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Does Student Mobility During Higher Education Pay?

Evidence From 16 European Countries

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Abstract

We use data from 16 European countries to study the effects of student mobility during higher education on future mobility, on the transition from education to employment and on hourly earnings five years after graduation. We control for several important pre-determined individual characteristics and proxies for ability, motivation and initiative that are likely to be correlated with both the mobility decision and the outcomes. The findings point to a positive association between mobility and future mobility and earnings, while the transition to employment seems to be slightly delayed. While the effects on future mobility are found in all countries and fields of education, the ones related to the labour market are only found in few of them. We also discuss and present evidence on possible mechanisms.

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1. Introduction

Studying abroad has become an important phenomenon and a relatively common experience in Europe and worldwide during the last two decades. In the literature, two types of student mobility are distinguished: degree/diploma mobility if the degree was obtained in a foreign country; and short-term mobility if only a part of the programme is done abroad. Both types of mobility have increased, along with the increase in the number of students in higher education.

Even though degree mobile students have constituted a constant share of students in higher education, around 2.3%, the figures involved are impressive: according to OECD (2013), the number of students enrolled in tertiary education outside their country of citizenship more than quadrupled between 1975 and 2011, from 0.8 million to 4.3 million students. Between 2000 and 2011, this figure more than doubled, corresponding to an average annual growth rate of 6.7% (OECD, 2013). For what regards short-term mobility, the Erasmus programme, financed by the European Commission, has had a crucial role: the number of students going abroad for studies under this programme has grown annually by an average of 5.5% since 2000 (DG EAC) and more than 2.3 million students have participated since its beginning in 1987.

The Bologna Process and EU programmes such as Erasmus, Tempus, Erasmus Mundus and Marie Currie contributed crucially to this increase. Furthermore, mobility has been stimulated by the increasing comparability and recognition of periods abroad in Europe, guaranteed by the European Credit Transfer and Accumulation System (ECTS) and European Qualifications Framework (EQF). The efforts into promoting mobility are to continue in the future. The strong policy support and financial incentives for mobility are evident particularly in the Europe 2020 Strategy and the *Erasmus+* 2014-2020 Programme (European Commission, 2013). Also, the importance attributed to student mobility by European authorities is clear in the benchmark adopted by the Council in November 2011, with the aim of promoting mobility in higher education: “By 2020, an EU average of at least 20 % of higher education graduates should have had a period of higher education-related study or training (including work placements) abroad, representing a minimum of 15 ECTS credits or lasting a minimum of three months.”

The striking increase in the number of mobile students and the large number of students currently undergoing a study period abroad, motivates the need to understand the determinants and impacts of this phenomenon. In this paper we aim to analyze to which extent spending some time abroad for study related reasons during higher education (short-term mobility) affects future mobility and labour market related outcomes up to 5 years after graduation.

In general, higher education stakeholders consider a period of study abroad as an advantage *per se* and therefore encourage it. Student mobility is seen as an instrument for individual development useful to the economy and to the society: it is believed to contribute to personal development and to enhance competences in fields like languages and intercultural understanding, consequently contributing to employability in an increasingly international labour market. These are the rationales on which the existence of extensive programmes supporting student mobility is based on.

Papatsibas (2006) point to two rationales of the Erasmus student mobility: i) an economic and professional rationale, by which student mobility is seen as a means to promote individual employability and the development of the European single labour market, as it would increase the individuals' predisposition to cross borders during their professional lives; ii) a civic rationale, by which student mobility would encourage international understanding, European consciousness and identity.

Literature Review

While the goals of mobility are well established, the actual determinants and impacts of this type of experience have been little studied by the economic literature. In general, the difficulty in studying such matter is the lack of data on mobility (Krupnik and Krzaklewska, 2006). There are some European countries, such as Germany and Norway, with rich data on mobility that enable to follow graduates over time. Other source of data are the reports from the European Commission aimed to evaluate the Erasmus programme. However, these are based on surveys to Erasmus students, failing to compare them with non-mobile students.

In a literature review on the determinants and impacts of student mobility, Rodrigues (2012) finds three well established findings. First, students with highly educated parents and having previous international exposure are more likely to study abroad, therefore constituting a selective group of students. Second, students consistently report personal development and improvement of language skills as the most important result of this international experience, and academic/career benefits are mentioned secondarily. Third, the effect of student mobility is stronger for the future career in horizontal dimensions (work abroad and international tasks) than in vertical dimensions (employment/unemployment and wages) (Rodrigues, 2012). In other words, being mobile does not have a significant effect on the success of the career but on the nature of the career, namely by making it more international or by increasing the probability to work abroad.

However, as highlighted in Rodrigues (2012), it should be kept in mind that the majority of the effects found cannot be totally attributable to the student mobility experience in the sense that mobile students are a selective group of students and differentiating characteristics are present even before the study abroad period. In fact, few studies control for pre-mobility differences between students and very few may claim to have identified the causal effect of mobility on the outcomes of interest. For instance, Wiers-Jenssen (2008) refers to studies supporting the idea that mobile students constitute a select group also in respect to personality traits and motivation, being more outgoing and having more initiative. This goes along with the employers' opinions that mobile students are more proactive, adaptable and problem-solvers (Bracht et al., 2006). Accordingly, if the aim is to study the effect of student mobility it is important to control for the differences between mobile and non-mobile students and to use an identification strategy that solves the problem of unobserved heterogeneity. As far as we know, only Parey and Waldinger (2010) and Oosterbeek and Webbink (2009) use an instrumental variables approach.

When it is impossible to use these kind of approaches that deal with the 'selection on unobservables', as it is the case in this paper, it is crucial to try to control for as many characteristics as possible to decrease the unobserved heterogeneity in the aim to get the closest estimate of the causal effect of mobility[1]. That is exactly the approach taken in this paper.

Contribution to the literature

This paper contributes to the literature in three different ways. First, it makes use of a graduate survey on 16 European countries, that has information on mobility during higher education, on future mobility and labour market related outcomes up to 5 years after graduation. To our knowledge, this is the first paper analyzing such a multinational source of data. Second, the data allow not only to study the effect of mobility, but also to explore the duration of the mobility experience. Furthermore, the effects are estimated in the pooled sample, but also by country and by field of education. Third, while the data in hand does not allow to solve completely the unobserved heterogeneity problem, we are able to control for an unusual set of individual characteristics. In particular, at least to some extent, we control for previous mobility capital, proxies for ability, motivation and proactivity. Given this possibility to reduce unobserved heterogeneity, propensity score matching methodology is used to identify the effect of mobility on future mobility and labour market outcomes. This brings some advantages when compared to the standard multivariate regression approach, as discussed below.

The rest of the paper is organized as follows. Next section presents the data and the variables used, along with basic descriptive statistics. Section 3 outlines the propensity score methodology. The results are presented in Section 4, while in Section 5 possible mechanisms and differences across countries are discussed. Section 6 presents sensitivity analysis and robustness exercises and the last section concludes.

[1] We have tried to use as instrumental variable the percentage of students in the home country that did Erasmus programme in the year before the graduate finished the higher education degree. However, this instrument was very weak and the IV approach was abandoned.

2. Data

The data used in this paper are from two related projects funded by the European Framework Programs: REFLEX (Research into Employment and professional FLEXibility) and HEGESCO (Higher Education as a GEnerator of Strategic Competences). Both projects consist of a large scale survey among graduates from higher education, 5 years after their graduation.

The REFLEX project was carried out in 2005 in fourteen countries (Austria, Belgium-flanders, Czech Republic, Estonia, Finland, France, Germany, Italy, Japan, The Netherlands, Norway, Portugal, Spain, United Kingdom), surveying around 70.000 graduates from ISCED 5A programmes who got their degree in the academic year 1999/2000. A similar project, HEGESCO, was done in 2008 in five other European countries (Lithuania, Poland, Hungary, Slovenian and Turkey), with a gross sample size of 30.000 graduates, finishing ISCED 5A programmes in the academic year 2002/2003. The combination of these two data sources enables a cross-country comparison of 19 European countries.

For comparability reasons, we focus only in countries from the European Union and Norway and disregard observations from Japan and Turkey. Furthermore, the Estonian observations are also dropped due to missing values in crucial explanatory variables. In total, data from 16 European countries are used. For more information about these surveys see Allen and van der Velden (2008, 2009).

Table 1 presents, in the first column, the number of respondents of the original sample. From these, we concentrate on respondents that are younger than 35 years old at the time of the survey and that finished higher education between 1998 and 2004. Due to these and other reasons, 9203 observations are dropped, so that the final sample used has 28321 observations. From the 9203 observations dropped, 18% was because there was no information on mobility, 46% because individuals were older than 35 years old, 8% because the year of graduation was before 1998 or after 2003 and other 8.5% due to no information on parents' education level. The remaining 18% were dropped due to missing values in other covariates.

The final 28321 observations used in the analysis are from 16 different countries. As it is clear from the last column of Table 1, there are some countries that are overrepresented in the sample:

Czech Republic account for 21% of the final sample, Spain for 11% and The Netherlands for 9%. In contrast, there are other countries that account for less than 2% of the sample, such as Portugal and Lithuania. Due to this country imbalance in the sample we do our analysis at two levels. First, we pool data for all countries, whereby a random sample of no more than 2.000 cases per country is drawn, as suggested in Allen and van der Velden (2008). This allows each country to contribute equally to the estimation, avoiding having the results driven by the most represented countries. Second, we do the analysis at country level, in which we take into account the full set of observations available for each country.

Table 1 – Number of respondents to the survey and final sample used in the analysis

	Number of respondents	**Final sample (no missing values)**	**Final sample (%)**
REFLEX countries			
Norway	2201	1515	5.3
Finland	2676	1952	6.9
The United Kingdom	1578	1084	3.8
Germany	1700	1118	3.9
Austria	1821	1158	4.1
The Netherlands	3425	2638	9.3
Belgium-Flanders	1291	1159	4.1
France	1700	1283	4.5
Italy	3139	2391	8.4
Spain	3915	3198	11.3
Portugal	645	478	1.7
Czech Republic	6791	5985	21.1
HEGESCO countries			
Slovenia	2923	1946	6.9
Lithuania	1009	466	1.6
Poland	1200	1098	3.9
Hungary	1533	852	3.0
Total	37551	28321	100

The overall response rate is 30%, which is reasonable and in line with other graduate surveys (see for instance Parey and Waldinger, 2010). For each country, the final sample was checked against the population, with only small deviations detected (Allen and van der Velden, 2008, 2009). We acknowledge that the graduates answering to the survey are more likely to be highly motivated and interested individuals than those who did not answer. On the one hand, this can lead to biased estimates, in that the effect to be found may not be valid for the entire population of graduates. For this reason the effects to be presented should be interpreted with caution. On the other hand, those answering to the survey may be a more homogenous group of graduates, and this may be seen as an advantage given that we rely on observable characteristics to identify the effect we are interested in. Another issue is the fact that the effects found for future mobility may be an underestimation of the true effects, given that graduates that are living abroad at the time of the survey are expectedly more difficult to track and to be included in the sample.

The remaining of this Section presents the treatment, outcome and explanatory variables used in the analysis as well as basic descriptive statistics.

Treatment variable

Both REFLEX and HEGESCO's questionnaires have the following questions related with mobility:

1) "Did you spend any time abroad during higher education for study?"
2) "If yes, for how many months?"

The question on mobility is rather vague and, in principle, can include different mobility experiences: to get credits for the degree programme (e.g. Erasmus), to participate in a language course or a summer school. Therefore, the type of mobility that is captured by this question is broad and should not be interpreted as simply the Erasmus mobility.

It is also important to clarify that the respondents received their university diploma from the home country and the mobile ones spent at least some period in another country, the host country, for study reasons. So, the effect of mobility to be estimated will measure this short-term learning mobility effect[2].

The treatment variable is a dummy variable (***mob_st***): equals one if the graduate answered positively to question (1), regardless of the duration, and zero if he has not been mobile. Next, in

[2] However, it is possible that some of the individuals in the sample are degree mobile students, i.e. individuals that finished secondary education in other country and moved to the home country to do their university degree. In fact, these students amount only to 3% of the sample and therefore are included. As a robustness check exercise we drop these potential degree mobile graduates from the sample to assess the extent to which their inclusion affect significantly the estimated effect of mobility.

order to explore the duration of the mobility experience (there is information on duration of mobility for 97.5% of mobile graduates), the mobile graduates are separated into four mutually exclusive groups according to the duration of the mobility experience: less than 3 months, between 3 and 6 months, between 6 and 12 months, and more than 12 months. The model in this case will estimate the effect of spending abroad a certain amount of time compared to not spending any time at all.

Table 2 shows that 19% of the graduates in the sample were mobile during higher education for study related reasons: around 33% were abroad for less than 3 months, 34% between 3 and 6 months, 26% between 6 and 12 months and around 6.5% for more than 12 months. Table 2 also shows the percentage of mobile students by country, evidencing that there are important cross-country variations. For instance, while in Germany and Austria more than 30% of graduates were mobile, in other countries this figure is lower than 15%: Lithuania, Portugal, Slovenia, Spain, Czech Republic and Hungary.

Table 2 – Percentage of mobile students and distribution by duration of mobility, by country

Country	**% Mobile**	**By Duration of Mobility**			
		Less 3 m	**3 to 6 m**	**6 to 12 m**	**More 12 m**
Italy	16.5	46.4	28.2	19.9	5.4
Spain	13.2	24.4	24.2	43.3	8.1
France	29.2	39.2	23.8	25.5	11.5
Austria	34.1	22.0	34.4	34.7	9.0
Germany	32.1	23.1	29.8	36.8	10.3
Netherlands	28.8	30.1	47.0	18.6	4.3
The United Kingdom	17.5	32.2	15.3	40.7	11.9
Finland	26.4	30.4	40.0	24.6	5.1
Norway	19.3	21.4	40.4	28.1	10.2
Czech Republic	13.2	42.3	33.6	20.0	4.1
Portugal	10.9	32.7	42.9	20.4	4.1
Belgium-fl	24.4	36.1	37.5	23.8	2.6
Slovenia	11.5	48.6	31.8	14.5	5.0
Lithuania	10.5	43.8	43.8	10.4	2.1
Poland	15.8	34.2	37.3	25.3	3.2
Hungary	13.3	51.4	33.3	12.6	2.7
Total	19.2	33.7	34.3	25.7	6.4

Source: REFLEX and HEGESCO, own computations

Another interesting dimension to explore is the field of the degree (see Table 3). There is information on 8 fields of the degree (in parenthesis is the percentage of mobile students that graduated in the correspondent field): i) Education (8%); ii) Humanities and Arts (18%); iii) Social Sciences, Business and Law (34%); iv) Science, Mathematics and Computing (8.5%); v) Engineering, Manufacturing and Construction (15%); vi) Agriculture and Veterinary (3%); vii) Health and Welfare (11%); and viii) Services (2%).

