants of magnitude, the 1990-2006 surge happens at a time where the US experienced an

24. For the EU15 emigration rates decrease in the 1990s only for the Irish and the Portuguese.

unprecedented period of economic expansion. In 2000 the per capita GDP was 30% lower in Europe than in the US, which was a larger gap than in the 1970s. Most of the gap happened over the 1990s and has not narrowed yet. The annual average GDP growth rate of the EU in the 1990s was 1.91% against 3.25% for the US (Gordon and Dew-Becker, 2005).[25] The biggest continental European countries, e.g. France, Germany and Italy, were significantly below this average. Thus at every level of skills incentives for Europeans to seek better rewards abroad should have increased during this period. Over the same period, Europe were catching up with the US in terms of educational attainment of its labor force, offering a new pool of well qualified and drainable workers easily able to step in the US jobs.

Hence, US's *pull* factors combined with higher skilled labor supply in Europe are probably a major determinant of the observed pattern in the magnitude of flows in the 1990s. As for the selectivity, the US growth process has boosted the salaries of the most qualified and the so-called knowledge workers resulting in a high skilled wage premium (Autor *et al.*, 2008) and a wider US-Europe wage gap for the most skilled workers. This gap has been amplified during the 1990s by the higher supply of skilled labor in Europe that has dampened the skill premia there.[26] For instance, the high school/college wage premium in the US were equal to 1.40, in 1980, 1.56 in 1990 and 1.64 in 2000; over the same periods the average European premium has remained much stable at respectively 1.47, 1.45, and 1.47.[27] Consequently, the US-Europe skilled wage premium gap has steadily increased. Yet, this higher gap has increased selectivity only at the upper end of the skill distribution since on average the selectivity of tertiary educated worker has decreased. For the specific occupations that have been considered, such as university instructors and researchers, public expenditures and policy probably matter a lot. Indeed, an important share of them is employed in the European public research and education system. In 2000, the US have spent 2.3% of their GDP in tertiary education against 1.1% in the EU15, and all the 5 large European countries considered are significantly below this average. Aggregate rates of R&D expenditures are another disparity with the US that directly affects the relative demand for people with scientific human capital and their relative wages (FIGURE 8).

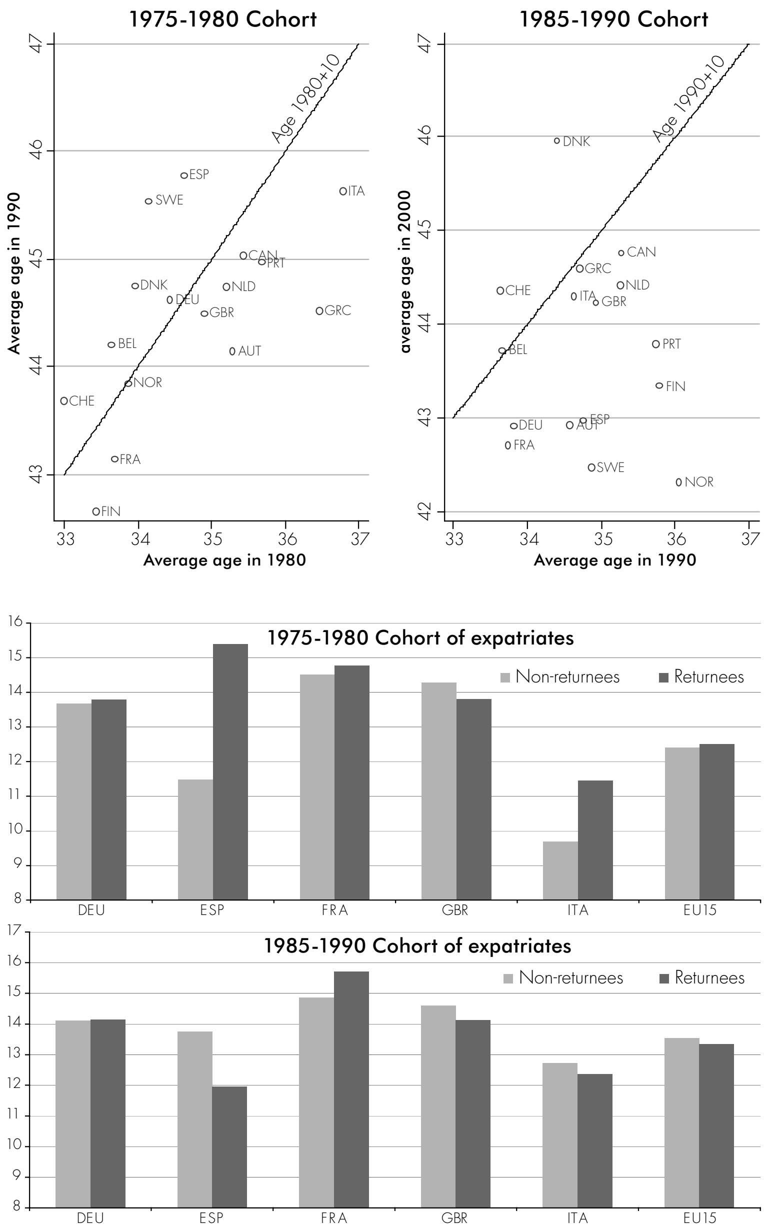
In March 2000, the European Council launched the Lisbon Strategy, aimed at making the European Union the most competitive knowledge economy in the world by 2010. A key element of this strategy was an increase in R&D spending. At the end of the 1990s, this has reached 1.8% of GDP on average in the fifteen European nations. The Lisbon objective was to raise it to 3% of GDP in 2010. But, in the majority of countries, this ratio has hardly increased and remains below 2% in 2006; only Sweden (already at more than 3% in 1995) and Finland meet the objective. Because of the complementarity between R&D spending

25. Within Europe there are some exceptions like Ireland and Luxembourg.

26. Another reason for skill premia to be lower in Europe is the existence of wage compression institutions (Acemoglu, 2003). However, it is unclear to what degree these have contributed to a wider US-Europe skilled worker wage gap over time.

