Regional Science and Urban Economics 120 (2026) 104232

Contents lists available at ScienceDirect

Regional Science and Urban Economics

journal homepage: www.elsevier.com/locate/regec

Dormitories or grants? Need-based aid and university students' mobility in Italy

Cristian Usala [a], Rinaldo Brau [b],*

[a] Department of Social and Political Sciences and CRENoS, University of Cagliari, Italy
[b] Department of Economics & Business and CRENoS, University of Cagliari, Italy

ARTICLE INFO

JEL classification:
C25
I23
I28

Keywords:
Need-based aid policies
Student mobility
University choice
Latent class logit
Heterogeneity in preferences
Regional variations

ABSTRACT

We study how Italy's need-based student-aid system (*Diritto allo Studio Universitario*, DSU) shapes first-time entrants' choices of where and what to study by linking administrative records on first-time enrolments to university characteristics and DSU service provision. Using a Latent Class Logit model that accounts for heterogeneity in preferences, we find that dormitory capacity for eligible students substantially increases enrolment: adding 100 places raises enrolment at an average-sized institution by 5.3–9.6% (equivalent to about 19 to 34 additional students). By contrast, grants show no statistically significant effect. Dormitory availability matters most for students who lack a nearby university and those in STEM fields. Simulations focused on alternative expansions of dormitory supply suggest that a nationwide increase reallocates enrolment toward central/northern hubs and higher-quality institutions, whereas regionally targeted support in the South only marginally curbs South-to-North flows.

1. Introduction

Most international institutions, such as the OECD (2022), recognise the fundamental role of tertiary education as an economic growth factor, especially in a knowledge-based economy. Higher education levels increase labour productivity, ensuring that individuals with a university degree have better earnings prospects and a lower risk of unemployment. Besides pointing to the share of the younger population that has achieved a tertiary degree, the public debate has directed its attention to two related issues: reducing the inequality of educational opportunities for freshmen with a disadvantaged socio-economic status, given that parental background influences the probability of accessing tertiary education in terms of income and educational achievement (e.g., Palmisano et al., 2022); the importance of matching students' aspirations and abilities with appropriate university programs, which appears critical to effectively aiding degree completion and enabling future higher earnings (e.g., Dillon and Smith, 2017).

To reduce students' socioeconomic barriers to accessing tertiary education and implement their preferred choice, governments provide national or, more often, local-level need-based support programs. In addition to affecting the income potential of direct beneficiaries, these policies aim to generate economic benefits at a broader level. Increasing the number of students fuels universities' potential, whose role, in turn, is fundamental to fostering local development by increasing the local supply of human capital and allowing local areas to benefit from the global scientific process (as in the seminal contribution by Krugman (1991)). In particular, the increase in the number of universities in one region is positively associated with its future growth capacity (Valero and Van Reenen, 2019) and productivity (Marrocu et al., 2022). These effects are unsurprising because students' enrolment in a given university (especially those studying away from home) 'locks' prospective highly productive workers in the surrounding area after graduation (e.g., Haapanen and Tervo, 2012). This leads to larger shares of high-skilled workers and, incidentally, of richer-than-average local taxpayers.

Overall, understanding the determinants of university attractiveness is of twofold importance: for local areas competing in the attraction of human capital and for the benefit of students who should be able to maximise opportunities related to their skills. We contribute to this by focusing on the first step of post-secondary careers: students' college choice among the many national alternatives. Specifically, we assess the role of need-based financial and in-kind policies in shaping location decisions, focusing on services provided through the Italian *Diritto allo Studio Universitario* (DSU) program. The DSU aims to ensure less advantaged students access to the Italian higher education system by providing various services such as grants, places in dormitories, and rent support policies. Comparable services exist in many countries (see Dynarski, 2002), and their effects on enrolment and attendance

* Corresponding author.
E-mail addresses: cristian.usala@unica.it (C. Usala), brau@unica.it (R. Brau).

https://doi.org/10.1016/j.regsciurbeco.2026.104232
Received 14 June 2024; Received in revised form 21 April 2026; Accepted 21 April 2026
Available online 14 May 2026

have been widely studied (e.g., Castleman and Long, 2016; Fack and Grenet, 2015).

In this study, we take advantage of a unique dataset that includes administrative data regarding the population of first-time enrolled students in the 2018–2019 academic year and detailed information regarding universities' characteristics and the supply of DSU policies (academic year 2017–18). These data allow us to exploit the variability in the provision of DSU services at the university/city level to separately identify the effects of the program's different policies and account for differences within institutions. Besides DSU services, we account for several other factors extensively studied in the literature, such as the role of distance (e.g., Suhonen, 2014); research and teaching quality (e.g., Gibbons et al., 2015; Biancardi and Bratti, 2019), and regional characteristics (Cattaneo et al., 2017).

We evaluate the impact of DSU policies by explicitly accounting for heterogeneity in students' preferences. To this end, we model students' decision-making within a discrete choice framework, estimating preference parameters using a Latent Class Logit (LCL) model. This specification offers two key advantages: it allows for flexible substitution patterns by relaxing the restrictive Independence of Irrelevant Alternatives (IIA) property that characterises standard Conditional Logit (CL) models,[1] and it captures unobserved heterogeneity by modelling observed choices as a finite mixture of latent student groups with distinct utility structures. We condition latent class membership on a set of individual characteristics. This allows us to uncover how these characteristics shape students' responses to policy-relevant attributes, such as financial aid or proximity, without requiring full interaction between all individual and alternative-specific variables, as would be in a standard CL model.[2] To model the complex and interrelated decisions underlying university enrolment, we adopt an estimation strategy based on a three-level overlapping nesting structure. The first level aggregates degree programs into Higher Education Units (HEUs), defined by the combination of university, field of study, and host city. The second level groups HEUs by disciplinary field. The third level distinguishes between HEUs located within and outside students' commuting areas, where accommodation policies are expected to play a prominent role. While most of the existing literature models post-secondary enrolment decisions at the university or regional level, we directly consider students' choices among HEUs – 636 mutually exclusive alternatives – by applying the procedure proposed by Von Haefen and Domanski (2018) to manage the resulting computational burden.

Although the LCL offers a semi-parametric approximation of students' preference distributions, enhancing robustness to unobserved heterogeneity, the estimation of DSU policy effects may still be subject to endogeneity concerns. In particular, potential endogeneity arising from policy adjustments in response to past student flows warrants careful consideration. A correlation analysis between past variations in student demand for grants and dormitories and subsequent changes in DSU service provision suggests that any adaptive policy responses are not empirically significant in our data. Nevertheless, to further address potential endogeneity, we exploit exogenous variation in funding allocations for new dormitory construction – stemming from specific national programs – to construct instruments within a control function framework and test the extent to which our estimates from a standard LCL model may be affected. We also address possible selection bias from students changing residence at enrolment by using, in robustness checks, high school location as a proxy for their original place of living. Clearly, the validity of these refinements must be weighed against the inherent limitations of a cross-sectional design, which limits the ability to exploit variation over time and to implement more robust identification strategies.

Our modelling strategy proves largely successful in predicting students' mobility choices. While it correctly identifies the chosen HEU in 15% of cases, its performance improves when predictions are aggregated: accuracy rises to 53% at the university level, 61% at the city level, and 81% when considering universities' hosting regions. Focusing on DSU policies, the model's estimates indicate that the supply of dormitory places exerts a positive and substantial effect on students' enrolment choices. Specifically, increasing the number of places reserved for students meeting a means-tested criterion by 100 units would lead to an increase in enrolment ranging from 5.3% (in the standard LCL model) to 9.6% (in the LCL model with the Control Function correction) at an average-sized institution. A smaller effect is found for dormitories available to all students regardless of financial need. In contrast, standard financial provisions, in the form of grants and rent support benefits, exhibit only minimal and inconclusive effects, suggesting a negligible role in shaping enrolment decisions. Our interpretation of these findings is that while grants may reduce students' living costs, they are ineffective in covering students' overall costs related to accommodation, which includes both direct costs, such as renting a room or flat, and indirect costs related to the uncertainty of the actual cost and search time for an accommodation in a distant location. This problem is likely pervasive in Italy, given that fewer than 12% of off-site students are accommodated in dormitories.

The results also reveal heterogeneity in students' preferences based on individual characteristics and field of study. Students who do not have a higher education institution in their local area are more responsive to the availability of dormitory places, as are those enrolled in public universities. This amplified sensitivity is also observed among students in STEM fields, whereas those studying Humanities and Social Sciences exhibit a lower responsiveness – measured in terms of marginal effects – to dormitory provision.

We illustrate the geographical implications of our findings, as well as the prospects for students inclined to relocate, through a simulation that explores how hypothetical changes to the DSU program could affect the distribution of students enrolled in degree programs across Italian provinces. We find that a hypothetical large-scale nationwide expansion of DSU policies would encourage enrolment in major university hubs in central and northern Italy, while also broadening access to high-quality institutions for talented students from disadvantaged backgrounds. This, in turn, would improve the overall alignment between student potential and the quality of higher education institutions. By contrast, increasing DSU support exclusively in southern regions would tend to redirect students toward institutions with lower quality indicators. Moreover, it would only partially reduce student out-migration, proving insufficient to reverse current brain drain trends.

