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# The Erasmus effect on earnings: a panel analysis from Siena


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## Abstract

This article examines the impact on salaries of Erasmus participation for graduates from the University of Siena. Specifically, it investigates whether mobile alumni experience an increase in terms of net monthly salaries. We use AlmaLaurea panel data for 2010 graduates from the University of Siena who were interviewed again in 2011, 2013 and 2015, making this study one of the very first to use panel data to track the Erasmus impact. Our results show the existence of a wage premium of around 7-9%. We employ a variety of techniques in order to address the endogeneity of the decision to participate in the programme including random effect estimation, instrumental variable estimation and propensity score matching.



JEL classification: I2, J24 J31

Key words: Erasmus program, graduates, wage premium, panel data, Almlaurea, pscore, instrumental variables



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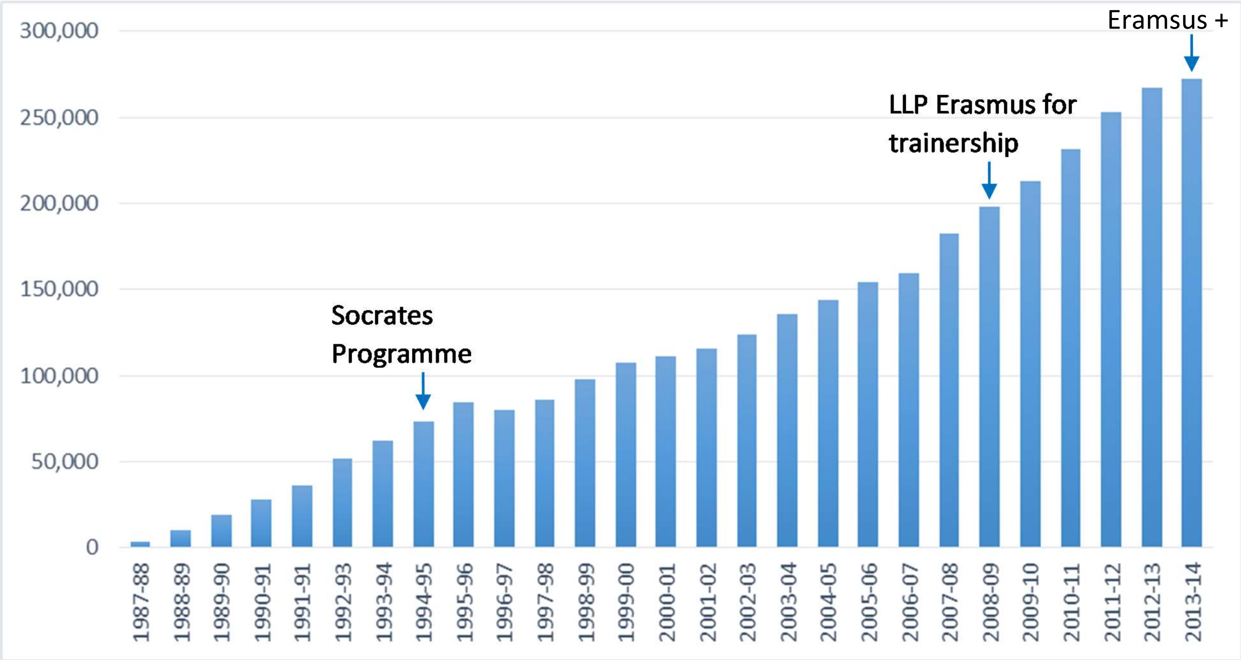
## Section 1: Introduction

Started in 1987 by the European Commission, the Erasmus programme has since then grown exponentially and is today the world's largest study abroad programme for university students.[2] From its inception until the academic year 2013/2014, the Erasmus programme processed over 3.3 million students, together with more than 470,000 university teachers and over 4,000 higher education institutions across the continent, giving them a unique opportunity to temporarily study and work abroad.[3] The current Erasmus+ edition started in 2014 and will operate until 2020, extending beyond study mobility to other initiatives aimed at both students and Higher Education Institutions (HEIs) staff. In conjunction with providing extra mobility options for about 4 million people, Erasmus+ has also seen a sizable increase in funding with a budget of €14.7 billion, corresponding to an increase of about 40% over the previous Lifelong Learning programme.[4] Erasmus for traineeship was initially encapsulated within the Erasmus framework in 2007 and has since then become increasingly popular, with about 60,000 students[5] having spent time working abroad in 2013-2014.

[2] Teichler 2004
[3] European Commission 2015, Erasmus Facts, Figures and Trends
[4] European Commission 2015, Erasmus + 2014 annual report
[5] Amounting to about 22% of all Erasmus students

*Figure 1.1 Erasmus student mobility*




*Source: Erasmus facts and figures 2013-2014*

International mobility is today considered to be a means to achieve personal growth and greater employability, to develop a global citizen well equipped to overcome job market mismatch, to escape from youth unemployment by providing employers with the skills that they look for, but occasionally fail to find, in graduates.[6]

Students wishing to go mobile generally need to apply in advance. For instance, at the University of Siena students are required to apply one year before departure to be eligible for an Erasmus scholarship. Home institutions then select applicants on the basis of their set of criteria. At Siena, students are selected on academic grades, the amount of CFU[7] accrued when applying, language skills and a motivational statement. While various studies financed by the European Commission[8] underline some similar features that students show before leaving for their Erasmus exchange – suggesting that students may self-select into the programme – according to the Erasmus Impact Study (i.e. EIS 2014), Erasmus does not appear to be a selective programme, since only slightly more than one in ten non-mobile students are unable to leave because they have not been selected.

[6] European Commission 2014, Erasmus Impact Study
[7] Credito Formativo Universitario, Italian equivalent of ECTS
[8] EIS (2014) and Janson, Kerstin, Harald Schomburg, and Ulrich Teichler 2009

Despite a growing body of research, whether participation in an Erasmus scheme leads to higher salaries upon graduation is still open to debate, with most studies featuring descriptive evidence or failing to address endogeneity concerns. The aim of this article is to investigate whether and to what extent participation in an Erasmus scheme affects future salaries for alumni from the University of Siena. This investigation will be carried out by combining a regression based strategy with both Instrumental Variables (i.e. IV) and propensity score matching (i.e. p-score) to directly address endogeneity concerns. We merged AlmaLaurea census data for graduates' profiles with employment conditions to create a panel dataset for alumni from the University of Siena. On these grounds, this article is the first study to track Erasmus outcomes on Italian graduates taking advantage of a panel structure.

The remainder of this article is structured as follows: Section 2 reviews existing research, Section 3 presents the data, Section 4 describes the Random effect model first, and then the IV and P-score approach used to address endogeneity concerns, Section 5 shows our results while Section 6 provides policy implications and concludes.

## Section 2: Literature review

Despite its outstanding reputation, existing evidence on the impact of the Erasmus programme is still mainly anecdotal or based on self-reported perceptions of alumni, employers and university officials. Moreover, with very few exceptions, nearly all the existing literature ignores endogeneity concerns on Erasmus students being a sub set of the population.

According to the Erasmus Impact Study,[9] Erasmus is not a selective programme because just 14% of non-mobile students did not go on Erasmus because they had been rejected. However, the result is found to change across macro areas in the European Union, as pointed out by the EIS regional analysis. The same number, in fact, ranged from around 7% - 9% for non-mobile students coming from Northern and Western Europe to about 20% for southern and eastern non-mobile students, demonstrating a tougher selection process and more interest in participating in the programme. Similarly, according to evidence collected in Souto – Otero et al. 2013, participation in an Erasmus exchange seems to ensue from a sequence of decision steps. Students are believed to consider personal agendas first, postponing issues concerning financial and administrative hurdles until they have already convinced themselves, fuelling the argument for self-selection into the programme. Moreover, as regards the reasons for mobility, students surveyed in the EIS ranked the opportunity to live abroad as being the highest motive, followed by improving command of a foreign language, meeting new people and building up soft skills. Conversely, going abroad to enjoy a "relaxed" academic year ranked lowest amongst the options presented in the report.

The above results raise serious doubts concerning the nature of Erasmus students, who may be different from the rest of the student population in terms of ability and motivation. This seems to be particularly so for Erasmus students from Southern and Eastern Europe who are commonly held to be amongst the most motivated and talented. Similarly, the main motivations that students gave for not participating were uncertainty over costs and personal relationships, with significant differences across the macro areas. In particular, students from southern Europe tended to report more reasons to become mobile while at the same time giving reasons for not doing so. This reflects both institutional and financial barriers coupled with uncertainty about benefits, while suggesting, at the same time, that those who actually go are indeed amongst the most motivated.[10]

Furthermore, the EIS offers a unique opportunity to compare personality traits before and after the mobility experience by recording students' personality through psychometric variables called memo©

[9] European Commission 2014, Erasmus Impact Study
[10] European Commission 2016, EIS regional analysis

factors values, namely: tolerance of ambiguity, curiosity, confidence, serenity, decisiveness and vigour. Developed by CHE Consult for the purposes of being closely representative of employability, memo© factors were measured both before and after mobility.

From an ex ante/ex post comparison, it is clear that Erasmus graduates are indeed different from the rest of the student population, displaying higher values when compared to their non-mobile peers. In particular, Erasmus students hold ex ante higher values for curiosity and serenity (i.e. +7% and +6% respectively).

At the same time, however, it is also true that in the EIS those who go abroad experience an increase in psychometric memo© factors, widening the advantage that Erasmus students enjoy over their non-mobile counterparts to about 42%. On considering an ex ante/ex post comparison, the Memo© total score for Erasmus students increased by 2%. It would take 4 years for non-mobile students to achieve the same gain.

Regarding jobs, tasks given to mobile employees reflect international competences gained while abroad. They tend more often to include handling international transactions and contacts, as shown below:

*Table 2.1: Job tasks mobile versus non-mobile alumni*

| What characteristics of internationalisation does your job today have | Mobile | Non – mobile |
|---|---|---|
| | % | % |
| **Jobs with characteristics of internationalisation** | 69 | 64 |
| **International business contacts** | 65 | 52 |
| **Cooperation with branches abroad** | 60 | 46 |
| **Customers abroad** | 58 | 45 |
| **Part of the staff is abroad** | 57 | 43 |
| **International travel** | 52 | 42 |
| **I moved abroad for my current job** | 35 | 18 |
| **My job does not have any characteristic of internationalisation** | 31 | 36 |

*Source: The European Commission 2014, EIS report*

Concerning earnings, however, empirical evidence is still mixed, with Erasmus alumni tending to be more sceptical about the impact of stay abroad periods on income and status.[11] Only 16% of them perceived a positive impact on wages in the VALERA surveys.[12] Nevertheless, according to the 2014 EIS report, income levels are likely to have changed for Erasmus graduates over time, with employers

[11] Teichler and Janson 2007
[12] Engel 2010

now starting to appreciate mobility more. Erasmus alumni are also more likely to hold managerial positions and greater responsibilities than their non-mobile peers, although the results seem to be different across regions, with maximum effects in Eastern European countries.[13] Similarly, 20% of employers across the Union claimed that they paid higher salaries to Erasmus graduates without work experience, while another 29% pointed to mobility as a prerequisite for being hired. Moreover, 39% of the employers interviewed in the EIS reported that they paid higher salaries to Erasmus alumni with five years of work experience, suggesting a possible widening wage premium for experienced employees. Results for Italian Erasmus graduates, provided by Cammelli et al. 2008 through between-groups comparisons, show that Erasmus mobile employees enjoy a wage premium of around 7% for those surveyed 1 year after graduation, increasing to 14% after 3 years in the labour market and finally reducing to 9% for Erasmus employees 5 years after university. Accordingly, the same authors also argue that benefits from an Erasmus scheme are more likely to be positively evaluated in the private sector, where internationally experienced alumni are found to be employed more often. Similar results were also reported by Jahr and Teichler 2002: in this case, despite not perceiving their income and status to be higher, internationally experienced alumni were found to earn about 8.8% more than their non-mobile peers. Likewise, on the basis of a propensity score matching analysis of 16 EU countries, Rodrigues 2013 argues that mobile graduates are more likely to earn higher salaries. Rodrigues reports that internationally mobile alumni interviewed 5 years after graduation enjoy an hourly earning premium of about 3%. Although her results extend beyond the Erasmus programme, by referring to all kinds of study abroad experiences, Rodrigues' estimates are found to be statistically significant for only a few countries. The largest effects are found in Italy and Poland, where mobile alumni reported an hourly earning advantage of about 12.2% and 16.4% respectively.