The field of degree in which mobility during studies is more common is in Humanities and Arts (34%), followed by Social Sciences, Business and Law and Agriculture and Veterinary (20% each), while it is less common in the Education sector (13%).

Outcome variables

We are interested in the impacts of mobility during higher education for study related reasons (*mob_st*) in two types of outcomes: on the probability of being mobile after graduation and on labour market related outcomes. Table 3 shows the basic descriptive statistics for the full sample, for the mobile and the non-mobile groups, and tests the equality of means between the two.

To measure future mobility, four binary variables are used. The first two are measures of cumulative future mobility, as they indicate whether the graduate was mobile at any point in time since graduation:

i) **Mobility after graduation**: whether the graduate spent any time abroad since graduation for either study or work related reasons;
ii) **Mobility after graduation work**: whether the graduate spent any time abroad since graduation for work related-reasons only.

The other two variables measuring future mobility concern mobility at a specific point in time:

iii) **Lived abroad 1st job**: whether the first job after graduation was located in a different country from the graduation one;
iv) **Lives abroad 5:** whether the graduate lives abroad at the time of the survey, i.e. 5 years after graduation.

Around 3% of the graduates lived abroad at the time of first employment. The same percentage of graduates lived abroad at the moment of the survey. The cumulative measures on future mobility are naturally higher: around 16% of graduates were mobile at some point after graduation for work reasons, while for either work or study related reasons this figure amounts to 21%. It is clear that the mobile graduates are significantly more likely to be mobile in the future, whatever the variable considered.

Regarding the labour market, we look into the transition period from education to employment and into the earnings per hour 5 years after graduation. The outcome variables are the following:

i) **Time to find 1st job** (in months): for those not working during higher education (71%), this variable measures the number of months it took to find the first job after graduation;

ii) **Hourly Earnings 5**: for those working at the time of the survey (90%), this variable measures the logarithm of gross earnings per hour worked, a common measure of productivity, corrected for country differences in purchasing power.

Table 3 shows that mobile graduates take longer to find the first job after graduation when compared to the non-mobile ones. Even though the difference is not very large (0.4 months), it suggests that they face a slightly more difficult transition from the education to the labour market. Whereas, at the time of the survey, there is no difference between mobile and non-mobile graduates in the probability of being employed (not presented in the table), it seems that mobile graduates earn on average more than 1.8 Euros per hour when compared to non-mobile graduates.

Control Variables

The REFLEX and HEGESCO data allow to control for important pre-treatment characteristics on which mobile and non-mobile graduates may differ, and this possibility is crucial for the methodology used. We estimate three models that differ in the explanatory variables included:

- First, we only include the treatment variable and some contextualizing variables, namely dummies for each country, dummies for the survey's year and dummies for the graduation year.

- Second, we add the following explanatory variables, that can be considered as pre-determined to the mobility experience during higher education:
    - demographical variables (gender, age and age squared at the time of the survey, highest education of parents);
    - mobility capital variables (whether the graduate is immigrant, whether the graduate has immigrant parents and whether he lived in other country from the graduation one at 16 years old);
    - variables related with secondary education (whether the secondary degree had general orientation, i.e. mainstream versus vocational, and the grade at this educational level[3]).
- Finally, we also control for an additional set of variables that are related with the higher education graduation, namely dummies for the fields of the degree (Education, Humanities and Arts, Social Sciences, Business and Law, Science, Mathematics and Computing, Engineering, Manufacturing and Construction, Agriculture and Veterinary, Health and Welfare, Services) and whether the programme gave access to a PhD, whether during the higher education degree the student did an internship as part of the programme, whether had working experience and made part of a volunteer organization.

All these variables are important, even though they differ in one crucial aspect: some capture characteristics and experiences before the mobility period, while the ones in the third group *may* concern the period after mobility. The variables in the second group are extremely important because concern the graduates' background in terms of parental education, proxy for ability and mobility capital variables, which the literature considers as the main determinants of the decision to go abroad. All these are pre-determined variables, thus exogenous to the treatment decision. In contrast, we acknowledge that the variables in the third group *might* be endogenous in the sense that: i) they might also be considered choice variables that resulted from the same decision process as the mobility; and/or ii) may have been themselves affected by the mobility experience. Even though they may not be necessarily pre-determined variables, we argue that

[3] These grades are measured in national scales, therefore for each country we divide the graduates into mutual exclusive groups according to the level obtained or to the grade percentiles, and a further group for the observations with missing grades.

they measure usual unmeasured characteristics of graduates that should be controlled for. For instance, the fact that they: i) did an internship; ii) worked during higher education; iii) were volunteers; or iv) any combination of these, indicate that these are proactive graduates, that take the initiative, are highly motivated and are able to deal with high workloads. Given that these personality traits are likely to be correlated with the mobility status and the outcomes we are interested in, it is important to control for them. However, the variables in the third group are added sequentially from the other sets of covariates, to assess the extent to which their inclusion impacts on the estimated effect.

Table 3 presents the covariates descriptive statistics for the full sample, for the mobile and non-mobile groups. On average, the graduates in our sample are 30 years old at the time of the survey. Around 40% are males, 40% of them have at least one highly educated parent, 6% have immigrant parents and 1% lived abroad at 16 years old. The majority followed a mainstream education in secondary school (77%) and did an higher education degree that gave access to a PhD programme (58%). While still enrolled in the degree, around 58% did an internship, 43% had a working experience and 20% did volunteering.

Mobile and non-mobile graduates differ significantly in all these dimensions. The most striking differences, of around 15 percentage points (p.p.), are related with the education of the parents and the performance of volunteer work. Furthermore, when compared to non-mobile graduates, the mobiles are more likely to have done an internship (6 p.p.), to have had work experience (10 p.p.), to have followed mainstream education (7.6 p.p.) and to have finished a university degree giving access to a PhD (10 p.p.). All these differences suggest that mobile graduates are a relatively advantaged group, with higher socio-economical background, with higher motivation and initiative. These differences reinforce the idea that it is important to control for all this information when attempting to get as close as possible to the causal effect of mobility.

Table 3 – Descriptive statistics for the full sample and for mobile and non-mobile graduates

	All sample		Mobile		Non-mobile		Equality Means test	
	Mean	**(s.d.)**	**Mean**	**(s.d.)**	**Mean**	**(s.d.)**	**Diff.**	**(s.d.)**
OUTCOMES								
Future mobility								
Mobility after graduation	0.209	(0.406)	0.385	(0.487)	0.167	(0.373)	0.218***	(0.006)
Mobility aft. grad. work	0.161	(0.367)	0.289	(0.453)	0.131	(0.337)	0.158***	(0.006)
Lived abroad 1st job	0.032	(0.175)	0.081	(0.272)	0.020	(0.140)	0.061***	(0.003)
Lived abroad 5	0.029	(0.167)	0.068	(0.251)	0.020	(0.139)	0.048***	(0.003)
Labour market								
Time find 1st job (months)	8.172	(11.12)	8.49	(11.64)	8.09	(10.98)	0.399**	(0.201)
Hourly Earnings 5 (in EUR)	12.22	(7.95)	13.74	(7.67)	11.87	(7.97)	1.87***	(0.135)
COVARIATES								
Demographic								
Male	0.390	(0.488)	0.370	(0.483)	0.395	(0.489)	-0.025***	(0.007)
Age	29.66	(2.180)	29.87	(2.149)	29.61	(2.185)	0.257***	(0.033)
Parents Educ. High	0.418	(0.493)	0.547	(0.498)	0.388	(0.487)	0.159***	(0.007)
Parents Educ. Medium	0.376	(0.484)	0.290	(0.454)	0.396	(0.489)	-0.106***	(0.007)
Mobility capital								
Migrant	0.025	(0.157)	0.041	(0.199)	0.021	(0.144)	0.020***	(0.002)
Parents immigrants	0.066	(0.249)	0.087	(0.282)	0.061	(0.240)	0.026***	(0.004)
Lived abroad at 16	0.012	(0.109)	0.026	(0.158)	0.009	(0.094)	0.017***	(0.002)
Secondary Degree								
Mainstream	0.772	(0.419)	0.834	(0.372)	0.758	(0.428)	0.076***	(0.006)
Grade (national)[4]								
Higher Education (HE)								
Accedd PhD	0.583	(0.493)	0.664	(0.472)	0.565	(0.496)	0.100***	(0.007)
Internship HE	0.573	(0.495)	0.622	(0.485)	0.562	(0.496)	0.060***	(0.007)
Work experience HE	0.430	(0.495)	0.510	(0.500)	0.411	(0.492)	0.099***	(0.007)
Volunteer HE	0.194	(0.395)	0.320	(0.467)	0.164	(0.371)	0.156***	(0.006)
Field of Education HE								
Education	0.117	(0.321)	0.080	(0.271)	0.125	(0.331)	-0.046***	(0.005)
Humanities and Arts	0.098	(0.298)	0.175	(0.380)	0.080	(0.272)	0.095***	(0.004)
Social Sciences	0.324	(0.468)	0.337	(0.473)	0.321	(0.467)	0.016**	(0.007)
Mathematics	0.097	(0.296)	0.085	(0.279)	0.100	(0.300)	-0.015***	(0.004)
Engineering	0.173	(0.379)	0.151	(0.358)	0.179	(0.383)	-0.027***	(0.006)
Agriculture	0.031	(0.173)	0.032	(0.175)	0.031	(0.173)	0.001	(0.003)
Health and Welfare	0.129	(0.335)	0.112	(0.316)	0.133	(0.339)	-0.020***	(0.005)
Services	0.031	(0.172)	0.027	(0.163)	0.031	(0.175)	-0.004	(0.003)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

[4] Given that grade obtained in the secondary degree is measured at the country level, it is impossible to present it in the table the descriptive statistics.

3. Methodology

The aim of this report is to estimate the effect of mobility during higher education on the outcomes using a Propensity Score Matching approach. Ideally, we would estimate the causal average treatment effect on the treated, that compares the actual outcome resulting from the mobility experience to the non-observable outcome (counterfactual) that would have resulted if the same graduate had not been mobile. The idea of matching is to match mobile and non-mobile graduates that are similar in the observable variables and to use the outcome of the latter group as a valid substitute for the non-mobility outcome. Given the impossibility to find exact comparable observations in all observable variables, the matching is done in the so called propensity score, i.e. the probability of being treated given the set of observables (Rosenbaum and Rubin (1983)). The first step is therefore to estimate the probability of being mobile, controlling for a rich set of covariates, and compare the outcomes between mobile and non-mobile graduates with similar propensity scores. More details on the methodology can be found in Appendix A.

A more simplistic way of estimating the effect of being mobile on the outcomes, controlling for covariates, would be through a multivariate regression analysis ($Y_i = \alpha + \beta D_i + \gamma \boldsymbol{X_i} + \varepsilon_i$)[5]. This approach estimates the correct treatment effect if and only if: i) the true model relating mobility to outcomes is a linear and additive one; and ii) the "selection on observables" hypothesis is true, i.e. if all variables correlated both with the treatment and outcome variables are observed and included in the model. While the Propensity Score Matching procedure also relies on the "selection on observables" assumption, it does not depend on functional forms assumptions. Compared to the regression approach, it has the additional advantage of restricting inference to the sample of mobile and non-mobile graduates that are actually comparable in their observable characteristics (common support). As far as the "selection of observables" issue is concerned, while we control for a rich set of covariates, that include graduates' socio-economic and international background and ability, it cannot be completely ruled out the existence of unobservable characteristics that may still bias the estimated treatment effect. Accordingly, we perform in Section 6 an exercise of sensitivity analysis that judges how the estimated effect is affected by potential unobserved factors (Ichino, Mealli and Nannicini, 2008).

[5] In Section 6 we present, as a robustness check, the results using the regression approach.

4. Results

This section starts by presenting the propensity score estimation, which is interesting on its own as it allows to analyze the determinants of the mobility experience during higher education. Next, we present the estimated effects of mobility during higher education.

4.1 Estimation of the propensity score

Table 4 presents the marginal effects of the probit model estimating the propensity score using the full set of covariates for the outcome with more observations, the mobility after graduation either for work or study related reasons.

Table 4 - Marginal effects for the probit model estimating the propensity score

Dependent variable: **mob_st**	
Male	-0.016***
(s.e.)	(0.005)
Age	0.122***
(s.e.)	(0.027)
Age squared	-0.002***
(s.e.)	(0.000)
Immigrant	0.033*
(s.e.)	(0.018)
Parents immigrants	0.006
(s.e.)	(0.010)
Lived abroad at 16	0.119***
(s.e.)	(0.029)
Parents educ. High	0.084***
(s.e.)	(0.007)
Parents educ. Medium	0.025***
(s.e.)	(0.007)
Mainstream sec.	0.048***
(s.e.)	(0.006)
Access PhD	0.045***
(s.e.)	(0.006)
Internship HE	0.042***
(s.e.)	(0.005)
Work experience HE	0.032***
(s.e.)	(0.005)
Volunteer HE	0.094***
(s.e.)	(0.007)
N	19161
R-squared	0.098

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

The results confirm the profile already described in the descriptive statistics: the probability of spending a period abroad for study during the higher education is higher for females, older graduates, and with highly educated parents, and for those holding a mainstream secondary degree. Interestingly, having lived abroad at 16 years old increases around 12 percentage points (p.p.) the probability of being mobile during higher education, being its most important determinant. This supports the idea that *mobility capital* is an important determinant of mobility. Another important determinant of mobility is being a volunteer during higher education, which increases the probability by almost 10 p.p. Moreover, graduates that did internships or worked during higher education are 3-4 p.p. more likely to study abroad. These results suggest that mobile graduates were students with more sense of initiative and motivation and preference for new experiences and probably with better capacity to deal with heavy workloads.