The rest of the paper is structured as follows. Section 2 reviews the literature and outlines the DSU program within the Italian higher education system. Section 3 describes the data, and Section 4 the empirical framework adopted. Section 5 presents the main findings, which are further examined through simulation analysis in Section 6. Section 7 concludes.

2. Background

2.1. Related literature

Since the work by Long (2004) on US high school graduates, students' enrolment and location decisions have been studied in a framework in which the chosen application arises from a decision process in which distance to institutes, college quality, and tuition fees play a significant role.

The role of distance always appears pivotal in determining where to study (town and university) and the chosen field (e.g., Suhonen, 2014)

[1] Terminology varies across disciplines. While the model is rooted in the Multinomial Logit framework (which includes models with alternative-specific variables) in transportation and marketing research, it is typically referred to as a Conditional Logit model in economics, following Mcfadden (1974).

[2] Such a specification is difficult to interpret and often computationally infeasible in the presence of hundreds of alternatives and multiple nests.

and less clear when focusing on the enrolment decisions: negligible according to the studies by Kelchtermans and Verboven (2010) on the Belgian region of Flanders and Gibbons and Vignoles (2012) on UK students; quite relevant according to Spiess and Wrohlich (2010), who have focused on German students.

Consistent with spatial competition models, the ‘product’s quality’ is expected to mitigate the repulsive effect of distance. For university degree programs, a critical component is the quality of academic research, whose role in Italy has been assessed in a few studies. Ciriaci (2014) finds that students’ migration flows from southern to northern regions positively correlate to the quality of research as measured by the Evaluation Research Exercise (VTR) for the 2001–2003 period. Subsequent contributions have shown that this effect may be heterogeneous, depending on students’ characteristics such as family background and field of study (Biancardi and Bratti, 2019; Bratti and Verzillo, 2019). The effect of research quality has been confirmed in several institutional contexts, such as the US (Bowman and Bastedo, 2009) and the UK (Chevalier and Jia, 2016), although the role appears substantial only for top-ranked universities. For most universities, other quality dimensions, such as mentoring, student satisfaction, and faculty infrastructure, usually have a more significant influence (Gibbons et al., 2015).

A detrimental role is also intuitively attached to the level of tuition fees. However, the empirical evidence is mixed and depends on the specific characteristics of the education system considered. For example, Murphy et al. (2019) have analysed the effect of the introduction of tuition fees in England, surprisingly finding that this policy has determined an increase in enrolment rates without widening the disparities of access between students from different economic backgrounds. By contrast, positive effects on college attendance have been found after eliminating tuition fees in Ecuador in 2008 (Molina and Rivadeneyra, 2021). Similarly, in the case of Germany, where tuition fees are either absent or set at relatively low levels, Hübner (2012) found that the introduction of tuition fees in a state determined a reduction in the conditional probability of enrolment among high school graduates.

Distance, university quality, and tuition fees interrelate with students’ socio-economic backgrounds. Less advantaged students, in terms of income and social networks, face the highest access barriers to tertiary education (Türk, 2019) and tend to enrol in their region of residence (Lupi and Ordine, 2009). An additional role is played by the economic conditions of the hosting areas (e.g., Giambona et al., 2017; D’Agostino et al., 2019; Columbu et al., 2021).[3]

Given the previous main drivers of student mobility, a few studies have investigated whether universities and regions can improve their attractiveness by reducing students’ migration, transportation, and accommodation costs through financial and in-kind support policies. The previous question has been generally addressed using experimental and quasi-experimental evidence arising from policy changes, as documented in the surveys by Page and Scott-Clayton (2016) and Dynarski et al. (2023). The more recent evidence presented in the latter study suggests that the magnitude of aid policy effects is strongly tied to their design. Need-based programs with simple designs and broad accessibility are the most effective, and even minor changes in policies that ensure the availability of grants and scholarships after admission can magnify the effect of these programs on students’ choices.[4]

Less commonly, alternative methods such as gravity models (e.g., Bratti and Verzillo, 2019) and discrete choice approaches (e.g., Pigini and Staffolani, 2015) have been used. These latter authors analyse enrolment decisions among Italian high-school graduates using a Conditional Logit model, highlighting the positive impact of financial incentives on university choice. A discrete choice framework is also adopted by Bernal et al. (2024), who shows that providing information on financial support increases the likelihood of choosing higher-quality institutions.

2.2. Institutional setting

Each high-school graduate can enrol in an Italian university in almost any subject without further requirements. Thus, the Italian Higher Education (HE) system implicitly selects students on an ex-post basis.[5] Italian universities are mainly funded by the Central Government, based on several indicators, with a primary role played by the number of students enrolled.

Italy shows a high level of social/intragenerational educational inequality, especially driven by parental class and education (see Contini et al., 2018, reporting dramatic differences – up to 25% – in university enrolment probabilities, depending on the parents’ SES; and Palmisano et al., 2022, who place Italy among the countries with the highest inequality of opportunity in access to university education in Europe). Parental support is often the main source of financial support, and this ties students to parents’ risk aversion, which exerts a negative role on university enrolment (Checchi et al., 2014). In this context, policymakers have relied on establishing a need-based student support system to increase equality of educational opportunities.

The most important initiative within this framework is the *Diritto allo studio Universitario* (DSU), which is usually managed by regional or sub-regional agencies responsible for institutes within their jurisdictions. At the national level, DSU was initially set up to encourage student enrolment and attendance from disadvantaged families, overcoming barriers related to family income (Prime Ministry Decree 390/2001). Grants and places in dormitories were identified as the primary support tools. For grants, the 2001 decree introduced an annual allocation of a national fund to the regions. In contrast, dormitory-related policies – based on the framework established by Law 338/2000 – have primarily relied on periodic competitive calls. Through these calls, selected DSU offices receive matching grants (covering up to 50% of the projected expenditure) to finance the construction of new dormitories or the renovation of existing facilities (there have been four allocation between 2001 and 2018; a recent, quite generous, fifth allocation plan has been financed by the Italian National Resilience and Recovery Plan (NRRP), but not fully implemented yet).[6]

In its current structure, as defined by Legislative Decree No. 68/2012, the program is organised at the regional level, with a network of local DSU offices responsible for one territorial area (e.g., a province

[3] Infrastructure endowment at origin and destination may facilitate long-distance student mobility.As shown by Cattaneo et al. (2016), this is the case of airports, whose presence and development have increased the long-distance migration flows of Italian students.

[4] In the Italian context, need-based aid primarily facilitates geographic mobility, allowing students to attend universities away from home, rather than increasing overall enrolment rates (Vergolini and Zanini, 2015). Quasi-experimental approaches have also been applied to related outcomes such as degree completion (Castleman and Long, 2016; Minaya et al., 2022) and dropout rates (Aina et al., 2022; Modena et al., 2020), in the latter case with evidence of reduced dropout among low-income students.

[5] This rule does not apply to applicants in medicine, health-related professions, primary education, and architecture. In these cases, the number of students is defined ex-ante, and the applicants are evaluated through an entry test. Universities may extend these rules to other subjects that require laboratory activities. A comparison between ex-ante and ex-post screening systems in the Belgian context is made by Declercq and Verboven (2018).

[6] It is worth emphasising that there is no ex ante allocation of funds among DSU offices or regions. Instead, a ministerial commission evaluates the quality of the projects submitted by DSU offices on a 100-point scale and compiles a ranking of eligible applications, funding them in order of merit until the available resources are exhausted. In the fourth allocation round (2018, following Ministerial Decree No. 936/2016), up to 15 points were awarded based on the excess demand for dormitory places. For the 2012 allocation (Ministerial Decree No. 26/2011), this criterion accounted for up to 10 points, while in the 2008 allocation (Ministerial Decree of May 22, 2007), it was worth up to 20 points.

and its towns) or for one specific university. These offices provide their services based on students' family Equivalent Economic Status Indicator (EES).[7] Depending on their EES, students can be classified as non-eligible (EES above the threshold) or eligible (EES below the threshold). Eligible students may benefit from two main kinds of benefits: grants and accommodation services.[8] The former consists of monetary transfers varying according to three location categories based on the distance from their hometown to the university city: on-site, commuting, and off-site students. On-site students residing in the university town or its metropolitan area receive the lowest grant amount. Commuting students, who travel daily from their residences, receive an intermediate grant amount. Off-site students can apply for the maximum grant amount. These students live at a travel distance that does not allow for regular daily commuting, according to DSU offices' criteria.[9] For grant allocation, a unique ranking is compiled for all eligible students, regardless of grant type, until the nationally provided funds are exhausted.

Accommodation services include the provision of places in dormitories managed by the local DSU office and, to a lesser extent, rent support schemes.[10] The same means-tested eligibility threshold used for grants applies to the allocation of dormitory places. For both grants and accommodation services available to first-year students, there are no quotas reserved for specific fields of study, meaning that, in principle, all available dormitory places could be assigned to students from the same academic discipline.

