The whether and where of graduate migration: Higher education graduates' mobility determinants and the role of higher education as a retention factor.

WORKING PAPER

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1. Introduction

The spatial distribution of human capital is a central concern of regional science. Skilled workers are not evenly distributed across space and can cluster in ways that reinforce regional disparities. They tend to concentrate in metropolitan areas, while peripheral regions struggle to attract and retain graduate workers. As these workers are crucial for productivity growth and economic diversification, understanding the mechanisms behind their spatial distribution is essential for regional policy.

Graduate migration occupies a privileged position in this literature. Higher educated workers are more mobile than the general population, and especially so at the moment of labour market entry. As such, they can be consequential for regional economic development, potentially fuelling or counteracting existing patterns of human capital distribution.

Yet, despite some research interest, an important question remains underexplored: to what extent does Higher Education Institutions' (HEIs) location determine where a graduate ends up working? If HEIs location generates genuine retention effects — independently of regional wage premia and labour market thickness — then investment in peripheral HEIs may be an effective instrument for addressing spatial imbalances in human capital accumulation. Conversely, if the apparent retention effect of peripheral HEIs simply reflects pre-existing characteristics of their student bodies, the policy case is much weaker. Distinguishing between these two interpretations is a key empirical challenge. Therefore, this is a particularly urgent question for peripheral regions.

Our study seeks empirical evidence on the determinants of intranational graduate mobility, using comprehensive survey data on recent higher education graduates in Portugal. The Portuguese case is a compelling one to look at given the country's regional imbalances, with labour market opportunities are heavily concentrated in the two main metropolitan areas – Lisbon and Porto. This has even led to regional policy featuring as a concern of some importance in higher education policy, namely in the distribution of available study places across public HEIs.

Therefore, we pose two related research questions. First, RQ1, to what extent are individual or regional characteristics significant in determining a graduate's job location? Second, RQ2, regarding the importance of a graduate's tie to the region in which they studied in HE: how does the chance of a graduate becoming employed in the region vary depending on where they studied?

To address these research questions, we resort to the Portuguese version of the Eurograduate dataset, which contains rich sociodemographic, educational, and employment information on Portuguese graduates. The 2022 survey was targeted at graduates 1 and 5 years after degree completion, and gathered a sizeable and representative sample. We first estimate the determinants of *whether* the graduate remains for employment in their study region through a binary logit model. We then address *where* the graduate is employed, through a conditional logit model where each option is a NUTS III region, aimed at assessing the extent to which the study link determines graduate mobility across regions.

We concluded that being a local student is the primary characteristic leading graduates to stay in the same region. Other significant characteristics for retention include having higher grades in higher education. After separating the analysis between local and non-local students we conclude that for local students, individual characteristics such as age, stronger higher education grades, being a female and graduating from a ISCED 5 formation all contribute for a higher retention probability. For non-local students, only a higher GPA in higher education and graduation from a university are relevant.

We also find that being a local and attending HEI in a region significantly increases the probability of a person being employed in that region, both when considering the joint and the separate effects of those ties. While the base probability for being employed in a peripheral region is 0.5-1%, HEI attendance increases that probability twenty-fold, translating to a 16 p.p. increase on average. For graduates who originated from the region, whose base probability for being employed there is around 30%, HEI attendance increases that probability by 28 p.p. on average.

The paper is structured as follows. Section 2 discusses the theoretical background to our analysis and reviews the relevant literature. Section 3 presents our dataset and a descriptive analysis of graduate mobility in Portugal. Section 4 specifies our modelling approach of the *whether* and *where* of graduate mobility and section 5 presents its results. Section 6 builds on the *where* model results with an in-sample predictive analysis of each region's graduate retention rate. Section 7 concludes.

2. Theoretical background and literature review

Local social networks are known to be crucial for job search and matching (Cingano & Rosolia, 2012). Higher studies may enable graduates to form relationships with peers, academic staff and local employees and employers – place-based social capital, formed in a specific institution/region. In so far as this can provide them with locally specific knowledge, graduates may learn about local employers and sectoral opportunities during their studies in ways that are difficult to replicate from a distance. Drawing on Sjaastad's (1962) human capital framework of migration, this reduces the effective cost of job search in the study region relative to elsewhere, since informational barriers are lower. Additionally, other personal costs, such as place attachment or personal relationships formed, may also come into consideration and deter graduates from moving from their study region.

Crucially, however, these arguments can also be made to some extent for a graduate's tie with their origin region – where they went to school before university. For many, the two regions coincide, which can confound the relative importance of each. It may also be the case that the tie effects are not additive, such that graduates who have moved to attend university stand to gain from having significant knowledge of two regions, unlike their peers who stayed in place.

Empirical analysis of graduate mobility requires a methodological approach that is mindful of these theoretical considerations. The main motivation for research on graduate mobility has been the role that HEIs can have on regional development. There is extensive literature on the subject that has highlighted that this role can be limited due to the job mobility of graduates, who do not necessarily have to work in the same place that they graduated from. Indeed, understanding the job location choice of higher education graduates is therefore very relevant, and assessing what the determinants are can help regional policy in improving the effect of HEIs in the territory. This is because the share of graduates staying in the same region as their higher education studies is highly variable (Krabel and Flother, 2014), This can be especially true for peripheral regions, where job opportunities, amenities, and social capital opportunities might be lower and be an important explanatory factor for lower retention, or may provide lower matching opportunities after graduation (Rehak and Eriksson, 2018). Higher education graduates are a particularly mobile group, since they have job opportunities beyond regional borders, and have higher propensity to move (Haussen and Uebelmesser, 2018).

Regarding the determinants of graduates' job location choice, the literature generally distinguishes them between individual-level determinants, which relate to the characteristics of the graduates, including previous mobility trajectories; and regional-level determinants, related to the economic capacities of regions to retain or attract graduates. This division is the classification used in RQ1.

For graduates' characteristics, an important set of determinants emerge. The work from Bjerke and Mellander (2017) assesses, for Sweden, whether graduates returned to their home region, or either migrated to a rural or urban region 5 and 10 years after their graduation. They have identified older graduates and graduates with children are more likely to return to their home region, while graduates with immigrant backgrounds and longer university educations are more likely to locate in urban regions. For Italian graduates, Fini et al. (2022) establish that having previous university mobility increases the likelihood of moving after graduation. Haussen and Uebelmesser (2018) share this result for German graduates during the first five years after graduation, while they identified married graduates and with children are less prone to move. Krabel and Flother (2014) also identify that the occurrence of a previous movement between school and HEI enhances the probability of job movement outside of the HEI region, but so does international mobility carried during the studies. They also add to the discussion by finding that students with lower grades are more prone to move. Parental education, especially if both parents are highly educated, is also more likely to higher migration, an effect also identified by Ahlin et al. (2018) for Swedish graduates, albeit more relevant for movements between school and HEI than between HEI and job. Gender is also a relevant variable in these contexts, but with mixed outcomes. For university graduates in Shanghai, Yu et al. (2025) identify female graduates return more often to their home region, while Rehak and Eriksson (2020) found the opposing effect for Swedish graduates one year after graduation.

Regarding regional variables as the second major set of determinants, the literature suggests that graduates are more likely to remain in, or move towards, regions with thicker labour markets and more suitable employment opportunities. Oggenfuss and Wolter (2019), for Switzerland's cantons, discuss how tax levels affect mobility, with higher tax levels reducing return mobility and increasing mobility after studying in those regions. In the same context, and on the other hand, GDP per capita seems to affect only the retention of those who studied in the same region. Haussen and Uebelmesser (2018) point out that higher unemployment in HEI regions increases out-migration, and a higher share of large firms reduces out-migration. Another determinant of the economic strength of regions is identified in Buenstrof et al. (2016), where better employment opportunities and higher wage levels increase the probability of choice of region for German graduates. In the work of Fini et al. (2022), regional variables are found to be stronger determinants of mobility than individual determinants. Rehák and Eriksson (2020) address particularly the question of regional HEI policy, for the Swedish example, sustaining that lower outward mobility from the study region can be attained if there is an increase in the quality of the match between education and regional labour markets.