In similar manner, the VALERA surveys provide evidence of mingling career-boosting effects for Erasmus with self-reported values for job tasks, time to first job and income found to fall over cohorts from 1988/9 to 2000/01. These findings led Engel 2012 to the conclusion that Erasmus is no longer viewed as a career booster but as a more general "door opener" in the labour market, with participation in mobility schemes regarded as a prerequisite. The results point to an Erasmus job market signal interpretation which would abate as the number of Erasmus graduates increases. Conversely, by comparing 2009 VALERA surveys with 2014 EIS results, employers declaring that they did not pay higher wages for mobile employees decreased from 90% in the VALERA to 51% in the EIS,[14]

[13] European Commission 2016, Erasmus Impact Study Regional analysis
[14] European Commission 2014, Erasmus Impact Study

fostering the idea that students can accumulate Erasmus human capital by going abroad, which is appreciated by employers on an ongoing basis.

Regarding salaries and study mobility, to the best of our knowledge the only study which has explicitly addressed endogeneity concerns is Messer and Wolter 2007, where the authors tried to establish a causality link between studying abroad and future income. By pooling data from two cohorts of Swiss students interviewed 1 year after graduation, their OLS results point to a small wage premium of around 3.3%. However, their estimate is not found to be robust because, once participation in an exchange programme is instrumented with mothers' education achievements, IV estimates are no longer significant. Although the results imply that no causal relationship can be attributed to participation in an exchange, it remains true that instruments based on parents' education outcomes have often been questioned in the literature[15] and are not deemed to fully satisfy the requirements to qualify as valid instruments, leading to biased results. This may be explainable on the grounds that the quality of parenting may have a direct effect on the ability of graduates, or on the quality of their previous schooling, thus failing to meet the exogeneity assumption required by IV estimation.

[15] Card 1999 and Deschênes 2007

## Section 3: Data

The data used in the article come from AlmaLaurea, an Italian nationwide inter-university consortium which collects graduates' profile information and then tracks their subsequent career paths. The sample used corresponds to the 2010 graduates' population from the University of Siena[16]. Notwithstanding the fact that we were limited in performing a nationwide analysis, we believe our data yield a much more accurate interpretation of the results, given our own experience as students at Siena. The 2010 graduates' population amounted to about 3,223 graduates broken down per level of studies as below:

*Table 3. 1: The graduate population*

| Degree | Profile 2010 | 1 year after Graduation (interviewed) | 3 years after Graduation (interviewed) | 5 years after graduation (interviewed) |
|---|---|---|---|---|
| **Bachelor Degree** | 1,837 | 1647 | Not-interviewed | Not-interviewed |
| **Single Cycle Degree[17]** | 226 | 207 | 186 | 180 |
| **Master Degree** | 1,023 | 940 | 804 | 729 |
| **Pre-Bologna process Degree** | 131 | Not-interviewed | Not-interviewed | Not-interviewed |
| **Total** | **3,223** | **2,794** | **990** | **909** |

We merged profile information with graduates' employment condition surveys at 1, 3 and 5 years after graduation to generate an unbalanced panel dataset. Bachelor degree holders and students who did not complete high school in Italy were dropped from the sample, since the former were only interviewed in 2011 and the latter displayed incomparable background information having completed high school abroad.[18] The following analysis will therefore focus on master and single cycle alumni who answered the mobility question, amounting to 1,192 individuals.[19] Finally, missing values for unanswered questions have been ignored in the analysis. Just prior to graduation, all students were asked to state any mobility periods that they had experienced during their university studies. Specific questions were also included to address mobility for any master student who had done an Erasmus during his/her bachelor degree. Overall, about 21.5% master and single cycle students[20] reported having studied abroad at some time during their university careers. Accordingly, most Siena mobile students went

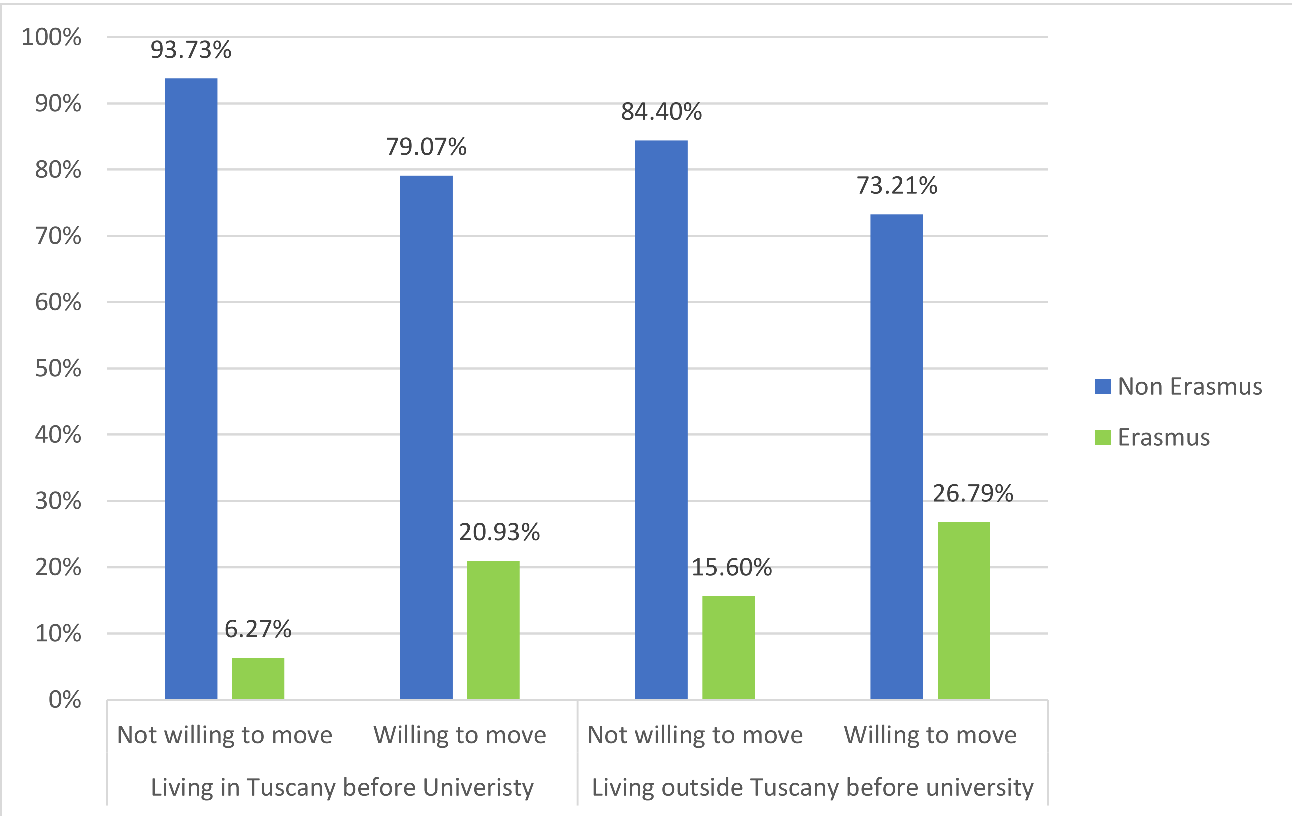
[16] The sample is thus part of the XIII sweep of the graduates' profile.
[17] Single cycle degrees are specific to disciplines like Law and Medicine lasting 5 or 6 years. Alumni obtain a title equivalent to a full master degree on conclusion of their studies.
[18] 53 students completed high school abroad.
[19] 1023 Master degree holders + 226 Single cycle degree holders – 53 alumni who completed high school abroad – 4 alumni who failed to respond to the mobility question = 1,192.
[20] 258 individuals out of 1,192.

abroad thanks to the Erasmus scheme because about 17% of the cohort analysed reported an Erasmus experience, amounting to about 78% of all mobile students.[21] By comparison, according to the AlmaLaurea 2015 national master graduates profile, 15.8% of all master graduates reported that they had studied abroad during their master degree, while 9.9% took advantage of an Erasmus or some other EU programme.

### 3.a Siena Erasmus students' profile

Those who went on Erasmus differed from those who did not especially in regard to the area of provenance. Most Erasmus alumni had already experienced some sort of mobility, albeit national[22], as they reported that they were resident in another region before enrolling at Siena. Similarly, study abroad periods seem to nurture or strongly reinforce a taste for subsequent mobility because Erasmus alumni also stated that they were more willing to change city for job reasons than their non-internationally mobile counterparts.

*Figure 3.1: willingness to move by area of provenance*




On considering fields of study, Erasmus alumni are more frequently found amongst those who study languages, economics, business and finance and socio-political subjects. Participation is instead very

[21] 201 individuals out of 258 mobile students engaged in an Erasmus activity.
[22] i.e.: Living outside Tuscany.

limited for those studying hard sciences, with Erasmus alumni representing the smallest share amongst medicine and chemistry-pharmacy graduates.[23]

Turning to family income and parents' education, the data are in line with previous findings, exhibiting the same pattern of results as in Cammelli et al. 2008. Erasmus alumni are the most numerous within families where at least one parent completed tertiary education (i.e. labelled as *Advantaged*), peaking at 20%. The same figure decreases by almost half, falling short of 11%, for less educated backgrounds, where the best educated parent completed middle school at most (i.e. labelled as *Very disadvantaged*).