As we detail in Section S1 in the Online Supplementary Material, 43.5% of students are classified as off-site according to DSU's offices classifications. However, only a tiny share of them may benefit from the availability of a place in a dormitory.[11] This weakness of the Italian tertiary education system, which not surprisingly has been taken into consideration in the NRRP reforms and goals,[12] entails high direct accommodation costs and indirect costs in terms of uncertainty and search effort for most of these students.

3. Data

Our analysis relies on integrating two primary data sources. The first is the MOBYSU.IT database, provided by the Italian National Student Archive (NSA), which contains detailed administrative records on students' university careers. Specifically, we obtained data on the full population of Italian students who began their university studies in the academic year 2018/2019. The second source is the USTAT open data portal,[13] which provides information on university characteristics and the supply of DSU services. This dataset also allows us to identify the actual locations of tertiary programs, which is crucial since some universities operate across multiple sites served by different DSU offices.

This data granularity enables us to define a 'choice set' whose elements are identified at the institution-program-location level. In line with Kelchtermans and Verboven (2010), we group all available programs into 636 aggregate Higher Education Units (HEU). Each HEU is defined according to three elements: university (e.g., La Sapienza), the town where the program that the student attends is provided (e.g., Rome), and the field of study (e.g., Engineering). The latter is recovered from the classification adopted by the NSA, which groups programs into 16 general fields, which only partially overlap with the standard ISCED-F 2013 classification.[14] Our definition of students' choice set is motivated by the fact that some Italian universities operate across multiple cities, often served by distinct DSU offices. It also accounts for differences in the availability of degree programs across branches of the same institution. Accordingly, all the HEU's observed attributes are defined by the information on the university providing the program, the field of study, the DSU office, and the characteristics of the hosting area.[15]

The case of some universities having separate locations is particularly challenging when defining the endowment of places in dormitories at the HEU level. First, we have aggregated the towns in the same metropolitan area. Second, we have worked on all those situations where universities are located in only one metropolitan area (sharing all the places provided by the university among the corresponding HEUs) and where the town hosts only one university (assigning all the places in the town to the hosted university). Finally, the remaining places have been assigned according to the rules available on the DSU offices' websites.[16] A direct association was available for grants and rent support services because students in the same university have the same set of available grants, regardless of the town that hosts the program.

We construct several indicators to capture the characteristics of DSU policies. For grant provision, we consider the total DSU expenditure at the university level. We rely on the one-year lagged values (i.e., academic year 2017/18, which represents the most recent information available to students at the time of enrolment in 2018/19). We use expenditures rather than the number of grants, since the latter may be endogenous to students' choices due to its dependence on the composition of enrolled students, as explained in Section 2.2.[17] For accommodation services, we recover the shares of places supplied to eligible and non-eligible students in 2017–18.[18] This information, combined with the number of places available in each university/town

[7] The EES has been used for identifying needy families in Italy since 1998. It depends on household components and takes into account total household income and (in part) wealth.

[8] DSU offices may provide other services (e.g., canteens and paid jobs to students not obtaining any grant). Non-eligible students may benefit from other services unrelated to the EES indicators (e.g., places in dormitories in some universities).

[9] In 2018/19, the nationally set annual scholarship amounts were €1950.44 for on-site students, €2852.71 for commuting students, and €5174.66 for off-site students, although actual cash amounts could vary depending on local rules reflecting differences in the living costs and on whether students received accommodation or meal services. Further details are provided in Section S1 in the Online Supplementary Material.

[10] Rent support is typically offered when DSU offices temporarily reduce the number of available dormitory places due to maintenance activities.

[11] According to the most recent data from the Italian National Agency for the Evaluation of University and Research Institutes (ANVUR, 2023), the average ratio between students and places in dormitories is 9.1.

[12] Mission 4, Component 1, Reform 1.7: *"It aims to add 60,000 sleeping accommodations, thus significantly reducing Italy's gap with the EU average regarding the share of students provided with housing facilities"* (Council of European Union, 2023, page 28).

[13] See USTAT website.

[14] The NSA fields are Business & Statistics, Chemistry & Pharmacy, Education, Engineering, Humanities, Languages, Law, Life & Natural Sciences, Mathematics and Physics, Psychology, Social & Political Sciences, Agriculture, Health & Welfare, Architecture, Defence studies. As we explain below, to focus on students' autonomous mobility choices, we do not consider students enrolled in the last four fields.

[15] The last columns of Table 2 in Section 5.1 and Table S4 in the Online Supplementary Material report the predictive accuracy and average marginal effects of an alternative specification based on university/city-level choice sets. As shown in the Tables, the results are very similar to those of the main specification discussed in the text. We thank an anonymous referee for this suggestion.

[16] This last step regarded the universities located in several towns, and those cases with at least one town characterised by hosting tertiary education programs supplied by more than one university.

[17] We thank an anonymous referee for highlighting this point. While using lagged variables helps mitigate the issue, it is reasonable to expect a considerable degree of persistence in students' enrolment patterns.

[18] In that year, the EES threshold (calculated as 100% of total household income plus 20% of household wealth) for being considered eligible for student support services was 23,000 euros, after appropriate scaling-up according to family size.

Table 1
Descriptive statistics on the supply of DSU services.

	Italy		Centre-North		South & Islands	
	Total	S/D ratio	Total	S/D ratio	Total	S/D ratio
Grants by students category						
- Off site students	78,835		61,807		17,028	
- On site students	36,648		23,417		13,231	
- Commuting students	63,114		31,383		31,731	
Total	178,597	67.9%	116,607	67.3%	61,990	69.1%
Grants expenditure						
- Total grants expenditure (Th.)	525,861		372,767		153,094	
- Euro per beneficiary student	2,944		3,197		2,470	
Places in dormitories						
- Eligible students	28,090		21,867		6,223	
- Non-eligible students	5,844		5,178		666	
Total	33,934	19.6%	27,045	18.6%	6,889	24.8%
Rent support services						
- Non-eligible students	2,759		1,086		1,673	
- Eligible students	5,698		4,639		1,059	
Total	8,457	56.6%	5,725	63.0%	2,732	46.7%

Note: The table reports the descriptive statistics on the supply of DSU services considering the entire country and the regions in the Centre-North and in South & Islands. The first panel shows information on the total supply of grants by beneficiaries' location status (on-site, commuting, off-site). The second panel shows information on the total expenditure for grants in millions of Euros. The third panel reports information on the total supply of places in dormitories by service category. The fourth panel contains information on rent support policies according to students' eligibility status. For each service category we report the ratio between the supply of the service and the number of students' applications (S/D ratio). Data refer to the academic year 2017–2018.

pair, yields two indicators of the dormitories potentially available to a HEU: places for eligible and places for non-eligible. We finally have information on the number of beneficiaries of rent support services, distinguishing between non-eligible and eligible students.

The USTAT database also provides information on the number of student applications each university has received for each service category. This information on services' latent demand is exploited in Section 6 to assess how changes in the supply of DSU policies affect the distribution of students among Italian provinces.

Table 1 summarises the total supply of DSU services across Italian macro-regions and service categories. The top panel reports the total number of grants, disaggregated by students' location status. The distribution of grants among student categories varies by macro-region: off-site students represent the majority in central and northern regions, while commuter students are more prevalent in the South. This pattern reflects the broader phenomenon of student out-migration from southern to northern Italy. Most dormitory places are allocated to eligible students, accounting for an average of 82.78% of all beneficiaries.

The table also includes the supply-to-demand (S/D) ratio for both grants and dormitory accommodations. These indicators reveal a more nuanced picture: Southern regions exhibit a slight advantage in grant expenditure per applicant and a more pronounced advantage in dormitory availability. However, this is partially counterbalanced by the greater provision of rent support grants in northern regions.

Thanks to NSA records, our dataset includes all students who obtained their high-school diploma in 2018 and enrolled in an Italian university for the first time in the 2018/2019 academic year. For each student, we observe the hometown, sex, high school institution, high school graduation mark, the chosen program, and the town hosting the chosen HEU. Given our focus on students' autonomous choices, we only consider enrolments in HEUs that require on-site attendance and are not determined by national-level ex-ante selection procedures.[19] Starting from the population of 228,352 students for whom we observe a home town in Italy, we exclude 38,257 students who are not enrolled in the fields considered, and 3028 students for whom we could not observe the high school graduation mark or the high school. We have retained 187,067 students enrolled in 1501 degree programs belonging to 11 fields of study. Section S2 in the Supplementary Material further describes our dataset focusing on students' characteristics.[20] The final database has been integrated with several information on universities' and hosting areas' characteristics whose role has often been highlighted in the literature (See Appendix A.1 in the Appendix for details) and that we use in our econometric analysis.[21]

4. Empirical framework

We model students' enrolment choices within a discrete choice framework, where individuals maximise their utilities by selecting one option from a set of mutually exclusive alternatives. Each alternative is characterised by a set of attributes, whose contribution to utility varies according to individual preferences.

