Do Europeans Come for the Money? An Analysis of High Skilled Mobility from Europe to the US

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Abstract

We study the phenomena of "brain drain" from Europe to the United States. We use both the US Census 1990 and European household surveys to predict the wage differential, corresponding to the difference between the actual wage of Europeans in the United States and the estimated wage that they would have received if they had stayed in Europe. Consistently with the Borjas-Ray model, we find that migrants from Europe are positively self-selected. The predicted wage gap has a significant effect on the propensity to move to the United States for British individuals but not for the French. Although quite sizeable, monetary incentives might actually be of second order in explaining the brain drain to the United States.

1 Introduction

The "brain drain" is an old theme in economics that has regained some actuality recently. The European press has raised concerns that the best skilled workers of the Old World were flying over to the United States at a dramatic rate. Newspapers have made headlines with old scientists, physicians and young entrepreneurs that have found a better work environment in the United States. Some blame the high level of taxes, while others emphasize the poor investment both in R&D and higher education. As a matter of fact, the expression "brain drain" has been used as a red flag by many politicians and lobbying groups to promote their own agenda. The evidence presented in the media is rather anecdotal and the lack of conclusive data has been underlined by various government reports.[1]

Nevertheless, three recent and well documented evolutions in industrialized countries have increased the risk of a significant brain drain. First, the world has become more open and mobile. Transportation costs have fallen and cultural gaps have tended to decrease, so that most young Americans and Europeans share, in many respects, a common culture. The knowledge of English has become widespread and the revolution in communication technologies has lowered dramatically the psychological cost of moving to another environment in another country. Secondly, technological change in the last decades of the twentieth century has been biased towards skill (Juhn, Murphy and Pierce 1993, Freeman and Katz 1994), in contrast to the technical change of the nineteen century that was biased towards unskilled workers (Goldin and Katz, 1999). At that time, massive migrations coming from Europe to the United States were based on industries needing arms and "not so much brain" or specific qualifications, contrary to modern trends. Third, Europe has maintained, relative to the United States, a lower level of inequality over the last decades[2]. Piketty and Saez (2003) show the divergence in the evolution of earnings for the 5% and 1% deciles of the income distribution in the United States, United Kingdom and France[3]. Wage inequality conditioning on education and experience has increased noticeably in the United States in all dimensions (Card and Lemieux, 2001).

Consequently, the evidence tends to suggest that skill is becoming much more rewarded in the United States. This evolution poses then different questions. Will high skilled European workers become more sensitive to the economic in-

[1] International Mobility of the Highly Skilled, OECD 2001; "L'Europe resiste au brain drain americain", Le Monde, 11.16.01; "L'exode des cerveaux: mythe ou realite?", El Pais, "Geopolitica, economia y globalizacion", Xavier Vives, 05.10.2003; French Parliamentary report Jean-Francois Poncet 2000; "De l'exode des competences a la mobilization des competences dans le cadre du co-developpement" Conseil Economique et Social, June 2001;"Brain drain und deutsche Universitats reform" Eberhard Demm, October 2001. We do not quote all the press coverage as well as all the reports from Canadian sources, but they show concern of governments and of the public alike.

[2] However, since technological change in the United States and Europe has been very similar, it might be that the lower inequality in Europe has been achieved at the cost of higher unemployment.

[3] See figure 2

centives and move to the United States? Will this threat the economic and social policies of European countries towards more egalitarian societies?

The political and media debate has led to believe that policies should be directed at reducing the brain drain. It is not clear however why it should be harmful in all cases for the source country. Mobility and interaction are far from being problems *per se*; they represent, on the contrary, a possibility to foster international research, the pooling of the best ideas and an enrichment of people, societies and cultures. Economists have recently stressed that the brain drain could actually have positive spillovers for the source country as it may enhance technology diffusion, as long as individuals keep close links with their home country or, in the extreme case, they return to their home country at some point. If this is the case, the debate on the brain drain should shift to a new concept, the "brain circulation", and how to foster it.

Our perspective is rather different, since it will focus on the causes of the brain drain as a pre-condition to study consistently the different policies to confront it. It is not the purpose of this paper to analyze why high skilled individuals are rewarded differently in European countries than in the United States. Instead, we pose a different and, to a certain extent, much shorter question: Do Europeans react to the wage differentials and move to the United States? Our intuition is that since Europe was a relatively safe place in the 80s, the wage gap should matter more for explaining migration to the United States than migration from politically unstable countries[4].

The empirical strategy implemented in this paper uses simultaneously the subsample of the US Census with data on Europeans as well as two European household surveys. We first construct a prediction of the wage that the Europeans[5] in the United States would have had if they had stayed in Europe and then compute the wage gap. In the last stage, we analyze the explanatory power of the wage gap in predicting the propensity to move to the United States. We present our results, based on English and French individuals in the United States, for year 1990, since the data for the year 1980 is not comparable enough and the US 2000 census microdata is not yet available at the time of writing.

Our results show that the wage gap is sizeable for both countries and relatively larger for France. We find that the wage gap has a positive and significant effect in the propensity to move for British individuals but, at the same time, it has no significant effect for individuals born in France. However, the wage gap explains only a very minor proportion of the variation observed in the propensity to move. One question that we do not consider is the role of specific policies in explaining the brain drain or its absence. It would be worth knowing whether some other government policies, like R&D spending, higher education or easiness to open a business, matter in the decision to move; since the large wage gap between the United States and Europe fails to explain the immigration pattern

[4]Stability of a country, political assassinations, whether it is under dictatorial regime or not usually explain a lot of the variation of migrants to the US. See Borjas (1987), table 8, p550.

[5]Along the paper we use the term Europeans in various occasions. Nevertheless, the empirical analysis focuses on individuals from France and the United Kingdom.

in the 80s. The forthcoming release of the 2000 US Census Public Use Micro-data Files will allow a more extensive study since in the last years of the 90s there was a very significant rise both in migration and wage income.

We review the literature on the brain drain in section 2 and present our data in section 3. Section 4 describes some stylized facts about the brain drain that fit particularly well the basic Roy-Borjas model. Section 5 discusses the methodology used to construct the wage gap variable and gives the estimated wage gaps. Section 6 presents our results concerning the impact of the wage gap on the propensity move while section 7 discusses the results obtained using an alternative approach. Section 8 concludes.

2 Literature

An exhaustive survey of all the literature relative to the brain drain is out of the reach of this paper, so we will only underline the main issues and results.

There exists an old literature in the late sixties that focused, with some exceptions, on the brain drain from developing countries. The book *The Brain Drain* (1968), by W. Adams comprises different studies about the brain drain at that time. The data they present is strikingly similar to the one one can find nowadays: many anecdotal stories and a few data from the Census or the immigration services. Adams sees ten reasons for the brain drain: (i) salary differentials (ii) professional opportunities (iii) lack of receptivity to change in the home country (iv) relevance of foreign training (v) lack of realistic manpower policies (overinvestment) (vi) technology gap (vii) political balkanization (viii) discrimination on non-economic grounds (ix) monopolistic restrictions in advanced countries (x) living working conditions[6]. It is worth citing the comment on the French case study that contrasts highly with the current alarmist view: "Personally, I know of no case of migration and I have never heard of any. All those forced to go to the USA during the war returned to France at the latest in 1947 or 1948."[7] The book concludes with few suggestions like to increase salaries, enhance professional opportunities, and eliminate discrimination.

The peak of this "old literature" was reached when J. Bhagwati, from MIT, suggested taxing the brain drain. He proposed to tax more the skilled workers who decided to stay in the United States after they completed their studies or training. The work that was done around this proposal was sum-up in a two volume book, "*Taxing the Brain Drain: A Proposal*" (1976) by J. Bhagwati and M. Partington. They review the changes in the legal environment needed to implement it and try to assess the possible revenue of the tax, as well as how it can be used, providing the most detailed data available. They also offer a survey of the theoretical models explaining the brain drain. Among them, P. Krugman and J. Bhagwati describe the work of Myer (1972) about the non-return rate of students educated in the United States. Its main results are that nonreturn was positively associated with per capita income in the home country

[6] W. Adams in The Brain Drain (1968), p 6-8 and Scott (1970).
[7] Robert Mosse, in W. Adams (1968), p 158.

and was negatively related to "political elitism"[8]. However Myer failed to give convincing evidence that income matters.

A more recent literature on the brain drain tries to study the current migration to the United States, which reached a peak in the end of the nineties. Better theoretical analysis has helped to understand the selection process of immigrants. In particular, G. Borjas (1987) develops a theoretical framework based on A. Roy's (1951) model. Immigration takes place when the expected earnings net of all costs of moving are higher in the receiving country than in the source country. This model has sharp predictions concerning the skill selection of migrants: those coming from places where rewards to skill are high will tend to be of low skill, and those coming from countries where return to skills is low will mostly be highly skilled[9]. A large literature has tried to test empirically whether the predictions of this selection model were accurate. Borjas and Bratsberg (1996) and Bratsberg (1995) show evidence of this skill selection for out-migration of foreign-born in the United States: the pattern of out-migration intensifies the selection generated by the original immigration flow. The authors estimate out-migration rates with data from the Immigration and Naturalization Service[10] and the US Census. The data from the INS has many caveats but it still gives a rough idea of return rates: European countries exhibit higher rates of return than Asian countries for the 1975-80 cohort, 18% on average, but this hides huge differences within Europe. The out-migration rates range from Poland with 1% of return to France with 80%. Poland and most communist countries are not a good example as the freedom to migrate was severely restricted. Notwithstanding this fact, one can still find considerable heterogeneity between Germany with 17% and the Netherlands with 66%, while the United Kingdom is around 30%. W. Huang present similar analysis for student brain drain with data related to student visas. He finds the same pattern of heterogeneity for non-return rates within Europe: ranging from Sweden (4.25%), France (4.89%) to higher rates for Germany (9.1%), Italy (15.7%) and Spain (16.9%). He concludes that pure income differentials do not play a predominant role in determining student brain drain, far after professional opportunities and political and social considerations. Ramos (1992) presents convincing evidence for Borjas' model with the case of Puerto Ricans, where migration policies do not interact with immigration flows. Borjas (1987) gives a typical example with the French case: an average immigrant from France earned 8% less than a comparable native person in 1970, while in 1980 he earned 10% more. Borjas concludes then that there has been an increase in the quality of the average French immigrant.

In most of this empirical literature, the variable used to capture the return to skills is the Gini coefficient: low inequality countries reward skill less than highly unequal countries and should experience a higher brain drain. More

[8] It seems that this reason is particularly directed at explaining France's low level of mobility and high rate of return.

[9] We will come back to this basic model in section 4.