Beyond economic and labour market strength, regional amenities also play a role. For graduates from Chinese "first-class" universities, Cui et al. (2022) find that, in addition to wages and employment levels, other characteristics (e.g., cinemas, public transport, innovation) and amenities (e.g., temperature, inclusiveness) are positively correlated with inflows. Other amenities, such as improved air quality, positively affect graduates' decisions to leave the Shanghai region (Yu et al., 2025).

Besides these individual and regional characteristics, there is one determinant that deserves separate attention, reflecting the link of individuals graduating to a particular region – the one where they attended HE – since it is a place where graduates have already accumulated information, familiarity and possible social or professional ties. Buenstorf et al. (2016), for German graduates, show that the university region has a strong independent effect on job location choice in that region, and a small effect on adjacent regions, suggesting universities can influence regional human-capital retention. Fidjeland et al. (2026) provide further evidence, for HE graduates in Norway, of the role of studying in a given region in increasing odds of working there, which the authors call "stickiness". That effect persists even after removing the three largest regions of the country and can be observed up to 7 years after leaving higher education. In the case of graduates in Belgium, Imeraj et al. (2018), even though focusing on residence location rather than job location, discuss the role of location-specific capital, such as local social or cultural knowledge, in settling in the same place as HE studies. Distance to HEI is a variable that strongly reduces attraction for future residence location.

The HEI region may also matter because it is part of a sorting process that occurs before graduates enter the labour market. That is precisely the main point of Ahlin et al. (2018), who study both transitions (from secondary school to higher education and then for higher education to the labour market) and conclude that the sorting of the most high-ability graduates happens at the choice of study location, not at the job location. As the job location effect is mainly driven by job characteristics, the authors find that excluding Stockholm – the capital region – leads the job location effect to be non-significant. Oggenfuss and Wolter (2019) show that those that were forced to change region to study in Higher Education, given there were no universities in the local region, have less likelihood of working to the home region than those that already studied in the home region, suggesting that student mobility induces graduate mobility; quoting, "In essence, students who left their canton of origin for the purpose of studying, independent of their motivation, have a lower probability to live in their canton of origin five years after graduation compared to students who studied in their canton of origin." (Oggenfuss and Wolter, 2019, p. 204)

This is the motivation for our second research question, as the region of study can be a distinct explanatory factor when analysing graduates' job location. Since, according to the literature, studying in a given region increases their probability of graduates to become employed there, even after accounting for individual characteristics and regional conditions.

However, the anchoring role of the study region may not operate in the same way for all graduates. In particular, graduates who were already local before entering HE and those who moved to the region to study may have different forms of attachment to the HEI region. For local graduates, employment in the study region may reflect both pre-existing family, social and territorial ties and educational continuity. For non-local graduates, remaining in the HEI region after graduation may indicate that the study period created new forms of attachment to the region, and it is therefore important to disentangle both effects.

In this sense, this argument is explored particularly by Rehák and Eriksson (2020), where the difference between local and non-local graduates is explicitly explored and is significant. Non-local and local graduates' behaviour differs, as non-local graduates are much more likely to migrate after graduation. The authors also discuss that graduating from a more prestigious university reduces the difference in retention between local and non-local graduates, but local graduates increase their out-migration. This distinction is directly relevant for the present study. We use graduates' local or non-local status to assess whether the association between the HEI region and employment location differs according to prior territorial attachment.

These determinants and results can be linked directly to the results of regional policy, which is not necessarily related to higher education policy. It is clear from Rehák and Eriksson (2020) that the location of HEI alone is not enough to retain the graduates in the place they studied, especially for those that are non-local to the region, and that regional absorption capacity seems to be the primary route for HE graduates retention (Krabel and Flother, 2014; Haussen and Uebelmesser; 2018). In their work, Cui et al., 2022 identify a specific talent policy destined to retain graduates for second-tier cities in China, and conclude these had a negative effect on attracting "first-tier" students, while jobs and urban amenities exerted a positive effect.

3. Data

The paper uses data from the EUROGRADUATE 2022 survey, which is a survey shared between 16 countries of the European Education Area. This study uses the Portuguese version of the dataset, as made available by the Directorate-General of Statistics for Education and Science (DGEEC). The target audience of the survey were the graduates of the academic years of 2016/2017 and 2020/2021 for the entire Portuguese HE system (excluding PhDs), with the goal of capturing their educational and labour market characteristics 5 years and 1 year after graduation, respectively. Using a census perspective, the survey was disseminated in late 2022, and 18 280 graduates were considered valid responses, corresponding to a coverage rate of 12.3% of the Portuguese system. This sample was considered representative of the country's graduates (Rodrigues et al., 2024).

Our main sample (N = 5 799) is composed of graduates of the 2020/21 academic year who are employed and for whom we have complete information on the three location variables of interest (see below). We do not include those who graduated in 2016/17 in this sample – the longer elapsed time may mean structurally different mobility behaviour – but analyse them as a separate sample in Table A 4 and Table A 5 of Appendix 4. We also consider a broader 2020/21 sample that includes unemployed graduates (N = 6 833).

The dataset provides a rich set of variables to study graduate mobility. For our individual-level modelling of graduate migration, we rely on sociodemographic variables (age, gender, GPA) and on educational experience (degree and HEI characteristics). Table 1 presents descriptive statistics for these variables in our sample, also divided by local/non-local status during HE. All variables are self-explanatory. We note that for both entry and degree GPA, the Portuguese grading system varies between 0 and 20, with all observations holding grades between 9.5 and 20 since these correspond to approved students. For degree fields, we present here a summary statistic for STEM/non-STEM, built from the 20 field classifications present in Eurograduate, which are fully detailed in Appendix 1.

Table 1 – Sample descriptive statistics

Variable	All	Local	Non-Local
N	5799	3072	2727
Age	27.3 (7.6)	27.5 (7.9)	27.0 (7.2)
Entry GPA	15.4 (1.9)	15.3 (1.9)	15.4 (2.0)
Degree GPA	15.1 (1.7)	15.1 (1.7)	15.1 (1.7)
Gender:			
Male	2113 (36.4%)	1160 (37.8%)	953 (34.9%)
Female	3661 (63.1%)	1902 (61.9%)	1759 (64.5%)
Non-binary or other	25 (0.4%)	10 (0.3%)	15 (0.6%)
Degree level:			
Short-cycle	179 (3.1%)	100 (3.3%)	79 (2.9%)
Bachelor	3234 (55.8%)	1779 (57.9%)	1455 (53.4%)
Master	1760 (30.4%)	921 (30.0%)	839 (30.8%)
Integrated Master	626 (10.8%)	272 (8.9%)	354 (13.0%)
Degree field*:			
Non-STEM	4529 (78.1%)	2399 (78.1%)	2130 (78.1%)

Variable	All	Local	Non-Local
STEM	1270 (21.9%)	673 (21.9%)	597 (21.9%)
HEI type:			
University	2377 (41.0%)	1312 (42.7%)	1065 (39.1%)
Polytechnic	3422 (59.0%)	1760 (57.3%)	1662 (60.9%)
HEI sector:			
Public	4511 (77.8%)	2256 (73.4%)	2255 (82.7%)
Private	1288 (22.2%)	816 (26.6%)	472 (17.3%)