27. The last section describes the data sources and the method used for these computations.

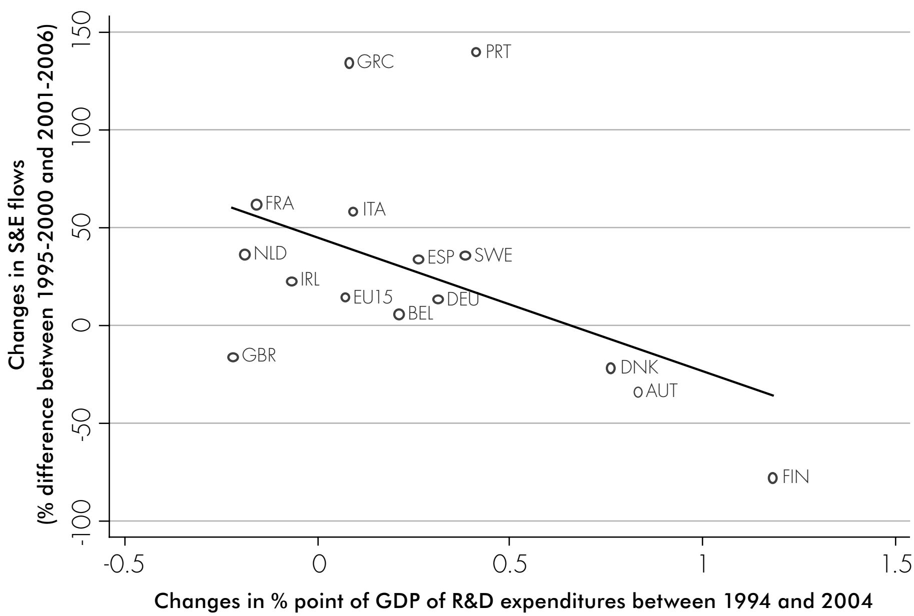
Figure 8 – Age and education of returnees vs non-returnees



Notes: The number of recent expatriates from each country has been used as weights to compute the EU15 averages. On the bottom panel, tests of equality of means (at 1% level) are rejected, except for Germany for both cohorts and for the EU15 for the 1975-1980 cohort.

and scientific human capital, higher R&D expenditures are expected to rise the productivity and the labor demand for those that absorb and create new knowledge. Interestingly, using data on R&D spending across EU15 countries obtained from Eurostat, FIGURE 9 shows that over the last ten years, countries that have increased their R&D spending more in proportion to their GDP are also those whose expatriation of S&E to the United States has increased the least. This correlation is obviously too rough and ready to form the basis for a causality. Nevertheless, the overall picture support the idea according to which the expatriation of S&E is due, at least to some extent, to the lack of resources dedicated to research in their countries, namely a *lack of demand*. Under these conditions, even if the brain drain remains quantitatively low, the fact that Europe exports a growing and an increasingly educated and skilled share of its workforce to the United States is a worrying symptom. This *lack of demand* hypothesis and the implication that it bears to assess the brain drain costs are investigated further in the next section.

Figure 9 – R&D expenditures in source countries and changes in S&E migration flows



Source: Eurostat for R&D expenditures.

3. European brain drain and the race between education and technology

3.1. Why are skilled Europeans moving west?

An appealing answer is provided by selection models *à la* Borjas (1987, 1994): European emigration is skilled biased because returns to skills are higher in the US than they are in Europe. However, this explanation clashes with the determinants of factor prices based on factor proportions. In a world of differences in factor returns based on differences in factors endowments, returns to skills should be higher in Europe. Therefore, European migration should be unskilled biased, while we should observe skilled Americans moving into Europe.[28] Then, what is making skilled European workers moving west? Eventually, answering that question is closely related to explaining differences of income *per* worker across countries.[29] Given that skilled labor is relatively more abundant in US than in Europe a sensible answer should (i) depart from the simple factor proportion approach and (ii) focus on the determinants of factors' returns instead of overall productivity. Namely, are the forces that explain both relatively higher returns to skills in the US and the relatively lower returns in Europe able to explain the skill composition pattern of European migration? I will show, using a simple supply and demand framework, that higher skilled labor supply was a common factor across European countries that does not explain differences in returns to skills. Instead, differences in skilled labor demand shifts are the main determinants of cross country differences in skilled wage premia. Accordingly, I find a strong and a negative correlation between these skill bias demand shifts and the skill selectivity of emigrants.

3.1.1. A simple supply and demand framework

Starting with the seminal contribution of Katz and Murphy (1992), an important and growing literature has questioned the surge of college wage premia in the US observed since the 1980s. This literature seeks to identify whether the rising wages of high relatively to low educated workers can be explained by combinations of demand and supply shifts that favor more educated workers. While it is still a totally not settled issue, the widespread consensus is that of a strong growth of relative demand for educated workers that outpaced that of skilled labor supply (Acemoglu, 2002). The later has been interpreted as the evidence of

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28. For instance, with a Cobb-Douglas production function $Y = AL_s^{\alpha} L_u^{1-\alpha}$, the skill premium is a decreasing function of the relative skill supply $\frac{L_s}{L_u}$, such that skilled workers have incentives to move from countries where skills are abundant to countries where complementary factors (unskilled workers) are more abundant. Instead in 2000, the US had the highest returns to skills of all OECD countries, amongst the highest share of skilled labor and they attract a very large share of global skilled workers from unskilled labor abundant countries (Docquier *et al.*, 2007).

29. This observation relates that question to the `neoclassical revival debate'. In this debate, one group of economists, most prominent among them are Mankiw *et al.* (1992), argues that an extended version of the neoclassical growth model can explain most of the variation in cross-country output. The other group argues that it does not explain most of the variation and other factors, summarized by barriers to technology adoption, are the causes of cross-country variations. Important papers that favor the latter point of view include Hall and Jones (1999), Bills and Klenow (2000) and, Caselli and Coleman (2006).