[10] The Immigration and Naturalization Service (INS) was recently renamed as Bureau of Immigration.

precisely, policies aiming at reducing inequalities will have a positive impact on the brain drain coming from Europe. However, most of the empirical literature tries to see the causes of the brain drain at a world level, where political freedom and stability play a much more important role than income differentials. By focusing on Europe, we would like to assess more precisely what matters in the brain drain from safe and stable countries.

Finally, some recent work by the IMF and OECD aims to assess the current knowledge of the brain drain. The IMF paper (1998) focuses on the brain drain from developing countries and neglects the flux within OECD countries towards the United States. The OECD report on "*International Mobility of the Highly Skille*d" (2001) gives, on the contrary, useful information about the trend within the OECD. The report stresses however the lack of accurate data that restrains researchers from performing precise tests. One study in the report by D. Martinelli inquires about the brain drain among young PhDs with a survey on French PhDs in 1999 living in France or abroad. The main result of this survey is to dampen the alarmist view: even on the rise, only 7% of French PhDs were abroad three years after having completed their studies, and 60% of them wanted to return at some point. The study stresses out that post-doctoral training is an increasingly more important part of the qualification of French PhDs.

3 Data

The main problem with our empirical strategy is the lack of exhaustive data. We face two difficult constraints: we need a very large database in order to obtain a sufficient number of observations of individuals from each country in the United States and, within this source, we need many precise variables to identify the highly skilled as well as their employment and wages.

3.1 Datasets

The main data set that we use is the US 1990 Census 5% subsample.[11] This is the most comprehensive source of data about foreigners working in the United States and, more precisely, Europeans. In contrast to the INS data, it provides very detailed information on income, working conditions and education for a very large sample of individuals. Our analysis is restricted to the 1990 US Census due to, first, the lack of cross country comparable variables for the 1980 Census and, second, the delay in the release of the 2000 Census. There are other sources of information about the highly skilled, notably the SESTAT data set, but the sample by country of birth is too small to be used to study properly the brain drain.

The second data set that we use is the 1990-1991 wave of the British Household Panel Survey. Naturally, it would be preferable to use a survey conducted

[11] Provided by the IPUMS, http://www.ipums.umn.edu/usa/index.html, see the citation for the full reference.

exactly in the same time period.[12] Unfortunately, the General Household Survey, the only British alternative, does not offer enough detailed information concerning the labor earnings and the occupation. Finally, for France, we use the Enquête Emploi 1990 prepared by INSEE, the French Statistical office. The European Household Panel Survey (EHPS) provides also an alternative source of data for most European Unions members. Nevertheless, the relatively small sample size as well as the cost of acquiring it oriented us towards a more careful analysis of a reduced number of national surveys.

The main problem when looking at different micro data sets is that they have different universes, have different designs, follow different methodologies and probably have different collection techniques. There is, logically, an a priori caution from the part of the economist when looking at attempts to use so called comparable micro data sets. The following sections discuss the main issues concerning these problems as well as the methodology used to adjust for them.

3.2 Our sample

We control for the issues discussed above in the following way. We carefully homogenize the universe of the three samples, dropping all types of individuals that are not included in the three surveys, and adjusting as well for the weights.

The first step is to identify the individuals that are likely to be affected by the brain drain and can give some insight about the reason to migrate. We first restrict our sample to those who entered the United States in between 1980 and 1990 and are currently working[13]. Ideally, we would like to account for all nationals as well as for the foreigners who spent a significant time in the Europe before moving to the United States. Many individual anecdotes point to the fact that the brain drain story is not restricted to native Europeans: immigrants who came to Western Europe from Africa, Asia our Eastern Europe to pursue further education may find it hard to integrate. Thus, they may prefer to move to the United States after completing their studies since skilled immigrants might be more welcomed there.[14] Unfortunately, the Census only identifies the country of birth and not the last country of residence, so that in this study we only focus on native Europeans.[15]

[12] The first wave of the BHPS covers the period from September 1990 to September 1991 and it is available on the British data archive website www.data-archive.ac.uk. The adjustment by PPP for the British case is done using 1991 as the reference year, in order to account for the timing difference with the US and French datasets.

[13] More precisely, we drop an individual if: (a) has been more than 10 years in the US, (b) is not employed, (c) is in institutional group quarters, (d) there is no information about his occupation, (e) is younger than 16 years old, (f) works less than 30 hours a week, (g) earns less than $4000 1990 dollars.

[14] We do not pretend to assess how well immigrants integrate in Europe relative to the US. We only want to point to the limitations of our sample. Recently B. Pivot, a famous French interviewer, devoted its TV show to foreigners who came to study in France but preferred to move to the US afterwards, so that probably it is not an unusual pattern.

[15] The INS files used to register immigrants according to the last country of residence but their data sets are much too narrow to be used for anything else than statistics on migration.

3.3 Comparability of variables

We focus on a very reduced set of variables[16] and redefine them in order to make them fully comparable. To give an idea with a very simple example, the age variable is not computed the same way in the three surveys: the US Census defines age as the age of the individual at April 1st, the official date of the census, whereas the BHPS defines it as the age at the time of the interview and the French Enquête Emploi as the age at the end of the calendar year. To account for this, we recompute the age at April 1st, using the actual date of birth available in the two surveys.

The three more problematic variables to homogenize cross-country are education, occupation and income. Education systems are organized in a different manner in each country, such that the degrees awarded are not always fully comparable. For instance, it is not possible to know how a British individual would report in the US Census his "first degree". He could answer either "some college, no degree", since he has completed only two years after high school, or "bachelor degree", if it seems to him closer to his own degree. We have converted the education variable in each survey into a new variable representing the average years of education required to obtain them. This variable ignores, unfortunately, issues relative to the intensity, contents, level or quality of education, a problem that is also common in within country analysis

We base our definition of occupations on the International Standard Classification of Occupations ISCO-88, that provides up to a 4 digit code to classify each occupation.[17] The British BHPS already uses this classification at the finest level. The United States uses instead a different classification that is fully comparable once recoded. We recode it using the program provided by H. Ganzeboom (1996).[18] For France, the conversion was made more difficult by the existence of a very specific French classification called CSP.[19] This classification obeys to different rules and even a different philosophy.[20] We could not access the program used by the INSEE to compute an equivalence between both classifications, even though the INSEE began to use an equivalent occupational variable in the Enquête Emploi in 1993. Thus, we recoded manually the four digit codes of the CSP into the three digit code of the ISCO-88.[21] Miscoding issues will become more problematic when the four digit classification is used. Therefore, even though we loss information, we use only the 2 and 3 occupation codes in our estimation. All results reported in the paper are based on the 2 digit code classification.

[16] Age, sex, education, income, marital status, occupation, number of children, labor force status, hours of work, weights, (See table in appendix for the precise recoding).

[17] This classification has been created by the International Labor Organization, ILO and has four levels of aggregation.

[18] See citation for full reference.

[19] Categories Socio-Professionelles - Socio-professional categories

[20] The literature on the differences between the French classification and the British one is huge, both in sociology and in statistical offices.

[21] Some specific denominations posed problems, but most of them did not affect the highly skilled. The conversion to a 3 digit code instead of to a 4 digit code reduces the extent of this problem. Our conversion codes are available on request.

Finally, the income variable presents different conceptual and practical concerns. From a theoretical perspective, it is not clear which measure should be chosen. The first distinction is whether we should focus on pre-tax or after-tax income, especially given the different level of taxation in each country. If we consider that taxes are used to finance services that benefit all individuals, then the pre-tax tax wage would be preferred. On the other hand, high wage individuals typically pay more in taxes than what they receive in services. Unfortunately, the tax system is highly complex and diverse across countries. For instance, payroll and consumption taxes vary considerably between Europe and the United States[22], as well as the precise definition of net and gross labor income. In addition, there are also tax incidence issues. In the present circumstances, we focus on pre-tax gross income, even though it may tend to underestimate the wage differential. The French wage variable gives the wage net of payroll taxes while the British and United States report the gross wage. We adjust the French measure by the amount of social payroll taxed paid by the employees in his pay bill to obtain a more comparable variable. For the United States, we select the total earned income measure, since it is the closest to the British and the French definitions. Notwithstanding these sizeable caveats in the wage variable, it is important to keep in mind that if this underestimation is, in relative terms, the same for all individuals in each country, we will still get consistent estimates for the slopes of our regression, while all the errors will end up in the constant term.[23]

3.4 Other caveats

Finally, there are also three other caveats for the choice of the compensation variable. Fringe benefits, which are impossible to estimate, are likely to vary quite a lot in different countries and also within country. This might be due to different tax systems as well as to business culture. Secondly, the adjustment of income measures by the Purchasing Power Parity does not account for within country regional price disparity (London, Paris and New York are relatively more expensive than Scotland, Auvergne and Ohio). This would pose a real problem if migrants to the United States were coming from a broad national

[22] We use Purchasing Power Parity data from the OECD. Let us remind here that PPP is based on after-tax prices, without adjusting for different consumption or value-added taxes.

[23] Our measure of wage differential or wage gap is defined as

$$WageGap_{ijl}^{US-home} = \ln\left(\frac{w_{ijl}^{US}}{w_{ijl}^{home}}\right) = \ln w_{ijl}^{US} - \ln w_{ijl}^{home}$$

If wages are measured with error, such that we observe $\breve{w}_{ijl}^{US} = w_{ijl}^{US} * \varphi^{US}$ and $\breve{w}_{ijl}^{home} = w_{ijl}^{home} * \varphi^{home}$, then

$$WageGap_{ijl}^{US-home} = \ln\left(\frac{w_{ijl}^{US}}{w_{ijl}^{home}}\right) + \ln\left(\frac{\varphi^{US}}{\varphi^{home}}\right)$$

As long as the second term is constant across individuals, the estimate for the slope will be consistent.

base while settling in the expensive areas of the United States. However, in general, the counterfactual for them is to live in expensive areas in Europe (relative to their national average). Thus, the bias is likely to be washed out. One final problem with using PPP is that part of the income gained in the United States might be saved in order to be spent in Europe after retirement. The optimization of an individual moving to the United States may well include this late return, which understates the true wage gap. Last and none the least, our wage variable measures compensation for a given level of employment. If unemployment differs largely between the two economies - as it is the case, even for the highly skilled - the wage underestimates the true incentives to move to the United States. This is a very serious problem that has already been stressed by other scholars[24]: the lack of job offers in private and public research is one of the reasons usually emphasized to explain the scientific brain drain to the United States.

Once we have derived the data, we use two different strategies. The first one is to construct an occupational propensity to move measure. That is, the first question that we are able to answer is whether occupations that have higher wage gaps have also higher mobility. The second approach, more problematic, consists in constructing a joined data set based on the three different data sets. In other words, we create a dataset that has both British in the United Kingdom and in the United States and another data set that has both French in France and in the United States. We will detail these approach in sections 6 and 7. In the mean time we are going to describe how the stylized facts about the brain drain fit a basic model of selection.