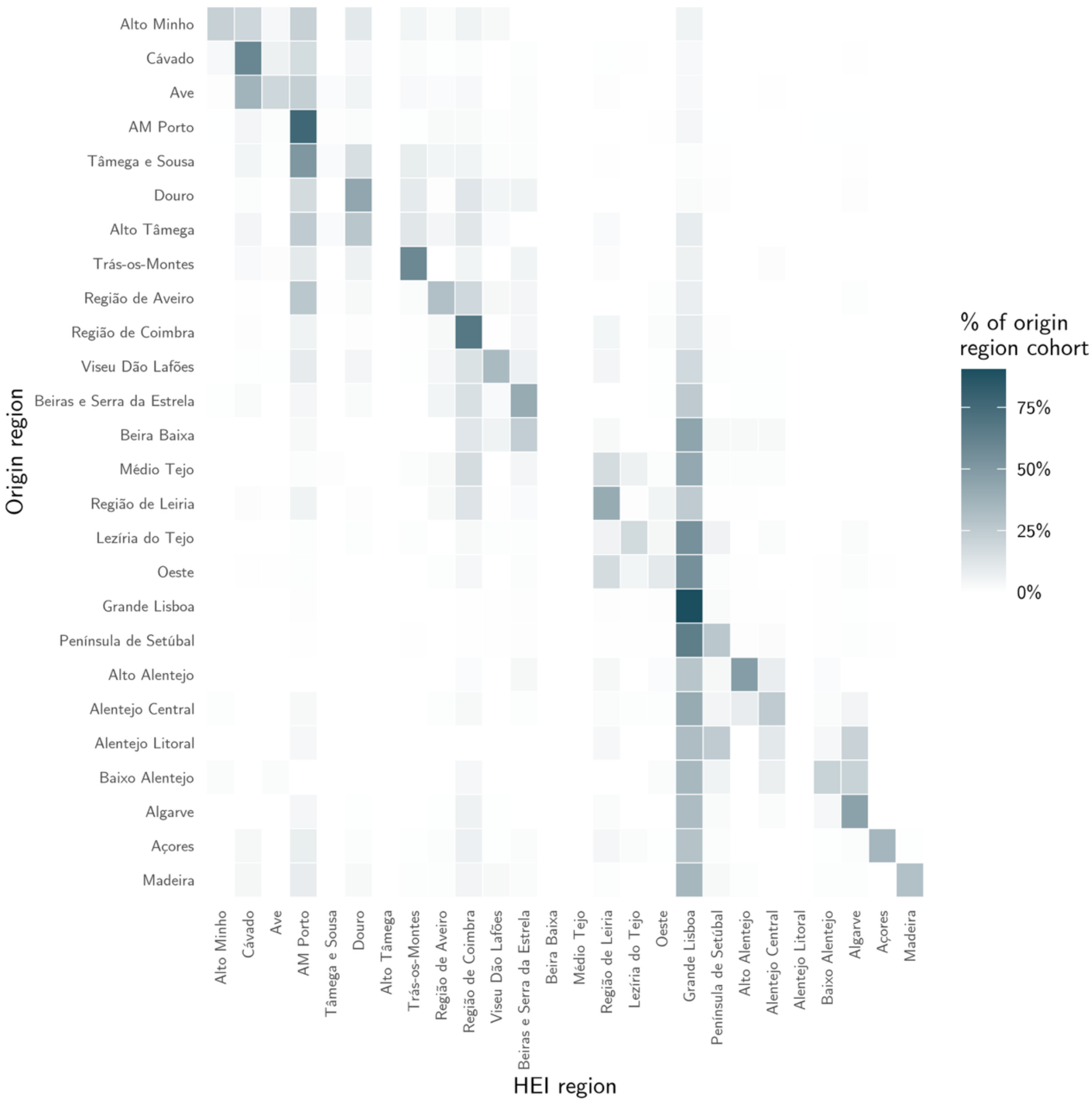
Continuous variables: mean (SD); categorical variables: N (%).

*Degree field: We consider 20 fields, fully detailed in Appendix 1.

Our portrayal of graduate mobility rests on three locational variables we collect for each graduate: the location of their school prior to entry to HEI, which we denote as the origin region; the location of the HEI they attended, denoted as the study region; and their main job location after graduation (denoted as the employment region). These variables are defined at the NUTS III level (26 regions, average population of 439 000), which is adequate in terms of both tractability and congruence with the usual framework of regional policy.

We now present a brief description of mobility patterns before and after HE in Portugal, as captured by our sample of 2020/21 graduates. Beginning with origin-study mobility, we find that 53% of individuals attended HE in their origin region. Figure 1 presents the mobility matrix between regions, where each tile's colour denotes the share of individuals from the origin region (left axis) who attend HE in each region (bottom axis) – the tiles add up to 100% horizontally. The regions are roughly ordered north to south.

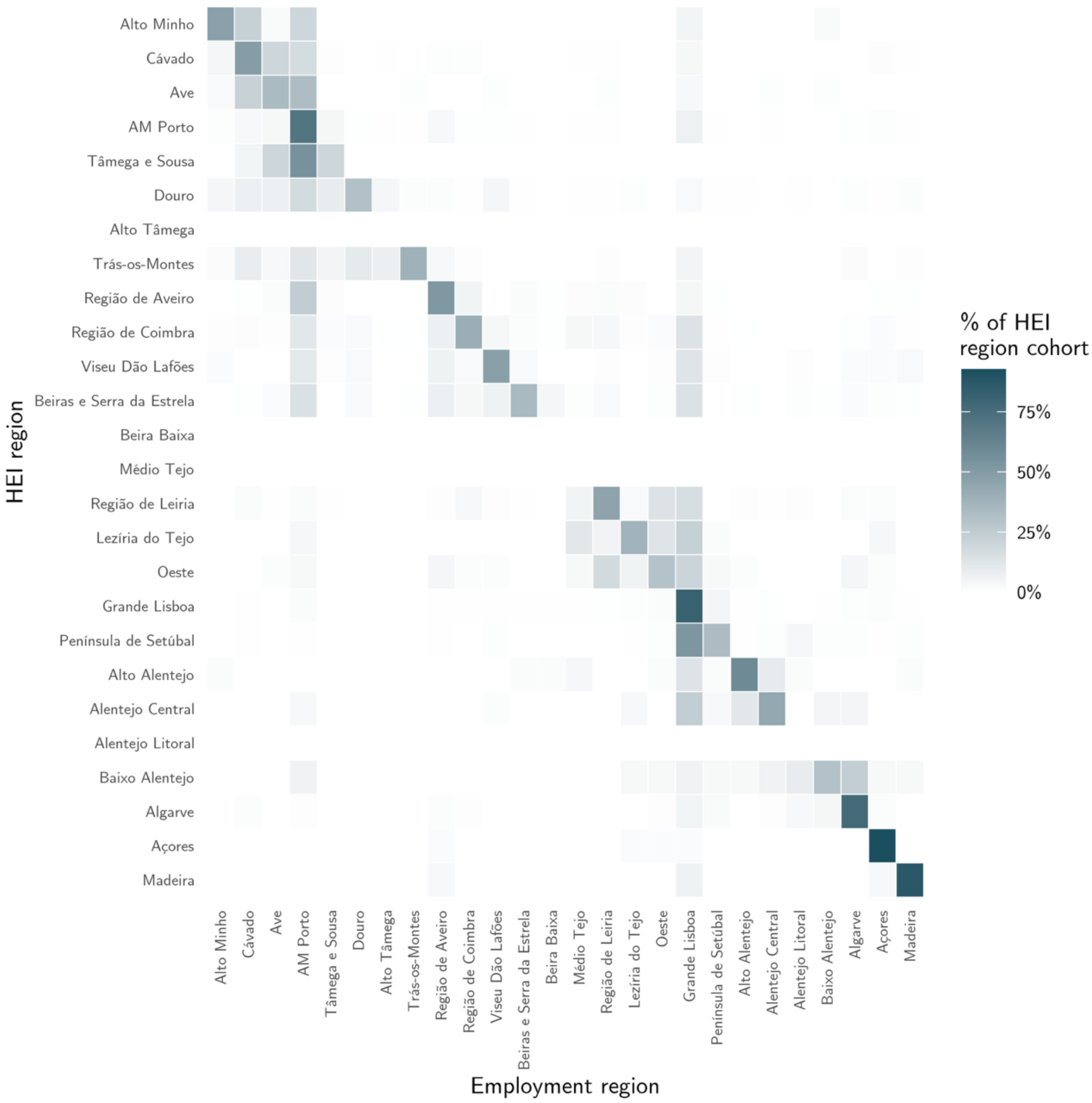
Figure 1 – Mobility matrix from origin to HEI