4.2 Estimated effect of mobility during higher education on outcomes

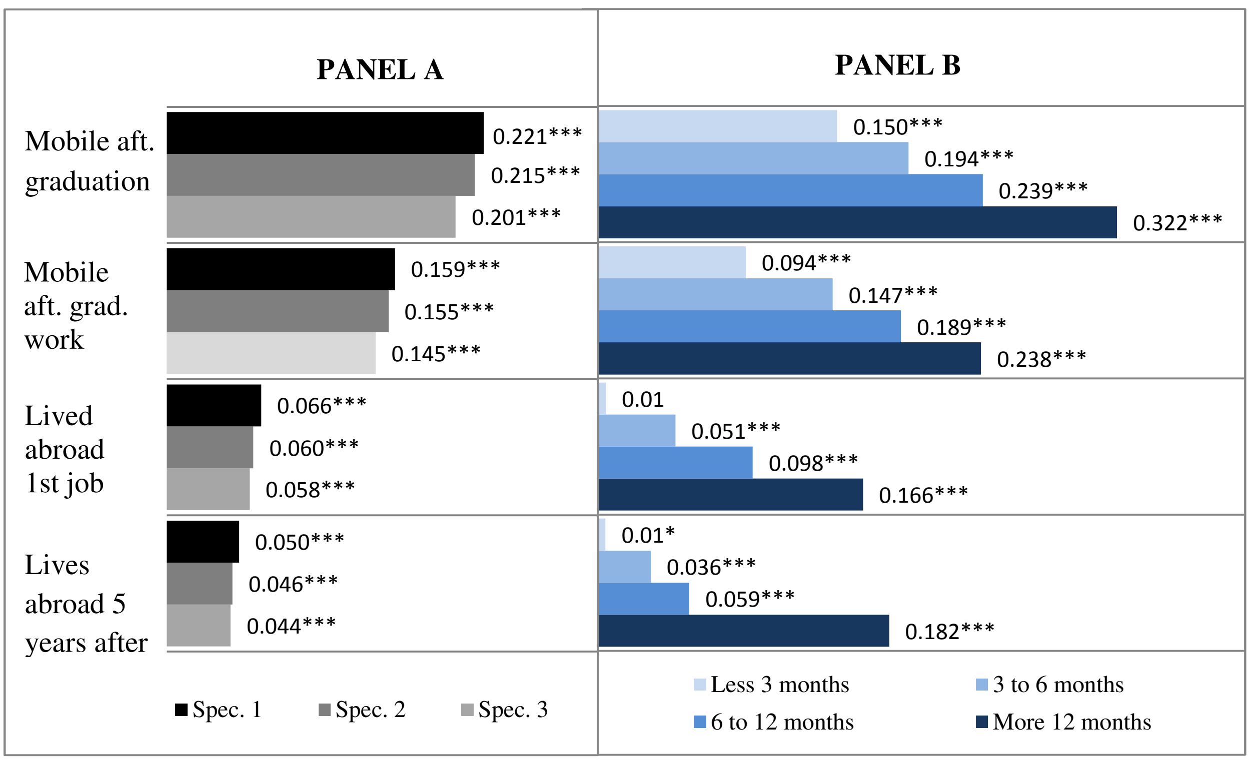
4.2.1 The estimated effect of mobility during higher education on future mobility

Figure 1 presents the estimated effect of mobility during higher education on the outcomes relating to future mobility and is divided in two panels: Panel A shows the estimated effect of being mobile for the three specifications mentioned above that differ in the covariates included in the estimation of the propensity score; Panel B presents the estimated effects of mobility, by duration of mobility, in which the control group is always the non-mobile graduates.

The first result to be noticed in Panel A is the fact that, as expected, the inclusion of more explanatory variables in the estimation of the propensity score decreases the estimated treatment effect. However, by comparing the results in columns (2) and (3), it should be highlighted that the difference between the estimated treatment effects is not substantially large. Even though we are controlling for some variables that could 'eventually' be associated with the post-treatment period, the estimates are not significantly affected. This fact is reassuring in the sense that these new factors do not affect dramatically the estimated effects and this is likely to be also the case for potential further unobserved heterogeneity. Hence, we consider the benefit of including these further variables, i.e. the possibility of controlling for variables that capture to some extent personality traits such as motivation and proactivity, to be higher than the ‘cost’ associated, i.e. the fact that they may not be pre-determined variables.

The results indicate that being mobile during higher education increases the probability of being mobile after graduation, regardless of the variable considered. As expected, the effects are higher for the variables measuring cumulative mobility during the five years after graduation: being mobile during studies increases the probability of going abroad, at any point in time during the following 5 years, for work related reasons and for work or study related reasons in 14 p.p. and 20 p.p., respectively. The probability of living abroad at a particular point in time is lower: the probabilities of living abroad in the first job after graduation and 5 years after graduation are 5 p.p. and 4 p.p. higher for mobile graduates, respectively.

Figure 1 - Estimated effects of mobility during higher education on future mobility



Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. See Table A.1 for the complete set of results, including standard errors.

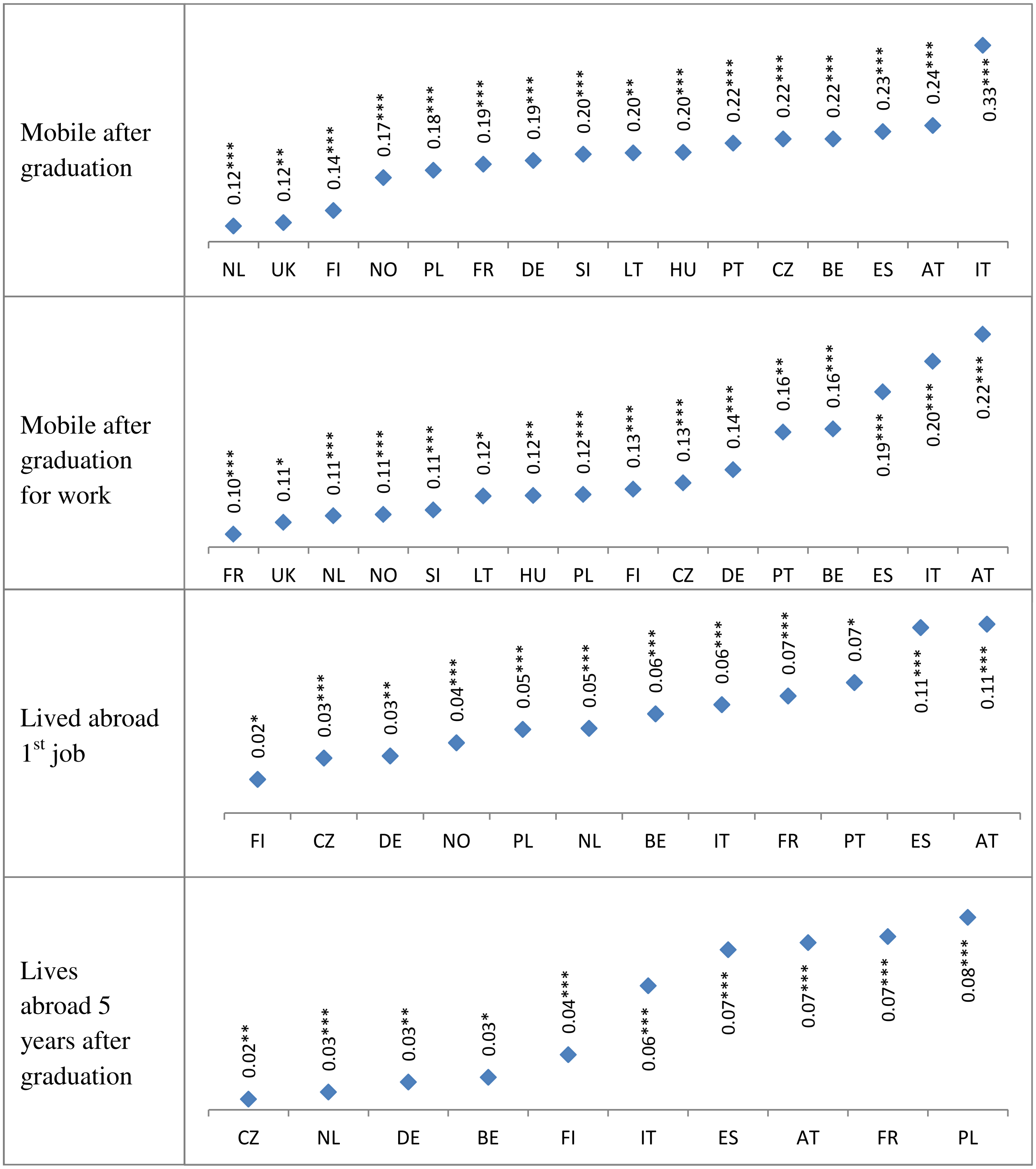
The results in Panel B show that there are heterogeneous effects depending on the duration of the mobility experience. Even though all the effects are significant and positive, the higher the duration of mobility during higher education, the higher is the effect on the probability of being mobile in the future, regardless of the outcome variable considered. For the outcomes measuring cumulative mobility during the 5 years after graduation, the effect of spending more than 12 months abroad is more than the double of the one associated with a maximum of 3 months. For the outcomes measuring future mobility at one point in time, this difference is much higher, as the 3 months effects are negligible.

Analysing the estimated effects by country (Figure 2), we conclude that mobility during higher education increases mobility after graduation in the majority of the 16 countries in the sample. The effect on mobility during the 5 years after graduation for work or study related reasons is significant in all countries, ranging from 11.8 p.p. in The Netherlands to 33 p.p. in Italy. Focusing only on mobility for working reasons, the effect is also significant in all countries, ranging from around 10 p.p. in France and The Netherlands to 22 p.p. in Austria.

When it comes to future mobility at one point in time, we see that the effect of mobility is not significant in all countries. Being mobile during higher education increases the probability of having the first job abroad in all countries, except in the UK, Slovenia, Lithuania and Hungary where the effect is not found to be significantly different from zero. The probability of living abroad at the time of the survey is not affected by previous mobility in the UK, Norway, Portugal, Slovenia, Lithuania and Hungary.

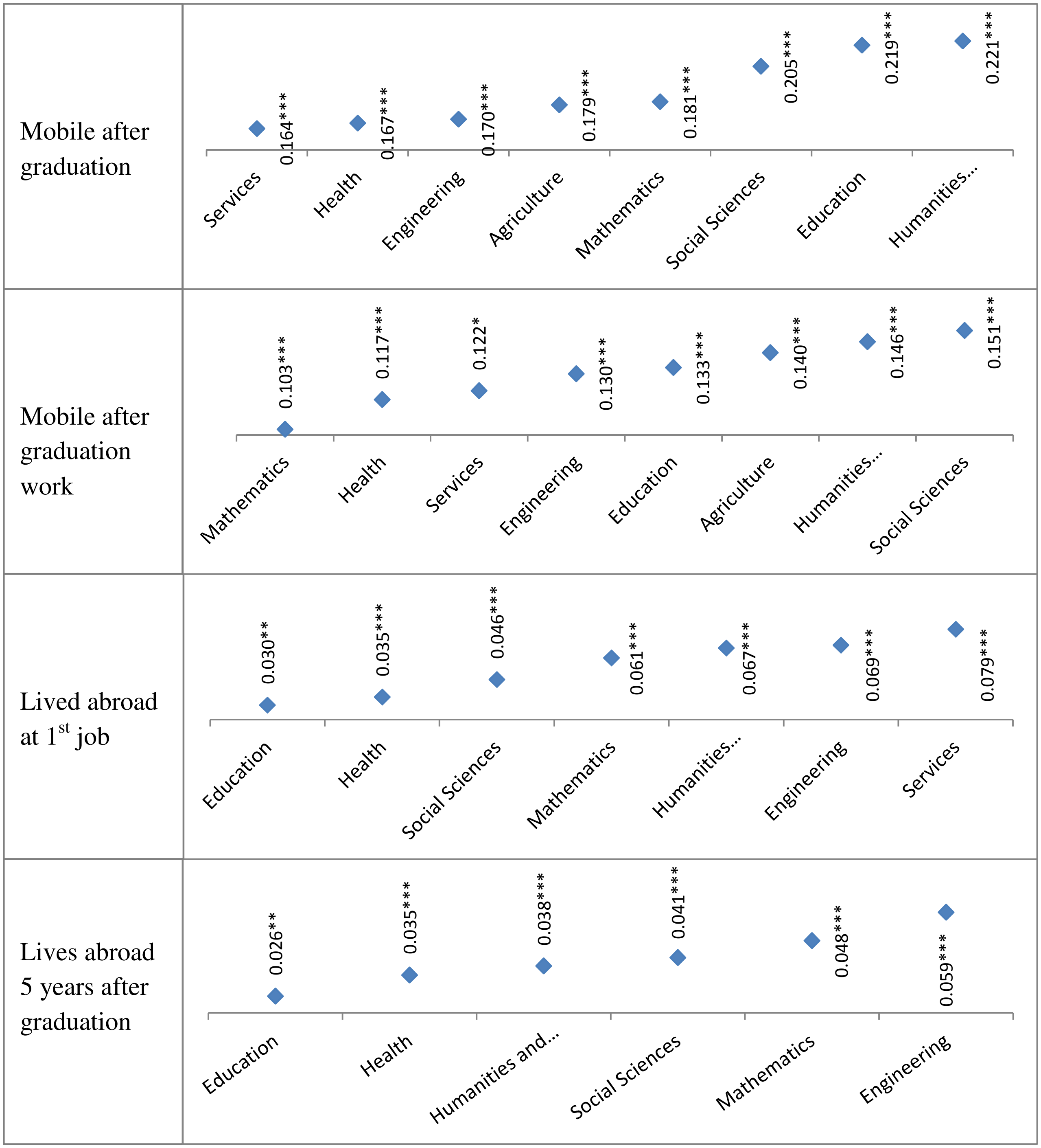
Moving to the effects by field of degree (Figure 3), the cumulative measures of future mobility are positively affected by mobility during higher education in all fields of education, but particularly in the fields of Humanities and Arts and Social Sciences. The probability of living abroad at first job and at the time of the survey is also positively affected in all fields of education, except in Agriculture and Services.

Figure 2 - Estimated effects of mobility during higher education on future mobility, by country



Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. See Table A.2 for the complete set of results, including standard errors. Only countries for which the estimated effect of mobility is significant are presented in the graphs. Countries ordered in ascending order of the estimated effect.