an ongoing skilled biased technological change (SBTC) that has accelerated at the end of the 1970s with the onset of computers and ICTs.[30] This SBTC has been identified within a simple formulation that posits that there are two groups in the labor market, skilled and unskilled workers. Both skills are demanded by the firms and critically these groups are imperfect substitutes in production. In two important contributions, Caselli and Coleman (2005, 2006) advocated the use of not only data on output and quantities to characterize differences in the production function across countries, but also data on skill prices. Using a similar methodology but within a framework closer to Acemoglu (2003), I uncover the skilled biased demand shifts from data on skill prices and skilled labor supply. Then, I explore to what extent supply and demand disparities explain differences in skilled labor wage premia across countries. Finally, I investigate whether we can relate changes in skilled labor demand shifts to changes in migrants' skills selectivity. The conceptual framework starts with a CES production function for *output per* worker, with skilled and unskilled labor and, with skill specific technological parameters whose changes are interpreted as skill specific technological demand shifts:[31]

$$y_{c,t} = \kappa_{c,t}^{\frac{\alpha}{1-\alpha}} [(A_{s,c,t}\ h_{s,c,t})^{\sigma} + (A_{u,c,t}\ h_{u,c,t})^{\sigma}]^{\frac{1}{\sigma}} \tag{3}$$

where $h_{s,c,t}$ and $h_{u,c,t}$ are the sub-aggregates for skilled and unskilled labor supply *per* worker in country c at period t and $\kappa_{c,t}$ is the capital output ratio.[32] The labor input in (3) is a CES aggregate in which the elasticity of substitution between skilled and unskilled labor is equal to $1/(1-\sigma)$. The state of the technology in country c at period t is represented by the set $(A_{s,c,t}, A_{u,c,t})$ This time and country specific technology converts one unit of skilled labor into A_s efficiency units and one unit of unskilled labor into A_u efficiency units. Because the technology is skill specific, the productivity of a country does not depend only on its level of human capital but also on its composition.[33] Likewise, the skill premium depends on the relative skilled labor supply and their relative efficiency. In a competitive equilibrium this skilled wage premium writes:

$$\omega_{c,t} = \frac{w_{s,c,t}}{w_{u,c,t}} = \left(\frac{A_{s,c,t}}{A_{u,c,t}}\right)^{\sigma} \left(\frac{h_{u,c,t}}{h_{s,c,t}}\right)^{1-\sigma} \tag{4}$$

30. Two consistent findings reviewed by Katz and Autor (1999) and Katz (2000) suggest that the skilled biased technological change is the culprit. The first is that the relative employment of more educated has increased rapidly within detailed industry and establishments in the US and other advanced countries. The second is a striking correlation between adoption of computer-based technologies and the increased use of educated labor within detailed industries, within firms and across plants within industries.

31. Previous implementations of this model are Katz and Murphy (1992), Autor, Katz and Krueger (1998), Acemoglu (2002, 2003), Goldin and Katz (2007), Autor, Katz and Kearney (2008). However, only in Acemoglu (2003) is the model applied to identify sources of cross-country inequality trends.

32. I follow Hall and Jones (1999) and Rodriguez and Klenow (2005) and use the capital output ratio instead of capital *per* worker as the former correctly captures differences in capital accumulation that are not attributable to productivity differences; Feyrer (2007) presents a formal proof of this claim.

33. Vandenbussche, Aghion and Meghir (2006) have developed a model where TFP growth depends on the composition of human capital.

The labor inputs $h_{u,c,t}$ and $h_{s,c,t}$, and the skilled-wage premium for each country and for the periods 1980, 1990 and 2000 are computed following the methodology of Caselli and Coleman (2006). The first step is to decide a partition of workers between skilled and unskilled. Since the focus here is on economically advanced countries, I follow the literature on the dynamics of skill premia in the US (Katz and Murphy, 1992) and classify as unskilled all those with an educational attainment below a college degree. More precisely, I consider the six groups of Cohen and Soto (2006) education data. Groups are sorted in ascending order by an index j corresponding to their education level. These groups are the non completed primary ($j=1$), the completed primary ($j=2$), the secondary non-completed ($j=3$), the completed secondary ($j=4$), the tertiary non-completed ($j=5$) and the tertiary completed education ($j=6$). Given this partition, all workers with an index j>4 are classified as skilled workers. Within each group of skills, workers are assumed to be perfect substitutes, but the more educated among them are more productive. Labor efficiencies in each group of skill are measured relative to the least educated individuals of that group. Hence, if e_j denotes the years of schooling to complete the curriculum j ($j=1,\ldots,6$) and l_j the share of workers with that curriculum, and β the Mincerian return to one additional year of education, the human capital series $h_{u,c,t}$ and $h_{s,c,t}$ for each countries are computed as:

$$h_{u,c,t} = \sum_{j=1}^{4} l_{j,c,t} * exp\left(\beta_{c,t} * \left(e_j - e_1\right)\right) \tag{5}$$

$$h_{s,c,t} = \sum_{j=5}^{6} l_{j,c,t} * exp\left(\beta_{c,t} * \left(e_j - e_5\right)\right). \tag{6}$$

The Mincerian returns to years of education $\beta_{c,t}$ are obtained from a unique panel data assembled by Hendricks (2002,2006).[34] Lately, the skill premia $\omega_{c,t}$ are estimated with the Mincerian coefficients consistently with the partition of skill group according to the formula: $\omega_{c,t} = exp(\beta_{c,t}\,\Delta S)$ where ΔS is the difference in years of schooling between the skilled and unskilled labor which is 11 years for most countries of the sample.[35] To compute the technology demand shifts parameters, $A_{s,c,t}$ and $A_{u,c,t}$, data series on capital output ratio and *output per* worker are needed and, the parameters σ and α have to be calibrated. The capital-output ratio series are those constructed by Klenow and Rodriguez-Clare (2005) and series of *output per* worker are from the Penn World Tables 6.1. I set the capital share in GDP α equal to 1/3, which matches the US historical value (Gollin, 2002) and is the standard convention. The parameter σ is related to the elasticity of substitution between skilled and unskilled labor, $1/(1-\sigma)$. Most of the studies on US data where skilled workers

34. The author has assembled these estimates from various sources and notably from Psacharopoulos and Patrinos (2002) and Walker and Westergaard-Nielsen (2001). I chose the estimates that are the closest to the census year considered and specifications that do not distinguish between male and female, and that control for experience and its square. Hence, I focus on workers with different education but similar experience. The use of estimates from different specifications has given similar results.

35. With this methodology, in 2000 the average earnings of college graduates exceed those of workers with primary education by a factor of 2.93 in the US and 2.28 in Europe; in 1980 these factors were respectively 2.08 and 2.15.