The diagonal line that can be made out from top left to bottom right evidences the pattern for students to remain in their origin region to attend HE. Along that line, we can make out the two regions with the highest level of retention (the two darkest tiles in the matrix), which correspond to the two largest urban areas of Portugal: Lisbon (Grande Lisboa, 90.4% of students remain), and Porto (AM Porto, 76.7% of students remain). One can also see a distinct attraction of students to these two main centres, by looking at the tiles along the vertical lines that correspond to these two regions. These vertical lines also reveal that the attraction is stronger if the migration region is closer. These data underscore the overarching importance of these urban centres within the Portuguese HE system.

Figure 2 presents the mobility matrix between regions for the flows after graduation, where each tile's colour denotes the share of individuals from the HEI region (left axis) that are employed in each region (bottom axis),

Figure 2 – Mobility matrix from HEI to employment



The tendency for retention is slightly stronger here, in line with the argument of Ahlin et al (2018) – overall, 63% of the graduates in our sample are employed in their HEI region. Dividing by local/non-local status, 40% of students who were non-local stay in the HEI region, while 83% of local students stay. Again, the largest urban areas show strong attraction effects: they keep most of their graduates, as they do not seem to shed the ones they attracted before back to their origin regions; in addition, they manage to attract more graduates from other regions (vertical lines). An interesting result is also in the autonomous island territories of Madeira and Azores, where outward migration occurs for studying (Figure 1), but there is strong retention of their own graduates for labour market purposes (Figure 2).

These preliminary findings suggest that the two main determinants of graduate migration are geographical links – as evidenced by the high regional retention percentages at each stage of mobility – and the baseline attractivity of the regions – as evidenced by the flows to the main urban areas.

4. Model specification

Our methodology examines the *whether* and *where* of graduate migration through two separate models. The first model predicts whether a graduate remains in their study region after graduation. We estimate a binary logit where the probability of individual i staying at that region is given by:

$$logit(P(\text{stay}_i)) = \alpha + \mathbf{X}_i\,\boldsymbol{\gamma} + \delta\,\text{NonLocal}_i + \mathbf{D}_i\,\boldsymbol{\lambda} + \varepsilon_i$$

Where stay_i is a dummy variable with the value 1 whenever the graduate studied in the same region as their HEI, $\mathbf{X}_i$ is a vector of individual characteristics, NonLocal_i is a dummy indicating the graduate's origin region differs from their higher education study region, $\mathbf{D}_i$ is a vector of region dummies capturing region-specific retention determinants and ε_i is an i.i.d. error. $\mathbf{X}_i$ is composed of graduate characteristics, including age, gender, GPA, degree level and field and HEI type and sector, with the corresponding variables being defined as detailed in Table 1. Region fixed effects are used in place of explicit regional covariates (such as wages, unemployment, amenities), as they allow regional heterogeneity to be absorbed without committing to a specific theory of what drives it; besides, such covariates are plausibly endogenous to graduate flows themselves. Similarly to Rehak and Eriksson (2020), we then estimate this model by separating the sample between students who had previously moved to study in HE, in order to assess whether the determinants of regional retention are different between these groups. The local/non-local distinction may also control for graduates' propensity to move, such that effects we uncover in the local sample may simply reflect pre-existing graduate characteristics, while effects we uncover in the non-local sample reflect actual effects of HE.

The second model predicts where the graduate migrates to and is designed to capture the strength of the origin and study tie effects. Similarly to Buenstorf et al. (2016), we estimate a conditional logit in which each graduate faces a choice among all 26 NUTS III Portuguese regions. The utility of individual i working in region j is:

$$u_{ij} = \alpha_j + \beta_1\,\text{Origin}_{ij} + \beta_2\,\text{Study}_{ij} + \beta_3\,\text{Both}_{ij} + \varepsilon_{ij}$$

Where u_{ij} is a variable that has value 1 if the graduate studies in region i and has its main employment in region j, α_j denotes region fixed effects capturing region-specific attraction rates, and the tie dummies are mutually exclusive categories: Origin_{ij} equals one if region j is the graduate's origin region but not their study region; Study_{ij} equal one if j is the study region but not the origin region; and Both_{ij} equals one if j is both. The reference category is regions with no tie to individual i. The mutually exclusive specification allows for the possibility that tie effects are not additive. In a subsequent specification, where we extend the sample to unemployed graduates, we model unemployment as if it were an additional 'option' alongside the 26 regions.

5. Model results

5.1. The whether model

Table 2 presents regression results of the first model, which predicts whether a graduate is employed in their study region after graduation. The first specification (1) is estimated without accounting for graduates' origin region or region effects, where it can be that just individual characteristics lead to very poor model fit. Adding local/non-local status in column (2) and region effects in (3) brings a sizable improvement in model fit and attests the very high significance of regional links to describing graduate mobility. From the results of column (3), we see that individual characteristics such as gender and entry GPA are not significant for staying, while the degree GPA appears to be very relevant, with students who fared better in their HE studies being more likely to stay. On the other hand, degree characteristics are significant as master graduates are more likely to leave than bachelor graduates. Due to the 20 fields considered in the estimation, we present their respective coefficients in Table A 2 of Appendix 2, where we detect an overall tendency for STEM graduates to remain in their regions, more so than their non-STEM peers.

Table 2 – *Whether* model results

	(1)	(2)	(3)	(4a)	(4b)
Sample	All	All	All	Local	Non-local
Region effects	No	No	Yes	Yes	Yes
Non-local		-2.078** (0.066)	-2.162** (0.073)		
Age	0.009* (0.004)	0.006 (0.005)	0.011* (0.005)	0.016* (0.008)	0.012 (0.007)
Gender: female	0.026 (0.064)	0.077 (0.072)	0.125 (0.077)	0.293* (0.120)	-0.039 (0.104)
Gender: non-binary	-0.018 (0.433)	0.180 (0.478)	-0.030 (0.502)	0.685 (1.108)	-0.432 (0.635)
Entry GPA	0.057** (0.016)	0.058** (0.018)	0.010 (0.020)	-0.036 (0.031)	0.042 (0.027)
Degree GPA	0.087** (0.021)	0.101** (0.024)	0.093** (0.026)	0.102* (0.040)	0.108** (0.035)
Level: Short-cycle	-0.009 (0.172)	0.020 (0.193)	0.335 (0.208)	0.977** (0.341)	-0.357 (0.320)

	(1)	(2)	(3)	(4a)	(4b)
Level: Master	-0.106 (0.084)	-0.054 (0.094)	-0.210* (0.102)	-0.223 (0.162)	-0.229 (0.137)
Level: Integrated master	-0.483** (0.133)	-0.393** (0.148)	-0.212 (0.164)	-0.215 (0.257)	-0.369 (0.211)
HEI type: University	0.370** (0.077)	0.540** (0.086)	0.175 (0.103)	-0.132 (0.166)	0.354* (0.139)
HEI sector: Private	0.292** (0.077)	0.021 (0.086)	-0.172 (0.101)	-0.026 (0.163)	-0.258 (0.136)
N	5654	5654	5654	2980	2674
Log likelihood	-3623.1	-3040.2	-2683.8	-1152.1	-1458.6
McFadden R^2	0.027	0.184	0.279	0.133	0.189

* $p < 0.05$, ** $p < 0.01$

N = 5654 lower than the main N = 5799 sample due to missing values.