In our data, we observe students' enrolments in $K = 1501$ degree programs grouped in $J = 636$ HEUs. Each HEU j offers K_j specific programs. An HEU is defined by the combination of the university offering the program (e.g., PoliMi), the town in which it is located (e.g., Milan), and the disciplinary field of the program (e.g., Engineering).[22] The student n who enrols in program k within HEU j derives utility:

$$U_{njk} = V_{nj} + \epsilon_{njk}, \tag{1}$$

[19] Accordingly, we exclude students enrolled in e-learning universities and those attending programs that rely upon an ex-ante screening system. We have also disregarded students who matriculated in very specific programs provided by just a few universities (agricultural and defence studies).

[20] It is worth highlighting that NSA data do not provide information on students' eligibility for DSU policies, i.e., we cannot identify whether the students have benefited from these policies. The amount of DSU services provided in each HEU is therefore considered, in the empirical model, as a general attribute indicating the 'strength' of the hosting institutions in terms of student aid. However, information on students' towns of residence is exploited to identify which students are potentially interested in these services.

[21] Table A.1 in the Appendix provides the definitions and the descriptive statistics of all the variables used in estimation.

[22] In our data, K_j ranges from 1 to 17.

where V_{nj} is the deterministic component of utility, which depends on observable characteristics of HEU j's and the preferences of student n, and ϵ_{njk} is a random component capturing unobserved factors at the program level. The deterministic component V_{nj} can be further specified to highlight the monetary impact of student support policies:

$$V_{nj} = \pi_{nj} + \alpha_n(y_n - \zeta_{nj} + DSU_{nj}), \tag{2}$$

where the first term π_{nj} represents the 'gross' expected utility to enrol in HEU j for student n, related to factors such as universities' quality and services (e.g., number of faculty members, presence of department of excellence) and hosting areas' characteristics (e.g., unemployment rates, regional GDP).[23] The second term in Eq. (2), through the individual-specific parameter α_n, captures the impact on student n's utility of the net change in disposable income resulting from enrolment in HEU j. This term depends on students' incomes y_n, expected enrolment and living costs ζ_{nj} for the HEU j, and potential savings on living expenditures arising from DSU policies (DSU_{nj}).

The ζ_{nj} cost component is proxied using three variables: the average tuition fees paid by students enrolled in HEU j, the travel time distance between the student's city of residence and the university, and the average housing purchase price per square meter in the hosting city, which serves as a proxy for accommodation costs.

The reduction in living costs resulting the DSU policies is captured through a set of variables related to financial incentives (grants and rent-support policies) and in-kind benefits (places in dormitories). These variables are defined according to students' location status (e.g., on-site, commuter, off-site) and the supply of services in each HEU. Therefore, students' utilities U_{nj} depend on the set of observables at the HEU level and students' individual preferences for HEU's attributes. These utilities shape students choice probabilities P_{nj} as follows:

$$P_{nj} = Prob(U_{nj} > U_{nj'}) \; \forall \; j \neq j', \tag{3}$$

that is, students maximise their utilities by choosing the HEU j associated with the highest utility in their choice sets.

In principle, the probability P_{nj} depends on both the attributes of the HEUs and the characteristics of the individual, and can be estimated using various approaches depending on the nature of the observed decision process. In our case, we aim to explicitly account for the nesting structure observed in students' choices, while also capturing heterogeneity in preferences arising from systematic variations in students' observable characteristics.[24] We start from a three-level nesting structure. The first level aggregates individual programs k into HEUs J. The second level groups HEUs by disciplinary field, thereby assuming that HEUs offering programs in the same field are perceived as closer substitutes. The third level distinguishes between HEUs located within a student's commuting area and those outside it, based on the classification used by DSU offices. Since distance affects both the material and immaterial costs of attending university, geographically closer HEUs may form a distinct group in students' perceived choice sets.[25] A distinctive feature of this nesting structure is that the nests overlap. For example, a student n primarily interested in a specific field may face a choice set in which HEUs fall into four overlapping categories: those located inside or outside the commuting area, and those that offer or do not offer programs in the chosen field.

To accommodate the nesting structure and capture preference heterogeneity driven by individual characteristics, we estimate a Latent Class Logit (LCL) model (Bhat, 1997; Train, 2009; McFadden and Train, 2000). The LCL belongs to the broader class of Mixed Logit (ML) models and approximates the distribution of individual preferences using a finite mixture of latent classes (rather than a continuous mixing distribution). Compared to continuous ML models, the LCL offers greater computational tractability in settings with a large number of alternatives and overlapping nests (Greene and Hensher, 2003; Hensher et al., 2015). These features make it particularly well-suited to our empirical context.

The LCL model can be written as follows. We assume that each student n belongs to one of Q latent classes q. Conditional on class q, choices among HEUs j follow a standard Conditional Logit (CL):

$$P_{nj|q} = \frac{\exp(V_{nj|q})}{\sum_{l=1}^{J} \exp(V_{nl|q})}, \qquad V_{nj|q} = x'_{nj}\beta_q,$$

where x_{nj} collects HEU attributes (including DSU variables and the nesting controls introduced below in Eq. (4)), and β_q is the vector of class-specific taste parameters. Class membership is modelled as a multinomial logit function of observed individual characteristics z_n:

$$H_{nq} \equiv \Pr(c_n = q \mid z_n) = \frac{\exp(z'_n\gamma_q)}{\sum_{s=1}^{Q} \exp(z'_n\gamma_s)}.$$

The unconditional choice probability is the resulting finite mixture:

$$P_{nj} = \sum_{q=1}^{Q} H_{nq}\, P_{nj|q}.$$

This formulation clarifies two main advantages of the LCL. The first concerns the relaxation of the Independence of Irrelevant Alternatives (IIA) property. To build intuition in our setting, consider two geographically close HEUs A and B and a farther HEU C. In a single CL, a change in an attribute of B (e.g., dormitory availability or other DSU-related services) would not affect the probability ratio $P(A)/P(C)$, because IIA implies that the ratio between A and C depend only on their own attributes. Therefore, an increase in $P(B)$ would cause the same proportional reduction in both $P(A)$ and $P(C)$. In the LCL, instead, students with a higher probability of belonging to a class with high sensitivity to travel distance will substitute primarily between A and B, whereas students in a different class may be comparatively more responsive to DSU-related attributes; aggregating these behaviours relaxes the IIA property allowing the probability ratio $P(A)/P(C)$ to change when B's attributes change.

The second advantage concerns the ability to capture preference heterogeneity related to students' attributes. Indeed, individual choice probabilities P_{nj} are computed by weighting class-specific probabilities using H_{nq}, which, in turn, depends on the individual characteristics z_n. Parametrising class membership with individual-level covariates allows class shares to vary systematically with observable traits, capturing heterogeneity in how students with different observable characteristics respond to policy-relevant attributes.[26]

We incorporate the three-level nesting structure as follows. First, since no program-level (k) is observed, we assume that the deterministic component varies at the HEU level j. To account for within-HEU heterogeneity, we include a term $\ln K_j$, where K_j is the number of programs offered by HEU j, thereby accounting for the dimension of each

[23] See Appendix A.1 for more details on the HEU characteristics included in the estimation.

[24] Some HEUs (within the same nest) are closer substitutes for each other than HEUs in different nests. Thus, an increase in the attractiveness of one alternative j would lead to a larger decrease in the probability of choosing other HEUs within the same nest, compared to those in different nests.

[25] Following a suggestion by an anonymous referee, in the Results section we also consider, as a robustness exercise, a fourth level of nesting in which any program in the same city belongs to the same nest. See Table 2 and Table S4 in the Online Supplementary Material for the results.

[26] For example, if male students are more responsive to monetary incentives than female students, this effect is accounted for by including gender in the class membership model. As noted by Hess (2014), this approach allows preference correlations to vary systematically with individual traits. For instance, students who value in-kind services may also place particular importance on other attributes, such as travel distance.

HEU in terms of the number of programs it offers.[27] Next, we model the disciplinary and geographic nesting levels by including dummy variables for each nest. These are specified as random and potentially correlated parameters (Train, 2009). Specifically, we include field-of-study indicators and a dummy equal to one if the student is classified as a commuter or on-site by the DSU office responsible for the HEU.[28] The utility in Eq. (1) thus becomes:

$$U_{nj} \equiv V_{nj}+\epsilon_{nj} \equiv \pi_{nj}+\alpha_n(y_n-\zeta_{nj}+DSU_{nj})+\gamma \ln K_j+\lambda_{area}+\lambda_{fields}+\epsilon_{nj} \quad (4)$$

where $\ln K_j$ captures the heterogeneity in HEU in terms of number of programs offered, λ_{area} and λ_{fields} are the set of nest-specific effects, and ϵ_{nj} is the unobserved component at the student-HEU level.

We estimate the LCL using an expectation-maximisation (EM) algorithm following the procedure suggested by Von Haefen and Domanski (2018), which reduces the estimation of LCLs to a set of simple CL models. This approach enables us to achieve consistent estimates even when using only a sub-sample of all observed alternatives. Specifically, we draw a sub-sample of 130 aggregate alternatives for each student (approximately 20% of the full choice set), including the chosen alternative and 129 random options (McFadden, 1978). The utility function in Eq. (4) includes only alternative-specific variables, as the LCL model estimation is based on a set of class-specific CLs, one for each latent class. As outlined above, systematic heterogeneity related to students' observable characteristics is captured through the class membership probability model, which includes the following individual-level covariates: macro-area of residence, high school graduation mark, gender, provincial unemployment rate, regional GDP, and two indicators for whether the student is classified as on-site or commuter for at least one university. Table A.1 reports the list of variables included in the estimation and the descriptive statistics.[29] Further details on the use of the EM algorithm are provided in Section S3 in the Online Supplementary Material.