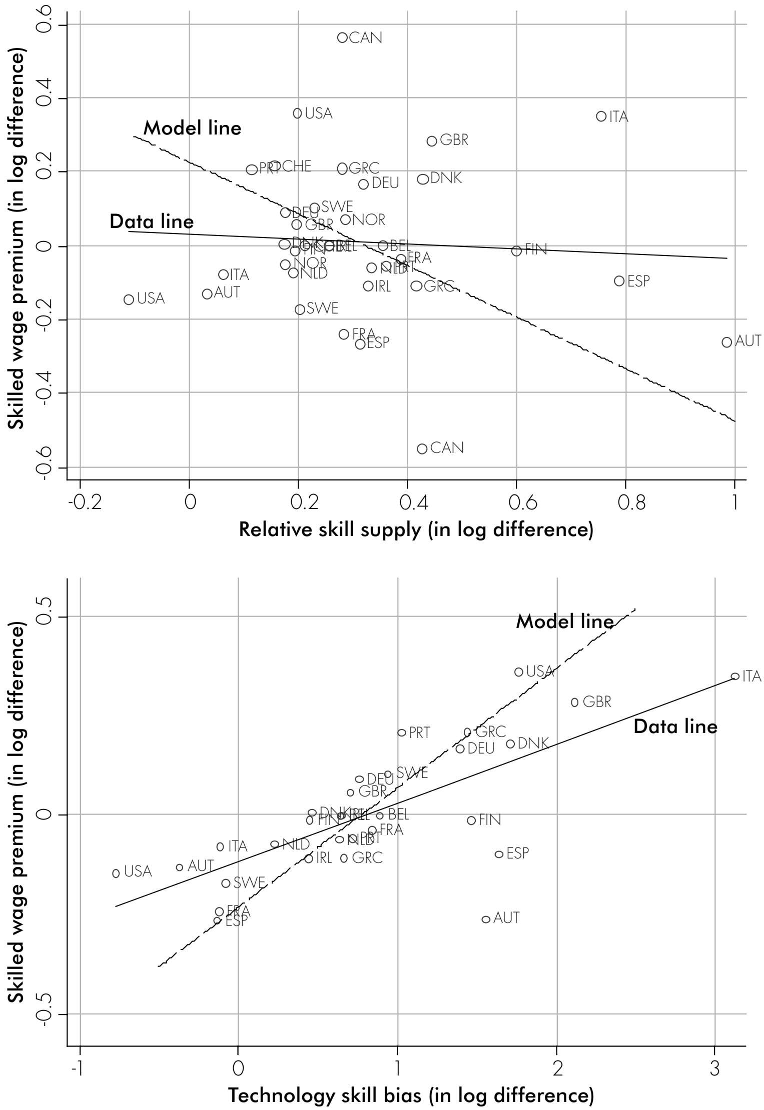
are identified as college educated opt for elasticities between 1 and 2. According to Johnson (1997) and Autor *et al*. (1998), the value of the elasticity to be used in the calibrations ought to lie between 1.4 and 1.5. Accordingly, I follow Caselli and Coleman (2006) and set the elasticity equal to 1.4, corresponding to a value of σ equal to 0.28. With this data at hand, equations (3) and (4) are used to back up the time series value of A_s and A_u for each countries.[36]

To consider the determinants of migration flows I start by decomposing differences in returns to skills across countries into their sources. Equation (4) suggests to look at differences in factor supply shifts and changes in technology, i.e. trends in demand shifts. The panel structure of the data allows controlling for countries fixed effect by first differencing the covariates and to correlate cross country changes in supply and demand to changes in returns to skills. The graphs of FIGURE 10 show a scatter plot against $\Delta \, log(\omega_{c,t})$ of $\Delta \, log\left(\frac{h_{c,u,t}}{h_{c,s,t}}\right)$ and $\Delta \, log\left(\frac{A_{c,s,t}}{A_{c,u,t}}\right)$. The top panel of FIGURE 10 does not reveal any positive or negative relationship between changes in skilled wage premium and changes in relative skilled labor supply. It is important to remind that the production function in (3) predicts that, for a given A_s / A_u, a one percentage point increase in the relative skilled labor supply decreases the skilled worker wage premium by $(1-\sigma)$%, this amount to a decrease of 0.72% (depicted as the model line in the top panel of FIGURE 10).

Thus, compared to the model prediction in (4), countries that have accumulated more human capital have a skill wage premium which is too high, and those that have accumulated less human capital have a premium which too low. Therefore, to make (3) fit the observed relationship between changes in skilled wage premia and changes in skilled labor supply it must be that countries with a steeper pattern of human capital accumulation have experienced a stronger skilled biased technological change A_s / A_u. This is supported by the data in the bottom panel of FIGURE 10, that shows a positive and a statistically significant correlation between changes in skilled labor technological demand shifts and the skilled labor wage premia: a skill bias demand shift of 1% is associated with a 0.16% increase in the skill wage premium. However, the relation is flatter than what is suggested by (4). Together, the graphs of FIGURE 10 are consistent with the idea that European countries with higher supply of skilled labor are also those where demand for skilled labor, driven by SBTC, has increased the most. The relations between labor supply and labor demand shifts are presented in TABLE 1 that reports the coefficients of a regression of $log\,(A_s / A_u)$, $log\,(A_s)$ and $log\,(A_u)$ on $log\,(h_s / h_u)$. Reported coefficients confirm the intuitions of previous graphs: changes in skilled labor supply are strongly and positively correlated with changes in technology skill bias. A further insight is that a higher skilled labor supply is associated with a higher absolute efficiency of skilled workers, but has no negatively significant impact on the efficiency of unskilled workers.

36. The exact formula are:
$A_{u,c,t} = \frac{y_{c,t}}{h_{u,c,t} * \kappa_{c,t}^{\frac{\alpha}{1-\alpha}}} * \left[1 + \omega_{c,t} * \left(\frac{h_{s,c,t}}{h_{u,c,,t}} \right) \right]^{-\frac{1}{\sigma}}$ and $A_{s,c,t} = \frac{y_{c,t}}{h_{s,c,t} * \kappa_{c,t}^{\frac{\alpha}{1-\alpha}}} * \left[1 + \frac{1}{\omega_{c,t}} * \left(\frac{h_{u,c,t}}{h_{s,c,,t}} \right) \right]^{-\frac{1}{\sigma}}$

Figure 10 – Labor supply and technological demand shifts determinants of skilled labor wage premia



Notes: Data corresponds to the values of the variables for the census years 1980, 1990 and 2000. All variables are expressed in log difference with respect to the previous census year. The data line is the fitted line of $\Delta log(\omega_{c,t})$ against $\Delta log(\frac{h_{c,s,t}}{h_{c,u,t}})$ in the top panel and of $\Delta log(\omega_{c,t})$ against $\Delta log(\frac{A_{c,s,t}}{A_{c,u,t}})$ in the bottom panel.