The largest effect of all appears to be regional, as non-local students, i.e. students who left home to attend university, are much more likely to leave after graduation. In columns (4a) and (4b) we examine the possibility that non-local students may differ structurally from local students by estimating the model separately for these two groups. The regression results are consistent with this hypothesis that the local/non-local distinction may control for graduates' propensity to move: we find that age, gender and attending a short-cycle degree are significant factors for local graduates remaining but not for non-local graduates; university graduates are more likely to stay than polytechnic graduates in the non-local sample, but no significant effects emerge in the local sample. Degree GPA is significant for both samples, which is consistent with it reflecting both graduate performance as well as degree/HEI specificities.

As a whole, these results suggest that geographical links and regional attractivity (even if not explicitly modelled) are the two main explanatory factors, in line with our prior descriptive analysis of graduate mobility, while graduates' individual characteristics play a smaller and more focalised role. As such, we turn to the *where* model as our main predictive model of graduate mobility, with its more distinctly spatial structure.

5.2. The where model

Column (1) of Table 3 presents estimation results of the *where* model, which predicts in which region a graduate is employed after graduation. Both origin and study ties exert a significant positive effect on the probability of working in a given region, even after controlling for the baseline attractiveness captured by the region effects, although the origin tie is larger than the study tie. The combined effect of having both ties in the same region is less than the sum of the two individual effects, consistent with the two mechanisms being substitutes in anchoring graduates to a location: one strong tie appears sufficient, and a second tie to the same place adds less at the margin.

Table 3 – *Where* model results

	(1)	(2a)	(2b)	(3a)	(3b)	(4)
Sample	All	STEM	Non-STEM	Bachelor + SC	Master	All + Unempl.
Origin	3.800**	3.466**	3.890**	4.012**	3.549**	3.790**
	(0.056)	(0.132)	(0.063)	(0.076)	(0.084)	(0.051)
Study	2.963**	3.216**	2.947**	3.042**	2.868**	3.062**
	(0.059)	(0.124)	(0.069)	(0.081)	(0.088)	(0.055)
Both	4.212**	3.997**	4.357**	4.382**	3.975**	4.055**
	(0.055)	(0.118)	(0.064)	(0.072)	(0.087)	(0.047)
N	5799	1270	4529	3413	2386	6833
Log likelihood	-6618.0	-1460.7	-5042.7	-3649.2	-2933.0	-9593.3
McFadden R^2	0.514	0.478	0.531	0.552	0.459	0.419

* $p < 0.05$, ** $p < 0.01$

Table 3 also expands on the robustness of the *where* model. First, we show that the exclusion of individual characteristics is not a major source of bias for the latter's results. We partition the samples along STEM/non-STEM graduates in columns (2a) and (2b) and along bachelor/master graduates in columns (3a) and (3b) and show that the estimated retention effects are very similar across specifications.

Furthermore, in column (4) we perform a further robustness check by assessing whether the retention effect may be upward biased by the fact that we are considering only graduates who have found employment. It is precisely the graduates who have a longer-standing unobserved connection to the region that may have a greater chance of securing employment there after graduation, therefore confounding the estimated effects. This requires an extension in sample – from N = 5 799 to N = 6 833 – and in methodology – we consider unemployment an additional alternative in the conditional logit, acting as an outside option. We find that the retention effects remain largely unchanged. Table A 3 of Appendix 3 presents the baseline attractivity for each region, based on the same regression structure.

6. Model predictions

Given the logit model structure, the ties we have estimated express the log-odds ratio between a pair of alternative regions which differ only by that tie. That is, using the full sample, for the Study tie (2.963), we estimate that a graduate is $e^{2.963} = 19.3$ times more likely to be employed in the region if they attended HE there than if they had no tie to the region at all. Though this is a large effect in relative terms, in absolute terms it may be small, since the base probability of a graduate being employed in a region to which they have no ties is very small, and even more so if it's a peripheral region. A similar calculation applies for the $Both$ tie (4.212). Meanwhile, the interpretation of the effect of studying in HE conditional on having attended school there ($Origin$ -> $Both$) cannot be gleaned directly from its coefficients as effects range across more than one region.

To assess whether the retention effects are of significant magnitude, we use the *where* model to compute in-sample predictions of the probabilities of graduates choosing each region for each of the four possible tie situations. The results are presented in Table 4, along with bootstrapped confidence intervals at 95% (1 000 runs).

It can be seen that the no-tie probabilities are very small for practically all regions (<1%). The effect of HE attendance on graduates who were not originally from the region can be gleaned by comparing the No tie with the Study tie probabilities. For peripheral regions, the average estimated effect is a 16 p.p. increase in the probability of being employed in the region after graduation. As for graduates who were already from the region, the retention effect can be gleaned by comparing the Origin tie with the Both ties probabilities, with the average estimated effect being a 28 p.p. increase for peripheral regions.

Table 4 – Predicted probabilities of being employed in each region

Region	No tie (%)	Study tie (%)	Origin tie (%)	Both ties (%)
Alto Minho	0.5 [0.4, 0.6]	13.1 [10.3, 17.2]	32.6 [26.7, 38.9]	60.6 [53.3, 67.4]
Cávado	1.0 [0.8, 1.2]	23.5 [20.3, 26.9]	48.8 [44.3, 53.1]	77.2 [73.8, 79.9]
Ave	0.9 [0.8, 1.1]	20.9 [17.5, 24.7]	49.2 [44.2, 53.9]	76.1 [71.4, 80.0]
AM Porto	**2.6 [2.3, 3.0]**	**48.6 [45.4, 51.7]**	**71.9 [69.0, 74.6]**	**89.9 [88.5, 91.0]**
Tâmega e Sousa	0.5 [0.4, 0.6]	10.9 [8.6, 13.9]	33.1 [28.2, 38.1]	62.3 [56.4, 67.9]
Douro	0.4 [0.3, 0.5]	13.7 [11.1, 17.0]	32.6 [27.1, 38.2]	58.0 [51.7, 63.6]
Trás-os-Montes	0.3 [0.2, 0.4]	11.3 [8.3, 15.0]	25.4 [20.1, 31.3]	51.7 [43.6, 59.2]
Algarve	0.9 [0.8, 1.2]	27.2 [22.9, 31.5]	38.8 [34.3, 43.5]	76.5 [72.2, 80.4]