Figure 3 - Estimated effects of mobility during higher education on future mobility, by field of education

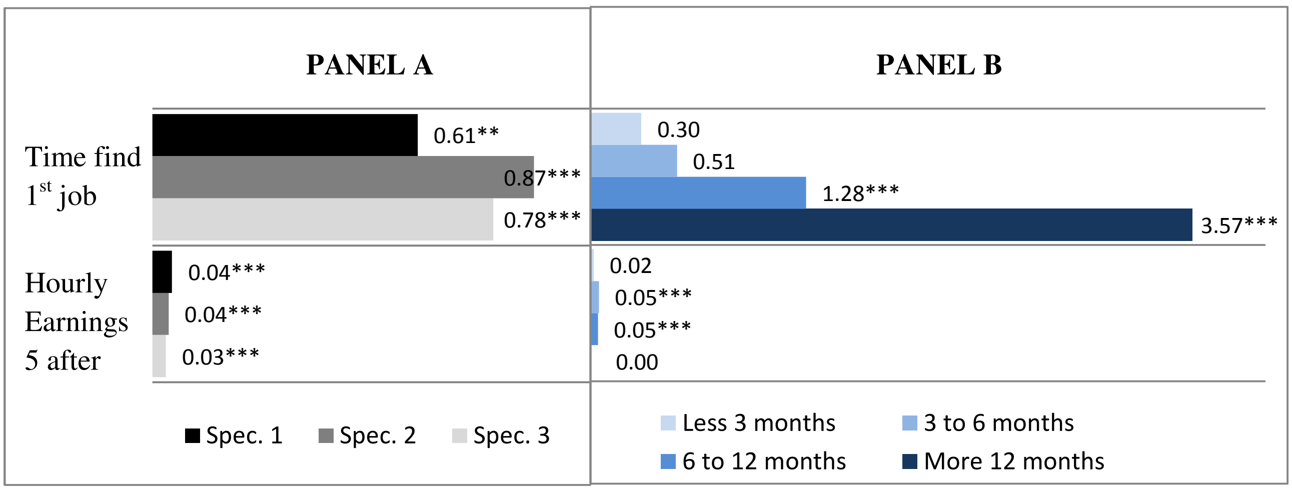


Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. See Table A.3 for the complete set of results, including standard errors. Only fields of education for which the estimated effect of mobility is significant are presented in the graphs. Fields ordered in ascending order of the estimated effect.

4.2.2 The estimated effect of mobility during higher education on labour market outcomes

Results not presented here show that being mobile during higher education does not affect significantly the probability of having ever been unemployed at some point during the 5 years after graduation nor the probability of being employed at the time of the survey[6]. As a consequence, we focus our analysis in the transition period from education to employment and to the hourly earnings at the moment of the survey (Figure 4).

Figure 4 - Estimated effects of mobility during higher education on future mobility



Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. See Table A.1 for the complete set of results, including standard errors.

We find that being mobile is associated with a longer transition to the labour market of around 0.8 months, which despite being statistically significant is nevertheless a rather small effect. In addition, we see in Panel B, that the effect is significant only for periods abroad of at least 6 months. In fact, being mobile during higher education between 6 and 12 months delays the finding of the first job by 1.3 months, while spending abroad more than 1 year increases the job search to 3.6 months. These delayed transition into the labour market might be the consequence of several mechanisms. First, it is possible that the mobile graduates lose their professional networks in the home country, leading to a longer search period to find the first job after

[6] Results available upon request.

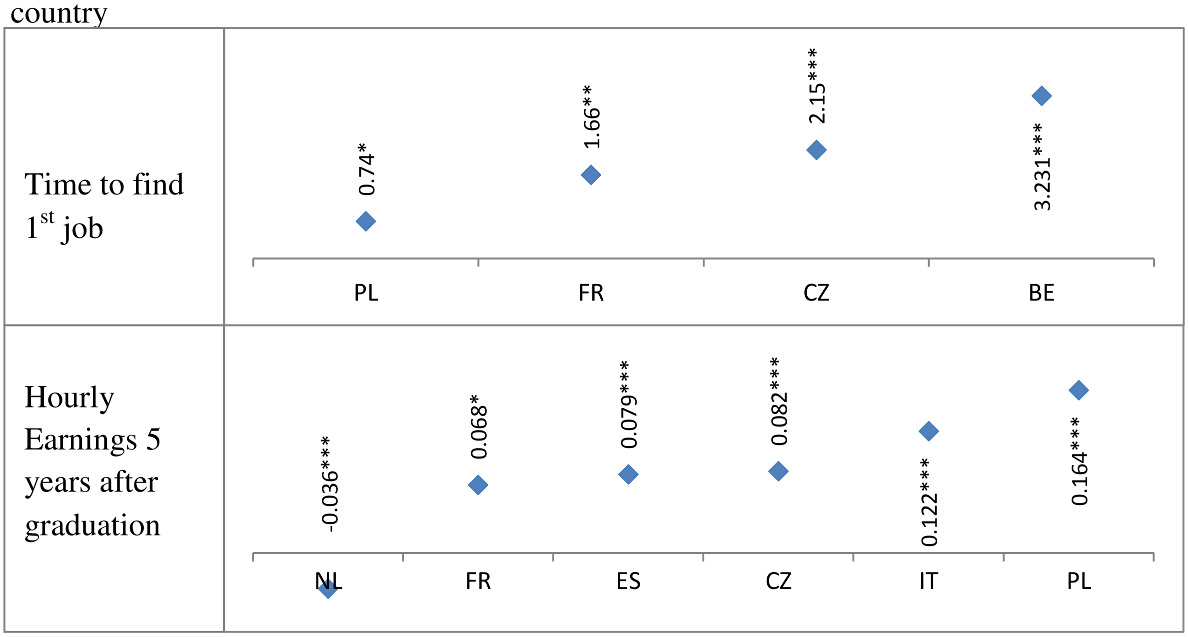
graduation. This mechanism might be exacerbated due to the fact that mobility periods occur closer to the end of the degree, rather than in the beginning. Second, it is also possible that mobile graduates develop a preference for internationality, increasing their *mobility capital*, leading them to search for a job abroad, which might take longer than the search for those focusing in the home country. Third, if employers do not value this mobility experience, it can be more difficult for graduates to find the first job. We discuss these and other possible mechanisms in the next section.

Regarding earnings, the results suggest that, 5 years after graduation, mobile students have a 3% higher hourly earnings than non-mobile students. In this case the effect does not increase monotonically with the duration of mobility, being significant only for periods abroad of 3 to 12 months. These graduates earn on average 5% more per hour compared to non-mobile students. These effects on hourly earnings could mean that mobility increases the productivity of graduates, and they are paid accordingly, and/or that mobility leads graduates to make future options that lead into higher payments (these could be working in the private sector, in international organisations, or continue studying). These hypotheses are further discussed in the next section.

The effect of mobility on the labour market outcomes is more heterogeneous across countries than the ones relating to future mobility (Figure 5). In fact, we find that mobility during studies has a significant effect on the time to find the first job after graduation only in a few countries: Poland (0.7 months) and France (1.6 m.), but particularly in Czech Republic (2.1 m.) and Belgium (3.2 m.). Similarly, tthe positive effect presented for hourly earnings in the pooled sample is only found in few countries: Poland (16%), Italy (12%), Czech Republic (8%), Spain (8%) and France (7%). Interestingly, in The Netherlands, this effect if negative: mobile graduates earn less 3.5% than their non-mobile counterparts.

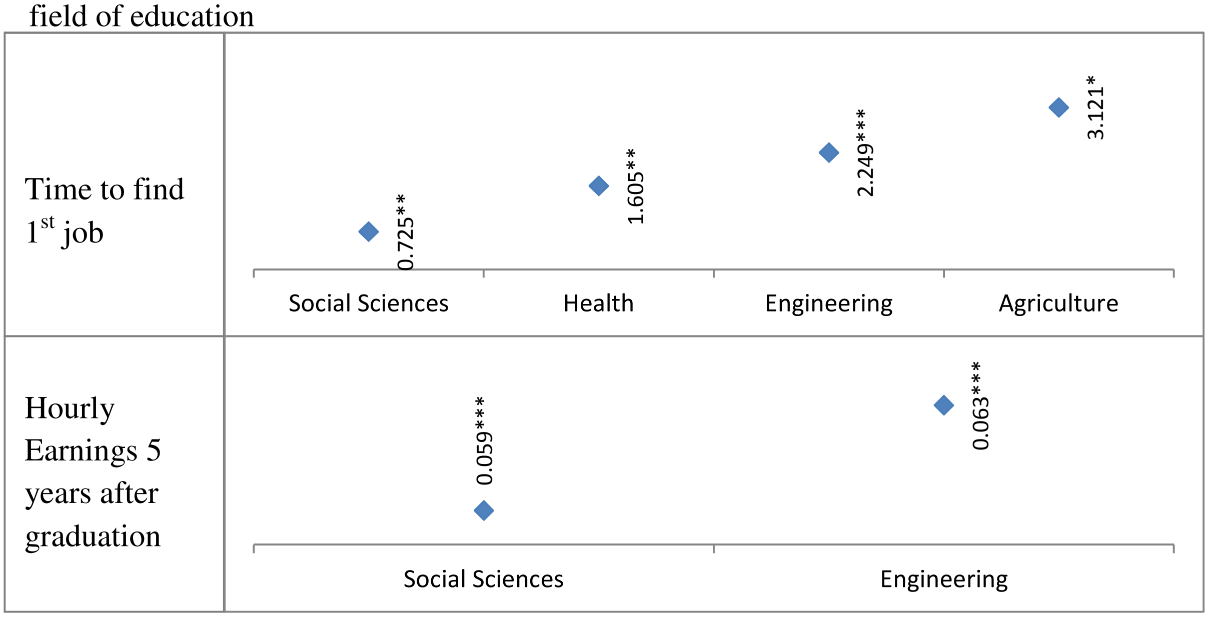
Moving to the analysis by field of degree (Figure 6), mobility is associated with longer job search specially in the fields of Engineering and Agriculture, but also in Social Sciences and Health and Welfare. Finally, mobility during higher education seems to have a positive impact on earnings only in the fields of Social Sciences and Engineering.

Figure 5 - Estimated effects of mobility during higher education on labour market outcomes, by country



Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. See Table A.2 for the complete set of results, including standard errors. Only countries for which the estimated effect of mobility is significant are presented in the graphs. Countries ordered in ascending order of the estimated effect.

Figure 6 - Estimated effects of mobility during higher education on labour market outcomes, by field of education



Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. See Table A.3 for the complete set of results, including standard errors. Only fields of education for which the estimated effect of mobility is significant are presented in the graphs. Fields ordered in ascending order of the estimated effect.

5. Discussion and possible mechanisms

5.1 Possible Mechanisms

The mechanisms through which mobility during higher education affects future mobility and labour market outcomes can be several, certainly some of them unobservable to the researcher. In this section we present a discussion on the possible mechanisms that can be assessed through the available data.

First, we look into a mechanism that can be linked to all the outcomes analysed: the ability to write and speak in a foreign language at the moment of the survey, reported by the respondent. We find that being mobile during higher education is associated with an increase of one category of this self-reported ability (0.966***[0.032]). Of course, we cannot attribute this increase totally to the mobility experience, since this language advantage could already be present before the period abroad. Second, we estimated the effect of mobility on the probability of following further studies after the degree observed in the data. In fact, we find that mobile graduates are 5 p.p. more likely to continue studying than non-mobile ones (0.045***[0.097]). Finally, we also considered some current work characteristics, such as whether the graduate works in the private sector and whether works in an organization with international operations. We concluded that mobile graduates are 3.8 p.p. more likely to work in the private sector and 11 p.p. more likely to be working in jobs/firms with international scope.

Next, we include some or all these mechanisms in the estimation of the effect of mobility to see to what extent it is affected. This exercise allows to, at least, understand whether there are other mechanisms playing a role or, on the opposite, if the mechanisms analysed explain all the effect estimated in the previous section.

For the future mobility outcomes, it only makes sense to control for the reported foreign language ability of the respondent. Including this as an explanatory variable decreases the effect of mobility during higher education substantially: for mobility after graduation for work or study reasons it decreases by 6 p.p. (20 to 14); for mobility after graduation for work the effect decreases 5.5. p.p. (from 14.5 to 9); for the probability of living abroad at first job it decreases by 1 p.p. (from 5.8 to 4.5); and for the probability of living abroad at the moment of the survey by around 2 p.p. (from 4.4 to 2.7). This drop, especially for the cumulative measures of future mobility, means that indeed foreign languages skills are an important mechanism and explain a considerable part of the effect of mobility during studies. Still, there are clearly other mechanisms playing a role. One of this is certainly the *mobility capital*, that is accumulated during the experience abroad, increasing the taste for international experiences. This cannot be directly assessed in the data. However, the fact that the effects of mobility increase with its duration, can be interpreted as a possible indicator of this mechanism: more time abroad develops more the taste for living abroad, which leads to higher probability of actually living abroad.

For the time to find the first job after graduation we further control for the following possible mechanisms: the foreign language skills; whether the graduate continued studying, as this could delay the entrance to the labour market; whether the first job was found in the home country or abroad, given that it could take longer to find a job abroad due to the lack of networks or other barriers. When all of these are included in the estimation, the estimated effect of mobility on the search time for the first job decreases from 0.78 months to 0.55 months, being the effect still statistically significant only at 90% significance level. In particular, the mechanism whose inclusion decreases the most the effect is the continuation of studies, suggesting that mobile students are more likely to continue studies, which in turn delays the entry to the labour market. Adding these further controls to the estimation by country, we find that for Poland the effect is no longer significant, while for the other 3 countries is still significantly different from zero (France: 2.41*[1.43]; Czech Republic: 2.22*** [0.79]; Belgium: 2.10** [088]).

Finally, for hourly earnings we control for the following mechanisms: whether the graduate continued studying; the working sector (private/public); whether the organization has international operations; foreign language ability; and for the country where the respondent lives at the moment of the survey. When all of these are included in the estimation, the effect of mobility, that before was 3%, becomes zero and statistically insignificant. This means that these variables are able to explain and absorb the entire effect estimated before. In other words, it means that mobility during higher education does not necessarily increases graduates' productivity, but leads to other factors that themselves explain why they earn more per hour worked. In general, this finding is also true for the estimations made by country. In fact, for

France, Spain, Czech Republic and Poland the effect of mobility on hourly earnings is no longer significant. On the contrary, for Italy (0.096** [0.041]) and The Netherlands (-0.032** [0.016]) a significant effect is still found after controlling for these mechanisms.