*Table 3.2: Erasmus participation by parents' ED and family income*

| **Count of Ever_erasmus** | **Mobility Status** | | |
|---|---|---|---|
| **Family Background** | **Non-Erasmus** | **Erasmus** | **Grand Total** |
| **Advantaged** | **80.00%** | **20.00%** | **100.00%** |
| No Financial aid | 80.06% | 19.94% | 100.00% |
| DSU Financial aid | 79.31% | 20.69% | 100.00% |
| **Disadvantaged** | **82.34%** | **17.66%** | **100.00%** |
| No Financial aid | 84.34% | 15.66% | 100.00% |
| DSU Financial aid | 76.76% | 23.24% | 100.00% |
| **Very disadvantaged** | **89.11%** | **10.89%** | **100.00%** |
| No Financial aid | 91.62% | 8.38% | 100.00% |
| DSU Financial aid | 84.44% | 15.56% | 100.00% |
| **Grand Total** | **83.04%** | **16.96%** | **100.00%** |

Differences in family income were controlled for by access to university DSU financial aid,[24] which, being administered regionally, differs within each Italian region. Since Siena is part of Tuscany, DSU scholarships are awarded on a family income basis, with students then having to complete a set amount of CFUs to continue to receive the scholarship in the following years. Financial aid provides a full tuition fee waiver together with free access to university canteens, a fixed instalment payment, as well as free accommodation for those not originating from Siena. Moreover, DSU scholarships also provide additional monetary funds on top of EU grants for students who decide to go on Erasmus. Regarding the academic year 2009-2010, mobile students who benefited from financial aid were granted an extra €1,900 maximum. Canteen meals and accommodation, which would have been free if in Siena, were also converted into another €2,300, totalling to about €4,200[25]. This would thus translate into a monthly

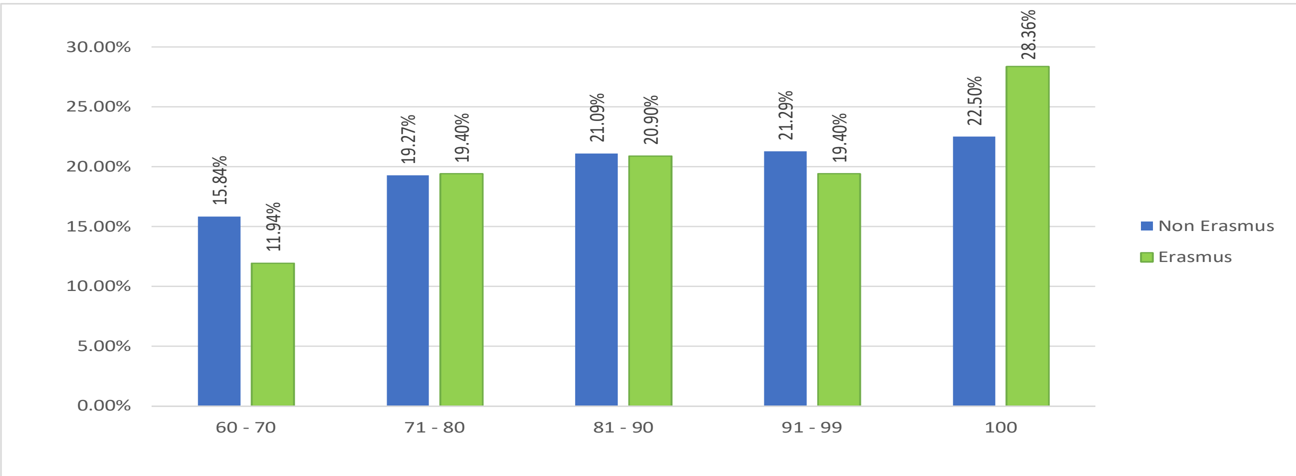
[23] A distribution chart is available in the appendix (3.1).
[24] Diritto allo Studio Universitario (DSU).
[25] Computation was based on students coming from another region, classifying as "fuorisede" those who obtained more resources than locals. Every meal was converted into 1.7 euros (1.7*2*360=1,232) while accommodation was valued at 128 euros per month (i.e. 128*10=1280). Hence 1900+1280+1232 = 4,412 euros for ten months.

scholarship of about 420 euros in addition to EU and national grants. Additional resources explain why students who benefit from DSU financial aid are also more likely to go abroad, representing the largest share within each category. From table 3.2 and given that EU scholarships do not consider family income, DSU scholarships are effective means to reduce financial pressure for students from disadvantaged backgrounds whose participation might otherwise be curtailed.

Inspection of data comparisons across parents' education outcomes for students who did not benefit from financial aid shows that it is those originating from more educated backgrounds who are more likely to go on Erasmus. As also suggested by Cammelli et al. 2008, more educated parents are more likely to expose their children to an international dimension, together with being more aware of the benefits that exchange programmes can yield. This is validated by the percentage of those going without additional financial aid, which is found to double, jumping from 8.38% for the very disadvantaged sub group to about 19.94% for the advantaged.

Moreover, those who left high school with higher marks, similarly to those who graduated from university with top marks, are more likely to go on Erasmus.[26] However, this is probably due to the selection process outlined above. Students are awarded an Erasmus scholarship mainly on the grounds of academic merit and linguistic knowledge, which encourages participation amongst high achievers.

*Figure 3.2: Erasmus mobility over high school marks*




[26] A histogram of the final degree mark distribution of both Erasmus and non-Erasmus graduates is available in the appendix (3.2).

## Section 4: The model

For each graduate, *i=1, 2,…, 1192,* and for each year, *t=2011, 2013, 2015,* we took the logarithm of net monthly earnings to estimate a Log - Lin wage premium equation on Erasmus participation and on a matrix of $K$ additional controls (i.e. $\mathbb{X}_i$):

$$\boldsymbol{logincome}_{i(T\,X\,1)} = \boldsymbol{\imath}_{(T\,X\,1)}\mathrm{c}_i + \boldsymbol{ever\_erasmus}_{(T\,X\,1)}\beta_1 + \mathbb{X}_{i(T\,X\,K)}\boldsymbol{\beta}_{(K\,X\,1)} + \boldsymbol{u}_{i(T\,X\,1)} \qquad (4.1)$$

Where $c_i$ is a scalar of time invariant individual components, $\boldsymbol{\imath}$ a vector of all ones and $\boldsymbol{u}_i$ is a vector of individual error terms for each year. Income information from the original AlmaLaurea graduates' employment condition survey was recorded in intervals, so that the logarithm of the average value of each income class was then used as the dependent variable (i.e. *logincome*).[27] Given that the dependent variable was recorded in monthly terms, we also included controls for differences in working hours, such as part time, permanent contracts and industry dummies.

Participation in an Erasmus scheme was controlled for by the dummy *ever_erasmus*, which also helped discriminate between exchange frameworks and those who had gone abroad on their own initiative. *ever_erasmus* only took value 1 if students declared that they had participated in either Erasmus for studies or Erasmus traineeship because we were unable to discriminate between the two. As cohort alumni all graduated in 2010, well before the introduction of the Erasmus+ scheme in 2014, international mobility was not a repeatable experience because students are unable to go abroad more than once during their university careers.[28] Hence, *ever_erasmus* took value 1 if students had ever taken advantage of the programme, capturing experiences during bachelors for master graduates as well. Nevertheless, students who went on an Erasmus programme to study minority languages or to take part in an Intensive programme were not recorded as Erasmus students given the different nature and the time frame extension of their programmes, which were unlikely to deliver the same effects as the traditional Erasmus schemes for studies and work.

As Erasmus students tend to represent a different subset of the graduate population, gender and family background controls were plugged in together with dummies for area of residence, parents' education achievements and whether students benefited from financial aid. Differences in university subject areas, degree marks and time to degree were accounted for as well. Potential concerns of ability bias were directly addressed by including high school diploma marks standardized by provincial averages.[29]

[27] Histogram for *logincome* is available in the appendix (4.1).
[28] It is now possible to go on Multiple Erasmus subject to cumulative time constraints (i.e. 12 months for first/second cycle degree vs 24 months for single cycle degrees).
[29] Data, for provincial averages, were provided by the Italian Ministry of Education.

Moreover, following Rodrigues 2013, we also included controls for whether alumni worked during university and their post-graduation experiences (e.g. additional master courses, apprenticeships and internships) to capture proactive and dynamic personality traits. In addition, job characteristics such as geographical area of employment, work experience, being overeducated and employed in the public sector were controlled for. Year random effects were also included to partial out the effects of the national economy on salaries because the economic crisis had hit Italy by the end of 2011 and could lead to underestimation otherwise.

To benefit fully from the panel structure of our dataset and given the time invariant nature of participation in mobility experiences, we decided to estimate the above equation using a random effects model. Compared to pooled OLS, random effects correctly estimate standard errors by explicitly recognizing serially correlated errors and thus applying feasible GLS. The decision to choose a random effects regression instead of pooling together individuals was reinforced by running a Breusch-Pagan test where the hypothesis of homoscedasticity for the error term was rejected at a significance level of 1%.[30]

Nevertheless, the validity of the random effects analysis hinged upon the assumption of independence between individual unobserved effects (i.e. $c_i$) and all the controls (i.e. $for\ all\ x_{jit} \in \mathbb{X}_i$):

$$Cov(x_{jit}, c_i) = 0 \tag{4.2}$$

The individual components are then absorbed into the composite error term $v_{it}$:

$$v_{it} = c_i + u_{it} \tag{4.3}$$

This allows us to rewrite our model (4.1) above as follows and apply feasible GLS:

$$\boldsymbol{logincome}_{i(T\,X\,1)} = \boldsymbol{ever\_erasmus}_{i(T\,X\,1)} * \beta_1 + \mathbb{X}_{i(T\,X\,K)}\boldsymbol{\beta}_{(K\,X\,1)} + \boldsymbol{v}_{i(T\,X\,1)} \tag{4.4}$$

Furthermore, to deliver robust results, given the nature of the dependent variable in the earning equation, recorded in classes, we also ran a random effects interval regression.

In addition to the regression models above we also carried out a p-score analysis in an attempt to reduce heterogeneity bias from selection on unobservables. Propensity score matching provides an effective way to measure the average treatment effect (i.e. ATE: $E[Y_1 - Y_0]$)overcoming the lack of counterfactual deriving from the impossibility to observe both outcomes for treated and untreated alumni. This approach is frequently used when assignment to treatment is not random because it

[30] Output for the Breusch-Pagan test is available in the appendix (4.2).

involves comparing outcomes for two similar individuals, with similar values over a set of covariates, but who differ from exposure to treatment. Propensity score matching consists of a first step where the probability of being treated (i.e. the p-score) is estimated. Treated and controls with similar p-scores are then matched, in a second step, to check differences in outcome values. The average treatment effect (ATE) is thus computed by contrasting the dependent variable for similar p-scores.

The first key assumption behind the propensity score is that the available set of covariates can explain treatment status (i.e. *ever_erasmus*), making outcome (i.e. *logincome*) independent from treatment once all covariates have been controlled for (i.e. ignorability assumption).[31] Furthermore, p-score matching also requires treated individuals to have a corresponding counterfactual with a similar p-score (i.e. balancing property). As an upside, results obtained through propensity scores matching do not depend on any functional form assumptions since the method is based on matching and contrasting values for the dependent variable. Moreover, the method also restricts the analysis to individuals with similar propensity scores. It reduces underlying heterogeneity and, unlike other matching models, does not match over a full set of covariates, thus overcoming the dimensionality problem arising from matching over a large number of controls in a small sample size. Finally, a propensity score matching is more robust than other approaches (e.g. IV) in cases of no underlying endogeneity, always producing reliable and efficient estimates.

However, despite having controlled for many characteristics, it is still possible that the above-described analyses fail to deliver causal and reliable estimates for Erasmus exchanges. This would hold true if self-selection by Erasmus alumni is mostly influenced by unobservables, thus casting endogeneity concerns in the random effects and violating the ignorability assumption, with the consequence of unreliable results. This would be the case if there are unobserved characteristics such as motivation or curiosity that cannot be controlled for but play a role in determining both the dependent and the independent variable, violating both the ignorability assumption, required by propensity score matching, and the independence assumption required by random effects.

An Instrumental Variable (i.e. IV) regression approach is a possible solution to the omitted variable problem. It requires the introduction of an instrument, $z_{it}$, which needs to meet two assumptions. Firstly, $z_{it}$ is required to strongly explain the endogenous variable; hence it needs to be partially correlated with $ever\_erasmus_{it}$. Secondly, it needs to be exogenous so that it influences the dependent only through its effect on the endogenous variable. The instrument should thus only

[31] Woolridge 2002.

influence income by its effect on Erasmus participation. Following Wooldridge 2009 the two assumptions can be stated as follows:

$$Cov(z_{it}, ever\_erasmus_{it}) \neq 0 \quad (4.5)$$

$$Cov(z_{it}, u_{it}) = 0 \quad (4.6)$$

where $z_{it}$ represents the instrumental variable, $ever\_erasmus_{it}$ is the endogenous variable and $u_{it}$ is the error term correlated with the endogenous. While the first assumption can be tested by checking the significance of the instrument in the first stage of the IV estimation, the latter assumption cannot usually be tested, apart from the case of over-identifying restrictions, and needs to be retained.