Region	No tie (%)	Study tie (%)	Origin tie (%)	Both ties (%)
Oeste	0.7 [0.6, 0.9]	18.5 [15.4, 22.2]	33.2 [28.8, 37.5]	71.1 [65.6, 75.5]
Região de Aveiro	1.0 [0.9, 1.2]	26.6 [22.6, 30.7]	50.4 [45.6, 54.9]	78.4 [74.4, 81.7]
Região de Coimbra	0.6 [0.5, 0.7]	18.9 [15.9, 21.7]	34.6 [30.3, 38.8]	66.9 [62.7, 70.8]
Região de Leiria	0.6 [0.5, 0.7]	18.6 [15.3, 22.2]	32.1 [27.8, 36.3]	66.1 [60.4, 70.4]
Viseu Dão Lafões	0.5 [0.4, 0.6]	14.6 [11.8, 18.0]	33.0 [28.0, 38.0]	62.7 [56.7, 68.2]
Beiras e Serra da Estrela	0.4 [0.3, 0.5]	12.0 [9.4, 15.0]	24.1 [19.6, 28.7]	55.6 [48.7, 61.7]
Grande Lisboa	**6.8 [6.1, 7.5]**	**69.5 [66.8, 71.6]**	**88.8 [87.0, 90.2]**	**95.7 [95.0, 96.2]**
Península de Setúbal	0.6 [0.5, 0.8]	15.5 [12.8, 18.6]	23.2 [19.9, 27.0]	68.2 [63.3, 72.7]
Baixo Alentejo	0.3 [0.2, 0.4]	7.2 [5.0, 10.4]	18.5 [13.4, 25.1]	46.3 [36.5, 57.0]
Lezíria do Tejo	0.5 [0.4, 0.7]	15.7 [12.4, 19.9]	26.4 [21.5, 31.5]	64.9 [57.0, 71.3]
Alto Alentejo	0.4 [0.3, 0.6]	15.5 [11.6, 20.1]	26.7 [21.4, 32.8]	59.3 [51.4, 67.1]
Alentejo Central	0.4 [0.3, 0.5]	12.6 [9.5, 16.2]	21.9 [17.3, 27.1]	54.8 [46.7, 62.0]
Açores	0.8 [0.7, 1.0]	18.7 [14.8, 22.6]	39.2 [34.3, 44.3]	74.3 [69.0, 78.7]
Madeira	0.4 [0.3, 0.6]	12.9 [9.3, 17.2]	24.7 [19.6, 30.1]	59.5 [51.1, 66.3]

Though the model is robust, we refrain from claiming these estimated effects are causal, for two main reasons. First, individual mobility is itself potentially endogenous to unobserved dispositions that plausibly affect both tie formation and location outcomes. Second, regional choice of employment may be confounded with unobserved social or geographic links, which themselves correlate to both study and employment region. These links may involve, for instance, personal connections to friends and family who live there or a familiarity with the region as a result of frequent visits to access economic or cultural services. Particularly for those graduates with both ties to the same region, the observed outcome may reflect decisions made much earlier — where to attend university, or whether to leave home at all — rather than an active comparison of job opportunities and quality of life across regions at the time of employment.

7. Conclusion

In this article, we addressed the movement patterns from non higher-education to higher education, and subsequently to the labour market, in the context of intranational migration in Portugal using NUTS III regions. In descriptive terms, we identified a stronger stickiness and attraction levels of both students and graduates for the main economic regions in the country (the NUTS III containing Porto and Lisbon), with a relative stronger retention effect between HE and job than between non-HE to HE. There are also important differences in the job movement patterns between those who had previously moved for HE studies than for those who did not.

We pose two related questions. First, to what extent are individual or regional characteristics significant in determining a graduate's job location? Second, regarding the importance of a graduate's tie to the region in which they studied in HE: how does the chance of a graduate becoming employed in the region varies depending on where they studied?

We addressed two research questions. Firstly, we tackled the determinants of the choice of graduates' job location, namely the determinants of the probability of working in the same NUTS III region as their higher education studies. We concluded that being a local student is the main characteristic that leads graduates to stay in the same region. Other significant characteristics for retention include having higher grades in higher education. Given the importance of the local variables in explaining the results, we proceeded with explaining the determinants for these separate samples, and we conclude that the determinants are indeed different for these students. For local students, individual characteristics such as age, stronger higher education grades, being a female and graduating from a ISCED 5 formation all contribute for a higher retention probability. On the other hand, for non-local students, only the stronger higher education GPA is relevant, while graduating from a university also represents a higher retention probability.

Secondly, we find that being a local and attending HEI in a region significantly increases the probability of a person being employed in that region, both when considering the joint and the separate effects of those ties. Based on the regression model, we then estimate the probabilities of graduates being employed in a given NUTS III region. For graduates with no previous tie to the region, whose base probability for being employed in a peripheral region is 0.5-1%, HEI attendance increases that probability twenty-fold, translating to a 16 p.p. increase on average. For graduates who originated from the region, whose base probability for being employed there is around 30%, HEI attendance increases that probability by 28 p.p. on average.

Though not strictly causal, the predictive associations we identify between early-life geographic ties and later employment location are informative for regional policy. Whether a graduate's continued presence in a region reflects active retention through locally-formed networks and opportunities, or simply the fact that they never had strong reason or means to leave, the practical policy-relevant conclusion is the same: the graduate remains in the region where they attended HE. The paper's results speak most directly to this outcome-level question of where human capital ends up, and are more agnostic as to the precise decision-making process that underlies it.

References

Ahlin, L., Andersson, M., & Thulin, P. (2018). Human capital sorting: The “when” and “who” of the sorting of educated workers to urban regions. Journal of Regional Science, 58(3), 581–610. DOI: https://doi.org/10.1111/jors.12366

Bjerke, L., & Mellander, C. (2017). Moving home again? Never! The locational choices of graduates in Sweden. *The Annals of Regional Science*, *59*(3), 707–729. https://doi.org/10.1007/s00168-016-0777-2

Buenstorf, G., Geissler, M., & Krabel, S. (2016). Locations of labor market entry by German university graduates: Is (regional) beauty in the eye of the beholder? Review of Regional Research, 36(1), 29–49. DOI: https://doi.org/10.1007/s10037-015-0102-z

Cingano, F., & Rosolia, A. (2012). People I Know: Job Search and Social Networks. *Journal of Labor Economics*, *30*(2), 291–332. https://doi.org/10.1086/663357

Cui, C., Wang, Y., & Wang, Q. (2022). The interregional migration of human capital: The case of “first-class” university graduates in China. Applied Spatial Analysis and Policy, 15, 397–419. DOI: https://doi.org/10.1007/s12061-021-09401-7

Faggian, A., & Mccann, P. (2009). Universities, Agglomerations and Graduate Human Capital Mobility. *Tijdschrift Voor Economische En Sociale Geografie*, *100*(2), 210–223. https://doi.org/10.1111/j.1467-9663.2009.00530.x

Faggian, A., & Franklin, R. S. (2014). Human capital redistribution in the USA: The migration of the college-bound. Spatial Economic Analysis, 9(4), 376–395. DOI: https://doi.org/10.1080/17421772.2014.961536

Fidjeland, A., Knutsen, T. K., & Stubhaug, M. E. (2026). Sticky places: The effect of college on where you live. Journal of Urban Economics, 152, 103843. DOI: https://doi.org/10.1016/j.jue.2026.103843

Fini, R., Meoli, A., & Sobrero, M. (2022). University graduates’ early career decisions and interregional mobility: Self-employment versus salaried job. Regional Studies, 56(6), 972–988. DOI: https://doi.org/10.1080/00343404.2022.2069236

Haussen, T., & Uebelmesser, S. (2018). Job changes and interregional migration of graduates. Regional Studies, 52(10), 1346–1359. DOI: https://doi.org/10.1080/00343404.2017.1381335

Imeraj, L., Willaert, D., Finney, N., & Gadeyne, S. (2018). Cities' attraction and retention of graduates: A more-than-economic approach. Regional Studies, 52(8), 1086–1097. DOI: https://doi.org/10.1080/00343404.2017.1362499

Krabel, S., & Flöther, C. (2014). Here today, gone tomorrow? Regional labour mobility of German university graduates. Regional Studies, 48(10), 1609–1627. DOI: https://doi.org/10.1080/00343404.2012.739282

Oggenfuss, C., & Wolter, S. C. (2019). Are they coming back? The mobility of university graduates in Switzerland. Review of Regional Research, 39(2), 189–208. DOI: https://doi.org/10.1007/s10037-019-00132-4

Rehák, Š., & Eriksson, R. (2020). Migration of university graduates and structural aspects of regional higher education. European Planning Studies, 28(10), 1941–1959. DOI: https://doi.org/10.1080/09654313.2019.1700483

Rodrigues, N., Oliveira, F., Biscaia, R., Silva, P., Rudakov, V., Inácio, A. (2024). Eurograduate 2022: Relatório Final. Available at https://www.dgeec.medu.pt/api/ficheiros/65fb21c70c7bc47914575919

Sjaastad, L. A. (1962). The Costs and Returns of Human Migration. *Journal of Political Economy*, *70*(5), 80–93.