5.2 Differences across countries

One of the most important results presented above was that some effects in the pooled sample are only found in some countries. This is particularly the case for labour market outcomes, while for future mobility outcomes the importance of mobility is more homogeneous. In this section, we explore and discuss some potential reasons for the differences found in the labour market outcomes. Notice that this analysis is exploratory and non-exhaustive. In order to understand better the differences between countries more data should be available and more research carried out.

One reason could be related with the main destination countries, and associated with this the relative quality of the university systems. While in the data we do not have information on the country of destination, we can infer from Erasmus data which countries are traditionally more common as destinations for periods abroad during higher education. For the academic year 2004/05, we can see that in general the main destinations were Spain, France and Germany (see Table A.8). Next we cross this information with a measure of the quality of the university system, the "U21 Ranking of National Higher Education Systems 2012" (see Table A.9), and plot in Figure 7 the estimated mobility effect on the two outcomes against the university ranking. Some interesting patterns appear in the hourly earnings graph: there seems to exist a negative relation between the two, i.e. the estimated effect of mobility is higher for countries with a lower university quality. This is intuitive: graduates from countries with lower university quality would gain from spending some time abroad in a higher quality system, and vice-versa (correlation = -0.53).

Another reason might be related with how the employers evaluate this mobility experience and how they rank it against other graduate's characteristics. We use the Eurobarometer on the 'Employer's perception of graduate employability' to measure the importance attributed to a study period abroad by the employers of each country. In total, to the question 'Is very important that new recruits have studied abroad', only 6% and 18% of employers strongly agree or rather agree, respectively, while 42% rather disagree and 33% strongly disagree. Figure 8 plot the estimated effect of mobility against the percentage of employers that answered 'strongly disagree' by country. Again, it is possible to identify a negative relation in the hourly earnings graph: the less employers disagree, the higher the estimated effect of mobility on earnings (correlation = -0.56).

Figure 7 – Estimated effects on labour market outcomes against ranking of higher education systems

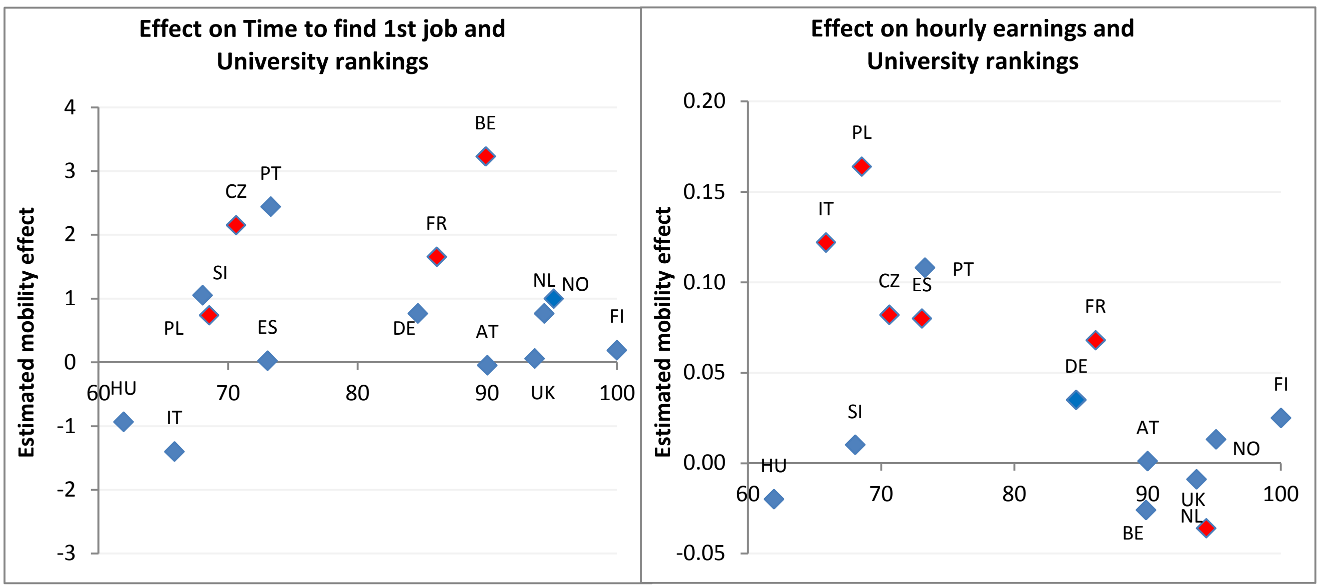
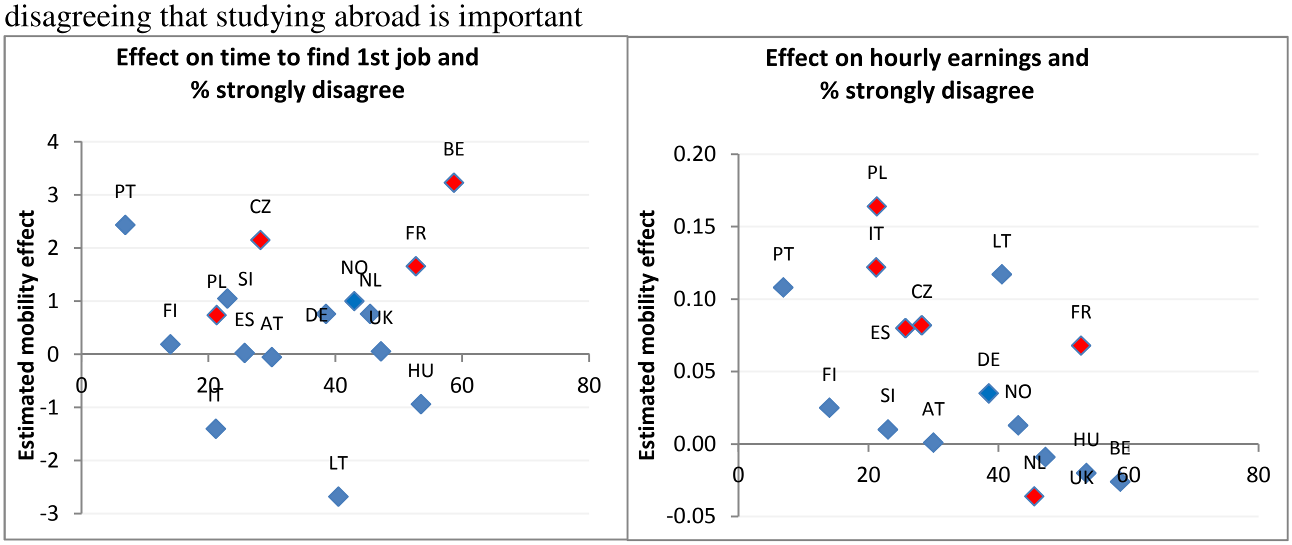


Figure 8 – Estimated effects on labour market outcomes against percentage of employers disagreeing that studying abroad is important



6. Sensitivity Analysis and Robustness Checks

In this section we start by implementing the sensitivity analysis to potential unobserved heterogeneity proposed by Ichino, Mealli and Nannicini (2008). Next, we run several robustness checks in which we appraise to which extent the estimated effects differ if some methodological assumptions are dropped or changed and the sample considered is different.

6.1 Sensitivity Analysis

The main assumption of the propensity score matching procedure is a non-testable one: that the researcher observes all the variables that are correlated both with the decision to be mobile and with the outcomes analysed. By controlling for a rich set of covariates, that aim to measure or proxy usual unmeasured factors, such as motivation and proactivity, we increase the plausibility of this assumption being valid.

In order to assess the sensitivity of the estimates to eventual unobserved heterogeneity the sensitivity analysis procedure proposed by Ichino, Mealli and Nannicini (2008) is performed. The idea is to simulate confounders, introduce them in the estimation and see to what extent they affect the previously presented effects of mobility on outcomes. We simulate the confounder in such a way that its distribution matches the distribution of some already used covariates[7].

The results of this exercise, presented in Annex C, show that the estimated effect of being mobile on the analysed outcomes is not substantially different from the one obtained without the potential confounders, suggesting that the estimated effects do not seem to be sensitive to potential unobserved heterogeneity.

[7] More details in Appendix C.

6.2 Robustness Checks

The effects presented in Section 4 were estimated using a particular sample, methodology and choosing particular options for the propensity score methodology. In this section we re-estimate the effect using different samples and methodology options.

First, instead of the propensity score matching, we estimate the results using multivariate regression models[8]. The results are presented in the Annex B, Table A.5. In general, the results are similar to ones already presented. As discussed in the methodology section, the difference stems for the functional forms assumed by the regression analysis and the imposition of the common support.

Second, we re-run the estimations using different options for the propensity score methodology and for the sample used. All these results are presented in Table A.6, along with the original estimated effects in column 1:

- Use a different matching algorithm, namely the Kernel matching function (column 2);
- With the Radius algorithm, do not trim the sample instead of trimming 1% of the sample (column 3);
- With the Radius algorithm, use a radius/calliper of 0.01 instead of 0.02 as in the original estimation. (column 4);
- With the Radius algorithm, do not trim and use a radius of 0.01 (column 5);
- In the original sample, it is possible that there are degree mobile graduates, i.e. individuals that did the entire degree in a foreign country. These graduates can eventually also be short-term mobile. The only way to avoid capturing these graduates is to drop from the sample those that were born in a different country plus those that lived abroad at 16 years old (column 6);
- In the original estimates we only considered graduates from 25 to 35 years old at the time of the survey. We also re-run the model for the extended samples of 25 to 40 years old and 25 to 50 years old (columns 7 and 8).

[8] Either ordinary least squares for continuous outcomes or probit models for binary outcome variables.

It is clear that the estimated effects obtained in each of the robustness check exercises are similar to the original ones. Therefore, we are confident that the estimates presented and discussed in Section 4 are not sensitive to the methodology used nor to the sample analyzed.

7. Conclusion

Using a European survey on higher education graduates five years after graduation, this report studies how student mobility during higher education is related to future mobility and labour market related outcomes, namely the transition from education to employment and hourly earnings five years after graduation. We are able to control for several important pre-determined individual characteristics and proxies of ability, motivation and initiative that are likely to be correlated with both the mobility decision and the outcomes. Therefore, even though we cannot claim to have estimated the causal effect of mobility, we are confident to have decreased unobserved heterogeneity considerably.

The main findings of the paper are as follows. First, student mobility is associated with a significant increase in the probability to be mobile after graduation and this effect is larger the more time is spent abroad. This result is also found when we estimate the effect of mobility by country and by field of education. Second, student mobility is associated with a slightly longer time to find the first job after graduation. This effect is however only significant for those being abroad for at least 6 months. Importantly, this effect is found to be significant in few countries and fields of education. Third, student mobility is associated with higher hourly earnings (3%), suggesting that it could lead to higher graduate productivity. However, we find that this effect is completely explained by other mechanisms, such as the sector of activity, further studying, the country of work, the language skills, among others. Furthermore, this effect is only significant for periods abroad between 3 and 12 months and in few countries and fields of education.

From a policy perspective, these results are important. While the future mobility is clearly stimulated by the mobility experience during higher education, the labour market outcomes analysed are affected only in some countries and in some fields of education. Accordingly we suggest that the discourse arguing that mobility enhances employability and labour market success should be used with caution and that further research should be carried out to understand differences found across countries.

Finally, it would be important to have more thorough and recent data on mobility. The data used in this report is for graduates from 1999/2000 and 2002/2003. In the meanwhile, several important changes have occurred in the higher education systems, the most important ones being the Bologna process and the creation of the European Higher Education Area. Furthermore, the phenomenon of short-term mobility during higher education has increased over the last decade. The number of students going abroad under the Erasmus programme has grown annually by an average of 5.5% between 2000 and 2011. As the number of graduates with this experience increases, further research should assess whether the effects are maintained or fade out over time.

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Appendix

Appendix A – Propensity Score Matching Methodology

The set of variables $(\boldsymbol{Y}, \boldsymbol{X}, D)$ is available for each unit in the sample: $(\boldsymbol{Y_i}, \boldsymbol{X_i}, D_i)$, for i = 1, . . . , N. D is the dummy variable indicating whether the graduate was mobile ($D_i = 1$) or non-mobile ($D_i = 0$) during the higher education studies. The interest is in estimating the effect of this treatment variable in the outcome variables $\boldsymbol{Y}$, controlling for the set of covariates $\boldsymbol{X}$ described. For simplicity, in this section we focus in one of the outcome variables Y, regardless of whether it is a binary or continuous one.

Propensity Score Matching

Let $(Y_1, Y_0)_i$ be the two *potential* outcomes of being treated ($D_i = 1$) or not treated ($D_i = 0$) for the *i-th* population unit. Obviously, for each graduate, only one of these outcomes is observed, depending on whether he was mobile or not. Ideally, we would estimate the causal average treatment effect on the treated, that compares the actual outcome resulting from the mobility experience to the non-observable outcome (counterfactual), i.e. the one that would have resulted if the same graduate had not been mobile, controlling for the set of pre-treatment characteristics $\boldsymbol{X}$:

$$\text{ATT} = E(Y_{1i} - Y_{0i} | D_i = 1, \boldsymbol{X})$$

In general, the idea of Matching is to match treated and non-treated individuals that are similar in their observables and to use the outcome of the latter group as a valid substitute for Y_0 in the above equation. Given the impossibility to find exact comparable observations in each observable variable X (curse of dimensionality), the matching is done in the so called propensity score, i.e. the probability of being treated given the set of observables. The use of the propensity score as a balance score has spread after Rosenbaum and Rubin (1983) proved that, if the propensity score balances the covariates, it is enough to match the propensity score to have independence between the treatment and covariates:

$$X \perp D \mid P(X) \rightarrow X \perp D \mid X$$

The propensity score matching implementation steps used in this paper are described below[9].

1[st] step: Estimate the propensity score

Given that the treatment variable is a binary one, indicating whether the graduate has been mobile or not during higher education, a probit model is used to predict the probability of being mobile:

$$p = \Pr(D = 1|\boldsymbol{X}).$$

2[nd] step: Check the covariates balance[10]

Rosenbaum and Rubin (1983) proved that the propensity score can be a balancing score in the sense that, if two observations have similar propensity scores, they are also similar with respect to each covariate *X* used for its estimation, regardless of the treatment status. However, this must be proven to be true in the specific sample used.