The IV identification strategy followed in this paper is similar to those adopted by Parey and Waldinger 2010 and Di Pietro 2015 because exposure to the Erasmus programme has been used as an instrument for actual participation. We thus exploit institutional features of the schooling system as instruments following an approach which has started to become popular in applied works[32]. Exposure to the programme would adequately satisfy both assumptions for robust IV estimates. The use of supply side instrumental variables should guarantee exogenous instruments because prospective students usually become aware of the number of Erasmus places once they have already enrolled, and besides, establishing new links requires time. In addition, exposure to the programme is also likely to strongly influence participation because previously mobile alumni are likely to share their experience with the next generations. We recorded exposure to the programme as the ratio of previously Erasmus mobile students to enrolled students at degree level.

Data for the instrument were obtained through the collaboration of the University international desk office. A full list of covariates used together with descriptive statistics is reported in the appendix (4.3).

[32] Card 1999.

## Section 5: Discussion of the Results

This section deals with the results from the above-described models and their interpretation. We will first show results from the random effects model and then proceed to propensity score matching and instrumental variables.

Table 5.1 below displays the results from the earning equation with random effects and robust standard errors:

*Table 5.1: Wage premium Random Effects*

| | Estimated Value of the coefficient |
|---|---|
| ever_erasmus | 0.0720** |
| prov_mark | 0.172** |
| Adv | 0.0544 |
| Dis | 0.00521 |
| financial_aid | -0.0772*** |
| Subject Dummies | ✓ |
| Geo Controls | ✓ |
| Other Covariates | ✓ |
| Year effects | ✓ |
| Industry Dummies | ✓ |
| N | 1613 |
| r2 overall | 0.5078 |
| Vce | Robust |

* p<0.1, ** p<0.05, *** p<0.01

Our results show a positive effect of our variable of interest (i.e. ever_erasmus) equal to 0.072. Since the dependent variable is expressed in a logarithmic scale, the regression shows a wage premium of around 7% enjoyed by Erasmus alumni compared to their non-mobile peers. These results corroborate descriptive findings by Cammelli et al. 2008 and Jahr and Teichler 2002, where Erasmus graduates were reported to benefit from a wage premium of similar magnitude. Signs of estimated coefficients for the other variables are as expected, with women earning less than men and graduates working in southern areas earning less than those employed in central Italy (i.e. base category). Likewise, graduates employed in the north, together with graduates who were already working while studying, are found to enjoy higher salaries. Compared to the base category (i.e. *education*), studying medicine, engineering or chemistry and pharmacy leads to the largest increases in salaries. Regarding background variables, having obtained financial help while at university is found to reduce future earnings, possibly capturing socio-economic disadvantages. Controls for more educated parents (i.e. *adv* and *dis*) fail to be significant despite having a positive sign compared to the base category (i.e.

*verydis*) where the best educated parent did not complete high school. The result is possibly due to ability controls which soak up the effects of originating from more educated families. In this regard, weighted high school marks (i.e. *prov_mark*) are found to be both strong and significant, while controls for graduation marks and time to degree turn out to be insignificant. The above model also features a set of firm industry dummies to capture salary differences in various economic sectors together with controls for part time, temporary contracts, subsequent training and controls for area of residence upon graduation (i.e. *Additional controls)*. Regarding year effects, wages in 2013 turn out to be lower than in 2011, indicating the effect of the economic crisis which began at the end of 2011. Nevertheless, there are signs of recovery in 2015 because there does not appear to be any statistically significant drop in wages.

Moreover, the same estimates held true on running an interval random effects regression. Furthermore, as a means of robustness, the above findings were also validated by performing a sensitivity analysis. As expected, excluding background and ability variables still delivered significant but slightly upwards biased results. The estimated coefficient for *ever_erasmus* was slightly higher (0.0770) when the regression did not include either ability proxy or socio-economic background variables. It shrank to 0.0743 when ability proxies were included in the model netting out missed variable bias, which was captured by the variable of interest. Eventually, once socio-economic background variables were also added, the estimated coefficient decreased further to 0.0720, underlining differences in wages captured by socio-economic background.[33]

As said in the previous section, given that Erasmus participation was not randomly allocated with a sub group of students potentially self-selecting into it, a propensity score approach was applied to deliver additional robustness to the result.

Following Garrido et al. 2014, we checked for specifications that satisfied the balancing property, imposing the common support option for overlap and choosing variables which explained both treatment and outcome. We thus ran *pscore,* a user written command introduced in Baker and Ichino 2002. The average treatment effect (i.e. ATE) was then computed by using Stata built-in *t-effects psmatch* command, which provides efficient estimates for ATE.

The Logit specification in Table 5.2 below was found to respect the balancing property and provide common support[34]:

[33] Output for the sensibility analysis and random effects interval regression is reported in the appendix (5.1 and 5.2).
[34] Full psmatch Stata output is available in the appendix (5.3).

*Table 5.2: Probability of going on Erasmus Logit estimates*

| | ever_erasmus |
|---|---|
| **Personality Traits proxies** | |
| std_working | 0.630*** |
| postdegree_appr | -0.325 |
| profile_appr | 0.476*** |
| **Geographich area of residence** | |
| north_res | 0.383 |
| south_res | 0.941*** |
| island_res | 0.279 |
| **Socio-economical background** | |
| Adv | 0.788*** |
| Dis | 0.641*** |
| financial_aid | 0.272 |
| **Ability** | ✓ |
| **Study Area** | ✓ |
| **Additional controls** | ✓ |
| N | 1692 |
| Pseudo r2 | 0.1865 |
| Vce | Oim |
| * p<0.1, ** p<0.05, *** p<0.01 | |

According to the estimates in Table 5.2, after controlling for ability, study area dummies and a large set of covariates (e.g. gender, working experience, kind of contract, etc), students from better educated families go abroad more often, which confirms findings in the literature. Moreover, the geographic area of residence appear to play a role in the willingness of students to leave for another country, with students from the south of Italy more likely to go on Erasmus. Despite appearing with a positive coefficient, having received financial aid is not found to be statistically significant. This is possibly due to the introduction of controls for family backgrounds, which are likely to have absorbed its effect. However, students who were working while at university were more likely to go on an Erasmus scheme, possibly capturing a more dynamic and proactive mindset commonly found in Erasmus graduates as well.

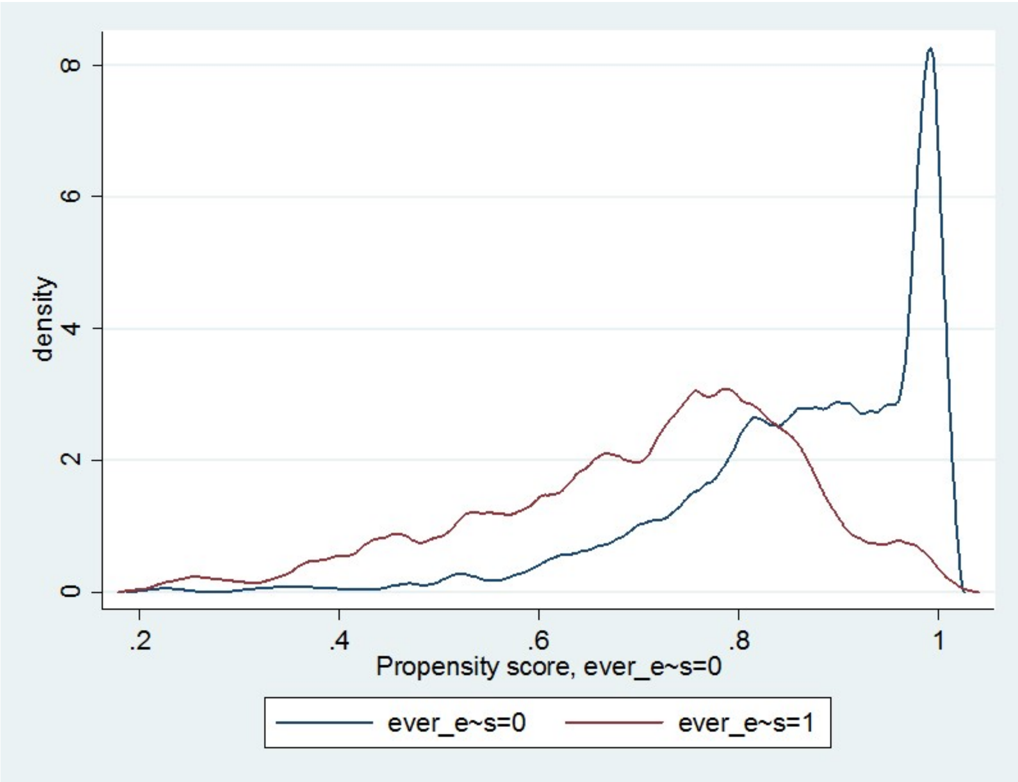
The average treatment effect for the earning specification is reported in Table 5.3 below:

*Table 5.3 ATE for income*

| | **treatment effect ever_erasmus 1 vs 0** | |
|---|---|---|
| | **ATE** | **S.D.** |
| **Logincome** | 0.0872** | (0.0334) |
| * p<0.1, ** p<0.05, *** p<0.01 | | |

The result confirms the estimates that we obtained from the regression based approach: participation in an Erasmus scheme is again found to increase salaries by about 8%. Besides meeting the balancing property, our specification also respects the overlap assumption, providing adequate overlap in the probability of receiving treatment for both treated and controls. Overlap in propensity scores can be evaluated graphically by plotting the density of the computed propensity score for treated and untreated individuals as reported in Figure 5.1 below:

*Figure 5.1: Overlap for Logincome*




Despite a moderate cone for untreated individuals, Figure 5.1 above shows adequate overlap, with the overlap assumption also confirmed by successfully imposing common support in the *pscore* command. Similarly, sufficient overlap is also required to successfully run the STATA built in *teffects psmatch* command to provide estimates.

Furthermore, following the Stata manual we also computed Inverse probability weighting estimators (I.e. IPW) to verify the solidity of p-score estimates and provide further evidence of overlap.[35] This represents an alternative to matching over propensity scores because inverse probability weighting

[35] IPW estimates would be unstable in case of violation of the overlap assumption as indicated in STATA Manual 2013

uses weighted averages of outcomes for treated individuals as counterfactuals for the non-treated ones by applying the correct weight in the sample and obtain overlap. IPW estimates consistently support results from propensity score matching with slightly larger figures (i.e. 10% vs 8.7%).[36]

Turning to IV estimates, our instrument *ratio_numb_going2006_7* records the share of the number of Erasmus mobile students in the academic year 2006/7 over enrolled students to consider differences in degree course sizes. From Table 5.4 below, it appears that exposure to the programme is a strong instrument, successfully predicting partition in Erasmus exchanges. Accordingly, our instrument delivers an F-test greater than the commonly used threshold of 10 suggested by Stock and Watson 2003 to discriminate between poor and strong instruments.