4.1. Identification challenges

The validity of our approach is challenged by the potential endogeneity of the DSU variables in relation to students' choices. At least in principle, various possible endogeneity issues need to be discussed and addressed. First, a correlation between the error term and the DSU regressors can arise due to unobserved heterogeneity in preferences and omitted variables. If students' preferences for DSU's policies and HEUs' characteristics are influenced by unobserved factors, observationally identical students will systematically make different decisions because of elements that are not accounted for in the analysis. This threat is mitigated by employing a very rich set of control variables for both HEUs' and hosting areas' characteristics, and by adopting a semi-parametric approach (the LCL) that approximates the continuous distribution of students' preferences using a discrete one. This approach avoids assumptions about the functional form of students' individual preferences and controls for unobserved heterogeneity. Importantly, because we parametrise class membership probabilities as a function of individual characteristics z_n, the latent class component is allowed to be systematically related to observables. In this sense, preference heterogeneity in the LCL need not be independent of observed traits, as the mixing distribution is conditional on z_n. This feature helps mitigate concerns that unobserved tastes correlated with observable characteristics could be absorbed by the error term and bias the estimated effects of DSU variables.

As an additional precaution, all data regarding DSU's supply and universities' features have been collected and used from the academic year 2017/2018, i.e., the academic year preceding the one in which we observe students' choices (2018/2019). This helps to neutralise the risk of contemporaneous reverse causality between students' choices and DSU office supply.[30]

However, an additional endogeneity concern could potentially arise if both the DSU offices and HEUs could to adjust their supply of DSU services in response to changes in demand through an adaptation mechanism, thereby raising the possibility of inverse causation. In such cases, as widely recognised in the literature (e.g., Bellemare et al., 2017), the use of lagged covariates does not offer a satisfactory solution to endogeneity stemming from non-contemporaneous reverse causality — for instance if the supply of DSU services in time $t-1$ (2017/2018) is influenced by the demand for services observed in year $t-2$ (2016/2017). This scenario may indeed occur, particularly in the case of scholarships, due to national funding rules, which stipulate that a portion of DSU funding distributed to regions (and subsequently to DSU offices) is based on the number of eligible students from the three previous academic years. To investigate whether such a data-generating process is present in our context, Figure S1 in the Supplementary Material displays the correlation between the change in grant expenditure in 2017–2018 and the average change in the number of eligible students over the three previous years (left panel) and the previous year alone (right panel). As shown, these correlations are virtually zero (and even slightly negative), therefore suggesting that adaptive processes, if any, are not practically relevant in our data.

Even in the case of dormitories, the capacity of DSU offices to adjust service supply in response to changes in demand from off-site students appears more constrained. First, as discussed in Section 2.2, between 2001 and 2018, DSU funding was not directly linked to past student demand. During this period, DSU offices could apply for four competitive calls to access 50% matching grants from the central government. This funding mechanism meant that only a subset of DSU offices received financial support. Moreover, the construction of new dormitories typically spans several years, making short-term adjustments highly unlikely. Second, dormitory facilities are periodically subject to renovation works, which may result in temporary closures lasting several years. Nevertheless, we cannot entirely rule out the possibility that a small share of accommodation places may be subject to short-term variation, for instance, through temporary agreements with hotels or other private housing providers, financed by internal or regional DSU funds. Taking all this into account, Figure S2 in the Supplementary Material provides evidence against the presence of adaptive responses: we observe a negative correlation between the 2017/18 supply and the variation in the number of applications, both when considering the previous year and the average of a three-year lag.

However, for robustness purposes, in the Results section, we test and correct for any remaining potential endogeneity impact related to

[27] As shown by Habibi et al. (2019), this is a parsimonious way to capture unobserved variation within aggregate options when disaggregated utility information is unavailable or unmanageable. The number of programs also has intrinsic interest, given its documented effect on student retention (Usala et al., 2024).

[28] Field-of-study indicators also help account for differences in unobserved characteristics of the field considered (e.g., average wage in the sector, employment opportunities after graduation).

[29] In principle, individual characteristics could be included in a fully interacted CL model by interacting all alternative-specific attributes with all individual-level variables. However, this approach becomes computationally burdensome with hundreds of alternatives, ignores the nesting structure, and requires estimating over 600 coefficients, significantly complicating interpretation. We report the results of this specification in Table 2 and Table S4 in the Online Supplementary Material and compare their performances with the LCL in Section 5.

[30] This also reduces the importance of a more subtle endogeneity source. Grants are awarded based on a single merit ranking until the available funds are exhausted. This causes the distribution of scholarships – among on-site, commuting, and off-site students – to depend on the number of students enrolled in each group. We thank an anonymous referee for pointing out this additional reason for not using data on the number of scholarships referred to the students' enrolment year.

the provision of dormitory places by means of a control function (CF) approach – and, of course, of the availability of a credible instrumental variable – thanks to its general direct applicability in a discrete choice framework. As shown by Petrin and Train (2010), the residual from a first-stage linear regression of the potentially endogenous variables against the exogenous variables and a set of proper instruments can be directly added to the utility function Eq. (1). The CF approach takes the following (triangular) structure:

$$DSU_{nj} = \beta_0 + \beta_1 x_{nj} + \beta_2 z_{nj} + \delta_{nj} \tag{5}$$

$$U_{nj} = V_{nj} + \rho\hat{\delta}_{nj} + \epsilon_{nj} \tag{6}$$

where DSU_{nj} is the endogenous supply of places in dormitories for eligible students, x_{nj} is the vector of exogenous covariates entering the deterministic component of the utility function (V_{nj}), z_{nj} represents the instrument for the endogenous variable within V_{nj}, and ρ the coefficient associated with the first stage residual $\hat{\delta}_{nj}$. A t-test of whether ρ is equal to zero will serve to detect the presence of endogeneity bias and decide whether to include $\hat{\delta}_{nj}$ in the estimation of the main equation.

The implementation of the previous framework requires valid instruments that are correlated with the DSU variables but plausibly orthogonal to students' choices. To this end, we exploit historical variations in national-level DSU financing for dormitory investments. Specifically, we draw on the 2012 MUR decree that allocated 287.932.509 euros to DSU offices for the construction of new dormitories for university students.[31]

As described in Section 2.2, these resources were awarded through competitive calls under Law 338/2000. Importantly for our purposes, the 2012 decree reports the awarded amounts at the beneficiary level corresponding to a DSU office–host city pair (e.g., Politecnico di Milano–Milano vs. Politecnico di Milano–Como). We digitised the decree table and constructed an instrument equal to the 2012 awarded amount (in million euros) associated with the DSU office–city serving each HEU in our choice set. The identifying variation comes from cross–(DSU office –city) differences in the 2012 allocations, including within-university differences across campuses located in different cities. We use this instrument in the first stage of our control-function approach. We conjecture that this investment shock (at time $t-6$) directly affected the dormitory capacity observed in 2017 (time $t-1$). As for its validity, it must affect students' enrolment choices only through its impact on dormitory capacity for eligible students. This exclusion assumption is plausible in our setting because the decree funds (in 2012) are earmarked for dormitory construction/renovation and, given the timing, cannot directly modify other HEU attributes entering students' utility in 2018.[32]

A further identification challenge concerns potential selection bias arising from students changing their official residence at the time of enrolment. Although strategic relocation is not advantageous (it may result in the loss of off-site status depending on the new residence, and it has no effect on the means-tested EES criterion), such behaviour may still occur. It could be driven by unobservable factors, such as sharing private accommodation with friends or relatives, motivated by the greater generosity of DSU services for off-site students. This may lead to an underestimation of the DSU's pull effect. To address this concern, we test the robustness of our results by using students' high school location, rather than their official residence, as a proxy for their original place of living.

As a final remark, we are aware that families (along with their children and future high school students) may strategically choose to reside in areas well equipped with public services, including hospitals and, crucially, higher education institutions. This clearly challenges the exogeneity of high-school students' locations; however, addressing such a selection mechanism lies beyond the scope of the present study.

5. Results

5.1. Key findings

We estimated the LCL model considering two to five latent classes, selecting the four-class model based on the Akaike and Bayesian Information Criteria (AIC, BIC). Estimates of students' utility function coefficients for each class and the mean parameters are shown in Table A.3 in the Appendix.

Table 2, Column 1, reports the percentage of correctly predicted choices for this specification. Students' choices were predicted by computing, for each individual, the probability of selecting one of the 636 Higher Education Units (HEUs) using Eq. (3) and the utility function estimated via the LCL model. Specifically, each student's predicted choice corresponds to the alternative with the highest predicted probability. Despite the large number of alternatives, the model predicts choices with good accuracy: 14.54% at the HEU level, compared to a random chance of 0.16% (1/636), performing about 94 times better. Aggregated mobility predictions show good performance: 52.91% at the university level, 60.95% at the city level, 61.71% at the province level, and 80.66% at the regional level. Fig. A.1 in the Appendix visually confirms the model's performance at the provincial level.