4 Basic model and stylized facts about the brain drain

We will base our empirical work on a very basic theoretical framework. There exist more sophisticated models concerning the brain drain but they rely on very strong assumptions that reduce their generality.[25] On the contrary, the basic model used by Roy (1951) and Borjas (1987) gives clear and simple insights on how income distribution should have a direct impact on the importance of the brain drain. We briefly remind to the reader the structure of this model and see how it can be adapted to the question we are addressing.

4.1 The model

Let us denote the United States by 0 and Europe by 1. Assume the Europeans in Europe have the earnings distribution described by eq. (1).

[24] See Martinelli in OECD 2002.

[25] V. Kwok and H. Leland (1982) suggest an interesting model but which rely on the asymmetry of information between employers in the home country and the US. It is thus specific at explaining the brain drain for foreign students who remain in the US after completing their studies.

$$\ln w_1 = \mu_1 + \varepsilon_1 \text{ where } \varepsilon_1 \sim N(0, \sigma_1^2) \tag{1}$$

The Europeans, if they were to migrate to the United States would have an earnings distribution of:

$$\ln w_0 = \mu_0 + \varepsilon_0 \text{ where } \varepsilon_0 \sim N(0, \sigma_0^2) \tag{2}$$

Define ρ as the coefficient of correlation between ε_0 and ε_1, i.e. the correlation between the way unobserved characteristics of workers will be evaluated in Europe and the United States. The difference between μ_1 and μ_0 reflects the difference in the average reward to skill in Europe and the United States.

The decision to migrate to the United States for an European depends on the expected reward for his skills in the United States relative to his wage in Europe after substracting the cost of emigrating to the United States.[26] We denote, after Borjas, the index function I that determines the migration choice. Emigration to the United States occurs when $I > 0$. P represents the emigration rate derived according to this model:

$$I = \ln(w_0/(w_1 + C)) \approx (\mu_0 - \mu_1 - C/w_0) + (\varepsilon_0 - \varepsilon_1) \tag{3}$$

where C is the cost of moving to the United States.

$$P = \Pr\left[\varepsilon_0 - \varepsilon_1 > -(\mu_0 - \mu_1 - C/w_0)\right] = 1 - \Phi(z) \tag{4}$$

where z is -(μ_0-μ_1-C/w_0)/$\sigma_{\varepsilon_0-\varepsilon_1}$ and Φ is the standard normal distribution.

The two following equations, derived by Borjas under the normality assumption, summarize the results of interest for our paper. $E(lnw_1|I > 0)$ is the average earnings that the Europeans who moved to the United States would have had in Europe and $E(lnw_0|I > 0)$ is the average earnings of the European migrants in the United States.

$$E(lnw_1|I > 0) = \mu_1 + \frac{\sigma_1\sigma_0}{\sigma_{\varepsilon_0-\varepsilon_1}}(\rho - \frac{\sigma_1}{\sigma_0})\lambda \tag{5}$$

where $\lambda = \Phi(z)/P$ is inversely related to the emigration rate.

[26] The relevant theoretical cost of emigration takes into account not only the monetary cost of arriving in the US (transport, visas...) and the cost of adapting to the US labor market (learning the language, how to behave in Amercian business relations, demonstrating its skills to the American employer) but also all sort of psychological costs (being away from its friends and family, missing the French baguette and Spanish jamon...) that are obviously impossible to measure properly for an economist. In a similar manner, the relevant wage should not be only the monetary compensation for the work but also the work opportunities offered (research funds, amenities...) and the social recognition of the work. For instance, all considerations apart, if business success is more recognised in the US than in France, it would worth for a young French entrepreneur to migrate to the US to start its own business.

$$E(lnw_0|I>0)=\mu_0+\frac{\sigma_1\sigma_0}{\sigma_{\varepsilon_0-\varepsilon_1}}(\frac{\sigma_1}{\sigma_0}-\rho)\lambda \tag{6}$$

For the brain drain to occur, we need $\rho > \min(\frac{\sigma_1}{\sigma_0}, \frac{\sigma_0}{\sigma_1})$. Borjas agrees that ρ should be positive and quite large for most industrialized countries since there is no obvious reason why able workers should be rewarded very differently in Europe than in the United States. Thus the remaining variable $\frac{\sigma_0}{\sigma_1}$ is key in determining both the existence and size of the brain drain from Europe to the United States. $\frac{\sigma_0^2}{\sigma_1^2}$ represents the ratio of the variance of the wage distribution in Europe relative to the United States. If $\sigma_1^2 > \sigma_0^2$, wage inequality is higher in the United States than in Europe and the brain drain will be sizeable. In the extreme case of no mobility cost, the brain drain will occur until the two distributions become similar.

4.2 Stylized facts on the brain drain

To motivate better our analysis, we show with simple data how the patterns of wage distributions and the characteristics of the Europeans in the United States fit well the basic model that we have discussed in the previous section.

Figure 1 illustrates the migration flux from Europe to the United States. We have scaled the number of migrants registered by the INS by the population in the source country to account for obvious size effects that are not very informative. One can easily notice the higher rate of migration of the British, which is not surprising since the language does not represent a barrier to mobility. The second most important group are the Swedish followed by the Germans. The propensity to move to the United States is much lower for the Latin countries, France, Italy and Spain. The striking fact, however, is the sharp increase at the end of the century, precisely the time of higher concerns about the brain drain in the European press. Unfortunately we will not address this late pattern of migration to the United States since the US Census 2000 is not available at the time of writing.

It is interesting to compare figure 1 with figure 2, which describes the divergence in the evolution of in income inequality between the United States, the United Kingdom and France, according to the estimations from Piketty and Saez (2003). We have used their data to present the evolution for the top 0.1% of the income distribution in the second half of the century.

There is a sharp increase of the income gap for the very rich in the 80s as well as an explosion at the end of the 90s. This last episode coincides with the increase of figure 1 of the migrants to the United States. Many simple stories, not necessarily related to the higher wage gap, could explain this pattern: the booming economy increased the need for labor force, driving the authorities to relax restrictions on visas; or, alternatively, the boom of the stock markets might have led many Europeans to believe in their possibility to create a successful start-up, so that they all rushed to the United States to become millionaires. But only a careful study of the US Census 2000 will shed light on these issues and assess the importance of this higher brain drain.

Figure 1: Immigration from Europe to the US in proportion of the home country 1989-2001.

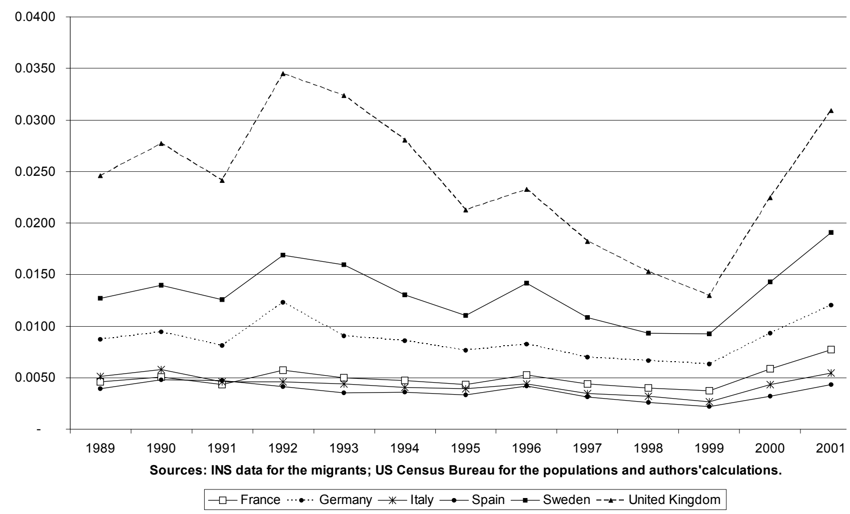


Figure 2: The top 0.1% income share in France, the U.S. and the U.K.,1945-1998

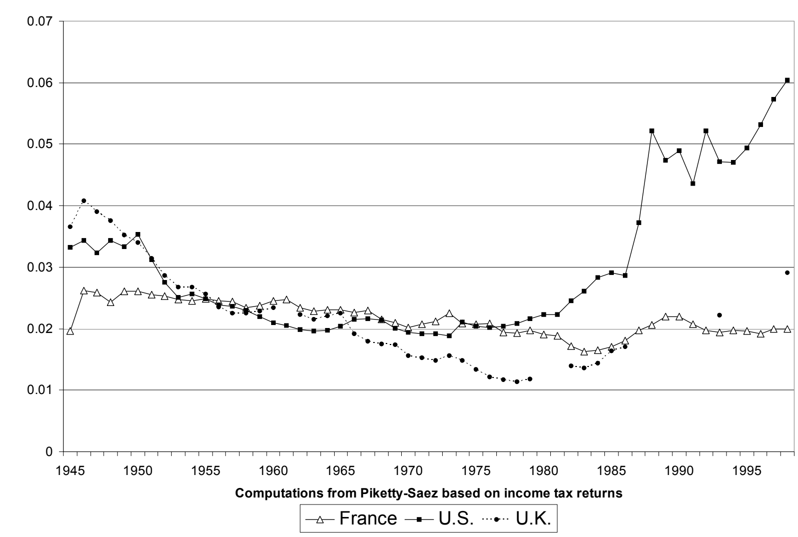


Figure 3: Distribution of educational attainment for individuals born in the UK

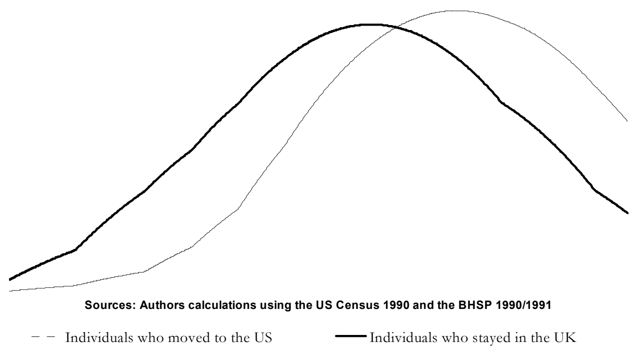


Table 4.2.1 presents the summary statistics of our different samples.[27] Consistently with the model discussed above, the migrants from both France and the United Kingdom are more educated, earn higher wage and are younger than average citizen both in the United States and Europe. Moreover, the typical "brain drain" occupations are overrepresented among the migrants relative to Europe and the US.

Figures 3 and 4 plot the distribution of educational attainment for both the French and the British[28], distinguishing between those who remained in their country of birth and those who moved to the United States. As expected, the distribution is skewed towards the right for the individuals who decided to move to the United States. This is a clear pattern of what can be described as "brain drain".