Venhorst, V., Van Dijk, J., & Van Wissen, L. (2011). An Analysis of Trends in Spatial Mobility of Dutch Graduates. *Spatial Economic Analysis*, *6*(1), 57–82. https://doi.org/10.1080/17421772.2010.540033

Yu, Y., Shen, J., Xin, G., & He, J. (2025). Leave or stay? The determinants of the migration behavior of university graduates in Shanghai. Eurasian Geography and Economics, 66(4–5), 583–605. DOI: https://doi.org/10.1080/15387216.2024.2425308

Appendix 1: Sample description

Table A 1 presents the breakdown by degree field of study of our main sample.

Table A 1 – Sample descriptive statistics by field

Variable	All	Local	Non-Local
Non-STEM:	4 529 (78.1%)	2 399 (78.1%)	2 130 (78.1%)
Business and administration	1 138 (19.6%)	661 (21.5%)	477 (17.5%)
Social sciences, journalism and information	506 (8.7%)	279 (9.1%)	227 (8.3%)
Health	664 (11.5%)	366 (11.9%)	298 (10.9%)
Arts	364 (6.3%)	156 (5.1%)	208 (7.6%)
Law	319 (5.5%)	165 (5.4%)	154 (5.6%)
Services	280 (4.8%)	166 (5.4%)	114 (4.2%)
Psychology	225 (3.9%)	122 (4.0%)	103 (3.8%)
Welfare	175 (3.0%)	92 (3.0%)	83 (3.0%)
Languages	112 (1.9%)	56 (1.8%)	56 (2.1%)
Teacher Training	145 (2.5%)	74 (2.4%)	71 (2.6%)
Medicine, Dental Studies	164 (2.8%)	70 (2.3%)	94 (3.4%)
Agriculture, forestry, fisheries, veterinary	100 (1.7%)	34 (1.1%)	66 (2.4%)
Humanities	73 (1.3%)	36 (1.2%)	37 (1.4%)
Architecture and town planning	87 (1.5%)	39 (1.3%)	48 (1.8%)
Education Science	81 (1.4%)	37 (1.2%)	44 (1.6%)
Pharmacy	92 (1.6%)	43 (1.4%)	49 (1.8%)
Generic / unknown	4 (0.1%)	3 (0.1%)	1 (0.0%)
STEM:	1 270 (21.9%)	673 (21.9%)	597 (21.9%)
Engineering, manufacturing, construction	831 (14.3%)	447 (14.6%)	384 (14.1%)
Natural sciences, mathematics and statistics	282 (4.9%)	133 (4.3%)	149 (5.5%)
ICT	157 (2.7%)	93 (3.0%)	64 (2.3%)

Appendix 2: *Whether* model: field and region results

Table A 2 presents the coefficients of the *whether* model associated to degree fields (omitted category: Alto Minho) and NUTS III regions (omitted category: Alto Minho).

Table A 2 – *Whether* model: field and region effects

	(1)	(2)	(3)	(4a)	(4b)
Sample	All	All	All	Local	Non-local
Region effects	No	No	Yes	Yes	Yes
(Intercept)	-1.894**	-1.039*	-1.009	-0.153	-5.269**
	(0.376)	(0.423)	(0.593)	(0.897)	(1.217)
Social sciences, journalism and information	0.069	0.112	-0.080	0.181	-0.244
	(0.126)	(0.139)	(0.151)	(0.259)	(0.193)
Health	-0.257*	-0.151	-0.391**	-0.094	-0.644**
	(0.112)	(0.125)	(0.138)	(0.220)	(0.192)
Arts	-0.575**	-0.368*	-0.324*	0.142	-0.549**
	(0.130)	(0.145)	(0.159)	(0.290)	(0.208)
Law	-0.239	-0.075	-0.269	-0.356	-0.229
	(0.143)	(0.159)	(0.171)	(0.270)	(0.221)
Services	-0.099	-0.162	-0.319	-0.108	-0.505
	(0.143)	(0.161)	(0.180)	(0.273)	(0.268)
Psychology	-0.488**	-0.476**	-0.324	-0.112	-0.404
	(0.164)	(0.183)	(0.198)	(0.316)	(0.265)
Welfare	-0.309	-0.249	-0.358	-0.275	-0.513
	(0.174)	(0.196)	(0.214)	(0.346)	(0.297)
Languages	-0.275	-0.228	-0.295	0.373	-0.563
	(0.214)	(0.239)	(0.263)	(0.555)	(0.326)
Teacher Training	-1.140**	-1.266**	-1.124**	-0.614	-1.835**
	(0.190)	(0.213)	(0.230)	(0.334)	(0.386)
Medicine, Dental Studies	-0.826**	-0.887**	-1.070**	-0.594	-1.238**
	(0.203)	(0.230)	(0.248)	(0.380)	(0.334)
Agriculture, forestry, fisheries, veterinary	-0.931**	-0.713**	-0.431	-1.297**	0.136
	(0.223)	(0.251)	(0.279)	(0.431)	(0.344)
Humanities	-0.499	-0.416	-0.692*	0.845	-1.368**
	(0.259)	(0.287)	(0.303)	(0.765)	(0.397)
Architecture and town planning	0.028	0.123	-0.373	-0.037	-0.430
	(0.252)	(0.281)	(0.303)	(0.551)	(0.373)
Education Science	-0.652**	-0.605*	-0.586*	-0.133	-0.940*
	(0.247)	(0.277)	(0.297)	(0.527)	(0.401)
Pharmacy	-0.195	-0.177	-0.374	0.145	-0.517

	(1)	(2)	(3)	(4a)	(4b)
	(0.237)	(0.267)	(0.301)	(0.549)	(0.390)
Generic / unknown	11.452	11.086	11.266	10.477	11.631
	(161.729)	(146.962)	(241.745)	(308.934)	(324.744)
Engineering, manufacturing, construction	-0.025	-0.031	0.133	-0.343	0.639**
	(0.107)	(0.120)	(0.130)	(0.186)	(0.181)
Natural sciences, mathematics and statistics	-0.281	-0.221	-0.056	-0.051	-0.069
	(0.149)	(0.165)	(0.182)	(0.298)	(0.230)
ICT	-0.079	-0.202	-0.382	-0.707*	-0.034
	(0.189)	(0.210)	(0.222)	(0.303)	(0.329)
Cávado			0.233	-0.041	1.455
			(0.395)	(0.567)	(1.059)
Ave			-0.419	-1.025	1.151
			(0.464)	(0.642)	(1.123)
AM Porto			1.231**	0.759	2.723**
			(0.386)	(0.552)	(1.050)
Tâmega e Sousa			-0.496	0.102	-0.043
			(0.706)	(1.285)	(1.469)
Douro			-0.198	-0.237	0.819
			(0.423)	(0.625)	(1.077)
Trás-os-Montes			0.134	-0.133	1.467
			(0.435)	(0.643)	(1.090)
Região de Aveiro			0.540	-0.414	2.149*
			(0.426)	(0.610)	(1.072)
Região de Coimbra			0.109	-0.311	1.502
			(0.393)	(0.563)	(1.055)
Viseu Dão Lafões			0.355	-0.293	1.900
			(0.440)	(0.618)	(1.100)
Beiras e Serra da Estrela			-0.066	-0.153	0.958
			(0.423)	(0.621)	(1.085)
Região de Leiria			0.205	-0.275	1.775
			(0.409)	(0.586)	(1.067)
Lezíria do Tejo			0.106	-0.788	1.913
			(0.509)	(0.749)	(1.129)
Oeste			-0.131	-1.046	1.730
			(0.485)	(0.727)	(1.112)
Grande Lisboa			2.118**	1.634**	3.582**
			(0.385)	(0.556)	(1.048)
Península de Setúbal			-0.732	-1.238*	0.603
			(0.417)	(0.574)	(1.113)
Alto Alentejo			0.900	0.046	2.628*