Considering that our endogenous variable (i.e. *ever_erasmus*) was a dummy, we substituted the IV first stage linear probability model with a probit, following Wooldridge 2002. We thus ran a two-step procedure where we first predicted the probability of going on Erasmus through a probit and then used predicted values as an instrument for IV regression. The results set out in Table 5.4 below report Wooldridge's 18.1 procedure with a first stage probit which includes *ratio_numb_going2006_7* to explain participation. We then used the predicted probability of participating in an Erasmus scheme as an instrument for *ever_erasmus* and computed a pooled instrumental variable wage premium equation. Cluster robust standard errors at individual level were used, given that we pooled individuals across time.[37]

[36] Full output for IPW is available in the appendix (5.4)
[37] Full output of both first and second stage equation are reported in the appendix (5.5)

*Table 5.4: Woolridge's 18.1 procedure for earnings*

| **First Stage (Probit): Ever_erasmus** | **Earnings** |
|---|---|
| Ratio_numb_going2006_7 | 3.268*** |
| Other Controls | ✓ |
| F – test | 16.40 |

| **Second Stage** | **Earnings** |
|---|---|
| Predicted ever_erasmus | 0.227* |
| Prov_mark | 0.161** |
| Adv | 0.0503 |
| Dis | -0.00470 |
| Financial Aid | -0.0775*** |
| Subject dummies | ✓ |
| Geographic controls | ✓ |
| Other covariates | ✓ |
| Industry dummies | ✓ |
| Year effects | ✓ |
| R2 | 0.485 |

* p<0.1, ** p<0.05, *** p<0.01

From the second stage in Table 5.4 above, the estimated Erasmus wage premium boosts to 22.6%, delivering a substantially larger effect than the one resulting from the random effects model. Accordingly, the standard error jumps to 0.119 for the former specification, indicating the relative inefficiency of IV estimation. Consequently, these findings suggest that IV results on earnings should be treated with caution because they are still possibly plagued by inefficiencies. This is validated by the fact that our estimates remain too large compared to the random effects regression, where Erasmus increased salaries by 7% with a standard error of about 0.0334. While it remains possible that the result is driven by the effect on compliers, who experienced the largest gain from the introduction of Erasmus (i.e. LATE interpretation), it is also likely that the limited sample size, coupled with not enough data variability and the aggregate nature of the instrument, being invariant within students of the same degree course, boosted the estimated returns upwards. Nevertheless, it also holds true that our earnings equation does not appear to suffer from endogeneity bias because we could reject the hypothesis of endogeneity on conducting a Hausman test.[38] Applying an IV approach in the case of no endogeneity would yield inefficient results and might in fact contribute to the imprecise estimates above and provide confidence, at the same time, in the reliability of the results from both random effects and p-score matching.

[38] Full output for the Endogeneity test is reported in the appendix (5.6).

## Section 6: Conclusions

This article has explored whether participation in an Erasmus scheme for studies or traineeships provides alumni with any statistically significant impact in terms of wage premium. We used an AlmaLaurea panel sample for master and single cycle degree holders from the University of Siena who graduated in 2010 and were interviewed again in 2011, 2013 and 2015.

Our descriptive analysis confirms the results in the existing literature with respect to the profile of the typical Erasmus student. Erasmus alumni are found to be indeed different from the rest of the graduate population. They reflect a higher mobility capital because they tend to originate more often from another region, thus already indicating a taste for national mobility. They are then more frequently found to study languages and economics, business or finance, possibly reflecting the structure of those degree programmes, which might facilitate going abroad, and the international skills required in those sectors. Moreover, Erasmus alumni are also reported to come from more educated families and to be among the most talented, having higher high school marks, possibly because of the selection process. Nevertheless, participation does not appear to be overly constrained by family income because students receiving DSU scholarships do not seem to experience any participation penalty. This result may derive from the additional monetary resources to which mobile students, benefiting from DSU scholarships, are entitled in Tuscany, calling for a more redistributive EU grant scheme to be applied across the continent as well.

In regard to the Erasmus effect on salaries, our random effects model consistently yielded a positive and significant wage premium of about 7% stemming from Erasmus participation. The result was consistent across a robustness analysis controlling for ability, via standardized high school marks, and family background controls. Moreover, given the nature of our dependent variable which was recorded in income classes, the result was also validated by an interval regression. Similarly, propensity score matching delivered a similar result, with Erasmus alumni found to enjoy a wage premium of about 8%. A positive wage differential was also found by instrumenting Erasmus participation with exposure to the programme. Its magnitude, however, was much larger and possibly imprecise because of the relative inefficiency of IV regression under the circumstances explained above. Wage premium results from the different models are summarized in Table 7.1 below:

*Table 7.1: The Erasmus impact on earnings*

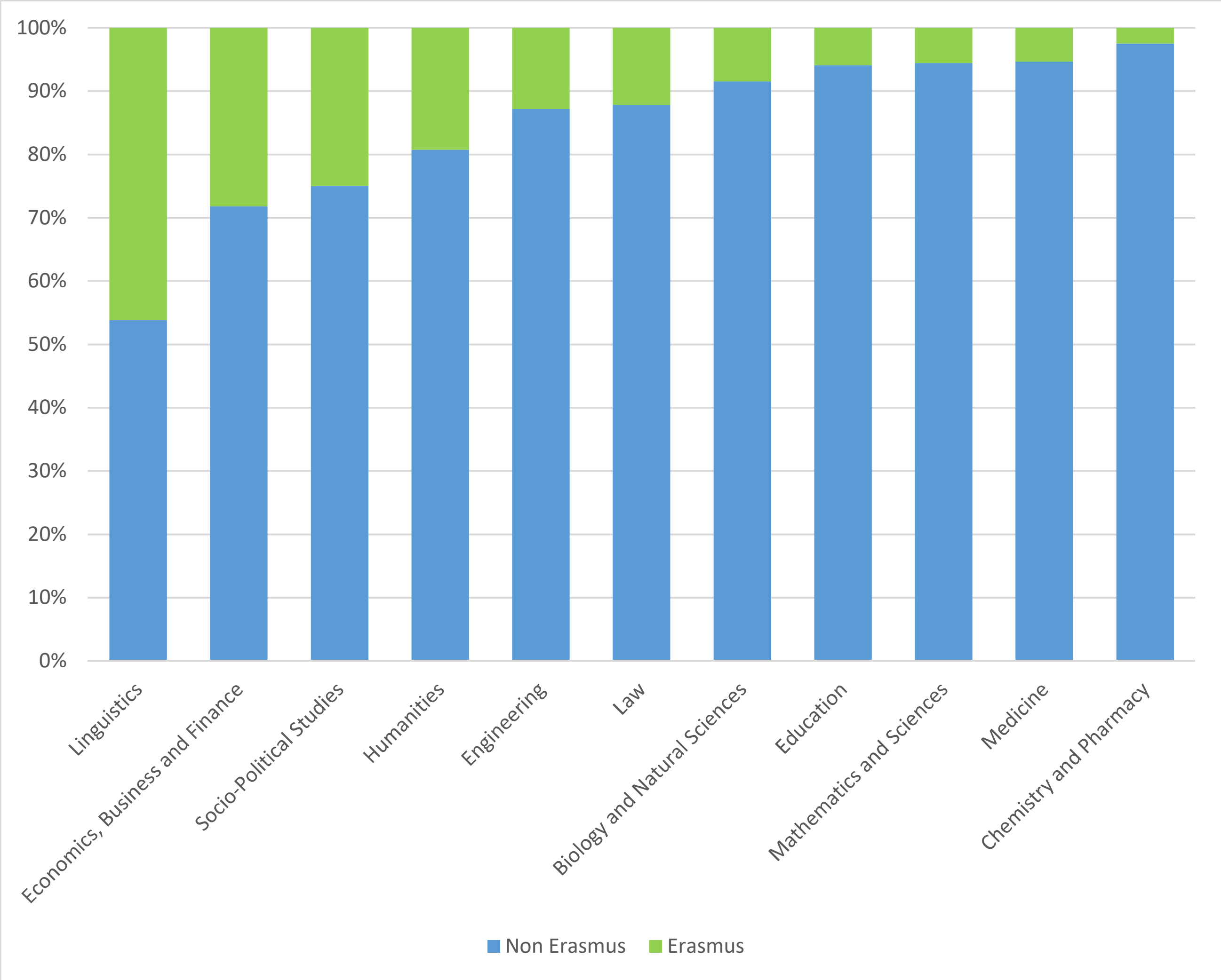
| Earning equation: ***Logincome*** **is the dependent variable** | | | | |
|---|---|---|---|---|
| | **Random effects** | **Interval Random Effects** | **P-score** | **IV Wooldridge's procedure** |
| **Ever_erasmus** | 0.0720** | 0.0742** | 0.0872*** | 0.227* |
| | (0.0335) | (0.0304) | (0.0334) | (0.119) |
| * p<0.10 ** p<0.05 *** p<0.01 | | | | |

It is thus clear from our descriptive and econometric findings that participation in an Erasmus scheme produces a solid salary advantage. Nevertheless, as pointed out in the literature and by our descriptive analysis, Erasmus participation seems to be constrained for some degree courses and individuals originating from less educated families, possibly reflecting asymmetric information issues or perhaps poorly structured degree programmes.

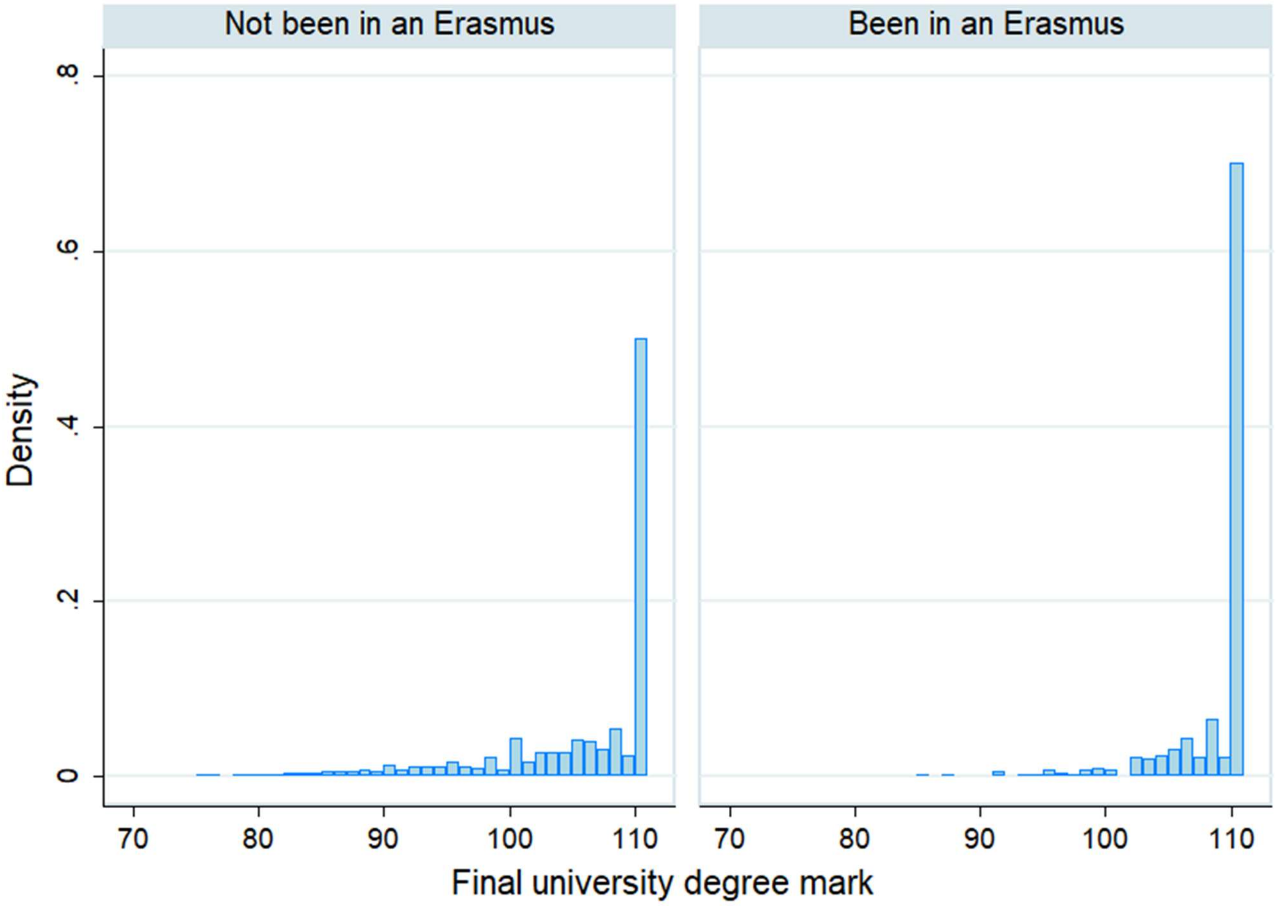
In regard to policy, therefore, although family income does not appear to be a major limitation at Siena, there is still much to do to attract students from a wider range of degree courses, i.e. the hard sciences, and those from less educated families. This would possibly require the introduction of mobility windows in most degree programmes and mentoring services for prospective applicants to help them prepare for an experience abroad. Additional work is also necessary to remedy asymmetric information on participation benefits to make sure that students are able to benefit fully from their educational experience. Further research is also required to corroborate our results and extend them across nationwide and European samples.