The final stylized fact we would like to stress is the timing of the brain drain. The mobility window is generally restricted to the young workers, since once they form a family moving out of the country becomes more problematic. Figures 5 and 6 give eloquent views of this pattern. On average, around 2/3 of the Europeans that entered the United States during the 80s were between 19 and 36 years old. This pattern emphasizes the role that higher education may have in fostering the brain drain. A young migrant from Europe arriving in the United States, even for a short and temporary period of time, might well become a permanent migrant afterwards.

[27] The tables are to be found at the end of the paper.
[28] These distributions have been estimated using a kernel regression.

Figure 4: Distribution of educational attainment for individuals born in France

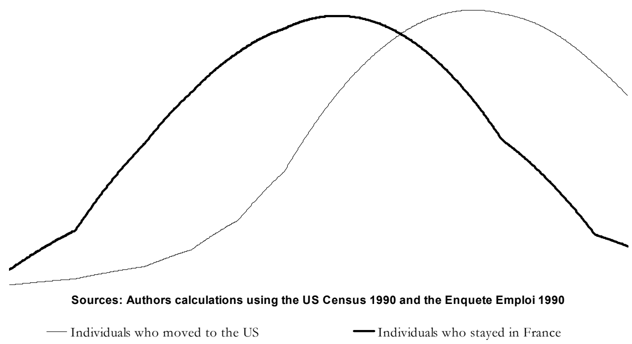


Figure 5: Distribution of the age of entry in the US of French migrants during the 80s

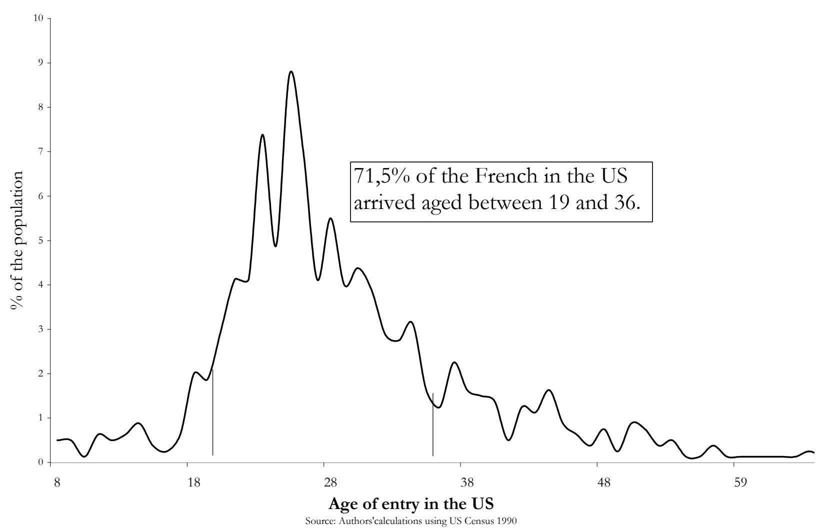
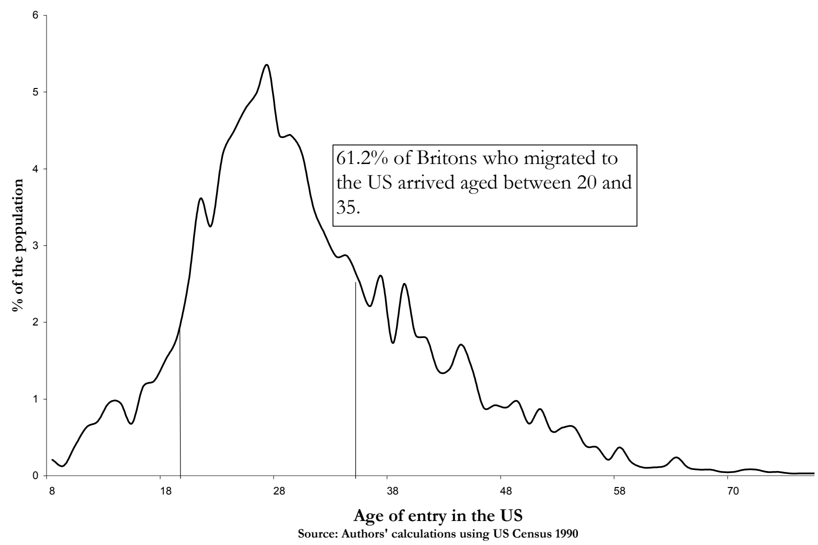


Figure 6: Distribution of the age of entry in the US of British migrants during the 80s



5 Wage Gap Estimation

5.1 Methodology

To shed light on the issue of different economic incentives faced in the United States and European countries, we need to define a measure of the wage differential controlling for observables. We define the wage gap as the difference between the wage that the same individual could earn in the United States and in his home country[29].

In principle, differences in the unconditional average wage gap could be attributed to three effects: differences in the distribution of measured characteristics of workers, differences in the rewards to measured characteristics and differences in the residual, which could reflect, among others, the impact of unobserved productivity or measurement error. The objective here is to isolate the difference in prices from the measured characteristics in order to compute a conditional wage gap. Different authors, like Blau and Kahn (2001), have already shown that rewards are significantly larger (and more unequal) in the United States than in Europe. The question that we answer here is whether the higher rewards do explain the migration to the United States.

[29] Home country refers to the European country of origin (France and the United Kingdom).

The first step of the procedure is to estimate a standard wage regression, separately by sex, both for the United States labor market[30] and the home country labor market, as shown in eq. 7. The endogenous variable is the logarithm of the standardized gross labor income and the regressors include the standardized variables for education attainment, experience, occupation, marital status and hours of work.

$$\ln w_{ijl}^{k} = \beta_0 + \beta_1 edu_{ijkl} + \beta_2 exp_{ijkl} + \beta_3 marital_{ijkl} + \beta_4 controls_{ijkl} + \beta_{5jk} + u_{ijkl} \quad (7)$$

$\ln w_{ijl}^{k}$ corresponds to the log wage for individual i, with occupation j, working in country k and born in country l. In addition, we include some quadratic as well as cubic terms to increase the precision of the prediction.

Ideally, we would like to observe the wage that the same individual has, at the same time[31], both in the United States and the home country, such that the wage gap for individual i could be defined as:

$$Wage\ Gap_{ijl}^{US-home} = \ln\left(\frac{w_{ijl}^{US}}{w_{ijl}^{home}}\right) = \ln w_{ijl}^{US} - \ln w_{ijl}^{home} \quad (8)$$

Instead, we need to predict the wage that Europeans in the United States would have earned if they had stayed in Europe. We use the estimated coefficients in the home country to obtain a first predictor of this wage. Nevertheless, the individuals that move to the United States are self-selected and, thus, they are not representative of the home country population. Consequently, comparing this fitted value to the wage realized in the United States will provide inconsistent estimates. More precisely, as long as the migrants are positively self-selected, this measure will tend to overestimate the wage gap, since if they had stayed in their home country their wage would have been higher than the fitted value.

To implement a more precise predictor, we begin with the following reduced wage equation:

$$\ln w_{ijl}^{k} = X_{ijkl}\beta + u_{ijl}^{k} \quad (9)$$

The residual can be interpreted as being composed by two elements: an individual's relative position in the residual distribution θ_{ijl}^{k} and the distribution function of the wage residuals conditional on all observables $F_k(\cdot \mid X_{ijkl})$, such that:

$$u_{ijl}^{k} = F_k^{-1}(\theta_{ijl}^{k}|X_{ijkl}) \quad (10)$$

[30] We used a smaller sample than the 5% US Census to estimate the wage equation (200,000 observations). Precision is not reduced in practice and the data set becomes easier to manipulate.

[31] It is worth noting at that point that life-time dimension of the wage distribution is put aside by this methodology. Countries might well "insure" older workers differently. Employers can pay younger worker less than their marginal productivity in order to offer increasing wage careers. If European employers do so more regularly than Americans do, even with no wage gap, one should expect young Europeans to move to the US with the expectation of returning to Europe later in life. We neglect this consideration to focus on the actual wage gap.

$$\ln w_{ijl}^{k} = X_{ijkl}\beta + F_{k}^{-1}(\theta_{ijl}^{k}|X_{ijkl}) \tag{11}$$

Note that, in general, we will have:

$$F_{US}(\cdot|X_{ijkl}) \neq F_{home}(\cdot|X_{ijkl}) \tag{12}$$

Here, we will interpret θ_{ijl}^{k} as the deviation from the mean of the distribution (i.e. the fitted value) relative to the standard deviation of the distribution:

$$\theta_{ijl}^{k} = \frac{u_{ijl}^{k}}{\sigma_{ijkl}} \tag{13}$$

We assume that $\theta_{ijl}^{US} = \theta_{ijl}^{home}$. In words, if the individual's wage in the United States is one-standard deviation above the fitted value, conditional on his observable characteristics, then if he had stayed in his home country his wage would also had been one-standard deviation above the fitted value. In addition, we assume, for simplicity, that $\sigma_{ijkl} = \sigma_{k} \ \ \forall i,j,l$ but, at the same time, we allow for $\sigma_{US} \neq \sigma_{home}$[32].

Consequently, the process to construct the set of wages that Europeans in the United States would have had if they had stayed in Europe is as follows. First, we apply the estimates of the home country wage regressions to the characteristics of the individuals who migrated to the United States, obtaining the fitted value $\ln \hat{w}_{ijl}^{home}$. Then, we estimate the standard deviation of the residual both in United States wage regression and in the home country wage regression. Finally, we compute the predicted wage $\ln \tilde{w}_{ijl}^{home}$ as shown in eq. (14).

$$\ln \tilde{w}_{ijl}^{home} = \ln \hat{w}_{ijl}^{home} + \hat{\theta}_{ijl}^{US} \cdot \hat{\sigma}_{home} = \ln \hat{w}_{ijl}^{home} + \left[\frac{\hat{\sigma}_{home}}{\hat{\sigma}_{US}}\right] \cdot \hat{u}_{ijl}^{US} \tag{14}$$

where

$$\hat{u}_{ijl}^{US} = \ln w_{ijl}^{US} - \ln \hat{w}_{ijl}^{US} \tag{15}$$

Once we have the predicted wage, we can estimate the wage gap. We will use two different measures of wage differential. The first one, the predicted wage gap, is defined by eq. (16), and it is the preferred measure.

$$Predicted\ Wage\ Gap_{ijl}^{US-home} = \ln\left(\frac{w_{ijl}^{US}}{\tilde{w}_{ijl}^{home}}\right) = \ln w_{ijl}^{US} - \ln \tilde{w}_{ijl}^{home} \tag{16}$$

$$Fitted\ Wage\ Gap_{ijl}^{US-home} = \ln\left(\frac{\hat{w}_{ijl}^{US}}{\hat{w}_{ijl}^{home}}\right) = \ln \hat{w}_{ijl}^{US} - \ln \hat{w}_{ijl}^{home} \tag{17}$$

[32] Preliminary results not reported here show that if we flexibilize this assumption and allow for $\sigma_{ijkl} \neq \sigma_{k} \ \ \forall i,j,l$ the main conclusions are not affected. That is, if we allow for an heteroscedastic error term, such that the standard deviation is conditional on all the observerd characteristics (i.e. a different distribution function for each combination of characteristics), we obtain very similar results.