	(1)	(2)	(3)	(4a)	(4b)
			(0.500)	(0.711)	(1.131)
Alentejo Central			0.147	0.115	1.426
			(0.484)	(0.736)	(1.124)
Baixo Alentejo			-0.239	0.682	-0.177
			(0.571)	(0.969)	(1.468)
Algarve			1.726**	1.111	3.313**
			(0.449)	(0.687)	(1.088)
Açores			2.089**	1.534	3.272*
			(0.660)	(0.815)	(1.630)
Madeira			1.353*	0.888	-9.395
			(0.672)	(0.820)	(324.745)
N	5654	5654	5654	2980	2674
Log likelihood	-3623.1	-3040.2	-2683.8	-1152.1	-1458.6
McFadden R^2	0.027	0.184	0.279	0.133	0.189

* $p < 0.05$, ** $p < 0.01$

Appendix 3: *Where* model: region effects

Table A 3 presents the coefficients of the *where* model associated to NUTS III regions. The conditional logit structure means these coefficients represent the baseline attractivity of each region, with the omitted option (Alto Minho for the first three columns, Unemployed for the last column) set to 0.

Table A 3 – *Where* model: region effects

	(1)	(2a)	(2b)	(3)
Sample	All	Bachelor + SC	Master	All + Unempl.
Alto Minho				-3.582**
				(0.139)
Cávado	0.763**	0.647**	0.953**	-2.872**
	(0.161)	(0.208)	(0.262)	(0.085)
Ave	0.701**	0.605**	0.828**	-2.908**
	(0.169)	(0.217)	(0.276)	(0.097)
AM Porto	1.650**	1.560**	1.820**	-2.088**
	(0.150)	(0.194)	(0.246)	(0.064)
Tâmega e Sousa	0.072	0.028	0.092	-3.550**
	(0.185)	(0.235)	(0.312)	(0.124)
Douro	-0.104	-0.052	-0.172	-3.672**
	(0.186)	(0.237)	(0.312)	(0.123)
Alto Tâmega	-0.529*	-0.657*	-0.330	-4.157**
	(0.250)	(0.330)	(0.390)	(0.206)
Trás-os-Montes	-0.356	-0.476	-0.165	-3.884**
	(0.208)	(0.263)	(0.350)	(0.150)
Região de Aveiro	0.827**	0.578**	1.150**	-2.803**
	(0.167)	(0.223)	(0.265)	(0.094)
Região de Coimbra	0.264	0.025	0.596*	-3.271**
	(0.166)	(0.222)	(0.264)	(0.091)
Viseu Dão Lafões	0.088	-0.202	0.490	-3.443**
	(0.183)	(0.242)	(0.289)	(0.117)
Beiras e Serra da Estrela	-0.203	-0.379	0.060	-3.738**
	(0.190)	(0.252)	(0.299)	(0.127)
Beira Baixa	-0.766**	-0.892*	-0.561	-4.408**
	(0.281)	(0.376)	(0.431)	(0.243)
Médio Tejo	-0.174	-0.329	0.042	-3.731**
	(0.204)	(0.266)	(0.327)	(0.149)
Região de Leiria	0.231	0.163	0.244	-3.287**
	(0.173)	(0.218)	(0.300)	(0.102)
Lezíria do Tejo	0.178	-0.018	0.463	-3.408**

	(1)	(2a)	(2b)	(3)
	(0.195)	(0.253)	(0.312)	(0.134)
Oeste	0.457**	0.262	0.743**	-3.152**
	(0.177)	(0.228)	(0.288)	(0.110)
Grande Lisboa	2.414**	2.474**	2.405**	-1.389**
	(0.149)	(0.190)	(0.246)	(0.057)
Península de Setúbal	0.322	0.019	0.743**	-3.235**
	(0.170)	(0.221)	(0.273)	(0.098)
Alto Alentejo	-0.052	-0.072	-0.116	-3.633**
	(0.211)	(0.263)	(0.375)	(0.153)
Alentejo Central	-0.234	-0.580*	0.219	-3.771**
	(0.207)	(0.278)	(0.319)	(0.150)
Alentejo Litoral	-0.367	-0.305	-0.552	-3.962**
	(0.251)	(0.310)	(0.448)	(0.207)
Baixo Alentejo	-0.569*	-0.752*	-0.340	-4.096**
	(0.244)	(0.312)	(0.401)	(0.197)
Algarve	0.725**	0.520*	1.013**	-2.900**
	(0.174)	(0.228)	(0.277)	(0.102)
Açores	0.612**	0.313	0.998**	-2.948**
	(0.180)	(0.239)	(0.281)	(0.111)
Madeira	-0.047	-0.019	-0.124	-3.675**
	(0.205)	(0.260)	(0.349)	(0.147)
N	5799	3413	2386	6833
Log likelihood	-6618.0	-3649.2	-2933.0	-9593.3
McFadden R^2	0.514	0.552	0.459	0.419

* $p < 0.05$, ** $p < 0.01$

Appendix 4: N + 5 cohort

We compare the results obtained from the main sample of the N+1 cohort (graduates of 2020/21) with the N+5 sample (graduates of 2016/17). Table A 4 presents estimation results of the *whether* model. Table A 5 presents estimation results of the where model.

Table A 4 – *Whether* model: comparison with N+5 cohort

	(1a)	(1b)	(2a)	(2b)
Cohort	2020/21	2020/21	2016/17	2016/17
Sample	Local	Non-local	Local	Non-local
Region effects	Yes	Yes	Yes	Yes
Age	0.016* (0.008)	0.012 (0.007)	0.033** (0.011)	0.005 (0.011)
Gender: female	0.293* (0.120)	-0.039 (0.104)	0.227 (0.158)	-0.115 (0.147)
Gender: non-binary	0.685 (1.108)	-0.432 (0.635)	13.766 (1692.507)	14.138 (535.412)
Entry GPA	-0.036 (0.031)	0.042 (0.027)	-0.050 (0.041)	0.114** (0.038)
Degree GPA	0.102* (0.040)	0.108** (0.035)	0.005 (0.053)	0.005 (0.048)
Level: Short-cycle	0.977** (0.341)	-0.357 (0.320)	0.450 (0.483)	-0.663 (0.656)
Level: Master	-0.223 (0.162)	-0.229 (0.137)	-0.120 (0.212)	-0.125 (0.189)
Level: Integrated master	-0.215 (0.257)	-0.369 (0.211)	-0.398 (0.329)	-0.271 (0.271)
HEI type: University	-0.132 (0.166)	0.354* (0.139)	-0.414 (0.221)	-0.003 (0.195)
HEI sector: Private	-0.026 (0.163)	-0.258 (0.136)	0.438 (0.226)	-0.305 (0.213)
N	2980	2674	1616	1509
Log likelihood	-1152.1	-1458.6	-687.7	-751.0
McFadden R^2	0.133	0.189	0.134	0.209

* $p < 0.05$, ** $p < 0.01$

Table A 5 – *Where* model: comparison with N+5 cohort

	(1)	(2)
Cohort	2020/21	2016/17
Origin	3.800**	3.624**
	(0.056)	(0.068)
Study	2.963**	2.574**
	(0.059)	(0.078)
Both	4.212**	4.149**
	(0.055)	(0.069)
N	5799	3229
Log likelihood	-6618.0	-4234.2
McFadden R2	0.514	0.476

* $p < 0.05$, ** $p < 0.01$