# Appendix

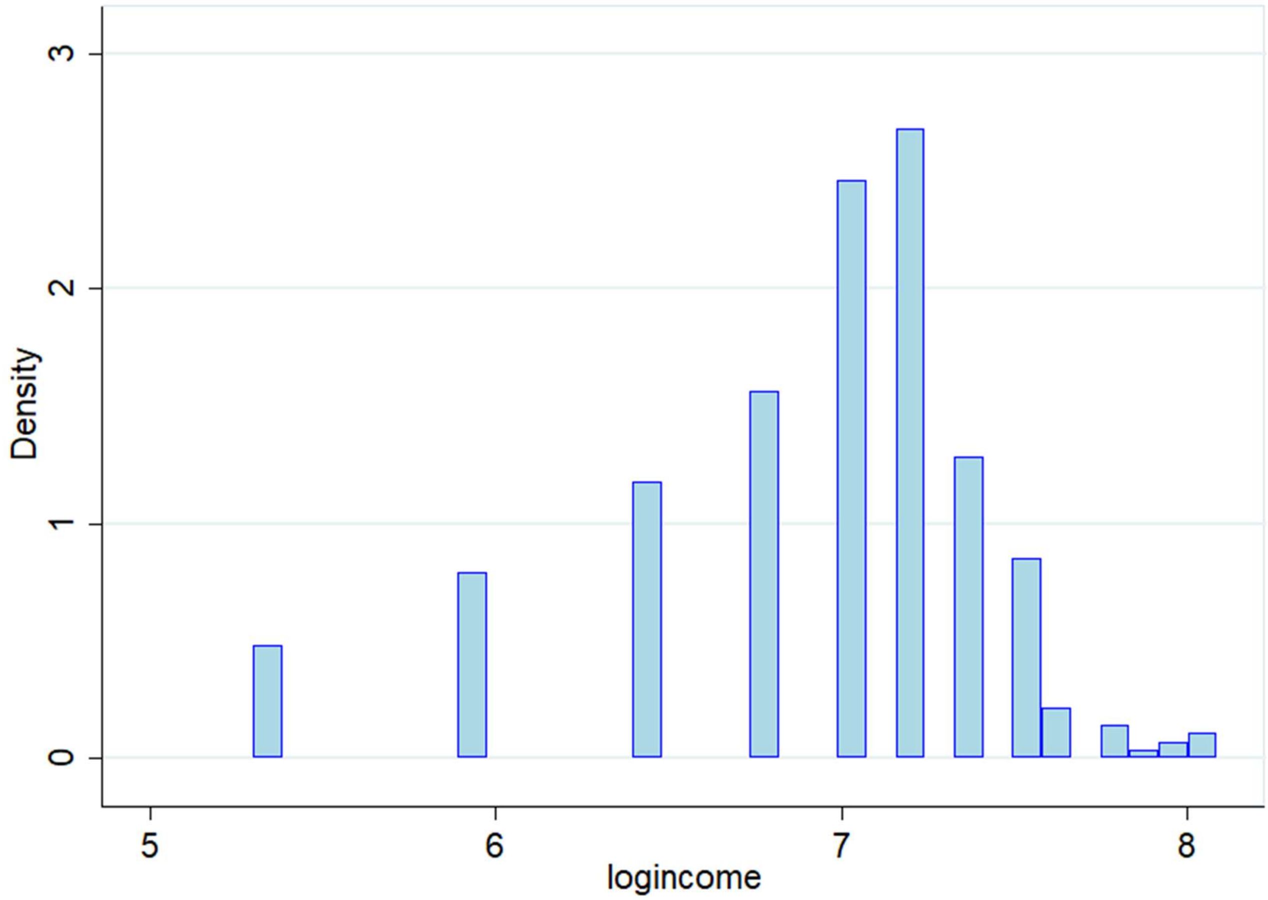
*3.1: Distribution of Erasmus across subject areas*



*3.2: Final degree mark distribution for Erasmus and non Erasmus alumni*



*4.1 Logincome Histogram*




*4.2: Breusch - Pagan test*

Test: Var(u) = 0
chibar2(01) = 38.27
Prob > chibar2 = 0.0000

*4.3a: Descriptive Statistics*

| Varlist | Label | Mean | S.d. |
|---|---|---|---|
| Logincome | =log of net monthly salary | 7.012835 | 0.508768 |
| ever_erasmus | =1 if ever participated in an Erasmus exchange | 0.168908 | 0.374723 |
| std_working | =1 if working while at university | 0.259352 | 0.43834 |
| postdegree_appr | =1 if completed an apprenticeship after graduation | 0.198027 | 0.39858 |
| profile_appr | =1 if completed an apprenticeship during university | 0.742706 | 0.437207 |
| experience[39] | =number of working months gained after | 16.0268 | 20.53513 |
| experience_sq | graduation | 678.4322 | 1140.755 |
| prov_mark | =high school mark weighted by provincial average | 1.117707 | 0.162633 |
| Female | =1 if female | 0.600223 | 0.489921 |
| Adv | =1 if best educated parent holds a university degree | 0.327722 | 0.469449 |
| Dis | =1 if best educated parent completed high school | 0.454546 | 0.498 |
| Verydis | =1 if best educated parent completed middle school or below | 0.217733 | 0.412763 |
| financial_aid | =1 if received regional financial help | 0.222035 | 0.415673 |
| Phd | =1 if completed a PhD | 0.014971 | 0.121458 |
| master_it | =1 if completed a master course in Italy after graduating | 0.091528 | 0.288407 |
| postdegree_internship | =1 if carried out an internship after graduation | 0.233413 | 0.423075 |
| ontime_grad | =1 if graduated within the expected time | 0.399218 | 0.489806 |
| degree_class | university degree mark (expressed in classes[40]) | 4.279453 | 0.961311 |
| over_ed | =1 if declared him/herself to be overeducated[41] | 0.147608 | 0.354814 |
| biology_naturalsciences | Study Area dummy | 0.108878 | 0.311529 |
| chemistry_pharmacy | Study Area dummy | 0.067839 | 0.251505 |
| economics_business_finance | Study Area dummy | 0.157454 | 0.364279 |
| Engineering | Study Area dummy | 0.032663 | 0.177779 |
| Humanities | Study Area dummy | 0.140983 | 0.348052 |
| Education | Study Area dummy | 0.015075 | 0.12187 |
| Law | Study Area dummy | 0.130653 | 0.337068 |
| Linguistics | Study Area dummy | 0.043551 | 0.204123 |
| mathematics_sciences | Study Area dummy | 0.015075 | 0.12187 |
| Medicine | Study Area dummy | 0.140983 | 0.348052 |
| sociopolitical_studies | Study Area dummy | 0.146845 | 0.354001 |

[39] Potential experience was computed by counting the number of months from graduation to the year of survey for employed graduates.
[40] Full label is provided below in appendix 4.4.
[41] Following Pastore and Caroleo, 2014 students are defined as over educated if they believe that their degree is neither required by law nor useful for their job.

| | | | |
|---|---|---|---|
| part_time | =1 if currently working Part time | 0.206192 | 0.404688 |
| public_sector | =1 if currently working Public sector | 0.227405 | 0.419279 |
| perm_contract | =1 if currently working Perm contract | 0.401984 | 0.490442 |
| South | =1 if currently working in the south | 0.082992 | 0.275951 |
| Islands | =1 if currently working in Sardinia or Sicily | 0.035067 | 0.184004 |
| Center | =1 if currently working in the centre | 0.639977 | 0.480147 |
| north_east | =1 if Currently working in the north-east | 0.064874 | 0.246376 |
| north_west | =1 if Currently working in the north-west | 0.138516 | 0.345541 |
| north_res | | 0.046064 | 0.209652 |
| center_res | Geographic Area of residence before graduation | 0.598828 | 0.490204 |
| south_res | | 0.265494 | 0.441658 |
| island_res | | 0.089615 | 0.285669 |
| law_sociopiticalstudies | Combined study area dummy | 0.249731 | 0.432896 |
| weighted_regional_highschool | =High school marks weighted by regional averages | 1.084839 | 0.164566 |
| weighted_regional_highschool_sq | | 1.203952 | 0.349493 |
| ratio_numb_going2006_7 | =ratio of Erasmus mobile students per degree programme in the 2006/7 academic year | 0.105854 | 0.099464 |
| N | | 3582 | |

*4.3b: Industry dummies*

Industry dummies Var list

| a13 | Freq. | Percent | Description |
|---|---|---|---|
| 1 | 29 | 1.16 | =1 for agriculture, forestry and fishery |
| 2 | 24 | 0.96 | =1 for publishing and press |
| 3 | 45 | 1.79 | =1 for energy and minerals |
| 4 | 70 | 2.79 | =1 for chemicals and petrochemicals |
| 5 | 34 | 1.36 | =1 for mechanics |
| 6 | 19 | 0.76 | =1 for electronics and electrotechnicals |
| 7 | 48 | 1.91 | =1 for manufacturing |
| 8 | 39 | 1.56 | =1 for designing and building |
| 9 | 458 | 18.26 | =1 for trade, hotels and public commercial services |
| 10 | 37 | 1.48 | =1 mail and transportation |
| 11 | 67 | 2.67 | =1 for advertising, communication and telecommunications |
| 12 | 208 | 8.29 | =1 for banking and insurance |
| 14 | 157 | 6.26 | =1 for legal, administrative and business consultancy (e.g. auditing) |
| 15 | 132 | 5.26 | =1 for other types of consultancy (e.g. translators) |
| 16 | 67 | 2.67 | =1 for ITC and data processing |
| 17 | 62 | 2.47 | =1 for B2B services (e.g. employment agencies) |
| 18 | 156 | 6.22 | =1 civil service (e.g. government officials and armed forces) |
| 19 | 164 | 6.54 | =1 for education and research institutions |
| 20 | 414 | 16.51 | =1 for health services (e.g. including hospitals) |
| 21 | 86 | 3.43 | =1 for leisure and culture |
| 22 | 150 | 5.98 | =1 for social services |
| 23 | 6 | 0.24 | =1 other activities |
| 99 | 36 | 1.44 | =missing value |
| Total | 2,508 | 100 | |

*4.4: Degree class full label*

| | degree_class |
|---|---|
| 1 | Up to 90 |
| 2 | 91 - 100 |
| 3 | 101 - 105 |
| 4 | 106 - 110 |
| 5 | 110 Distinction |