Table 2 also reports predictive accuracy for CL benchmarks and a few robustness analyses discussed in Section S4.2 of the Online Supplementary Material. The predictive performance of the baseline CL is broadly similar to that of the LCL at aggregated geographic levels (city/province/region). By contrast, the LCL performs better at the university level, and the main improvement emerges at the finest (and most demanding) level of disaggregation, i.e. the HEU level, where it outperforms the CL benchmark. In our application, this pattern is consistent with the fact that the LCL can accommodate both unobserved heterogeneity (through class-specific tastes) and observed heterogeneity in a parsimonious and interpretable way (by allowing class membership to depend on individual characteristics), which is particularly valuable when distinguishing among closely related HEUs within a large choice set.

It is useful to interpret the regression results through the lens of average marginal effects (AMEs). AMEs measure how students' choice probabilities change in response to a one-unit increase in a given HEU attribute. They summarise the information embedded in the class-level estimates of the LCL model. While these estimates primarily offer a flexible semi-parametric approximation of students' preferences (and are therefore not always directly interpretable) AMEs translate them into intuitive quantities. Importantly, they account for student heterogeneity, as they are computed considering the full set of individual characteristics.[33]

Table 3 reports the AMEs for all choice attributes in the model. For each AME, the table reports the standard errors computed via Krinsky–Robb parametric simulation.[34] For key DSU-related variables,

[31] Ministerial decree 12 August 2012, (GU Serie Generale n.301 28-12-2012). Allocation table available here.

[32] Unfortunately, variation in national legislation is not helpful for deriving credible instruments for grant expenditure. National funds have varied over the years, but the allocation rules have always been tied to the number of eligible students from the three previous academic years.

[33] As detailed in Eq. (A.3) in the Appendix.

[34] In details, we draw $R = 500$ parameter vectors $(\beta,\gamma)^{(r)} \sim \mathcal{N}\left((\hat{\beta},\hat{\gamma}), \widehat{\mathrm{Var}}(\hat{\beta},\hat{\gamma})\right)$. For each draw, we recompute class-conditional choice probabilities and posterior class membership probabilities, and then recompute the AME. Standard errors are the standard deviation of the simulated AME distribution. As described in the empirical framework, $(\hat{\beta},\hat{\gamma})$ are estimated on the reduced choice sets with 130 randomly sampled alternatives per individual, while predicted probabilities and AMEs (and their simulation-based standard errors) are computed on the full choice sets with 636 alternatives.

Table 2
Percentage of correctly predicted choices.

Level of aggregation	LCL	CL inter	CL	LCL w/CF	LCL city	LCL school	LCL aggr
Higher Education Unit level	14.54%	12.92%	11.87%	14.55%	14.59%	3.88%	
University level	52.91%	52.12%	49.26%	52.99%	52.98%	7.61%	55.33%
University city level	60.95%	60.12%	60.41%	60.95%	61.05%	14.15%	62.42%
University province level	61.71%	60.84%	61.03%	61.70%	61.81%	14.16%	63.04%
University region level	80.66%	79.60%	79.48%	80.69%	80.65%	21.62%	80.55%

Note: The table reports, for each level of aggregation, the percentage of students for which the highest estimated choice probability is associated with the observed choice. Each percentage is the ratio between the number of students for whom the model predicts the observed choice and the total number of students. For example, the rate at the city level is computed as the ratio between the number of students for which the model predicts the chosen hosting city and the total number of students. Column LCL reports the results of the specification used in the main text. Column CL inter shows the results obtained with the standard Conditional Logit approach interacting all individual characteristics with all continuous attributes of HEUs to include student-level covariates. Column CL shows the results obtained with the standard Conditional Logit approach without accounting for student-level covariates. LCL w/CF shows the results when using the Control Function approach. LCL city includes an additional level of nesting given where all universities in students' city are considered in the same group. LCL school considers students' high school instead of the municipality of residence for the definition of distances and DSU location statuses. LCL aggr is estimated considering the entire set of 149 university/municipality combinations (it does not consider the field of study nests). See Section 4.1 for more details on the robustness checks.

we complement this with kernel density distributions of individual marginal effects (Figure S3 in the Supplementary Material).

Let us first focus on the results in Table 3 for DSU services. We note sizeable and precisely estimated effects for dormitory places, whereas grant expenditures are not statistically distinguishable from zero. Dormitory places reserved for eligible students have a positive, highly significant impact on the probability of choosing an HEU (AME = 0.000099, s.e. = 0.000008, $p < 0.01$). With 187,067 freshmen, this implies that 100 additional places would attract about 18.5 additional students to the HEU, corresponding to roughly a 5.3% increase for an average-sized HEU with 349 enrollees.[35] This result is robust across individuals: the distribution of individual AMEs is strictly positive despite preference heterogeneity (see the right plot on the top panel of Figure S3 in the Supplementary material). The effect is also positive for places available to non-eligible students (AME = 0.000037, s.e. = 0.000013, $p < 0.01$), but it is smaller in magnitude (Δ Studs = 6.8) and the distribution is more dispersed, with a non-negligible share of individual AMEs having the opposite sign (Figure S3, central panel, left plot).

The most notable null result concerns grant expenditure. The AME for a one-million-euro increase in grants is very close to zero (−0.000005, s.e. = 0.000003) and is not statistically distinguishable from zero. Consistent with this, the left plot in the top panel of Figure S3 shows that a large share of individual AMEs (36.9%) is estimated to be positive, with a distribution tightly centred around zero. This pattern suggests that, although grants reduce living costs, they do not address 'iceberg' costs such as uncertainty, search time, and the effort required to secure housing, which can be essential in students' location choices.[36] A similar logic applies to rent support grants, often perceived as fallback options when dormitories are unavailable. These grants do not eliminate search costs and are typically introduced temporarily during renovations. Consistent with this interpretation, and looking to the standard errors reported in Table 3, their effect on where to enrol is negligible overall: slightly positive for non-eligible students, but not precisely estimated, while it is negative for eligible ones, and more precisely estimated, likely due to their association with dormitory shortages, although with substantial individual heterogeneity (Figure S3, central panel, right plot).

Overall, monetary provisions such as grants and rent support have limited influence on the distribution of students across HEUs. In contrast, dormitory availability plays a more decisive role. The impact of other contributing factors beyond the DSU indicators – including HEU characteristics and location-related variables – is discussed in Section S.3.1 of the Supplementary Material.

5.2. Heterogeneity

In the original spirit of McFadden and Train (2000), we view mixing distributions as a tool to approximate any choice probability implied by a random utility model. Accordingly, we use the LCL primarily as a discrete approximation rather than as a structural model of latent "types". In practice, however, finite mixture models are often discussed in terms of the latent classes identified by the estimation algorithm, since parametrising class membership with individual-level covariates helps reveal how observable traits shape students' responses to policy-relevant attributes.[37] In this descriptive sense, we cautiously venture to draw insights from Table A.3, which combines class-specific estimates for DSU-related variables (top panel) with individual characteristics (bottom panel). For instance, the third latent class shows a strong positive response to dormitory availability for both eligible and non-eligible students. This group mainly includes students from the Islands and the South (the reference category), who lack access to any HEU on-site or within commuting distance. Conversely, grants and rent support are less attractive for this group, likely because they are seen as insufficient to offset the broader costs of leaving home. In contrast, the first latent class (where the grant coefficient is positive and significant) appears to consist mainly of students from the South with an on-site alternative. Even in the second class, mostly composed of freshmen in the Centre-North with access to a local HEU, grants still play a modest role in shaping preferences.

We additionally assess how students' preferences are shaped by their individual characteristics using the results reported in Table 4, which show how the AMEs of DSU-related policies vary across subgroups defined by gender, high school performance, and local HEU availability. For each subgroup-specific AME, we also indicate the share of individual marginal effects with a sign opposite to the subgroup mean.[38] Starting with gender, both male and female students respond positively to dormitory places for eligible students, with a slightly

[35] The AME reported above is a marginal effect on a choice probability. In logit-type models, marginal effects scale with $p(1-p)$. With 636 alternatives per choice set, choice probabilities are typically small. Thus, AMEs can appear numerically small even when the implied changes in enrolments are economically meaningful.

[36] The role of certainty appears crucial in recent reviews on the effectiveness of need-based aid policies (e.g., see the survey by Burland et al., 2023).

[37] For instance, students who value in-kind services may also place particular importance on other attributes, such as travel distance.

[38] For readability, Table 4 focuses on subgroup differences and within-group heterogeneity (opposite-sign shares) and therefore does not report Krinsky–Robb simulation-based standard errors, in contrast to Table 3, where we report simulation-based standard errors for the main AMEs.

Table 3
Average marginal effects to HEU attributes.