In addition, we will also use an alternative measure of wage gap, based on the fitted values of both and defined by eq. (17). This measure is less precise since it discards some valuable information, mainly, the residual variance. Moreover, since the individuals who migrate are not likely to be on the conditional average and the United States generally rewards positive deviations more than European countries, this measure would tend to underestimate the wage differential for those who migrate. Nevertheless, it summarizes, to certain extent, the wage gap based on observable characteristics. Finally, we also estimate the wage that the Europeans who did not migrate would have received in case they had moved to the United States. We follow an equivalent procedure as the one described above and compute similarly the associated wage gap.

Before turning to the empirical estimation some comments about the methodology used are in place. First, we assume that individuals are forward looking when deciding whether to move. In other words, they have a consistent forecast of the wage that they would receive in the following years[33] both in the United States and in the home country. Consequently, comparing the two wages few years after they moved is appropriate. Second, the relevant variable in deciding whether to migrate is the lifetime income in both countries. We assume, therefore, that annual income constitutes a consistent forecast for lifetime income or, in other words, that lifetime income profiles are equivalent in both countries. Third, we assume that all the residual corresponds to unobserved characteristics of the individual. We assume that either there are no employer-employee matching effects or, in case they exist, that the quality of the employer-employee match in the home country would be the same as in the United States for every individual. Fourth, the wage gap estimates will probably have a problem of classical measurement error, so that our estimates may be biased downwards due to the attenuation bias. Fifth, the wage regression estimation ignores the problems of endogeneity, especially in the education decision. For our purposes this does not represent a serious problem since we do not pretend to infer causality (i.e. to estimate the returns to schooling) but, instead, we use education as a proxy for ability and human capital, either inherited or acquired in school.

5.2 Results

We proceed now to estimate the wage gaps. First, we estimate eq. (7), separately for men and women, for the United States, United Kingdom and France. Table 5.2.1 at the end shows the estimates of the wage equations, including the two-digit occupation dummies. The estimated coefficients have similar magnitude and sign for the different countries, as we would have expected. Note, however, that the curvature for education for the United States is relatively higher than for the United Kingdom and France, suggesting that the United States rewards skill more than European countries. Experience seems to be more rewarded for both United States and United Kingdom than for France.

[33] From 1 to 10 years, depending on the individual.

Based on this results, we estimate both the predicted and the fitted wage gaps, as defined by equations (16) and (17), for the Europeans who migrated to the United States as well as for those who stayed at home. Results are presented in table 5.2.2. As expected, the fitted wage gaps are lower than the predicted wage gaps, but the correlation is still quite high (0.57 for the French, 0.86 for the British). The results consistently show that individuals who migrate have, on average, a higher wage differential than those who stayed. For instance, an average male full-time British worker would earn 6.8% more if he were to move to the United States but, among the British who migrated to the United States, the wage gap amounts to 20%. Thus Britons who moved faced three times bigger wage gap than Britons who stayed. This result is not surprising given the selection of the migrants to the United States, but remains significantly large. Equivalent results hold for British women as well as for the French, providing some suggestive evidence that the wage gap has an effect on the decision to migrate. More precisely the wage gap is bigger for the French men living in the United States than for the British ones, reflecting the higher wage inequality in the United Kingdom compared to France. Therefore, it seems that the selection of the Europeans who move to the United States obeys to the predictions of the simple Borjas-Roy model and, consequently, the wage gap constitutes a good candidate to explain the brain drain.

Since the average predicted gap could hide significant variations and the theory predicts different patterns for individuals in the top of the distribution, we push further the analysis of our predicted wage gap. Figures 7 and 8 graph the distributions of the predicted wage gap for both the individuals (men and women) that moved and the individuals who stayed in the United Kingdom and France. Again, it is clear that the distribution of those who migrate is to the right of the distribution of those who stayed, suggesting again the existence of an effect of the wage gap on the decision to move.

6 Cross-Occupation Analysis

6.1 Methodology

In the previous section we derived a measure of the wage differential between the United States and the United Kingdom and France. The objective now is to estimate the effect that the wage gap has on mobility. Ideally, we would like to have a measure of the propensity to move for each individual, and estimate how this propensity is affected by the different variables. This is obviously unfeasible, as one can only be in one place at the same time. Therefore we approximate the individual's propensity to move by the propensity to move of his occupation. In other words, the question that we answer in this section is, basically, whether occupations that have higher wage gaps also have a higher propensity to migrate, controlling for the other characteristics of the occupation[34].

[34]Note that this procedure makes the simplifying assumption that individuals who migrate would have had the same type of occupation if they had stayed in the Europe. Since we are

Figure 7: Distribution of the predicted wage gap for individuals born in France

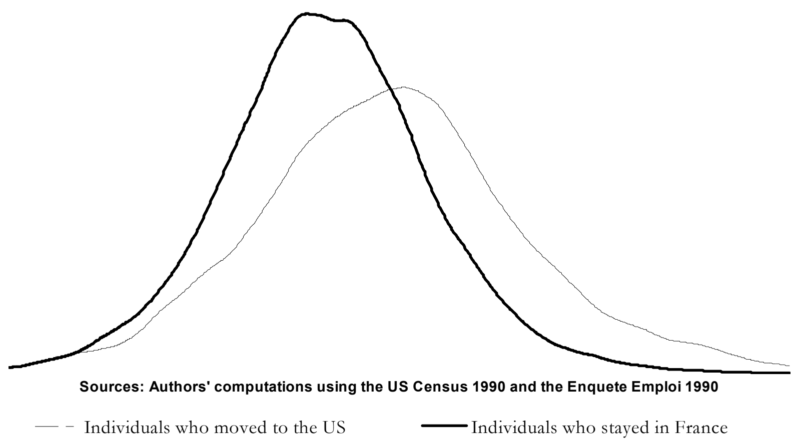
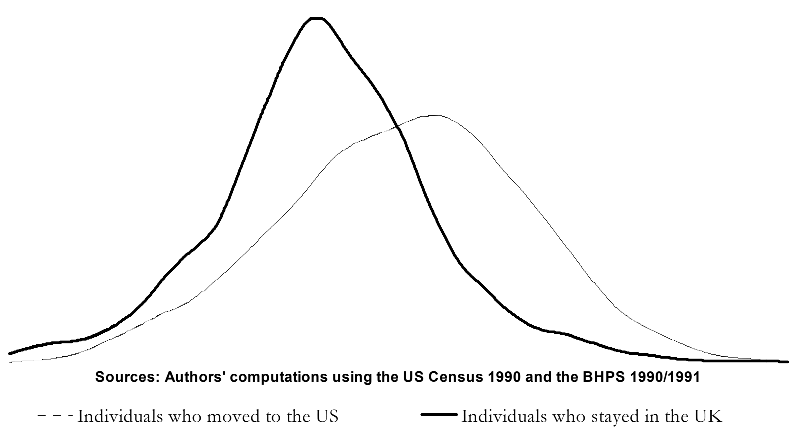


Figure 8: Distribution of the predicted wage gap for individuals born in the UK



The first step is to create a measure of the propensity to move by occupations. We define the propensity as the number of migrants to the United States in one occupation relative to the total number of individuals working in that occupation, as shown in eq. (18). Let NUS_{lj} be the number of individuals from country l and occupation j in the United States and N_{jl} the number of individuals in occupation j in country l.

$$Prop_{jkl} = \frac{NUS_{lj}}{N_{jl} + NUS_{lj}} \tag{18}$$

We then estimate the following equation:

$$Prop_{ijkl} = \alpha_0 + \alpha_1 WageGap_{ijkl} + \alpha_2 Edu_{ijkl} + \alpha_3 Exp_{ijkl} + \alpha_6 Controls_{ijkl} + \varepsilon_{ijkl} \tag{19}$$

We include also quadratic and cubic terms for education, experience and the wage gap as well as the wage level as control. Again, note that the interpretation is not necessarily that an extra year of education raises the propensity to move but that, instead, occupations with more "able" people (either inherited or acquired in the educational system) have also a higher propensity to move.

6.2 Results

Table 6.2.1 presents the estimates for equation (19). Columns (1) and (3) show that the predicted wage gap has a significant impact on the propensity to move to the United States for the British when controlling only for the level of education and experience. When we introduce additional controls the main result is unchanged, although there might be non linearities in the impact of the wage gap on the propensity to move. Moreover, the effect is larger for those with higher levels of education and lower experience. Thus, a one point increase in the wage gap rises the propensity to move by 0.002. This number seems, at first sight, very small, so it is useful to remind that the propensities themselves are very small. For instance, given the average propensity of 0.00599 for a British male, a one point increase in the wage gap increases the propensity to move by 34%. The same calculation for a British female amounts to 80%. The positive effect of the wage gap on mobility is here much more striking. In 1990, according to the INS, 16,000 Britons arrived in the United States. An increase of 0.002 in the propensity to move means that the flow of British immigrants would raise to 21,000 a year. That is, on other words, the number of British living in the United States should increase, in principle, by 114,900 individuals[35].

Table 6.2.2 presents similar results for the French case of equation (19). This time the predicted wage gap is not significant anymore. This results underline

using the 2-digit occupational codes, which are relatively aggregated, it is not very likely that they would shift occupation. Instead, if we had used the 4-digit codification (the most precise classification available) this would probably constitute a serious problem.

[35] It is not very clear whether the rate of convergence should follow the same trend. The 114,900 number comes from the computation of 0.2% of the British population in 1990.

how important cultural reasons are to explain mobility of workers, even of the very skilled. We would like, however, to point out that one should not think of "cultural" explanations as the entire story. Specific policies might actually play also a large role. Comparisons with other European countries would be here helpful to understand why the French are not responsive to changes in the wage gap when deciding whether to move to the United States.

Note, nevertheless, that the explanatory power of these regressions is very small, both for the French and the British, suggesting the existence of additional factors that would have a much larger impact on explaining mobility. Therefore, the main conclusion at this point is that the wage gap has a strong significant effect on the propensity to move but, at the same time, it fails to explain most of the variance in the mobility. This suggests the need to find alternative ways to account for these "other variables".