*5.1: Sensibility analysis earning equation*

| | logincome | logincome | logincome |
|---|---|---|---|
| ever_erasmus | 0.0770** | 0.0743** | 0.0720** |
| | (0.0339) | (0.0337) | (0.0335) |
| std_working | 0.0611** | 0.0758** | 0.0874** |
| | (0.0295) | (0.0299) | (0.0307) |
| postdegree_appr | 0.0742** | 0.0738** | 0.0706** |
| | (0.0310) | (0.0309) | (0.0310) |
| profile_appr | 0.0103 | 0.00821 | 0.00422 |
| | (0.0292) | (0.0292) | (0.0291) |
| experience | 0.0207*** | 0.0207*** | 0.0206*** |
| | (0.00615) | (0.00613) | (0.00615) |
| experience_sq | -0.000227** | -0.000226** | -0.000227** |
| | (0.0000727) | (0.0000726) | (0.0000727) |
| female | -0.0385 | -0.0544** | -0.0417 |
| | (0.0250) | (0.0251) | (0.0258) |
| phd | 0.0863 | 0.0628 | 0.0630 |
| | (0.0723) | (0.0726) | (0.0734) |
| master_it | 0.0166 | 0.0147 | 0.0109 |
| | (0.0329) | (0.0332) | (0.0327) |
| postdegree_internship | 0.0268 | 0.0271 | 0.0237 |
| | (0.0233) | (0.0234) | (0.0234) |
| over_ed | -0.0738** | -0.0687** | -0.0676** |
| | (0.0295) | (0.0295) | (0.0298) |
| biology_naturalsciences | 0.226** | 0.216* | 0.207* |
| | (0.106) | (0.111) | (0.116) |
| chemistry_pharmacy | 0.411*** | 0.425*** | 0.387*** |
| | (0.107) | (0.114) | (0.117) |
| economics_business_finance | 0.324** | 0.308** | 0.290** |
| | (0.102) | (0.108) | (0.112) |
| engineering | 0.395*** | 0.380*** | 0.361** |
| | (0.103) | (0.110) | (0.114) |
| humanities | 0.0929 | 0.0783 | 0.0632 |
| | (0.105) | (0.111) | (0.115) |
| law | 0.0950 | 0.0927 | 0.0681 |
| | (0.116) | (0.120) | (0.123) |
| linguistics | 0.229** | 0.201* | 0.174 |

| | | | |
|---|---|---|---|
| | (0.107) | (0.114) | (0.118) |
| mathematics_sciences | 0.184 | 0.194 | 0.194 |
| | (0.125) | (0.129) | (0.128) |
| medicine | 0.396*** | 0.387** | 0.353** |
| | (0.118) | (0.123) | (0.127) |
| sociopolitical_studies | 0.256** | 0.247** | 0.226** |
| | (0.0989) | (0.105) | (0.109) |
| part_time | -0.480*** | -0.478*** | -0.473*** |
| | (0.0313) | (0.0315) | (0.0314) |
| public_sector | 0.0361 | 0.0400 | 0.0426 |
| | (0.0427) | (0.0429) | (0.0426) |
| perm_contract | 0.121*** | 0.122*** | 0.124*** |
| | (0.0198) | (0.0197) | (0.0198) |
| south | -0.138** | -0.134** | -0.135** |
| | (0.0568) | (0.0568) | (0.0562) |
| islands | -0.0459 | -0.0403 | -0.0479 |
| | (0.0901) | (0.0898) | (0.0891) |
| north_east | 0.110** | 0.106** | 0.110** |
| | (0.0472) | (0.0473) | (0.0463) |
| north_west | 0.123*** | 0.123*** | 0.125*** |
| | (0.0339) | (0.0334) | (0.0333) |
| north_res | -0.0698 | -0.0673 | -0.0748 |
| | (0.0647) | (0.0635) | (0.0626) |
| south_res | 0.00279 | 0.00353 | 0.0197 |
| | (0.0318) | (0.0321) | (0.0323) |
| island_res | -0.0203 | -0.0217 | -0.00924 |
| | (0.0551) | (0.0555) | (0.0559) |
| 2013.year | -0.156** | -0.156** | -0.150** |
| | (0.0677) | (0.0675) | (0.0679) |
| 2015.year | -0.0380 | -0.0378 | -0.0289 |
| | (0.0816) | (0.0813) | (0.0819) |
| d_company_sector1 | 0.0128 | 0.0153 | 0.0248 |
| | (0.120) | (0.119) | (0.117) |
| d_company_sector2 | -0.252** | -0.250** | -0.248** |
| | (0.0844) | (0.0823) | (0.0813) |
| d_company_sector3 | 0.0626 | 0.0649 | 0.0616 |
| | (0.0704) | (0.0701) | (0.0692) |
| d_company_sector4 | 0.0104 | 0.00313 | 0.00665 |
| | (0.0591) | (0.0587) | (0.0590) |
| d_company_sector5 | 0.0841 | 0.0883 | 0.0863 |
| | (0.0780) | (0.0779) | (0.0765) |
| d_company_sector6 | 0.0424 | 0.0349 | 0.0303 |
| | (0.116) | (0.117) | (0.116) |
| d_company_sector7 | 0.0347 | 0.0348 | 0.0344 |
| | (0.0655) | (0.0643) | (0.0639) |
| d_company_sector8 | -0.292** | -0.291** | -0.290** |

| | | | |
|---|---|---|---|
| | (0.126) | (0.127) | (0.126) |
| d_company_sector9 | -0.0912* | -0.0863* | -0.0731 |
| | (0.0488) | (0.0495) | (0.0492) |
| d_company_sector10 | -0.00308 | -0.00181 | 0.00285 |
| | (0.0797) | (0.0782) | (0.0772) |
| d_company_sector11 | -0.122* | -0.121* | -0.127* |
| | (0.0712) | (0.0717) | (0.0728) |
| d_company_sector12 | 0.0162 | 0.0124 | 0.0184 |
| | (0.0539) | (0.0535) | (0.0536) |
| d_company_sector13 | -0.134** | -0.134** | -0.130** |
| | (0.0568) | (0.0568) | (0.0567) |
| d_company_sector14 | -0.116* | -0.114* | -0.108* |
| | (0.0641) | (0.0636) | (0.0639) |
| d_company_sector15 | -0.103* | -0.100* | -0.0924 |
| | (0.0568) | (0.0565) | (0.0571) |
| d_company_sector16 | -0.0141 | -0.00823 | -0.00472 |
| | (0.0711) | (0.0719) | (0.0721) |
| d_company_sector17 | 0.0158 | 0.0156 | 0.0248 |
| | (0.0552) | (0.0545) | (0.0562) |
| d_company_sector19 | 0.0415 | 0.0436 | 0.0493 |
| | (0.0651) | (0.0655) | (0.0666) |
| d_company_sector20 | -0.151** | -0.153** | -0.161** |
| | (0.0622) | (0.0628) | (0.0631) |
| d_company_sector21 | -0.153** | -0.149** | -0.146** |
| | (0.0653) | (0.0655) | (0.0661) |
| d_company_sector22 | 0.268** | 0.255* | 0.249 |
| | (0.129) | (0.154) | (0.153) |
| prov_mark | | 0.154* | 0.172** |
| | | (0.0797) | (0.0801) |
| degree_class | | 0.0150 | 0.0143 |
| | | (0.0133) | (0.0133) |
| ontime_grad | | 0.0120 | 0.0150 |
| | | (0.0241) | (0.0242) |
| adv | | | 0.0544 |
| | | | (0.0348) |
| dis | | | 0.00521 |
| | | | (0.0288) |
| financial_aid | | | -0.0772** |
| | | | (0.0283) |
| _cons | 6.505*** | 6.277*** | 6.261*** |
| | (0.127) | (0.147) | (0.151) |
| r2 | 0.5000 | 0.5032 | 0.5078 |
| N | 1623 | 1623 | 1613 |
| vce | robust | robust | robust |

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

*5.2: Random effects interval regression*

| | logincome |
|---|---|
| ever_erasmus | 0.0742** |
| | (0.0304) |
| std_working | 0.0791*** |
| | (0.0263) |
| postdegree_appr | 0.0706** |
| | (0.0301) |
| profile_appr | 0.000404 |
| | (0.0255) |
| experience | 0.0191*** |
| | (0.00572) |
| experience_sq | -0.000207*** |
| | (0.0000674) |
| prov_mark | 0.166** |
| | (0.0739) |
| female | -0.0414* |
| | (0.0236) |
| phd | 0.0630 |
| | (0.0923) |
| master_it | 0.0161 |
| | (0.0295) |
| postdegree_internship | 0.0183 |
| | (0.0228) |
| ontime_grad | 0.0119 |
| | (0.0228) |
| degree_class | 0.0149 |
| | (0.0128) |
| over_ed | -0.0681** |
| | (0.0267) |
| biology_naturalsciences | 0.222** |
| | (0.0888) |
| chemistry_pharmacy | 0.378*** |
| | (0.0951) |
| economics_business_finance | 0.292*** |
| | (0.0883) |
| engineering | 0.362*** |
| | (0.100) |
| humanities | 0.0726 |
| | (0.0873) |
| law | 0.0875 |
| | (0.0928) |
| linguistics | 0.176* |
| | (0.0971) |
| mathematics_sciences | 0.195 |
| | (0.127) |

| | |
|---|---|
| medicine | 0.349*** |
| | (0.0950) |
| sociopolitical_studies | 0.230*** |
| | (0.0852) |
| part_time | -0.481*** |
| | (0.0253) |
| public_sector | 0.0470 |
| | (0.0341) |
| perm_contract | 0.127*** |
| | (0.0219) |
| south | -0.125*** |
| | (0.0420) |
| islands | -0.0426 |
| | (0.0687) |
| north_east | 0.114** |
| | (0.0459) |
| north_west | 0.119*** |
| | (0.0329) |
| north_res | -0.0740 |
| | (0.0531) |
| south_res | 0.0141 |
| | (0.0305) |
| island_res | -0.0142 |
| | (0.0494) |
| adv | 0.0574* |
| | (0.0314) |
| dis | 0.00600 |
| | (0.0276) |
| financial_aid | -0.0757*** |
| | (0.0277) |
| 2013.year | -0.140** |
| | (0.0600) |
| 2015.year | -0.0293 |
| | (0.0695) |
| _cons | 6.296*** |
| | (0.136) |
| sigma_u | |
| _cons | 0.208*** |
| | (0.0123) |
| sigma_e | |
| _cons | 0.272*** |
| | (0.00477) |
| N | 1613 |
| vce | oim |