On the top panel, the model line corresponds to the elasticity of skilled wage premium to skilled labor supply, which is $1-\sigma = 0.72$, and on the bottom panel to the elasticity of skilled wage premium to the technology skill bias shift, which is $\sigma = 0.28$.

Table 1 – Factor supply and technology skill bias

	Dependent variable		
Dependent variable	$log(A_s/A_u)$	$log(A_s)$	$log(A_u)$
$\boldsymbol{log(h_s/h_u)}$	2.02*	1.93**	– 0,25
R^2	0,48	0,51	0,33
Number of observations	28	28	28

Notes: These are all OLS estimations where all variables are first differenced, and all estimations include a year dummy. The symbol ** indicates that the coefficient is statistically significantly different from zero at 1%, the symbol * at 5%, and no symbol that it is not statistically significantly different from zero.

These results are consistent with those of Acemoglu (2003) who, with a different methodology, found that differences in skilled wage premium between Europe and the US are partly due to lower labor demand shifts toward skilled workers in Europe.[37] Also related are the results of Caselli and Coleman (2006) that show that richer countries, that are those with higher skilled labor supply, use more efficient technologies for skilled labor. However, by focusing on changes in relative productivity, instead of *output per* workers, and changes in relative skill supply, I reach additional insights potentially useful to explain determinants of cross-country migration patterns. Namely, I can ask whether cross country differences in relative demand can explain differences in skilled bias migration patterns. Selection migration models, *à la* Borjas (1987), embedded in a factor proportion model with skill neutral demand shifts would suggest that as skilled labor supply increases in Europe, returns to skill decrease and the selectivity increases. However, previous cross-country data show that this need not be the case if the SBTC outstripped changes in skilled labor supply.

Figure 11 portrays the relation between emigrants' skill selectivity, measured as the share of tertiary educated among expatriates to that share among stayers, and skilled labor relative supply. Figure 11 shows that the selectivity of emigrants is negatively and statistically significantly correlated with the rate of SBTC. This negative correlation is interpreted as preliminary evidence that countries with more dynamic demand shifts for skilled labor have accommodated higher skilled labor supply and lower rate of emigration of skilled labor.[38] This result supports further the idea suggested in figure 9 according to which labor outflows reflect the weakness of demand for skilled labor in Europe.

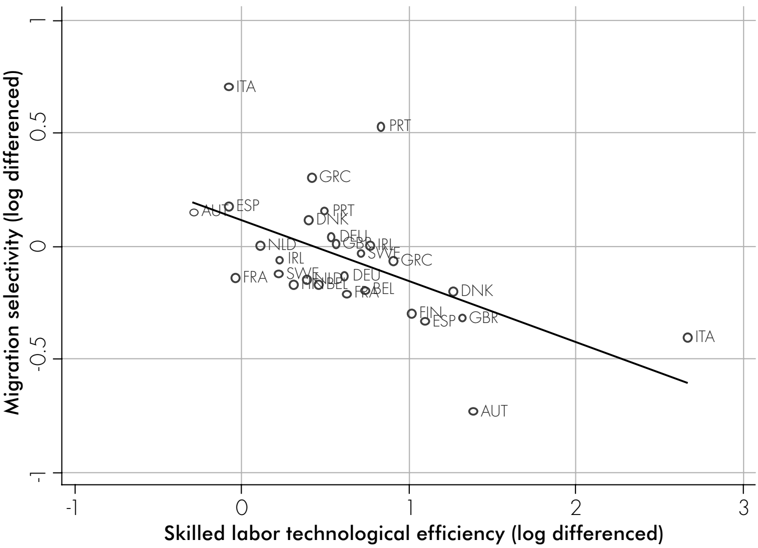
Acemoglu (1998) has developed an analytical framework in which technological change is skilled biased by design. In the short run a higher supply of skilled labor depresses returns to skills, but later on (medium run) as firms find it more profitable to develop skill-complementary technologies, the demand for skills outstrips the supply and the returns increase. Goldin and

37. Acemoglu (2003) attributes the weaker demand for skilled labor in Europe to institutional wage compression, such as the minimum wage, that makes firms more willing to adopt technologies complementary to unskilled workers.

38. A similar pattern is obtained if I consider the relation between selectivity and log (A_s / A_u).

Katz (2007) have recently described this tendency for demand shifts to outpace relative skilled labor supply as a "race between education and technology". They show that the surge in skill premium is a symptom that the technology has been winning the race between 1980 and 2005.[39] One important conclusion reached by this literature is that a higher supply of a factor can trigger an endogenous response of firms' technological choices in a way that undo falling relative productivity of that factor. In what follows, I use this technological adjustment process to assess the costs of the European brain drain in the medium run. Namely, I assess the brain drain impact on source countries' productivity, allowing the technology to adjust to changes in skilled labor supply consistently with cross-country data on skilled labor relative supply and skilled labor relative productivity.

Figure 11 – Skilled labor demand shifts and skilled labor emigration selectivity



Notes: Migration selectivity is measured using the index $S_{j,t,c}$ as $\frac{s^m_{tertiary,c,t}}{s^n_{tertiary,c,t}}$; the index is computed for recent migrations flows (less than 10 years) in 1980, 1990 and 2000.

39. The historical investigation of Goldin and Katz (2008) on US data shows that this pattern is specific to the post 1980 period. One need to go back to the early 20th century to find that skilled biased demand shift outstripped relative skill supply. For instance between 1920 and 1950 the wage structure narrows as education was winning the race over technology.