7 Joined Dataset Analysis

The cross-occupation approach presented in the previous section has mainly two drawbacks. First, by focusing on the occupational categories it does not allow to estimate the effect that individual characteristics by itself have on the propensity to move. Second, it has a very low explanatory power and this could be due to the empirical strategy used. Therefore, in this section we present some suggestive evidence on these two issues using an alternative approach.

The idea is to construct a joined dataset that includes both the individuals who stayed in the home country and the ones who moved to the United States, correcting by the appropriate weights. This approach is, clearly, very sensitive to the problems of measurement error, which may lead the results instead of the underlying variables.[36]

We generate a categorical variable taking the value 1 if the individual moved to the United States and 0 if he remained in the home country. Following the same methodology from above, we compute the wage gap of both individuals who stayed in their home country (i.e. how much extra or less would they have earned in the United States) and the individuals who moved (i.e. how much less or extra would they have earned if they had stayed in their home country). The same caveats discussed in the previous sections apply here. Finally, we estimate the following regression, using linear probability regression as well as a Probit and a Logit regression, separately for men and women:

$$y = f(wage\ gap, edu, exp, marital, interactions, controls) + \varepsilon \qquad (20)$$

We interact the wage gap with the other explanatory variables. We also include quadratic and cubic terms for the education, experience as well as the wage level as a control.

[36] Note that merging microdata from different sources, even after generating standardized variables in the different variables, is very problematic. Therefore, this section is presented more as a motivation for future research than as conclusive evidence.

Table 7.2.1 shows the main results of the estimation, based on a Probit model[37]. The same patterns of the impact of the wage gap on the decision to move can be seen here. The British react significantly to the wage gap whereas for the French the coefficient is not significant. Moreover, the effect is larger for those with more education and less experience. The estimates also show that educational attainment has a positive and significant effect in the propensity to move for all 4 subpopulations. This suggests that individuals are positively self-selected even after controlling for the wage gap. At the same, experience has a negative effective effect, not surprisingly since most individuals who migrate are at the beginning of their professional careers, as we discussed before. Finally, note that the explanatory power here is also very small, as seen in the OLS regression, increasing the confidence in the cross-occupational approach as well as suggesting the need to identify the additional factors that induce mobility.

8 Conclusions

Along this paper we have provided a detailed analysis of the brain drain from Europe to the United States, given the scarce data available. This is a particularly difficult exercise given the numerous problems that researchers encounter when dealing with cross-country comparisons of micro data. However, we have succeed in constructing a predicted wage gap evaluating the increased wage each individual in France and in the United Kingdom was facing when deciding to move to the United States. This wage gap depends on the wage distribution of the home country: France, with lower inequality than both the United Kingdom and the United States has a higher average wage gap than the United Kingdom for those individuals that move to the United States. This constructed variable exhibits a distribution that fits well the Borjas-Roy model of self-selection of immigrants. The skills of migrants are negatively correlated with the wage inequalities in the home country. Consequently, the brain drain as a threat to redistributional policies in Europe is not only a theoretical possibility but it is likely to have a significant influence, if not quantitatively, yes qualitatively.

The impact of the wage gap on the propensity to move to the United States differs largely for France and the United Kingdom. It is not significant in the French case and large and significant for the British case. The interpretation of this result is clearly that even for countries with similar level of development, with stable and safe institutions, the wage gap with the United States is only a small part of the brain drain story. In particular, the obvious cultural and linguistic differences between France on one side and the United Kingdom and the United States on the other side seem to play a much bigger role than the noticeable wage gap.

The forthcoming release of the US Census 2000 will shed some more light on the brain drain mechanism since both the wage gap and the migration to the United States increased considerably during last years of the 90s. The French

[37]Tables 7.2.3, 7.2.4, 7.2.5 and 7.2.6 report the estimates for this equation under different specifications using Probit, Logit as well as standard OLS estimates.

case could be very instructive since the flux to the United States has almost doubled in the last years of the decade. Either the wage gap has increased in a similar way or the sensitivity of the French to the economic incentives has increased relative to the cost of moving. An expansion of this analysis to other European countries could also bring more elements to sort out between cultural effect and other policies as R&D spending and higher education. A final improvement would be to use more precise data on the different tax systems, in order to be able to distinguish between what could be considered as excessive taxation relative to the United States and what corresponds to a simple payment for the services provided by the government. We have adjusted gross wages to obtain an equivalent treatment of the payroll taxes in the three countries of interest, but there is definitely room for improvement in this regard.

To concluded, looking at the wage gap between the United States and France and the United Kingdom, one has to realize that the question of interest might rather be why there is so little brain drain to the United States than why there is so much. Particularly, why so few French move to the United States should be regarded as a mystery relative to economic theory.

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Table 4.2.1: Summary Statistics

	Born in the United Kingdom		Born in France		Born in the US
	Living in the US	Living in the UK	Living in the US	Living in France	Living in the US
Number of observations	3029	3689	579	52480	624665
Average wage	36926	20425	35877	17362	21197
Educational Attainment	14.19	10,54	14.84	9.1	11.16
Average Age	35,74	37.35	33.86	38.85	35.11
Proportion of Science Professors	9.9	3.55	0.1	1.39	1.6
Proportion of Medical Doctors	0.6	0.25	1.38	1.05	0.26
Proportion of College Professors	2.39	1	2.94	0.41	0.34

Source: Authors' calculations from the US. Census, the British Household Panel Survey and the *Enquete Emploi*.

Table 5.2.1: Estimated Wage Regressions

Dependent Variable: lnwage

	United States		United Kingdom		France	
	Men	Women	Men	Women	Men	Women
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Education	-0.1790	-0.2156	-0.11927	0.25435	-0.01396	0.06222
	[0.000]	[0.000]	[0.105]	[0.011]	[0.377]	[0.000]
Education Squared	0.0163	0.0170	0.01242	-0.0229	0.00516	-0.00278
	[0.000]	[0.000]	[0.094]	[0.023]	[0.002]	[0.088]
Education Cubic	-0.0003	-0.00027	-0.00031	0.00073	-0.0001	0.00009
	[0.000]	[0.000]	[0.189]	[0.021]	[0.040]	[0.067]
Experience	0.06772	0.04444	0.05997	0.05652	0.04257	0.03106
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience Squared	-0.00166	-0.00135	-0.00147	-0.00205	-0.00078	-0.00064
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience Cubic	0.00001	0.00001	0.00001	0.00002	0	0
	[0.000]	[0.000]	[0.009]	[0.000]	[0.006]	[0.033]
Hours Worked	0.00772	0.00806	-0.00019	0.00107	0.00926	0.00401
	[0.000]	[0.000]	[0.897]	[0.707]	[0.000]	[0.000]
Marital Status	0.00564	0.00405	0.01223	-0.00771	0.02291	0.0019
	[0.023]	[0.040]	[0.280]	[0.557]	[0.000]	[0.575]
R-squared	0.36	0.31	0.31	0.37	0.48	0.43
n	130266	89731	2389	1234	22089	15447

Note:

-P-values are reported in brackets[ ]

-All the regressions include 2-digit occupation dummies, which are not reported here.

Table 5.2.2: Average Wage Gaps

	Born in the United Kingdom				Born in France			
	Living in the UK		Living in the US		Living in France		Living in the US	
	Men	Women	Men	Women	Men	Women	Men	Women
Predicted Wage Gap	0.068	-0.045	0.200	0.100	0.085	-0.041	0.265	0.134
Fitted Wage Gap	0.068	0.010	0.187	0.119	-0.020	-0.052	0.143	0.101

Source: Authors' calculations from the US. Census, the British Household Panel Survey and the *Enquete Emploi* .

Table 6.2.1: Estimation of the Wage Gap Effect on Mobility
using the Cross-Occupation Approach for the United Kingdom

Dependent variable: Propensity to Move				
	Women		Men	
Variable	(1)	(2)	(3)	(4)
Predicted Wage Gap	0.0048551	0.0032671	0.0025124	0.0020901
	[0.000]	[0.001]	[0.000]	[0.000]
Education	0.0002061	-0.000024	0.0002533	-0.0004633
	[0.000]	[0.945]	[0.000]	[0.326]
Experience	-0.0000195	0.0000608	-0.0000057	-0.0000425
	[0.113]	[0.291]	[0.527]	[0.364]
Education Squared		-0.000009		0.0000186
		[0.817]		[0.680]
Experience Squared		-0.0000026		0.0000022
		[0.286]		[0.263]
Education Cubic		0.000001		0.0000005
		[0.435]		[0.727]
Experience Cubic		0		0
		[0.562]		[0.118]
Predicted Wage Gap Squared		0.0099956		0.0070092
		[0.000]		[0.000]
Predicted Wage Gap Cubic		-0.008057		-0.0109663
		[0.179]		[0.000]
R-squared	0.118	0.141	0.1	0.126
n	1037	1037	1703	1703

Note:
- P-values are reported in brackets[ ].
- Table 6.2.3 in the appendix reports the estimates for this equation based on different especifications.

Table 6.2.2: Estimation of the Wage Gap Effect on Mobility
using the Cross-Occupation Approach for France

Dependent variable: Propensity to Move				
	Women		Men	
Variable	(1)	(2)	(3)	(4)
Predicted Wage Gap	-0.0002537	-0.0004676	-0.0001319	-0.00001
	[0.440]	[0.304]	[0.627]	[0.977]
Education	0.0000516	-0.0005398	0.0001148	-0.0012202
	[0.189]	[0.164]	[0.010]	[0.000]
Experience	0.0000134	0.0000782	0.0000124	0.0000729
	[0.247]	[0.184]	[0.182]	[0.166]
Education Squared		0.0000359		0.0000968
		[0.340]		[0.001]
Experience Squared		-0.0000045		-0.0000026
		[0.168]		[0.395]
Education Cubic		-0.0000005		-0.0000021
		[0.623]		[0.025]
Experience Cubic		0.0000001		0
		[0.122]		[0.635]
Predicted Wage Gap Squared		0.0012947		0.0000601
		[0.175]		[0.943]
Predicted Wage Gap Cubic		-0.0011665		-0.0007965
		[0.255]		[0.264]
R-squared	0.018	0.097	0.05	0.141
n	201	201	314	314

Note:
- P-values are reported in brackets[ ].
- Table 6.2.4 in the appendix reports the estimates for this equation based on different especifications.