3[rd] step: Check and impose the common support[11]

The propensity score matching approach imposes the common support by restricting inference to the sample constituted of treated and non-treated units that have comparable propensity scores. Accordingly, observations whose propensity score is lower than the minimum and higher than the maximum in the opposite group are dropped from the analysis. This property is one of the advantages of the propensity score method when compared to the regression one as, in the latter, the comparison of treated and non-treated individuals might be done using extrapolations in one of the groups. On top of imposing the common support, 1% of the treated observations are dropped, the ones at which the propensity score density of the control observations is the lowest (*option trim=1%*).

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[9] To estimate the treatment effect we use the following version of Stata written command psmatch2 (Leuven and Sianesi, 2003): psmatch2 mob_st covariates, radius caliper(0.02) outcome(y) common trim(1)
The standard errors are obtained by bootstrapping, with 50 replications: bootstrap r(att), reps(50): psmatch2 mob_st covariates, radius caliper(0.02) outcome(y) common trim(1)

[10] The covariate balance check is presented and discusses in Appendix D.

[11] The number of treated observations dropped due to imposition of the common support are presented and discusses in Appendix D.

4th step: Match treated and non-treated units

In the final step, treated and non-treated observations with similar propensity scores are matched using an appropriate algorithm. In this paper 'Radius' matching is used, which matches each treated observation with all the observations for which the difference in the propensity score is lower than 2% in absolute terms, radius=2% (option *calliper=2%*). The control group of observation *i* is the following set of observations:

$$A_i = \{p_j : \|p_i - p_j\| < r\}$$

5th Step: Estimation of the treatment effect

Finally, the treatment effect is calculated as the average of the difference between the outcome variable in the matched treated and non-treated groups:

$$ATT = \frac{1}{N_{D=1}} \sum_{i \in \{D=1\}} \left[y_i - \frac{1}{N_{D=0}} \sum_{j \in \{D=0, A_i\}} y_j \right], \text{where } A_i = \{p_j : \|p_i - p_j\| < r\}$$

When the treatment is a multiple one, as is the case of the duration of mobility, a series of binomial models are run as suggested by Lechner (2001): in each model, the treatment is being abroad for a specific period of time and the control group is the non-mobile group of graduates.

Appendix B – Tables presenting the estimated effects of mobility from all specifications

Table A.1 – Estimated effects of mobility

	Panel A: Estimated effect of being mobile			Panel B: Estimated effect by duration of mobility			
				Less 3 m	3 to 6 m	6 to 12 m	More 12 m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mobile after graduation	0.221***	0.215***	0.201***	0.150***	0.194***	0.239***	0.322***
(s.e.)	(0.008)	(0.009)	(0.008)	(0.016)	(0.017)	(0.014)	(0.035)
Mobile after grad. Work	0.159***	0.155***	0.145***	0.094***	0.147***	0.189***	0.238***
(s.e.)	(0.008)	(0.008)	(0.008)	(0.013)	(0.014)	(0.016)	(0.025)
Lived abroad 1st job	0.066***	0.060***	0.058***	0.008	0.051***	0.098***	0.165***
(s.e.)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.011)	(0.027)
Lives abroad 5	0.050***	0.046***	0.044***	0.008*	0.036***	0.059***	0.182***
(s.e.)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.010)	(0.023)
Time to find 1st job	0.606**	0.871***	0.779***	0.302	0.514	1.278***	3.567***
(s.e.)	(0.249)	(0.128)	(0.241)	(0.349)	(0.362)	(0.483)	(1.178)
Hourly Earnings 5	0.045***	0.037***	0.031***	0.021	0.051***	0.045***	-0.005
(s.e.)	(0.011)	(0.010)	(0.009)	(0.016)	(0.013)	(0.018)	(0.045)
Variables included:							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demog.+Secondary+International	No	Yes	Yes	Yes	Yes	Yes	Yes
Higher Education	No	Yes	Yes	Yes	Yes	Yes	Yes
Field of education HE	No	No	Yes	Yes	Yes	Yes	Yes

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. In Panel B the full set of covariates is included.

Table A.2 – Estimated effects of mobility during higher education by country

	Austria	Belgium-fl	Czech Rep	Germany	Finland	France	Hungary	Italy
Mobile after graduation	0.236***	0.220**	0.220***	0.195***	0.136***	0.190***	0.205***	0.330***
(s.e.)	(0.031)	(0.030)	(0.017)	(0.026)	(0.023)	(0.033)	(0.049)	(0.032)
Mobile aft. grad. work	0.222***	0.163***	0.130***	0.138***	0.126***	0.098***	0.122**	0.205***
(s.e.)	(0.029)	(0.029)	(0.021)	(0.032)	(0.027)	(0.033)	(0.056)	(0.029)
Lived abroad 1st job	0.108***	0.057***	0.031***	0.033**	0.019*	0.067***	0.037	0.062***
(s.e.)	(0.024)	(0.017)	(0.008)	(0.014)	(0.011)	(0.017)	(0.028)	(0.015)
Lives abroad 5	0.068***	0.029*	0.023**	0.028**	0.036***	0.070***	0.026	0.056***
(s.e.)	(0.020)	(0.016)	(0.010)	(0.012)	(0.012)	(0.014)	(0.024)	(0.015)
Time find 1st job	-0.486	3.231***	2.153***	0.765	0.190	1.657**	-0.936	-1.401
(s.e.)	(0.726)	(0.756)	(0.472)	(0.954)	(0.724)	(0.837)	(1.454)	(0.877)
Hourly Earnings 5	0.008	-0.026	0.082***	0.035	0.025	0.068*	-0.020	0.122***
(s.e.)	(0.031)	(0.025)	(0.026)	(0.032)	(0.021)	(0.035)	(0.195)	(0.039)

	Lithuania	Netherlands	Norway	Poland	Portugal	Slovenia	Spain	UK
Mobile after graduation	0.204**	0.118***	0.175***	0.184***	0.215***	0.202***	0.229***	0.122**
(s.e.)	(0.080)	(0.201)	(0.027)	(0.040)	(0.078)	(0.033)	(0.029)	(0.052)
Mobile aft. grad. work	0.122*	0.109***	0.110***	0.123***	0.161**	0.113***	0.186***	0.105*
(s.e.)	(0.070)	(0.022)	(0.026)	(0.047)	(0.076)	(0.026)	(0.025)	(0.055)
Lived abroad 1st job	-0.010	0.049***	0.040***	0.048***	0.075*	0.005	0.106***	0.047
(s.e.)	(0.015)	(0.011)	(0.015)	(0.020)	(0.044)	(0.009)	(0.016)	(0.043)
Lives abroad 5	0.055	0.025***	0.007	0.075***	0.012	0.027	0.066***	0.050
(s.e.)	(0.042)	(0.007)	(0.012)	(0.030)	(0.025)	(0.017)	(0.014)	(0.034)
Time find 1st job	-2.680	0.739	1.001	0.738*	2.441	1.052	0.026	0.061
(s.e.)	(2.079)	(0.503)	(0.755)	(0.430)	(2.261)	(1.199)	(0.724)	(1.415)
Hourly Earnings 5	0.117	-0.036***	0.013	0.164***	0.108	0.010	0.079***	-0.009
(s.e.)	(0.195)	(0.014)	(0.028)	(0.055)	(0.119)	(0.041)	(0.028)	(0.058)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The full set of covariates is included.

Table A.3 – Estimated effects of mobility during higher education by field of education

	Education	Humanities and Arts	Social Sciences	Mathematics	Engineering	Agriculture	Health and Welfare	Services
Mobile after graduation	0.219***	0.221***	0.205***	0.181***	0.170***	0.179***	0.167***	0.164***
(s.e.)	(0.023)	(0.021)	(0.013)	(0.026)	(0.019)	(0.056)	(0.024)	(0.058)
Mobile aft. grad. work	0.133***	0.146***	0.151***	0.103***	0.130***	0.140***	0.117***	0.122*
(s.e.)	(0.022)	(0.017)	(0.013)	(0.023)	(0.021)	(0.047)	(0.017)	(0.065)
Lived abroad 1st job	0.030**	0.067***	0.046***	0.061***	0.069***	0.038	0.035***	0.079***
(s.e.)	(0.012)	(0.012)	(0.007)	(0.016)	(0.011)	(0.053)	(0.009)	(0.029)
Lives abroad 5	0.026**	0.038***	0.041***	0.048***	0.059***	0.025	0.035***	0.033
(s.e.)	(0.012)	(0.009)	(0.006)	(0.017)	(0.011)	(0.020)	(0.010)	(0.021)
Time find 1st job	0.090	-0.686	0.725**	-0.215	2.249***	3.121*	1.605***	-1.210
(s.e.)	(0.720)	(0.737)	(0.361)	(0.755)	(0.625)	(1.659)	(0.657)	(1.703)
Hourly Earnings 5	0.043	0.034	0.059***	-0.004	0.063***	-0.008	-0.038	0.049
(s.e.)	(0.031)	(0.030)	(0.012)	(0.029)	(0.019)	(0.069)	(0.039)	(0.057)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The full set of covariates is included.

Appendix C – Sensitivity analysis and robustness exercises

Ichino, Mealli and Nannicini (2008)

We allow that there are unobserved confounding factors that are related to both variables and that make the treatment variable endogenous and assume that this unobserved factor can be summarized in a binary variable, U:

$$\Pr(D = 1|Y, X, U) = \Pr(D = 1|X, U).$$

First, we impose the values of the parameters that characterize the distribution of U, by imposing the probability that U equals 1 by treatment and outcome status: p_{ij}, i indicating $T = \{0,1\}$ and j indicating $Y = \{0,1\}$[12].

Second, we simulate values for this confounding variable according to the underlined distribution. Third, we include this confounder in the estimation of the propensity score along with the already included covariates. Finally, we estimate the average treatment effect for the treated. These three last steps are repeated several times for different simulations of U, so that we get an average treatment effect on the treated and standard error for each distribution of U considered. By considering several distributions of U, we assess the robustness of the estimated effect with respect to these.

[12] This exercise is only done for binary outcome variables, i.e. for the future mobility ones.

Table A.4 – Sensitivity analysis: Effect of "calibrated" confounders

	Mobility after graduation						Mobility after graduation work					
	Fraction U=1 by T & Y						Fraction U=1 by T & Y					
	P00	P10	P01	P11	Average Effect	(s.e)	P00	P10	P01	P11	Average Effect	(s.e.)
No confounder	0	0	0	0	0.201***	0.009	0	0	0	0	0.145***	0.008
Neutral	0.50	0.50	0.50	0.50	0.202***	0.009	0.50	0.50	0.49	0.51	0.145***	0.008
Gender	0.37	0.35	0.50	0.41	0.203***	0.009	0.37	0.35	0.52	0.44	0.147***	0.008
Volunteer	0.18	0.33	0.25	0.37	0.191***	0.014	0.18	0.33	0.25	0.38	0.136***	0.013
Lived abroad at 16	0.01	0.03	0.02	0.04	0.199***	0.009	0.01	0.03	0.02	0.04	0.143***	0.009
Parents' education	0.40	0.56	0.46	0.56	0.195***	0.011	0.40	0.56	0.47	0.55	0.140***	0.010
Access PhD	0.50	0.62	0.60	0.69	0.194***	0.012	0.51	0.63	0.59	0.70	0.139***	0.010
Mainstream	0.80	0.85	0.76	0.84	0.203***	0.009	0.80	0.85	0.75	0.83	0.147***	0.008
Internship	0.61	0.65	0.55	0.59	0.202***	0.009	0.60	0.63	0.57	0.60	0.146***	0.008
Work Experience	0.41	0.52	0.42	0.53	0.199***	0.009	0.41	0.51	0.43	0.54	0.143***	0.008
Immigrant	0.02	0.05	0.03	0.05	0.200***	0.009	0.02	0.05	0.03	0.05	0.144***	0.008
Parents Immigrant	0.06	0.09	0.08	0.11	0.200***	0.009	0.06	0.09	0.08	0.11	0.144***	0.008

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The full set of covariates is included.

Table A.4 – (continued)

	Lived abroad at 1st job						Lives abroad 5 years after graduation					
	Fraction U=1 by T & Y						Fraction U=1 by T & Y					
	P00	P10	P01	P11	Average Effect	(s.e)	P00	P10	P01	P11	Average Effect	(s.e.)
No Confounder	0	0	0	0	0.058***	0.005	0	0	0	0	0.044***	0.004
Neutral	0.50	0.49	0.52	0.51	0.058***	0.005	0.50	0.49	0.52	0.51	0.045***	0.004
Gender	0.39	0.37	0.44	0.38	0.058***	0.005	0.39	0.37	0.42	0.42	0.045***	0.004
Volunteer	0.19	0.35	0.25	0.33	0.055***	0.006	0.19	0.35	0.19	0.31	0.043***	0.005
Lived abroad at 16	0.01	0.02	0.13	0.14	0.054***	0.006	0.01	0.02	0.13	0.19	0.040***	0.007
Parents' education	0.41	0.56	0.46	0.55	0.056***	0.005	0.41	0.56	0.49	0.50	0.043***	0.005
Access PhD	0.51	0.64	0.60	0.72	0.056***	0.005	0.51	0.64	0.64	0.67	0.043***	0.005
Mainstream	0.79	0.85	0.72	0.81	0.058***	0.005	0.80	0.85	0.67	0.75	0.045***	0.005
Internship	0.60	0.63	0.51	0.52	0.058***	0.005	0.60	0.64	0.47	0.47	0.045***	0.004
Work Experience	0.41	0.52	0.45	0.52	0.057***	0.005	0.41	0.52	0.44	0.47	0.043***	0.005
Immigrant	0.02	0.04	0.14	0.15	0.055***	0.005	0.02	0.04	0.15	0.20	0.042***	0.005
Parents Immigrant	0.06	0.09	0.20	0.19	0.056***	0.005	0.06	0.09	0.18	0.25	0.043***	0.005

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The full set of covariates is included.