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

*5.3: full p-score output with balancing property*

The treatment is ever_erasmus

| ever_erasmus | Freq. | Percent | Cum. |
|---|---|---|---|
| 0 | 2967 | 83.11 | 83.11 |
| 1 | 603 | 16.89 | 100.00 |
| Total | 3570 | 100.00 | |

| ever_erasmus | Coefficient | Std. Err. | z | P>\|z\| | [95% Conf. Interval ] | |
|---|---|---|---|---|---|---|
| std_working | 0.630 | 0.167 | 3.760 | 0.000 | 0.302 | 0.958 |
| postdegree_appr | -0.325 | 0.251 | -1.300 | 0.195 | -0.816 | 0.167 |
| profile_appr | 0.476 | 0.178 | 2.680 | 0.007 | 0.127 | 0.825 |
| experience | 0.007 | 0.022 | 0.340 | 0.736 | -0.035 | 0.050 |
| experience_sq | 0.000 | 0.000 | -0.240 | 0.807 | -0.001 | 0.001 |
| prov_mark | 5.678 | 5.358 | 1.060 | 0.289 | -4.824 | 16.180 |
| female | -0.263 | 0.165 | -1.600 | 0.110 | -0.586 | 0.059 |
| postdegree_internship | 0.067 | 0.165 | 0.400 | 0.687 | -0.257 | 0.390 |
| biology_naturalsciences | -0.233 | 0.833 | -0.280 | 0.780 | -1.866 | 1.400 |
| chemistry_pharmacy | -1.462 | 1.040 | -1.410 | 0.160 | -3.500 | 0.577 |
| economics_business_finance | 1.731 | 0.767 | 2.260 | 0.024 | 0.228 | 3.234 |
| engineering | 1.043 | 0.824 | 1.270 | 0.206 | -0.572 | 2.657 |
| humanities | 1.313 | 0.771 | 1.700 | 0.089 | -0.198 | 2.825 |
| linguistics | 2.931 | 0.791 | 3.700 | 0.000 | 1.380 | 4.482 |
| mathematics_sciences | -0.075 | 1.275 | -0.060 | 0.953 | -2.575 | 2.424 |
| medicine | -2.366 | 1.258 | -1.880 | 0.060 | -4.832 | 0.100 |
| law_sociopiticalstudies | 1.214 | 0.760 | 1.600 | 0.110 | -0.276 | 2.703 |
| public_sector | -0.314 | 0.228 | -1.380 | 0.169 | -0.761 | 0.133 |
| perm_contract | -0.284 | 0.175 | -1.620 | 0.105 | -0.627 | 0.059 |
| north_res | 0.383 | 0.307 | 1.250 | 0.212 | -0.218 | 0.984 |
| south_res | 0.279 | 0.192 | 1.450 | 0.146 | -0.098 | 0.656 |
| island_res | 0.941 | 0.244 | 3.850 | 0.000 | 0.462 | 1.420 |
| adv | 0.788 | 0.238 | 3.300 | 0.001 | 0.320 | 1.255 |
| dis | 0.641 | 0.217 | 2.960 | 0.003 | 0.217 | 1.066 |
| financial_aid | 0.272 | 0.185 | 1.470 | 0.141 | -0.090 | 0.633 |
| weighted_regional_highschool | 8.915 | 9.036 | 0.990 | 0.324 | -8.795 | 26.625 |
| weighted_regional_highschool_sq | -6.685 | 3.334 | -2.010 | 0.045 | -13.219 | -0.151 |
| _cons | -11.831 | 3.895 | -3.040 | 0.002 | -19.466 | -4.197 |

Note: the common support option has been selected
The region of common support is [.00619829, .75558358]

Description of the estimated propensity score in region of common support

Estimated propensity score

| | Percentiles | Smallest | | |
|---|---|---|---|---|
| 1% | .0067964 | .0061983 | | |
| 5% | .0096615 | .0062135 | | |
| 10% | .0153996 | .0063794 | Obs | 1516 |
| 25% | .0613336 | .0064779 | Sum of Wgt. | 1516 |

| | | | | |
|---|---|---|---|---|
| 50% | .1492548 | | Mean | .1750995 |
| | | Largest | Std. Dev. | .1422109 |
| 75% | .2472119 | .7254932 | | |
| 90% | .372032 | .7286576 | Variance | .020224 |
| 95% | .4632176 | .7391632 | Skewness | 1.104308 |
| 99% | .6114297 | .7555836 | Kurtosis | 4.134268 |

Step 1: Identification of the optimal number of blocks

The final number of blocks is 5

This number of blocks ensures that the mean propensity score is not different for treated and controls in each block

Step 2: Test of balancing property of the propensity score

**The balancing property is satisfied**

This table shows the inferior bound, the number of treated and the number of controls for each block

| | ever_erasmus | | |
|---|---|---|---|
| Inferior block of p-score | 0 | 1 | Total |
| .0061983 | 525 | 21 | 546 |
| .1 | 370 | 59 | 429 |
| .2 | 291 | 123 | 414 |
| .4 | 51 | 52 | 103 |
| .6 | 8 | 12 | 20 |
| Total | 1245 | 267 | 1,512 |

**Note: the common support option has been selected**

*5.4: IPW*

| | Ipw<br>logincome |
|---|---|
| ATE | |
| r1vs0.ever_erasmus | 0.102*** |
| | (0.0304) |

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

*5.5: Woolridge's 18.1 procedure for earnings*

| | ever_erasmus | logincome |
|---|---|---|
| ratio_numb_going2006_7 | 3.268*** | |
| | (0.807) | |
| ever_erasmus | | 0.227* |
| | | (0.119) |
| std_working | 0.319** | 0.0606** |
| | (0.151) | (0.0300) |
| postdegree_appr | -0.0623 | 0.0735** |
| | (0.176) | (0.0330) |
| profile_appr | 0.215 | -0.0122 |
| | (0.143) | (0.0276) |
| Experience | 0.00240 | 0.0191*** |
| | (0.0196) | (0.00661) |
| experience_sq | -0.0000236 | -0.000204*** |
| | (0.000230) | (0.0000771) |
| prov_mark | -0.153 | 0.161** |
| | (0.402) | (0.0766) |
| Female | -0.240* | -0.0272 |
| | (0.136) | (0.0237) |
| Phd | 0.368 | 0.0637 |
| | (0.440) | (0.0794) |
| master_it | 0.223 | 0.0133 |
| | (0.164) | (0.0345) |
| postdegree_internship | -0.00407 | 0.00910 |
| | (0.116) | (0.0235) |
| ontime_grad | -0.316** | 0.0276 |
| | (0.134) | (0.0239) |
| degree_class | 0.214*** | 0.00923 |
| | (0.0787) | (0.0127) |
| over_ed | 0.330** | -0.0857*** |
| | (0.138) | (0.0298) |
| biology_naturalsciences | 0.669 | 0.224** |
| | (0.658) | (0.112) |
| chemistry_pharmacy | 0.0917 | 0.360*** |
| | (0.750) | (0.113) |
| economics_business_finance | 1.267** | 0.250** |
| | (0.578) | (0.111) |
| Engineering | 1.011 | 0.344*** |
| | (0.644) | (0.113) |
| Humanities | 0.685 | 0.0672 |
| | (0.574) | (0.112) |
| Law | 1.148* | 0.0674 |
| | (0.624) | (0.120) |
| Linguistics | 1.967*** | 0.113 |
| | (0.611) | (0.126) |
| mathematics_sciences | 0.683 | 0.165 |
| | (0.746) | (0.125) |
| Medicine | 0.111 | 0.299** |
| | (0.715) | (0.119) |
| sociopolitical_studies | 0.746 | 0.194* |

| | | |
|---|---|---|
| | (0.565) | (0.107) |
| part_time | -0.0288 | -0.506*** |
| | (0.131) | (0.0313) |
| public_sector | 0.149 | 0.0352 |
| | (0.205) | (0.0419) |
| perm_contract | -0.0672 | 0.158*** |
| | (0.120) | (0.0213) |
| South | -0.131 | -0.119*** |
| | (0.245) | (0.0453) |
| Islands | 0.515 | -0.0332 |
| | (0.349) | (0.0858) |
| north_east | -0.265 | 0.142*** |
| | (0.270) | (0.0470) |
| north_west | -0.139 | 0.112*** |
| | (0.182) | (0.0324) |
| north_res | 0.281 | -0.0976 |
| | (0.286) | (0.0598) |
| south_res | 0.219 | -0.00312 |
| | (0.173) | (0.0295) |
| island_res | 0.217 | -0.0410 |
| | (0.262) | (0.0533) |
| Adv | 0.323* | 0.0503 |
| | (0.189) | (0.0344) |
| Dis | 0.283 | -0.00470 |
| | (0.174) | (0.0278) |
| financial_aid | 0.203 | -0.0775*** |
| | (0.157) | (0.0267) |
| year_2013 | 0.00244 | -0.138* |
| | (0.230) | (0.0732) |
| year_2015 | -0.0244 | -0.0384 |
| | (0.315) | (0.0835) |
| _cons | -3.413*** | 6.345*** |
| | (0.759) | (0.148) |
| Industry Dummies | ✓ | ✓ |
| N | 1680 | 1611 |
| pseudo r2/ r2_a | 0.253 | 0.485 |
| Vce | cluster | cluster |

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

*5.6: Endogeneity Test for Logincome*

| | ever_erasmus | logincome |
|---|---|---|
| ratio_numb_going2006_7 | 0.902*** | |
| | (0.000) | |
| ever_erasmus | | 0.272* |
| | | (0.060) |
| erasmus_res | | -0.201 |
| | | (0.159) |
| std_working | 0.0689* | 0.0561* |
| | (0.051) | (0.060) |
| postdegree_appr | -0.0164 | 0.0727** |
| | (0.542) | (0.028) |
| profile_appr | 0.0339 | -0.0144 |
| | (0.219) | (0.600) |
| experience | -0.000761 | 0.0194*** |
| | (0.852) | (0.003) |
| experience_sq | 0.0000151 | -0.000207*** |
| | (0.750) | (0.007) |
| prov_mark | -0.0561 | 0.157** |
| | (0.459) | (0.040) |
| female | -0.0395 | -0.0243 |
| | (0.126) | (0.310) |
| phd | 0.0682 | 0.0624 |
| | (0.501) | (0.451) |
| master_it | 0.0368 | 0.0127 |
| | (0.256) | (0.711) |
| postdegree_internship | -0.00744 | 0.00961 |
| | (0.788) | (0.678) |
| ontime_grad | -0.0573** | 0.0301 |
| | (0.025) | (0.222) |
| degree_class | 0.0339** | 0.00782 |
| | (0.011) | (0.538) |
| over_ed | 0.0615** | -0.0876*** |
| | (0.049) | (0.004) |
| biology_naturalsciences | 0.215** | 0.222* |
| | (0.037) | (0.052) |
| chemistry_pharmacy | 0.167 | 0.358*** |
| | (0.116) | (0.002) |
| economics_business_finance | 0.316*** | 0.238** |
| | (0.001) | (0.039) |
| engineering | 0.240** | 0.337*** |
| | (0.034) | (0.003) |
| humanities | 0.170* | 0.0616 |
| | (0.067) | (0.590) |
| law | 0.288*** | 0.0640 |

| | | |
|---|---|---|
| | (0.006) | (0.601) |
| linguistics | 0.571*** | 0.0944 |
| | (0.000) | (0.483) |
| mathematics_sciences | 0.184* | 0.143 |
| | (0.088) | (0.265) |
| medicine | 0.209** | 0.294** |
| | (0.028) | (0.016) |
| sociopolitical_studies | 0.212** | 0.185* |
| | (0.017) | (0.093) |
| part_time | -0.00209 | -0.506*** |
| | (0.936) | (0.000) |
| public_sector | 0.0228 | 0.0384 |
| | (0.525) | (0.354) |
| perm_contract | -0.0154 | 0.159*** |
| | (0.514) | (0.000) |
| south | -0.0379 | -0.116*** |
| | (0.427) | (0.009) |
| islands | 0.0833 | -0.0351 |
| | (0.359) | (0.679) |
| north_east | -0.0492 | 0.145*** |
| | (0.368) | (0.002) |
| north_west | -0.0324 | 0.113*** |
| | (0.479) | (0.000) |
| north_res | 0.0664 | -0.0998 |
| | (0.342) | (0.101) |
| south_res | 0.0444 | -0.00415 |
| | (0.240) | (0.887) |
| island_res | 0.0704 | -0.0451 |
| | (0.284) | (0.384) |
| adv | 0.0620* | 0.0456 |
| | (0.055) | (0.190) |
| dis | 0.0510* | -0.00763 |
| | (0.073) | (0.784) |
| financial_aid | 0.0442 | -0.0810*** |
| | (0.184) | (0.003) |
| year_2013 | 0.00636 | -0.142* |
| | (0.897) | (0.051) |
| year_2015 | -0.00979 | -0.0410 |
| | (0.882) | (0.621) |
| _cons | -0.291** | 6.353*** |
| | (0.023) | (0.000) |
| N | 1682 | 1613 |
| r2_a | 0.183 | 0.494 |
| Vce | cluster | cluster |

p-values in parentheses
* p<0.1, ** p<0.05, *** p<0.01

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