Variable	AME	Δ Studs
Places for eligible/100	0.000099*** (0.000008)	18.47
Places for non-eligible/100	0.000037*** (0.000013)	6.85
Grants : Expenditures (Mill.)	−0.000005 (0.000003)	−0.89
Rent support: Eligible/100	−0.000071*** (0.000016)	−13.22
Rent support: Non-eligible/100	0.000082* (0.000044)	15.38
Places in colleges/100	−0.000005 (0.000006)	−0.89
Distance	−0.000052*** (0.000005)	−9.72
Lag HighSchool students	0.000040*** (0.000007)	7.56
Scholars/100	0.000054*** (0.000005)	10.07
Field of study scholars	0.000001*** (0.000000)	0.26
Share of foreign scholars	−0.036600** (0.015112)	−6847
K_j	0.000470*** (0.000022)	87.87
Excellence departments	0.000139*** (0.000041)	26.01
Average fee/1000	0.000049 (0.000042)	9.24
Non-DSU scholarships	−0.000026*** (0.000005)	−4.86
Public funding (Mill.)	−0.000006*** (0.000001)	−1.04
Private	−0.001341*** (0.000244)	−251
Destination housing price	0.000000 (0.000000)	0.01
Destination regional GDP	−0.000007 (0.000007)	−1.38
Destination Prov. Unemp.	−0.000053*** (0.000014)	−9.83
Commuting area	0.001501*** (0.000218)	281

Notes: The table reports average marginal effects (AMEs) related to HEU's attributes included in the estimation and the equivalent expected variation in the number of enrolled students (Δ Studs). Simulation-based standard errors are in parentheses and are obtained via Krinsky–Robb parametric simulation with 500 draws. For each draw we recompute class-conditional choice probabilities and posterior class membership probabilities and then recompute AMEs. Parameters are estimated on reduced choice sets with 130 randomly sampled alternatives per individual, while predicted probabilities and AMEs are evaluated on the full choice sets with 636 alternatives. Δ Studs are computed by multiplying the marginal effect for the total number of students (187,067). Significance stars are based on two-sided p-values with:
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

stronger effect for males. The difference is more pronounced for places for non-eligible students (AME = 0.00006 vs. 0.00002), possibly reflecting a greater male propensity to consider private HEUs, for which such places are more common. By contrast, the negligible effects of grants are essentially negative, mainly driven by the female component. When disaggregated by high school performance, differences remain modest for eligible places. However, better students are more responsive to dormitories for non-eligible students, consistent with merit-based admission to these facilities.

More marked differences emerge regarding local HEU supply. Students without a local HEU (AME = 0.00011) and commuters (AME = 0.00010) show the strongest response to dormitory availability, as housing support is most valuable when relocation is necessary. Conversely, students with a local HEU show the weakest response. The effect of grants remains small and negative across all groups.

Finally, the bottom panel of Table 4 reports AMEs by field of study. The strongest effects for dormitory places (eligible and non-eligible) are found in Life & Natural Sciences, Chemistry & Pharmacy (0.00011), Business & Statistics, and Engineering. In contrast, fields such as Education, Languages, and Psychology show weaker or near-zero effects, suggesting lower dependence on dormitory availability in enrolment decisions.

6. Simulation analysis

Alternative configurations of DSU services – especially student housing – can reshape the geography of university enrolment mobility. This may have important equity implications for access to higher-quality institutions and to degree programs better aligned with students' preferences, especially for financially constrained students and for those whose choices depend on dormitory availability.

To explore these potential impacts, we conduct a series of simulation exercises to explore how the geographical distribution of enrolled students would respond to changes in the supply of DSU services, specifically, the availability of dormitory places for eligible students, which emerges as the most impactful policy lever. We adopt a conservative approach by using estimates from the standard LCL. As such, the following exercise should be interpreted as providing a lower-bound estimate of the effects, compared to those we would expect using the Control Function specification of the LCL.

We simulate students' distribution using the sample enumeration technique (Train, 2009), which yields the estimated population in each group (i.e., provinces) as the sum of individual choice probabilities. Accordingly, we compute the unconditional choice probability of student n following (Pacifico and Yoo, 2013):

$$P_{nj} = \sum_{q=1}^{Q} \hat{H}_{nq} P_{nj|q}, \text{ with } P_{nj|q} = \frac{exp(V_{nj|q})}{\sum_{l=1}^{J} exp(V_{nl|q})}, \tag{7}$$

that is, the probability that student n chooses the HEU j is computed by weighting the class-specific probability $P_{nj|q}$ with students' posterior class membership probability $\hat{H}_{q|n}$. Therefore, we can obtain the predicted number of students in each HEU by summing the individual choice probabilities for each HEU. This framework allows flexible estimation of the spatial distribution of students within any chosen geographical unit. Specifically, by aggregating the predicted enrolments across all HEUs within the same Italian province, we derive an estimate of the provincial student population.

As a first step, we simulate the baseline distribution of students by fixing DSU policy indicators at their observed values. The observed and ex-ante simulated distributions are shown in Fig. A.1. First-year students are concentrated in 11 main provinces: four attracting more than 10,000 new enrolments per year (Milan and Turin in the North, Rome in the Centre, Naples in the South), and seven in the range of 4500–10,000 (Bologna and Padua in the North; Florence and Pisa in the Centre; Bari, Palermo, and Salerno in the South).[39] We then compare the ex-ante simulated distribution to three alternative hypothetical scenarios. For each of them, Fig. 1 reports the predicted variation in student population in each Italian province hosting at least a HEU. These variations are computed as the difference between the number of students enrolled in the baseline scenario and the number in each alternative configuration. Orange and red shades indicate provinces experiencing a decline in student numbers, while green shades highlight provinces with projected gains.

In the first scenario (No Places), the availability of dormitory places reserved for eligible off-site students is set to zero across all HEUs. As shown in the left panel of Fig. 1, this policy shock would lead to significant enrolment losses in several provinces that host historically

[39] See Table S5 in the Online Supplementary Material for more details on the simulated scenarios.

Table 4
Average marginal effects of DSU policies: supply of HEU and chosen field of study.

	Places for eligible		Places for non-eligible		Grants expenditures	
	AME	Δ Studs	AME	Δ Studs	AME	Δ Studs
Average	0.000099 (0.0000)	18.5	0.000037 (0.2688)	6.8	−0.000005 (0.3687)	−0.9
Sex:						
Females	0.000095 (0.0000)	9.8	0.000019 (0.4785)	2.0	−0.000008 (0.1483)	−0.9
Males	0.000103 (0.0000)	8.7	0.000058 (0.0113)	4.9	−0.000000 (0.6393)	−0.0
H. S. final mark quantiles:						
0%–50%	0.000100 (0.0000)	9.4	0.000030 (0.3186)	2.9	−0.000006 (0.3125)	−0.5
50%–100%	0.000098 (0.0000)	9.1	0.000043 (0.2182)	4.0	−0.000004 (0.4258)	−0.4
HEUs in students' local area:						
HEU in city	0.000094 (0.0000)	8.5	0.000033 (0.2574)	3.0	−0.000003 (0.4090)	−0.3
HEU in commuting area	0.000102 (0.0000)	7.0	0.000037 (0.2820)	2.6	−0.000006 (0.3319)	−0.4
no HEU in students' area	0.000107 (0.0000)	2.9	0.000048 (0.2729)	1.3	−0.000007 (0.3281)	−0.2
Type of University:						
Private	0.000082 (0.0000)	1.0	0.000027 (0.3252)	0.3	0.000000 (0.5250)	0.0
Public	0.000100 (0.0000)	17.5	0.000037 (0.2650)	6.5	−0.000005 (0.3583)	−0.9
Field of study:						
Business & Statistics	0.000110 (0.0000)	3.6	0.000058 (0.1065)	1.9	−0.000005 (0.3599)	−0.2
Chemistry & Pharmacy	0.000113 (0.0000)	1.2	0.000052 (0.2294)	0.6	−0.000010 (0.1568)	−0.1
Education	0.000079 (0.0000)	0.4	−0.000040 (0.9071)	−0.2	−0.000009 (0.0119)	−0.0
Engineering	0.000098 (0.0000)	3.5	0.000054 (0.0040)	1.9	0.000001 (0.7572)	0.0
Humanities	0.000094 (0.0000)	1.5	0.000025 (0.3753)	0.4	−0.000006 (0.2460)	−0.1
Languages	0.000079 (0.0000)	1.2	−0.000005 (0.6354)	−0.1	−0.000005 (0.2088)	−0.1
Law	0.000094 (0.0000)	1.5	0.000032 (0.3082)	0.5	−0.000005 (0.2782)	−0.1
Life & Natural Sciences	0.000128 (0.0000)	2.1	0.000072 (0.2138)	1.2	−0.000015 (0.0997)	−0.3
Math. & Physical Sciences	0.000099 (0.0000)	1.1	0.000051 (0.0077)	0.6	0.000001 (0.7618)	0.0
Psychology	0.000068 (0.0000)	0.4	−0.000020 (0.7128)	−0.1	−0.000002 (0.3046)	−0.0
Social & Political Sciences	0.000088 (0.0000)	1.9	0.000008 (0.5051)	0.2	−0.000005 (0.2330)	−0.1

Notes: The table reports the AME of DSU policies indicators and the equivalent expected variation in the number of enrolled students (Δ Studs) for each group of student. Students are grouped according to their sex, high school graduation mark, the supply of HEU in their local area, and the chosen field of study. Each AME is computed as the average of the individual marginal effects computed for the students in each specific group. For example, the AME for females is computed as the average of the individual marginal effect among female students. Δ Studs is computed by multiplying each AME for the number of students in the group. For each average estimate, we also report in parenthesis the share of individuals that present an estimated marginal effect with an opposite sign with respect to the average.

prominent universities: Bologna and Turin in the North; Florence, Pisa, and Pesaro-Urbino in the Centre. These locations are currently characterised by a good endowment of dormitories, similar to a few provinces in the South, such as Bari and Cosenza. Thus, the removal of dormitory support would reduce the mobility of financially constrained students, leading to a general shift in enrolments toward more peripheral provinces, which would benefit from retaining a larger share of their local student population.