Table A.5 – Robustness check exercise – Estimated treatment effect on the treated applying multivariate regression

	PANEL A	PANEL B: By duration of mobility			
	(spec. 3)	Less 3 m	3 to 6 m	6 to 12 m	More 12 m
Mobile after graduation	0.202***	0.162***	0.205***	0.251***	0.344***
(s.e.)	(0.009)	(0.015)	(0.014)	(0.017)	(0.034)
Mobile aft. grad. work	0.140***	0.101***	0.151***	0.191***	0.248***
(s.e.)	(0.008)	(0.013)	(0.013)	(0.016)	(0.033)
Lived abroad 1st job	0.048***	0.013**	0.052***	0.092***	0.140***
(s.e.)	(0.004)	(0.006)	(0.008)	(0.011)	(0.025)
Lives abroad 5	0.036***	0.010**	0.038***	0.058***	0.162***
(s.e.)	(0.004)	(0.005)	(0.007)	(0.009)	(0.026)
Time to find 1st job	0.818***	0.308	0.495	1.265***	3.681***
(s.e.)	(0.241)	(0.387)	(0.362)	(0.423)	(1.100)
Hourly earnings 5	0.034***	0.028	0.073***	0.073***	0.000
(s.e.)	(0.010)	(0.018)	(0.013)	(0.019)	(0.035)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.
In Panel B the full set of covariates is included.

Table A.5 – Robustness check exercise – Estimated treatment effect on the treated applying multivariate regression (continued)

	Austria	Belgium	Czech Rep	Germany	Finland	France	Hungary	Italy
Mobile after graduation	0.234***	0.233***	0.221***	0.187***	0.123***	0.194***	0.200***	0.319***
(s.e.)	(0.031)	(0.035)	(0.019)	(0.028)	(0.023)	(0.029)	(0.053)	(0.028)
Mobile aft. grad. work	0.213***	0.170***	0.129***	0.130***	0.114***	0.091***	0.108**	0.182***
(s.e.)	(0.030)	(0.034)	(0.018)	(0.024)	(0.022)	(0.025)	(0.048)	(0.024)
Lived abroad 1st job	0.117***	0.021***	0.024**	0.013***	0.012	0.040***	0.007	0.046***
(s.e.)	(0.022)	(0.008)	(0.010)	(0.005)	(0.009)	(0.012)	(0.005)	(0.012)
Lives abroad 5	0.069***	0.029**	0.019***	0.025**	0.031***	0.044***	0.015	0.050***
(s.e.)	(0.021)	(0.013)	(0.005)	(0.011)	(0.011)	(0.011)	(0.012)	(0.014)
Time to find 1st job	-0.267	3.291***	2.610***	0.596	-0.377	2.057**	0.021	-1.527*
(s.e.)	(0.699)	(0.762)	(0.625)	(0.720)	(0.688)	(1.040)	(0.042)	(0.862)
Hourly earnings 5	0.002	-0.022	0.080***	0.037	0.035**	0.060*	0.021	0.120***
(s.e.)	(0.026)	(0.024)	(0.021)	(0.030)	(0.018)	(0.032)	(0.042)	(0.034)

	Lithuania	Netherlands	Norway	Poland	Portugal	Slovenia	Spain	UK
Mobile after graduation	0.221***	0.118***	0.162***	0.201***	0.183**	0.194***	0.201***	0.128***
(s.e.)	(0.075)	(0.019)	(0.029)	(0.043)	(0.071)	(0.033)	(0.025)	(0.042)
Mobile aft. grad. work	0.133**	0.104***	0.087***	0.138***	0.140**	0.106***	0.147***	0.098**
(s.e.)	(0.066)	(0.018)	(0.022)	(0.041)	(0.062)	(0.027)	(0.022)	(0.038)
Lived abroad 1st job	0.045	0.041***	0.030**	0.038**	0.020	0.002	0.068***	0.024
(s.e.)	(0.041)	(0.008)	(0.012)	(0.016)	(0.015)	(0.002)	(0.014)	(0.018)
Lives abroad 5	-0.022	0.020***	0.006	0.080***	0.000	0.019*	0.016***	0.054**
(s.e.)	(0.098)	(0.006)	(0.006)	(0.026)	(0.000)	(0.010)	(0.005)	(0.021)
Time to find 1st job	-2.166	0.908*	0.905	0.000	1.260	1.250	-0.016	0.415
(s.e.)	(1.349)	(0.521)	(0.659)	(0.002)	(1.766)	(1.026)	(0.739)	(1.008)
Hourly earnings 5	0.176	-0.034***	0.001	0.000	0.086	0.022	0.076***	-0.027
(s.e.)	(0.129)	(0.013)	(0.022)	(0.002)	(0.069)	(0.036)	(0.027)	(0.048)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.
The full set of covariates are included.

Table A.5 – Robustness check exercise – Estimated treatment effect on the treated applying multivariate regression (continued)

	Education	Humanities and Arts	Social Sciences	Mathematics	Engineering	Agriculture	Health and Welfare	Services
Mobile after graduation	0.225***	0.232***	0.204***	0.187***	0.180***	0.189***	0.162***	0.218***
(s.e.)	(0.025)	(0.020)	(0.013)	(0.027)	(0.020)	(0.050)	(0.020)	(0.053)
Mobile aft. grad. work	0.130***	0.157***	0.142***	0.097***	0.137***	0.160***	0.112***	0.158***
(s.e.)	(0.022)	(0.018)	(0.012)	(0.024)	(0.019)	(0.047)	(0.018)	(0.047)
Lived abroad 1st job	0.041***	0.078***	0.039***	0.064***	0.069***	0.021	0.041***	0.102***
(s.e.)	(0.015)	(0.012)	(0.006)	(0.017)	(0.012)	(0.019)	(0.012)	(0.039)
Lives abroad 5	0.040***	0.050***	0.035***	0.052***	0.065***	0.008	0.039***	0.008
(s.e.)	(0.015)	(0.011)	(0.006)	(0.016)	(0.012)	(0.010)	(0.012)	(0.069)
Time to find 1st job	0.302	-0.495	0.733**	0.015	2.623***	2.619*	0.993*	-0.003
(s.e.)	(0.651)	(0.629)	(0.355)	(0.758)	(0.550)	(1.382)	(0.515)	(1.247)
Hourly earnings 5	0.041	0.037	0.062***	0.005	0.061***	-0.003	-0.047	0.055
(s.e.)	(0.028)	(0.023)	-0.012	(0.025)	(0.018)	(0.049)	(0.034)	(0.044)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.
The full set of covariates is included.

Table A.6 – Robustness check exercises – Estimated treatment effect on the treated for alternative specifications and samples

	Original	Kernel matching	No Trimming	Calliper= 0.01	Both	No Degree	Age 25-40	Age 25-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile after graduation	0.201***	0.202***	0.201***	0.201***	0.200***	0.205***	0.200***	0.201***
(s.e.)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Mobile aft. grad. work	0.145***	0.146***	0.144***	0.145***	0.144***	0.148***	0.144***	0.145***
(s.e.)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Lived abroad 1st job	0.058***	0.058***	0.058***	0.058***	0.059***	0.055***	0.056***	0.056***
(s.e.)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Lives abroad 5	0.044***	0.045***	0.044***	0.045***	0.045***	0.040***	0.044***	0.043***
(s.e.)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Time to find 1st job	0.779***	0.785***	0.754***	0.791***	0.753***	0.861***	0.726***	0.704***
(s.e.)	(0.263)	(0.262)	(0.262)	(0.263)	(0.263)	(0.269)	(0.255)	(0.255)
Hourly earnings 5	0.031***	0.033***	0.030**	0.030**	0. 029**	0.033***	0.027**	0.025**
(s.e.)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)

Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.
The full of covariates is included.

Appendix D - Covariate balance and common support checks

Panel A of Table A.7 in the annex presents the tests for the covariate balance power of the propensity score. It shows that, in fact, the propensity score balances the covariates. This conclusion comes from the fact that: i) the covariates have predicted power (relatively high Pseudo R2) in the raw sample, while have zero pseudo-R2 in the matched sample; ii) the covariates are jointly significant in the raw sample, while turn out to be jointly insignificant in the matched sample. Furthermore, Figures A.1 show the percentage of standardized bias by covariate included in the propensity score, for the raw and matched sample. It is clear that once the sample is matched, the standardized bias is close to zero in all models.

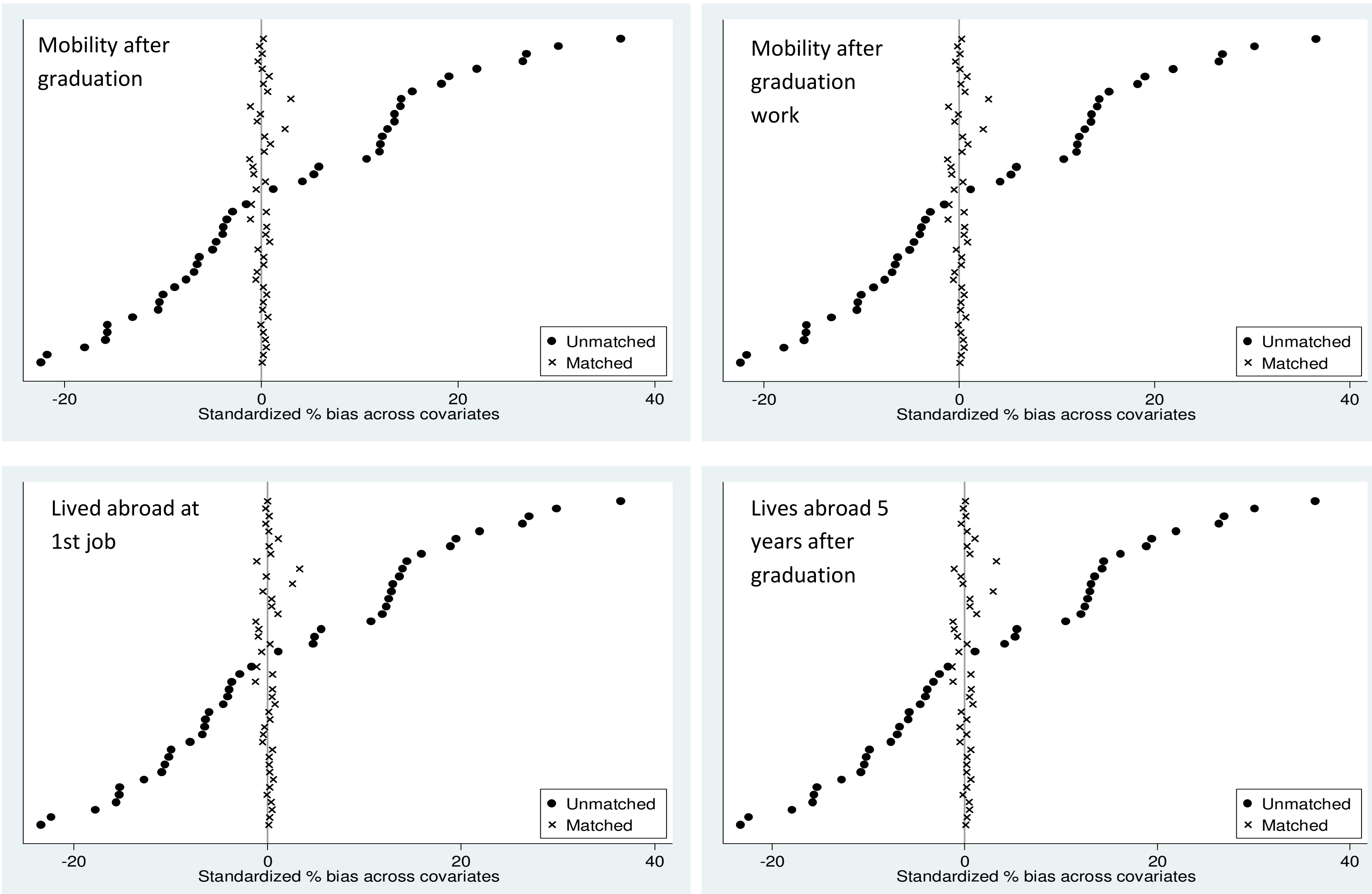
When analyzing and imposing the common support between treated and control groups, we find that there is a good overlap of the propensity scores. Figures A.2 show the distribution of the propensity score for the control and treated groups, and identify the observations that were dropped from the latter group due to lack of support. Indeed, the number of treated units dropped due to the imposition of the common support is low (see Panel B of Table A.7).

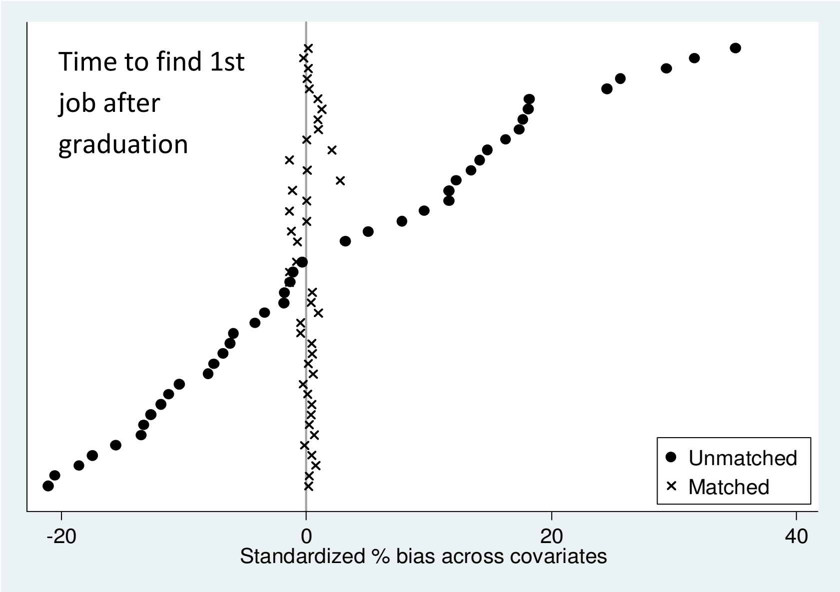
Table A.7 – Results on Covariate Balance tests and number of observations dropped due to the imposition of the common support