3.2. Brain drain costs in an era of skill-biased technological change

In this last section I develop a productivity based brain drain index that incorporates the idea that technology differences across countries ($A_{s,c,t}$, $A_{u,c,t}$) reflect an equilibrium response to differences in factor supply. To underscore the implications of previous graphs it is useful to rewrite the production function of *output per* worker as follows:

$$y_{c,t} = \kappa_{c,t}^{\frac{\alpha}{1-\alpha}} A_{u,c,t}\, h_{u,c,t} \left[1 + \left(\frac{A_{s,c,t}}{A_{u,c,t}} \right)^{\sigma} \left(\frac{h_{s,c,t}}{h_{u,c,t}} \right)^{\sigma-1} * \left(\frac{h_{s,c,t}}{h_{u,c,t}} \right) \right]^{\frac{1}{\sigma}} \qquad (7)$$

$$y_{c,t} = \kappa_{c,t}^{\frac{\alpha}{1-\alpha}} A_{u,c,t}\, h_{u,c,t} \left[1 + \omega_{c,t} * \left(\frac{h_{s,c,t}}{h_{u,c,t}} \right) \right]^{\frac{1}{\sigma}}$$

These formulations make clear that, for a positive skilled wage premium $\omega_{c,t}$, an increase in skilled labor supply increases *output per* worker. Emigration in this supply-demand framework is equivalent to a decrease in the relative supply of skilled labor $\frac{h_{s,c,t}}{h_{u,c,t}}$ and to an increase in $h_{u,c,t}$. Conversely, if all recent expatriates return home in year *t*, the share of skilled labor increases and that of unskilled labor decreases; this is the scenario that I simulate. To emphasize the brain drain productivity cost in a supply-driven skilled biased technological environment, two scenarios are considered. In the *short run scenario*, the "return" migrants raise the share of skilled workers in the economy which increases the average human capital *per* worker and aggregate labor productivity. However, due to the dilution of the technology which is fixed, this productivity gain is dampened by the fact that the skill premium $\omega_{c,t}$ decreases. In a second scenario, the *medium run scenario*, the higher supply of skilled labor triggers a skill bias demand shift; i.e. technology is winning the race against education. As a consequence, the skill premium $\omega_{c,t}$ returns to its value before the supply shock. This second scenario is consistent with the data of FIGURE 10.[40] Moreover, and consistently with results of TABLE 1, I assume that the technological adjustment operates through an "absolute" skilled bias, i.e. the rise in A_s / A_u is driven by a higher A_s. Thus, I assume that the technological adjustment is sluggish, it materializes in the medium run, but it is high enough to undo the negative impact that higher skilled labor supply has on the skilled labor relative productivity.

To simulate these two scenarios I simply need to add the human capital of returnees to the initial human capital series in the corresponding census years. The new series of human capital are computed as:

$$\widetilde{h}_{k,c,t} = h_{k,c,t} + e_{c,t} * \left(h_{k,c,t}^{m} - h_{k,c,t} \right) \qquad k = s,u \qquad (8)$$

40. This amount to assume that the elasticity of skill bias demand shift A_s / A_u to the relative supply of skilled labor h_s / h_u is equal to $-\frac{1-\sigma}{\sigma}$ which is a value very close to the value of 2.02 presented in TABLE 1.

where $e_{c,t}$ is the emigration rate,[41] $h_{k,c,t}$ is the quantity of labor type k per non-expatriate labor, and $h^m_{k,c,t}$ is the labor type k per returnee; both are computed as in equations (6). Typically, due to skill bias migration: $h^m_{s,c,t} - h_{s,c,t} > 0$ and $h^m_{u,c,t} - h_{u,c,t} < 0$ and returnees contribute to a better skill mix in the economy as $\frac{\tilde{h}_{s,c,t}}{\tilde{h}_{u,c,t}} > \frac{h_{s,c,t}}{h_{u,c,t}}$. The short run impact on productivity is:

$$BD^{sh}_{c,t} = \left(\frac{\tilde{h}_{u,c,t}\left[1+\left(\frac{A_{s,c,t}}{A_{u,c,t}}\right)^{\sigma}\left(\frac{\tilde{h}_{s,c,t}}{\tilde{h}_{u,c,t}}\right)^{\sigma}\right]^{\frac{1}{\sigma}}}{h_{u,c,t}\left[1+\left(\frac{A_{s,c,t}}{A_{u,c,t}}\right)^{\sigma}\left(\frac{h_{s,c,t}}{h_{u,c,t}}\right)^{\sigma}\right]^{\frac{1}{\sigma}}} - 1 \right) * 100 \tag{9}$$

and the medium run impact is:

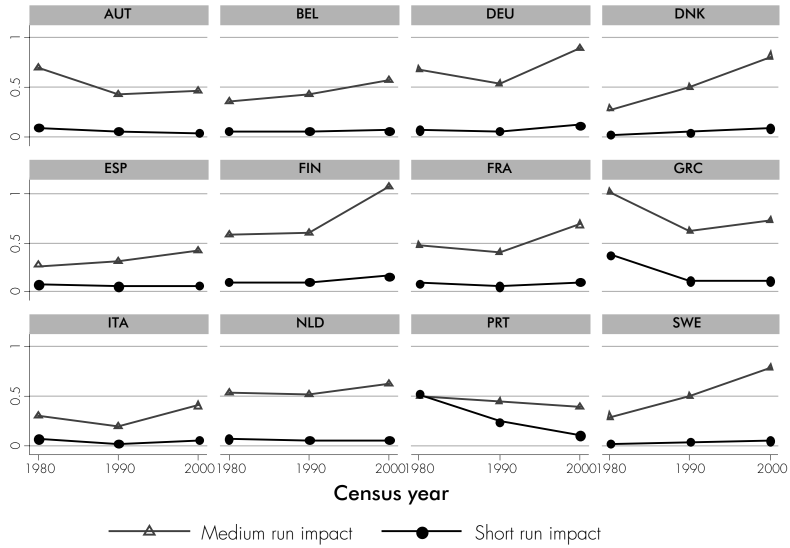
$$BD^{me}_{c,t} = \frac{\tilde{y}_{c,t}}{y_{c,t}} = \left(\frac{\tilde{h}_{u,c,t}\left[1+\overline{\omega}_{c,t}\left(\frac{\tilde{h}_{s,c,t}}{\tilde{h}_{u,c,t}}\right)\right]^{\frac{1}{\sigma}}}{h_{u,c,t}\left[1+\overline{\omega}_{c,t}\left(\frac{h_{s,c,t}}{h_{u,c,t}}\right)\right]^{\frac{1}{\sigma}}} - 1 \right) * 100 \tag{10}$$

where $\omega_{c,t}$ is the before shock skill premium computed as in (4).