Table 6.2.3: Estimation of the Wage Gap Effect on Mobility using the Cross-Occupation Approach for the United Kingdom

	Dependent variable: Propensity to Move															
	Women								Men							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Predicted Wage Gap	0.0059824		0.0048551		0.0039845		0.0032671		0.004088		0.0025124		0.0018554		0.0020901	
	[0.000]		[0.000]		[0.000]		[0.001]		[0.000]		[0.000]		[0.000]		[0.000]	
Fitted Wage Gap		0.0076466		0.0076931		0.006499		0.0031088		0.0054274		0.0042961		0.0029352		0.0019474
		[0.000]		[0.000]		[0.000]		[0.007]		[0.000]		[0.000]		[0.000]		[0.015]
Education			0.0002061	0.0000334	0.0001984	0.0003584	-0.000024	-0.0000859			0.0002533	0.0001278	-0.0004959	-0.0004672	-0.0004633	-0.0006029
			[0.000]	[0.380]	[0.555]	[0.273]	[0.945]	[0.803]			[0.000]	[0.007]	[0.289]	[0.300]	[0.326]	[0.179]
Experience			-0.0000195	-0.0000391	0.0000688	0.0000455	0.0000608	0.0000192			-0.0000057	-0.0000211	-0.0000366	-0.0000579	-0.0000425	-0.0000654
			[0.113]	[0.001]	[0.233]	[0.426]	[0.291]	[0.735]			[0.527]	[0.028]	[0.437]	[0.183]	[0.364]	[0.133]
Education Squared					-0.0000357	-0.0000593	-0.000009	-0.0000053					0.0000198	0.0000138	0.0000186	0.0000312
					[0.352]	[0.092]	[0.817]	[0.883]					[0.658]	[0.745]	[0.680]	[0.459]
Experience Squared					-0.0000031	-0.0000031	-0.0000026	-0.0000016					0.000002	0.0000024	0.0000022	0.0000027
					[0.202]	[0.216]	[0.286]	[0.519]					[0.317]	[0.195]	[0.263]	[0.149]
Education Cubic					0.0000019	0.0000025	0.000001	0.0000006					0.0000005	0.0000006	0.0000005	-0.0000001
					[0.134]	[0.030]	[0.435]	[0.591]					[0.707]	[0.629]	[0.727]	[0.962]
Experience Cubic					0	0	0	0					0	0	0	0
					[0.381]	[0.351]	[0.562]	[0.810]					[0.152]	[0.096]	[0.118]	[0.070]
Fitted Wage Gap Squared								0.0107612								0.0092049
								[0.003]								[0.000]
Fitted Wage Gap Cubic								0.0062998								-0.0089414
								[0.474]								[0.000]
Predicted Wage Gap Squared							0.0099956								0.0070092	
							[0.000]								[0.000]	
Predicted Wage Gap Cubic							-0.008057								-0.0109663	
							[0.179]								[0.000]	
R-squared	0.091	0.118	0.118	0.134	0.13	0.143	0.141	0.169	0.061	0.083	0.1	0.101	0.118	0.118	0.126	0.124
n	1037	1179	1037	1179	1037	1179	1037	1179	1703	1834	1703	1834	1703	1834	1703	1834

Note: P-values are reported in brackets[ ].

Table 6.2.4: Estimation of the Wage Gap Effect on Mobility using the Cross-Occupation Approach for France

Dependent variable: Propensity to Move																
	Women								Men							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Predicted Wage Gap	-0.0002415		-0.0002537		-0.0005534		-0.0004676		-0.0000275		-0.0001319		-0.0005164		-0.00001	
	[0.452]		[0.440]		[0.105]		[0.304]		[0.907]		[0.627]		[0.036]		[0.977]	
Fitted Wage Gap		0.0004764		0.0004876		-0.0026478		-0.0022708		0.0002759		-0.0001958		-0.0042567		-0.003804
		[0.363]		[0.437]		[0.003]		[0.014]		[0.549]		[0.808]		[0.000]		[0.001]
Education			0.0000516	0.0000197	-0.000546	-0.0011066	-0.0005398	-0.0013361			0.0001148	0.0000896	-0.0010219	-0.0018722	-0.0012202	-0.0020785
			[0.189]	[0.550]	[0.144]	[0.022]	[0.164]	[0.083]			[0.010]	[0.043]	[0.000]	[0.000]	[0.000]	[0.000]
Experience			0.0000134	0.0000128	0.0000724	0.0001212	0.0000782	0.000122			0.0000124	0.0000194	0.0000747	0.0001018	0.0000729	0.0001005
			[0.247]	[0.190]	[0.207]	[0.006]	[0.184]	[0.006]			[0.182]	[0.040]	[0.145]	[0.052]	[0.166]	[0.055]
Education Squared					0.0000362	0.0000737	0.0000359	0.0000893					0.0000816	0.0001334	0.0000968	0.0001504
					[0.324]	[0.089]	[0.340]	[0.184]					[0.002]	[0.000]	[0.001]	[0.001]
Experience Squared					-0.0000041	-0.0000065	-0.0000045	-0.0000063					-0.0000028	-0.0000049	-0.0000026	-0.0000047
					[0.195]	[0.009]	[0.168]	[0.012]					[0.346]	[0.115]	[0.395]	[0.129]
Education Cubic					-0.0000005	-0.0000012	-0.0000005	-0.0000015					-0.0000018	-0.0000025	-0.0000021	-0.0000029
					[0.620]	[0.318]	[0.623]	[0.413]					[0.045]	[0.002]	[0.025]	[0.024]
Experience Cubic					0.0000001	0.0000001	0.0000001	0.0000001					0	0.0000001	0	0.0000001
					[0.136]	[0.014]	[0.122]	[0.022]					[0.575]	[0.221]	[0.635]	[0.246]
Fitted Wage Gap Squared								-0.0071296								-0.002045
								[0.013]								[0.532]
Fitted Wage Gap Cubic								0.0052012								0.0005867
								[0.361]								[0.880]
Predicted Wage Gap Squared							0.0012947								0.0000601	
							[0.175]								[0.943]	
Predicted Wage Gap Cubic							-0.0011665								-0.0007965	
							[0.255]								[0.264]	
R-squared	0.003	0.004	0.018	0.012	0.087	0.102	0.097	0.137	0	0.001	0.05	0.038	0.129	0.191	0.141	0.194
n	201	231	201	231	201	231	201	231	314	347	314	347	314	347	314	347

Note: P-values are reported in brackets[ ].

Table 7.2.1: Probit Estimation of the Wage Gap Effect on Mobility
using the Joined Dataset.

Dependent variable: Decision to Move				
	United Kingdom		France	
	Men	Women	Men	Women
Variable	(1)	(2)	(3)	(4)
Predicted Wage Gap	0.556271	0.941035	0.052823	0.175684
	[0.000]	[0.000]	[0.528]	[0.060]
Education	0.10428	0.043844	0.109928	0.090629
	[0.000]	[0.000]	[0.000]	[0.000]
Experience	-0.009417	-0.005824	-0.019551	-0.0098
	[0.000]	[0.000]	[0.000]	[0.001]
n	4102	2275	22403	15648

Note:
- P-values are reported in brackets[ ].
- Tables 7.2.3, 7.2.4, 7.2.5 and 7.2.6 in the appendix report the estimates for this equation under different especifications using Probit, Logit as well as standard OLS estimates.

Table 7.2.3: Estimation of the Wage Gap Effect on Mobility using the Joined Dataset for Men in the UK

	Dependent variable: Decision to Move											
	Probit Estimates				Logit Estimates				Linear Probability Model Estimates			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Predicted Wage Gap	0.556271	0.368222			1.385897	0.973851			0.010619	0.004394		
	[0.000]	[0.001]			[0.000]	[0.002]			[0.000]	[0.000]		
Fitted Wage Gap			0.639145	0.310844			1.592688	0.922907			0.014743	0.004578
			[0.000]	[0.012]			[0.000]	[0.008]			[0.000]	[0.005]
Education	0.10428	0.266874	0.096601	0.140627	0.330092	0.743554	0.308912	0.345069	0.000713	0.012809	0.00069	0.012846
	[0.000]	[0.070]	[0.000]	[0.351]	[0.000]	[0.113]	[0.000]	[0.510]	[0.000]	[0.000]	[0.000]	[0.000]
Experience	-0.009417	-0.011243	-0.009855	-0.022483	-0.027855	-0.015931	-0.02882	-0.045678	-0.000089	-0.000366	-0.000111	-0.00048
	[0.000]	[0.371]	[0.000]	[0.072]	[0.000]	[0.677]	[0.000]	[0.234]	[0.000]	[0.024]	[0.000]	[0.006]
Education Squared		-0.022809		-0.012913		-0.054164		-0.024173		-0.001462		-0.001477
		[0.089]		[0.349]		[0.192]		[0.602]		[0.000]		[0.000]
Experience Squared		-0.000723		-0.000261		-0.002889		-0.001553		0.000003		0.000007
		[0.126]		[0.581]		[0.048]		[0.296]		[0.599]		[0.270]
Education Cubic		0.000792		0.00053		0.001771		0.00101		0.000052		0.000053
		[0.039]		[0.178]		[0.125]		[0.430]		[0.000]		[0.000]
Experience Cubic		0.000016		0.00001		0.000056		0.000039		0		0
		[0.006]		[0.086]		[0.001]		[0.036]		[0.569]		[0.976]
Fitted lnwage in the US		0.204093		0.295108		0.567338		0.76725		0.002698		0.00352
		[0.040]		[0.003]		[0.061]		[0.012]		[0.012]		[0.003]
Marital Status		0.113019		0.104049		0.289704		0.261801		0.00098		0.000989
		[0.000]		[0.000]		[0.000]		[0.001]		[0.000]		[0.000]
R-squared									0.005	0.01	0.006	0.01
n	4102	4102	4234	4234	4102	4102	4234	4234	4102	4102	4234	4234

Note: P-values are reported in brackets[ ].

Table 7.2.4: Estimation of the Wage Gap Effect on Mobility using the Joined Dataset for Women in the UK

Dependent variable: Decision to Move												
	Probit Estimates				Logit Estimates				Linear Probability Model Estimates			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Predicted Wage Gap	0.941035	0.593527			2.634509	1.467771			0.013203	0.006728		
	[0.000]	[0.000]			[0.000]	[0.001]			[0.000]	[0.000]		
Fitted Wage Gap			1.085469	0.361913			3.082571	0.852994			0.01779	0.004838
			[0.000]	[0.045]			[0.000]	[0.108]			[0.000]	[0.055]
Education	0.043844	-0.080437	0.032109	-0.126207	0.1309	0.041538	0.095	-0.319293	0.000464	0.001339	0.00039	0.001564
	[0.000]	[0.636]	[0.000]	[0.390]	[0.000]	[0.962]	[0.000]	[0.642]	[0.000]	[0.690]	[0.000]	[0.661]
Experience	-0.005824	-0.026345	-0.006373	-0.040708	-0.017275	-0.080478	-0.019245	-0.117909	-0.00006	-0.00044	-0.000088	-0.000671
	[0.000]	[0.054]	[0.000]	[0.002]	[0.000]	[0.051]	[0.000]	[0.003]	[0.002]	[0.095]	[0.000]	[0.019]
Education Squared		0.013917		0.014951		0.013689		0.036201		-0.000156		-0.000186
		[0.383]		[0.290]		[0.862]		[0.571]		[0.659]		[0.618]
Experience Squared		-0.00071		-0.000244		-0.001808		-0.000524		-0.00001		-0.000006
		[0.196]		[0.649]		[0.245]		[0.729]		[0.424]		[0.659]
Education Cubic		-0.000572		-0.000562		-0.000827		-0.001327		0.000005		0.000005
		[0.228]		[0.188]		[0.713]		[0.477]		[0.680]		[0.664]
Experience Cubic		0.00002		0.000016		0.000055		0.000043		0		0
		[0.005]		[0.023]		[0.004]		[0.022]		[0.079]		[0.106]
Fitted lnwage in the US		0.744246		0.946684		2.099179		2.638294		0.012424		0.01686
		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]
Marital Status		0.083128		0.076337		0.229506		0.208858		0.000963		0.000912
		[0.000]		[0.001]		[0.001]		[0.001]		[0.004]		[0.012]
R-squared									0.004	0.005	0.003	0.005
n	2275	2275	2418	2418	2275	2275	2418	2418	2275	2275	2418	2418

Note: P-values are reported in brackets[ ].