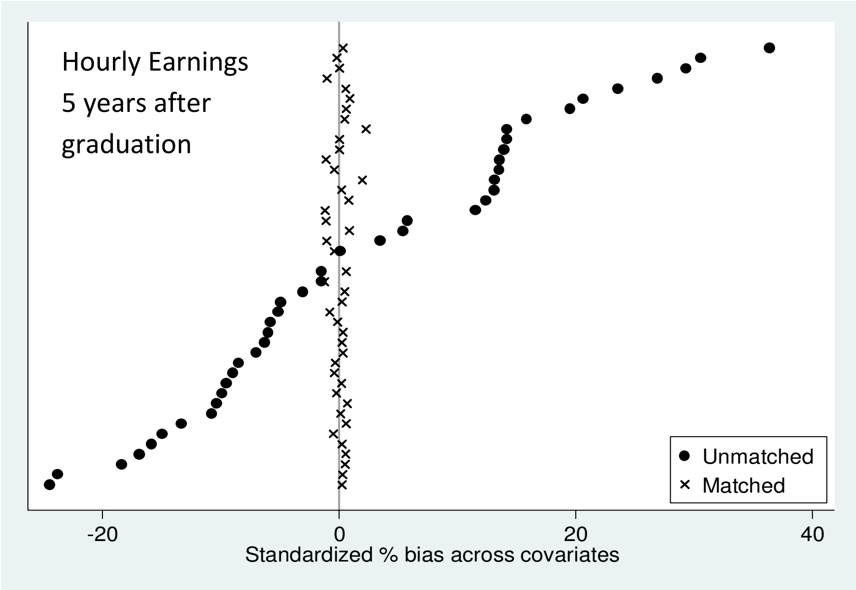
		PANEL A Covariate Balance Tests						**PANEL B Common Support**		
		(1)		**(2)**		**(3)**				
Outcomes		Pseudo R2	LR Chi2 (p-value)	Pseudo R2	LR Chi2 (p-value)	Pseudo R2	LR Chi2 (p-value)	**(1)**	**(2)**	**(3)**
Mobility after graduation	Raw	0.034	662.9 (0.000)	0.057	1111.5 (0.000)	0.090	1739 (0.000)	0	39	39
	Matched	0.000	27.27 (0.160)	0.000	3.68 (1.000)	0.000	3.98 (1.000)			
Mobility after grad. Work	Raw	0.034	662.8 (0.000)	0.057	1111.9 (0.000)	0.090	1741 (0.000)	0	39	39
	Matched	0.003	27.34 (0.160)	0.000	3.68 (1.000)	0.000	4.05 (1.000)			
Lived abroad 1st job	Raw	0.035	667.9 (0.000)	0.057	1103.3 (0.000)	0.090	1723 (0.000)	5	38	38
	Matched	0.003	36.2 (0.021)	0.000	2.99 (1.000)	0.000	4.29 (1.000)			
Lives abroad 5	Raw	0.035	676.0 (0.000)	0.058	1117.0 (0.000)	0.090	1733 (0.000)	0	39	39
	Matched	0.003	36.6 (0.019)	0.000	3.55 (1.000)	0.000	4.63 (1.000)			
Time to find 1st job	Raw	0.035	491.3 (0.000)	0.060	845.3 (0.000)	0.095	1328 (0.000)	23	28	28
	Matched	0.002	14.36 (0.854)	0.000	2.48 (1.000)	0.000	4.02 (1.000)			
Hourly Earnings 5	Raw	0.036	565.1 (0.000)	0.060	970.6 (0.000)	0.093	1440 (0.000)	2	33	31
	Matched	0.003	25.8 (0.215)	0.000	2.76 (1.000)	0.000	2.98 (1.000)			

Note: To evaluate the covariate balance power of the propensity score, we estimate a probit model of the propensity score on all the covariates included in two samples: first, in the raw/unmatched sample and, second, in the matched sample. The Pseudo R2 is the R2 of this estimation and the LR Chi2 is the likelihood-ratio test of the joint insignificance of all the regressors in the same estimation.

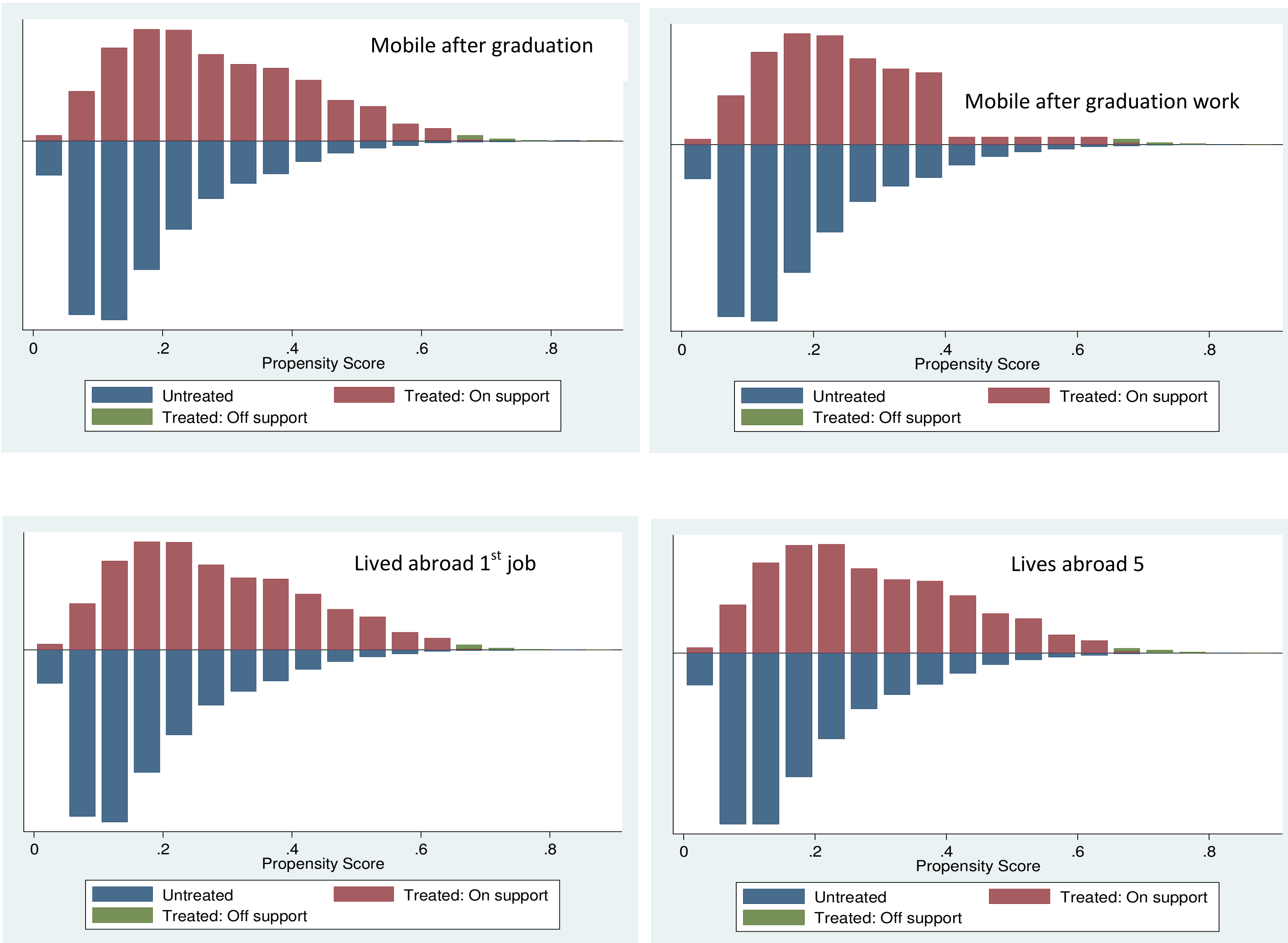
Figures A.1 – Graphs plotting the standardized percentage bias in each covariate in the raw and matched samples – one graph for each dependent variable

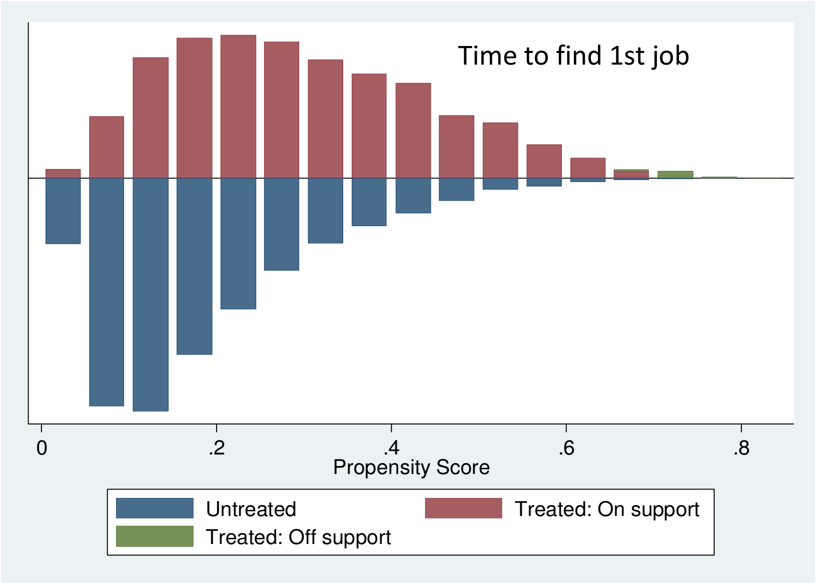



Time to find 1st job after graduation
Unmatched
Matched
-20
0
20
40
Standardized % bias across covariates

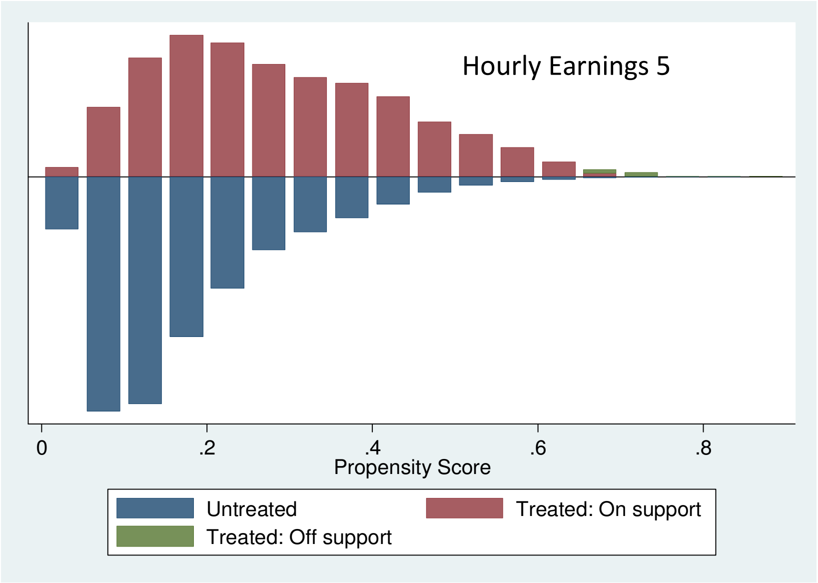

Hourly Earnings 5 years after graduation
Unmatched
Matched
-20
0
20
40
Standardized % bias across covariates

Figures A.2 – Graphs plotting the distribution of the propensity score for treated and control groups, before and after the imposition of the common support – one graph for each dependent variable





Time to find 1st job
0
.2
.4
.6
.8
Propensity Score
Untreated
Treated: On support
Treated: Off support



Hourly Earnings 5
0
.2
.4
.6
.8
Propensity Score
Untreated
Treated: On support
Treated: Off support

Appendix E – Data on Erasmus and Ranking of higher education systems

Table A.8 - Students going in Erasmus by destination country (%), 2004-2005

	Country of destination													
	BE	DK	DE	GR	ES	FR	IE	IT	NL	AT	PT	FI	SE	UK
Austria	1.9	2.7	6.1	1.2	17.0	13.4	3.7	11.6	5.4	-	2.3	5.8	9.0	9.8
Belgium	-	2.5	6.0	1.4	25.7	20.6	1.6	7.0	5.5	3.1	5.3	5.2	4.0	4.8
Czech Rep	3.4	3.3	24.1	1.7	8.5	13.2	1.6	4.5	5.4	5.8	4.6	6.4	4.3	8.8
Germany	1.4	2.1	-	0.8	21.0	19.2	3.8	8.0	4.0	1.9	1.5	4.6	7.9	13.8
Finland	3.2	0.8	8.0	2.0	12.9	10.7	2.5	4.9	9.6	5.9	2.0	-	2.4	12.8
France	1.7	2.8	13.3	1.0	24.0	-	5.0	7.3	3.9	1.9	1.3	3.6	5.5	21.2
Hungary	3.6	2.0	10.8	1.0	36.5	16.1	1.6	-	3.2	1.8	4.8	2.0	2.3	8.2
Italy	5.4	3.0	26.3	1.9	6.8	12.2	0.3	10.3	7.0	5.2	1.9	8.9	2.7	4.7
Lithuania	5.4	10.6	20.0	1.4	5.5	6.9	1.2	5.8	2.4	3.1	3.7	12.9	8.9	2.2
Netherlands	4.3	3.9	8.6	1.0	19.5	11.3	2.2	6.5	-	2.4	2.0	6.5	9.0	13.0
Norway	2.1	4.5	15.6	0.9	17.2	13.4	1.3	7.7	8.3	3.9	2.0	1.0	2.8	12.8
Poland	5.2	5.7	26.7	2.0	9.1	12.9	1.2	7.5	4.8	2.7	3.6	4.5	4.0	5.7
Portugal	5.0	1.8	6.8	1.1	25.7	8.0	0.5	17.4	5.9	1.4	-	2.6	2.5	4.3
Slovenia	4.6	3.6	19.1	0.8	12.7	8.8	0.5	9.2	5.4	12.0	5.1	4.4	4.2	4.4
Spain	5.5	2.9	12.1	0.8	-	16.1	2.6	22.2	5.8	1.6	5.4	2.6	3.7	13.7
UK	1.6	1.9	13.7	0.5	22.9	29.7	0.4	9.3	5.3	1.8	1.3	3.0	3.5	-

Source: European Commission, Erasmus statistics http://ec.europa.eu/education/erasmus/statistics_en.htm

Table A.9 – Ranking of national higher education system 2012

	AT	BE	CZ	DE	ES	FR	FI	HU	IT	NL	NO	PL	PT	SI	UK
Ranking	90	90	71	85	73	86	100	62	66	94	95	69	73	68	94

Source : U21 Ranking of national higher education systems 2012.

Note: The highest is normalized to 100 and all others scores are computed against 100.

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Abstract

We use data from 16 European countries to study the effects of student mobility during higher education on future mobility, on the transition from education to employment and on hourly earnings five years after graduation. We control for several important pre-determined individual characteristics and proxies for ability, motivation and initiative that are likely to be correlated with both the mobility decision and the outcomes. The findings point to a positive association between mobility and future mobility and earnings, while the transition to employment seems to be slightly delayed. While the effects on future mobility are found in all countries and fields of education, the ones related to the labour market are only found in few of them. We also discuss and present evidence on possible mechanisms.

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