The graphs in FIGURE 12 display these two productivity-based measures of the brain drain. They emphasize the large gap between the two measures. Short run productivity impacts are very small, even compared to the magnitude of departures rates of FIGURE 1. As an illustrative example, the French and German departures in the 1990s represented respectively 0.11% and 0.2% of their source country population and 0.5% and 0.6% of their tertiary educated workers. Upon their returns, in 2000 those expatriates would increase the labor productivity in France and Germany by respectively 0.1% and 0.12%. These very small results are not surprising in light of the literature that investigates the sources of cross country income differences, such as Jones (1999) and Caselli (2005). This literature shows that cross country differences in factor inputs, and human capital in particular, do little to account for cross country differences in productivity *per* worker. Adding a *little* quantity of human capital to a country has a *very little* impact on its productivity. However, in a medium run, once technological demand shifts adjust to the higher skilled labor supply, the labor productivity in France and Germany would increase by 0.68% and 0.90%, which are values 7 times larger than the short run ones. Productivity losses in medium run reflect more closely losses of tertiary educated workers. Medium run costs of emigration have increased in most countries, and the 1990s outflows turn to be the most costly in terms of productivity, even though the brain drain of college educated workers is fairly stable since the 1970s (see FIGURE 3).

41. This is not exactly the rate that appears in (1), but there is a very close relation as $e_{c,t} = \frac{M_{c,t}}{M_{c,t}+N_{c,t}} = \frac{em_{c,t}}{1+em_{c,t}} \approx em_{c,t}$ for $em_{c,t}$ small, which is clearly the case here.

Figure 12 – The impact of the brain drain on source countries'productivity (% of GDP *per* worker)



Notes: To ease the reading, Ireland and Great Britain have been omitted from the graphs. Given their high emigration rates, these countries have the highest impacts.

Moreover for most of countries, disparities between short and medium run impacts have increased in the 1990s. A detailed look at equations (9) and (10) shows that the gap between the short and medium impact depends positively on the skilled wage premium, therefore on the demand for skilled labor.[42] The latter remark implies that although countries with high demand for skilled labor have a relatively lower drain of educated workers (see FIGURE 11), they are still the ones whose brain drain costs in terms of productivity are the highest. For instance in the 1990s, Portuguese expatriates represent 0.75% of Portugal tertiary educated workers, and the Finish expatriates represented 0.6% of Finland tertiary educated workers (4/5 of the Portugal share). Upon their return, the Finish would increase their home country productivity by 0.16% in the short run and the Portuguese by 0.12%. In the medium run, i.e. once the technology adjusts to the supply shock, labor productivity would increase by 1.1% in Finland and by only 0.4% in Portugal. Thus, once differences in technological efficiency of skilled labor in Portugal and Finland are taken into account, the productivity loss is much higher in Finland than it is in Portugal. And so, despite the fact that emigration of skilled labor is lower in Finland and that skilled labor is relatively scarce in Portugal.

The main lesson from these simulations is that technology differences across countries could lead to different conclusions regarding the distribution of the brain drain costs across countries. Namely, countries that are more abundant in skilled labor (Scandinavian countries, Germany)

42. It suffices to differentiate the relation (9) and (10) with respect to h_s / h_u , in differentiating (10) $\bar{\varpi}$ is assumed to be constant.

have also higher demand for those workers because their technologies are strongly skill biased. Thus, productivity losses for these countries are potentially higher than they are for countries with lower demand for skilled labor.

4. Conclusion

Globalization and the global shifts into knowledge economy are making skills and talents amongst the most sought-after resources. A greying Europe cannot afford to be complacent about its attractiveness for skills and talents, whether it is domestic or foreign as both are eventually two sides of the same coin. In this paper I have provided an in depth descriptive and quantitative assessment of one possible threat caused by the increasing global competition for talents and skills which may result in a European brain drain to the US.

The small magnitude involved could suggest that the issue is of little concern; even a look at tertiary educated workers does not reveal any acceleration of the phenomenon. However, moving across the knowledge ladder reveals a strong occupational selectivity operating within the group of tertiary educated: emigrants are increasingly concentrated in occupations that are the key to the knowledge based economies. Thus, I have shown that the brain drain of researchers has increased. A similar selectivity has been found in terms of unobservable productive skills in the US labor market. These findings provide support that emigrants are increasingly selected at the upper tail of their source countries' labor quality. Europe could also do much better in making those that have left return home, especially the most skilled. Indeed, a tentative assessment suggests that less emigrants are returning back, once they do, they are likely to be older and, if anything, relatively less educated. In a second part of the paper, I dig into the rational and the consequences of these flows. I identify a negative relationship between skilled labor demand shifts in source countries and emigration selectivity: countries with a more dynamic demand for skilled labor are also those with the lowest increase of migration selectivity. Which I have interpreted as preliminary evidence that the brain drain is a symptom of the lack of demand for skilled labor in Europe that has followed the rise in skilled labor supply in the 1990s. Lately, using the concept of supply driven skilled biased technological change, I have shown that the brain drain is much more costly once the technological adjustment triggered by lower supply of human capital is taken into account.

To give a broad picture of the phenomenon, I have purposely abstracted from a number of issues. In particular, the paper has only scratched the surface of the rationales behind the observed migration flows. Future research will further exploit cross-countries differences in the timing and composition of migration flows that ought to be related to differences in skilled labor productivity. One possible direction that is suggested by Acemoglu (2003) is to link the weaker demand for skilled labor in Europe to its higher institutional wage compression. A natural question is how important are these institutions compared to differences in tax policy for instance in explaining the observed patterns of migration. A contribution of this paper has been to show that outflows are stronger among S&E workers. In this context, one may want to assess the impact of policies that specifically affect the demand for workers in S&E occupations, such as R&D expenditures or tertiary education spending. As for the implications in terms of productivity, a more general approach would consider the issue within an endogenous growth model to go beyond the medium term. This approach could account for the possible beneficial knowledge spillover from emigrants along the directions of Grossman and Helpman (1991) and Wolfgang Keller (2004). The exact sources of the residual wage distribution uncovered in section 2 would also deserve an in-depth investigation to disentangle true changes in emigrants' quality from better distribution over time across occupations, industries or geographic localities. This could provide interesting insights on the most attractive industries, occupations and areas; which would allow being more precise about US specific pull factors and the most drainable European workers.