Table 7.2.5: Estimation of the Wage Gap Effect on Mobility using the Joined Dataset for Men in France

	Dependent variable: Decision to Move											
	Probit Estimates				Logit Estimates				Linear Probability Model Estimates			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Predicted Wage Gap	0.052823	0.097029			0.025827	0.296086			0.001333	0.00019		
	[0.528]	[0.251]			[0.919]	[0.254]			[0.000]	[0.444]		
Fitted Wage Gap			0.218831	0.433805			0.233686	1.521094			0.004088	0.00093
			[0.243]	[0.045]			[0.674]	[0.029]			[0.000]	[0.037]
Education	0.109928	-1.529394	0.093438	-1.509476	0.347167	-5.197119	0.31064	-5.240565	0.000464	-0.004852	0.000408	-0.004621
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience	-0.019551	-0.081379	-0.01855	-0.096315	-0.063314	-0.231608	-0.06311	-0.268581	-0.000021	-0.000908	-0.00001	-0.000777
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.030]	[0.000]
Education Squared		0.154802		0.151512		0.53146		0.527146		0.000465		0.000451
		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]
Experience Squared		0.002423		0.003491		0.006705		0.009665		0.000032		0.000026
		[0.015]		[0.000]		[0.023]		[0.001]		[0.000]		[0.000]
Education Cubic		-0.004409		-0.004325		-0.015221		-0.015055		-0.000012		-0.000012
		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]
Experience Cubic		-0.000024		-0.000043		-0.000064		-0.000119		0		0
		[0.109]		[0.004]		[0.171]		[0.011]		[0.000]		[0.000]
Fitted lnwage in the US		-0.117737		-0.153255		-0.451978		-0.685658		-0.00011		-0.000281
		[0.391]		[0.305]		[0.274]		[0.151]		[0.811]		[0.501]
Marital Status		0.233417		0.224569		0.700313		0.677525		0.000997		0.000943
		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]
R-squared									0.004	0.006	0.003	0.005
n	22403	22403	25772	25772	22403	22403	25772	25772	22403	22403	25772	25772

Note: P-values are reported in brackets[ ].

Table 7.2.6: Estimation of the Wage Gap Effect on Mobility using the Joined Dataset for Women in France

Dependent variable: Decision to Move												
	Probit Estimates				Logit Estimates				Linear Probability Model Estimates			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Predicted Wage Gap	0.175684	0.067494			0.362096	0.113858			0.001411	0.000007		
	[0.060]	[0.569]			[0.265]	[0.782]			[0.000]	[0.984]		
Fitted Wage Gap			0.368187	-0.758833			0.618408	-2.52649			0.003374	-0.002163
			[0.113]	[0.002]			[0.445]	[0.003]			[0.000]	[0.004]
Education	0.090629	-1.174165	0.073177	-1.334703	0.304448	-3.688278	0.260103	-4.440794	0.000311	-0.002455	0.000287	-0.002983
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.017]	[0.000]	[0.003]
Experience	-0.0098	-0.072365	-0.009565	-0.08196	-0.035461	-0.216413	-0.035198	-0.254993	-0.000003	-0.000383	0.000003	-0.000422
	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.665]	[0.000]	[0.620]	[0.000]
Education Squared		0.114511		0.12323		0.365159		0.412504		0.000224		0.00026
		[0.000]		[0.000]		[0.000]		[0.000]		[0.030]		[0.009]
Experience Squared		0.002038		0.002432		0.005814		0.007655		0.000012		0.000013
		[0.031]		[0.013]		[0.066]		[0.027]		[0.000]		[0.000]
Education Cubic		-0.003263		-0.003384		-0.010465		-0.011361		-0.000006		-0.000006
		[0.000]		[0.000]		[0.000]		[0.000]		[0.072]		[0.033]
Experience Cubic		-0.00002		-0.000028		-0.000053		-0.000088		0		0
		[0.148]		[0.063]		[0.269]		[0.109]		[0.002]		[0.000]
Fitted lnwage in the US		0.465548		0.647466		1.409711		2.011118		0.001603		0.002077
		[0.029]		[0.000]		[0.042]		[0.001]		[0.011]		[0.001]
Marital Status		0.178657		0.155129		0.56783		0.497891		0.000568		0.000531
		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]
R-squared									0.002	0.003	0.002	0.003
n	15648	15648	17284	17284	15648	15648	17284	17284	15648	15648	17284	17284

Note: P-values are reported in brackets[ ].

DATA APPENDIX

Summary of variables used as well as the equivalence with the original survey definition.

Variable Label	US Census	Enquete Emploi France	BHPS UK	Variable derived
Age	AGE : from 0 to gives the person's age in years as of their last birthday prior to or on the day of enumeration (April 1). Top codes: 90 years	AG: age is expressed in completed years at the 31st December of the survey. Top codes 99 years. NAIA: year of birth NAIM : month of birth	AAGE: age at date of the interview AAGE12: age at 1.12.1991 ADOBM: month of birth ADOBY: year of birth ADOID, ADOIM date of interview	AGE
Sex	SEX : male =1; female =2	S : male =1; female =2	ASEX: male =1; female =2	SEX
Birth Place	BPL: France = 421; UK = 413; Germany = 453; Spain = 438	PNAI: if born outside of France	APLBORNC: country of birth	
Marital status	MARST: married, spouse present 1; married, spouse absent 2;separated 3; divorced 4; widowed 5; Single 6	M: single 1; married 2; widowed 3; divorced 4	AMLSTAT: married 1; separated 2; divorced 3 widowed 4; never married 5	MARITAL: single or never married 1; married 2; widowed 3; divorced or separated 4
Education	EDUC99	DIPL1: highest degree obtained ADFE: age of end of study (00 = no school; 0 to 34; 35 = older than 35; 99 = still at school)	ASCEND: School leaving age AQFEDHI: highest educational qualification AGFACHI: highest academic qualification	EDU : (see below) 5;9;12;14;16;18
Occupation	OCC: 4 digit occupation classification. We used the conversion tables from H.	P: We have computed the by hand the equivalence with the international classification	AJBSOC: Occupation (SOC), current main job (3 digit classification) AJBISCO:	OCU

	Ganzeboom to obtain the equivalent codes for ISCO-88	ISCO-88 to the three digits level.	international SOC (4 digit classification) AMRJSOC: SOC of most recent job	
Wage	INCWAGE in US$	SALRED: monthly wage in FF corrected for non response	AFIMNL: Labour income last month AFIMN: total income last month AFIYRL: annual labour income 1.9.90-1.9.91 AFIYR: annual income	WAGE and LNWAGE
Children	CHBORN: number of children surviving (asked to women)	ENFC90 : number of children in the household	ANCHILD: nber of own children in household	CHILDREN
Labor force	LABFORCE: NA 0; not in the labor force 1; in the labor force 2	ACT: in the labor force 1; unemployed 2; not in the labor force 3	AJBSTAT: current labour force status: SE 1; In paid employ 2; unemployed 3; Retired 4; Family care 5 Student 6	
Hours of work		HH: Usual number of hours worked per week	AJBHRS: Nber of hours normally worked per week AJSHRS: hours worked per week (self-employed)	HOURS
Income	INCTOT: total pre-tax personal income	No variable about total income PRIMM: monthly value of extra salary income ALC: unemployment benefit	APAYGYR: total earnings in last 12 months (gross)	

Matching of education variable from original coding to our constructed equivalent

US Census name	French Enquete Emploi	British BHPS	Equivalent years of schooling
EDU99	DIPL1	AAFEDHI	EDU
No school completed 01	Aucun diplome 01	No qualification 12	
	En cours d'etudes initales 16	No qualification, still at school 13	Dropped (=.)
1st-4th grade 04	CEP (Certificat d'Etude Primaire) 02	CSE grades 09	5
9th grade 06 10th grade 07 11th grade 08 12th grade, no diploma 09	BEPC seul 03 CAP, BEP seul 04 CAP, BEP et BEPC 05 BEI, BEC, BEA 06	O-levels 07 Trade apprenticeship 10	9
High School graduate, or GED 10	Baccalaureat general seul 08 Baccalaureat technologique, pro 07 Baccalaureat general et diplome technique secondaire 09	A-levels 06	12
Some college, no degree 11	1er cycle universitaire 13 BTS, DUT 12	City & Guilds 04	14
Associate degree, occupational program 12	Paramedical ou social sans baccalaureat general 10 Paramedical ou social avec baccalaureat general 11	Nursing qualifications 05 Clerical or Commercial Qualifications 08	16
Associate degree, academic program 13		Teaching qualifications 03	16
Bachelor's degree 14		University or CNNA first degree 2	16
Master's degree 15 Professional degree 16 Doctorate degree 17	2e ou 3e cycle uni. 14 Grande Ecole, dipl. Ingenieur 15	University or CNNA higher degree 1	18

Notes: UNESCO provides an International Standard Classification of Education, ISCE-97 that decomposes education in 6 levels of education with 2 levels of tertiary education. We build also a variable edu with 6 levels that we identify with an equivalent years of education. With the variable of the surveys, another possibility for us would have been to compute the education from the variable "age leaving school". As simple as it sounds, it would confuse the time spent to achieve a degree with the amount of education received. By making an equivalent in years of schooling we lose some of the information taking into account in the surveys. Keep in mind in particular that we aggregate years of general schooling with years of professional schooling that might matter a lot in the case of France and the UK.
One specific problem in our classification is the upper level education where we agregate all degree from master to PhDs in order to reflect the lack of specification in the British and French surveys.
We have doudts about the actual place of "trade apprenticeship" and City and Guilds for the British case.