A. T.[43]

43. I gratefully acknowledge the Centre d'Information et de Recherche sur l'Economie Mondiale (CIREM) for its support. I thank Martine Carré, Benjamin Carton, Jacopo Cimadomo, Sebastien Jean and Olena Havrylchyk for very useful comments on the paper. I thank Rick van der Ploeg, fellows of the "Growth Agenda for Europe" at the European University Institute, and Gilles Saint-Paul for stimulating discussions and suggestions that have led to this research project. I have benefitted from remarks of participants at the Knowledge for Growth conference in Toulouse, the European Economic Association congress in Milan and the European Association of Labor Economists in Amsterdam. Remaining errors are my own.

Appendix 1

Table A1.1 - Number of observations on European expatriates by census and country of birth

	1980	1990	2000	2006	Total by country
AUT	2,911	2,310	1,872	371	7,464
BEL	1,200	1,110	1,206	259	3,775
DEU	29,465	34,956	38,789	7,600	110,810
DNK	1,161	1,132	1,062	210	3,565
ESP	2,184	2,832	3,726	747	9,489
FIN	731	675	781	151	2,338
FRA	4,613	5,987	6,930	1,346	18,876
GBR	22,065	24,438	28,061	5,657	80,221
GRC	7,709	7,054	6,986	1,134	22,883
IRL	6,450	6,104	5,882	907	19,343
ITA	24,019	18,854	16,114	2,475	61,462
NLD	3,590	3,548	3,552	650	11,340
NOR	1,432	1,037	1,003	163	3,635
PRT	6,396	7,685	8,453	1,470	24,004
SWE	1,390	1,394	1,694	359	4,837
Total Europe by year	115,316	119,116	126,111	23,499	384,042

Note: Based on tabulations of individuals age 25-64 in 1980-2006 censuses. The 1980, 1990 and 2000 censuses are 5% sample of the total population. The 2006 census is a 1% sample of the total population.

Table A1.2 – Characteristics of European expatriates in each US census year

	1980	1990	2000	2006
Percent female	56.96	54.78	52.71	51.11
Age distribution:				
Percent Under 35	25.12	25.42	20.19	17.72
Percent 35-50	38.89	38.5	42.29	37.95
Percent 36-65	35.99	36.08	37.52	44.33
Distribution of years in the US:				
0-5 years	7.91	7.9	10.54	9.11
6-10 years	9.1	6.21	7.15	7.68
11-15 years	13.38	6.94	7.3	6.69
16-20 years	14.06	9.17	6.95	7.19
21+ years	55.55	69.77	68.06	69.32
Education:				
Percent < 12 years of schooling	32.54	19.26	11.37	8.02
Percent with 12 years of schooling	35.99	33.61	29.04	25.64
Percent with 1 to 3 years of college	15.27	24.94	27.72	27.97
Percent with 4+ years of college	16.18	22.19	31.87	38.36
Mean years of Schooling	11.44	12.32	13.31	13.86
Geographic distribution:				
Northeast	44.4	38.25	33.29	29.72
Midwest	17.42	15.25	14.27	14.09
South	16.38	22.86	28.14	31.02
West	21.8	23.65	24.31	25.17
Labor market outcomes:				
Percent employed:				
Men	88.18	87.61	84.16	84.16
US men natives natives	*85.59*	*85.14*	*82.17*	*81.87*
Women	52.35	60.51	62.62	65.15
US Women natives	*54.64*	*66.32*	*68.39*	*68.66*
Percent Self-employed:				
Europeans	9.52	11.65	11.88	12.9
US natives	8.09	9.03	9.12	49.61
Mean Hourly Wage (2000$):				
Men	24.00	25.00	29.36	29.40
Women	14.31	15.11	18.53	19.50
*Mean Log Wage Gap relative to US white natives (*100):*				
Men	5.5247	14.0321	17.3472	22.158
Women	0.4144	3.3366	5.7101	49.7387
Percent of total US population (Age 25-64)	1.90	1.74	1.61	1.44
Sample size	115,316	119,116	126,111	23,499

Note: Based on tabulations of individuals age 25-64 in 1980-2006 censuses. The 1980, 1990 and 2000 censuses are 5% sample of the total population. The 2006 census is a 1% sample of the total population. Statistics for the US natives are for white individuals.

Table A1.3 – Summary statistics of covariates used in the wage regressions

	1980	1990	2000	2006
Gross log hourly wage rate	3.08	3.16	3.20	3.24
	(0.63)	*(0.64)*	*(0.72)*	*(0.68)*
Potential experience	14.53	16.75	17.60	21.17
	(9.84)	*(9.17)*	*(9.84)*	*(10.47)*
(Potential experience)^4 (in 1000)	232.21	262.12	315.9	514.12
	(465.38)	*(470.08)*	*(499.54)*	*(649.69)*
Average years of education	17.92	17.70	17.70	17.49
	(1.29)	*(1.12)*	*(1.12)*	*(0.96)*
% female	0.29	0.36	0.41	0.49
	(0.46)	*(0.48)*	*(0.49)*	*(0.50)*
% Speak very well English	0.96	0.96	0.95	0.98
	(0.19)	*(0.20)*	*(0.22)*	*(0.15)*
% married	0.72	0.71	0.68	0.71
	(0.45)	*(0.45)*	*(0.47)*	*(0.45)*
Number of observations	519,254	619,294	672,562	731,553

Note: Figures are for the sample of full time employed salaried, white workers ages 25-64 in the US. Figures are means based on the 1% sample US censuses for white US natives and from the 5% sample for Europe-born workers, except for the year 2006 where it is also based on the 1% sample. Hourly wages are computed as the yearly gross wage income divided by the total hours worked by year. Total hours worked by year have been obtained by multiplying the usual hours worked by week, by the number of weeks worked by year. Standard deviations are in parentheses.

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