The second scenario simulates the expansion in dormitory supply planned under the Italian National Recovery and Resilience Plan (NRRP; see Section 2.2), which foresees the creation of 60,000 new places nationwide. In the absence of detailed information on the future geographical allocation of these places, we distribute them based on the number of student housing applications at the university level. Following NRRP guidelines, 40% of the total supply is first allocated to universities in the South and Islands, and the remaining 60% to those in the Centre and North. Within each area, places are then assigned proportionally to the gap between the number of eligible applicants and the number of dormitory places currently available. As a result, universities with a higher share of unmet demand receive a larger portion of the new supply. This *All HEUs* scenario generates a marked polarisation effect: most provinces contribute to a substantial increase in enrolments in three of the four major university hubs: Turin and Milan in the North, and Rome and Pisa in the Centre. Conversely, Naples, the main university destination in the South, experiences a significant decline, likely due to the high share of on-site students who

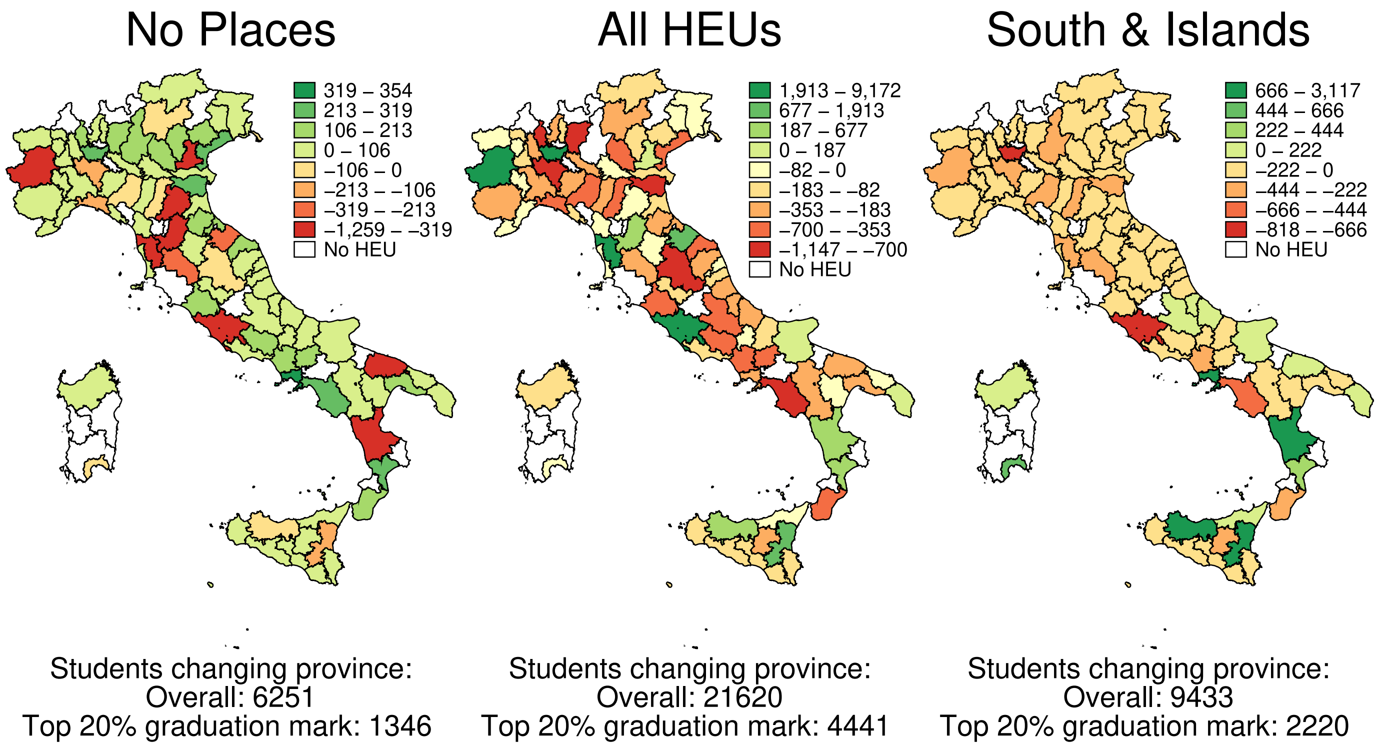

Fig. 1. Changes in students' population by Italian provinces.
Notes: The figure reports the predicted variation in the population of students in each Italian province for each policy scenario considered. Yellow and red provinces register a negative variation compared to the ex-ante scenario. Green provinces register a positive variation. In each map, we also report the total number of students who have changed provinces. White provinces are those that do not host any HEU. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

are particularly sensitive to dormitory availability in other locations. As shown in Table S5 in the Supplementary Material, which maps colours to Italian provinces, the main beneficiaries include provinces with a substantial observed gap, such as Pisa, Pesaro-Urbino, and Catania. In contrast, provinces located near the main hubs – such as Brescia, Bergamo, and Pavia (in the Milan area) – record the largest losses.

Overall, the comparison between these first two simulations suggests that DSU policies strongly affect the set of feasible alternatives for less advantaged students, either enabling or constraining their ability to move beyond their local area and access major university centres.

A widely debated issue concerning current patterns of student mobility is the potentially long-term detrimental impact on peripheral areas of the country, particularly on provinces in the Italian Mezzogiorno.[40] In line with this concern, the third simulation scenario (*South & Island*) explores whether and to what extent a targeted policy favouring southern regions could mitigate student out-migration from the South to central and northern Italy. Following the logic used in the *All HEUs* scenario, which aligns with the NRRP goals, we increase the supply of dormitory places, but allocate the additional places exclusively to HEUs located in the South and the two main islands. The third panel of Fig. 1 illustrates how this policy would redirect student flows toward most southern provinces, particularly those where students obtained their high school diplomas. However, the overall quantitative impact remains limited: only 9433 students would relocate to a different province. This modest effect reflects the fact that HEU choice is also influenced by broader characteristics of the hosting area – such as per capita income and unemployment rate – as well as by the quality of the HEUs (albeit to a lesser extent). Interestingly, the redirection effect appears stronger among students with higher high school graduation marks, who are overrepresented among those who relocate: 23.5% of them are in the top 20% of the distribution of high school graduation marks.

Beyond geographical redistribution, DSU services also influence the type of higher education institution students choose, along two key dimensions: field of study and institution quality. This can be assessed thanks to the modelling strategy adopted, which captures student choices at the highly disaggregated level of the single HEU. Table 5 reports the percentage changes in student populations across scenarios, disaggregated by the number of *Departments of Excellence* (top panel) and by field of study (bottom panel). As shown in the "*All HEUs*" column, the provision of DSU services is associated with a shift toward higher-quality institutions: the number of students enrolling in HEUs with at least four Departments of Excellence increases by 73%, while those with fewer than two departments experience a decline of approximately 10%. In contrast, data in the *South & Islands* column suggest that favouring southern universities may lead to a reduction in the overall quality of the institutions chosen by students.

Another interesting impact regards the distribution of students among fields of study. The bottom panel of Table 5 shows that, under a scenario involving a substantial expansion of dormitory places, students are more likely to choose STEM degree programs. This suggests that improved access conditions may also influence students' academic orientation, potentially by reducing the weight of geographical or financial constraints in their decision-making process.

7. Conclusions

We have investigated the role of students' support policies in the Italian *Diritto allo Studio Universitario* (DSU) program by adopting a general discrete choice framework, in which DSU services represent a

[40] See, for example, Attanasio and Enea (2019) on the North–South divide in student mobility choices in Italy. See also Haapanen and Tervo (2012) for the case of Finland and Oggenfuss and Wolter (2019) for Switzerland.

Table 5
Changes in students' populations by excellence departments and field of study.

	No places %	All HEUs %	South & Islands %
N. of excellence department:			
High ($n \geq 4$)	−0.9	72.7	−6.2
Medium ($2 \leq n < 4$)	−4.0	12.4	−4.0
Low ($n < 2$)	1.4	−9.8	1.8
Field of study:			
Humanities	−0.4	−2.3	0.3
ELSS	1.6	−10.3	−0.4
STEM	−1.4	11.2	0.2

Notes: The table reports the predicted variation in the population of students according to the number of excellence departments in the chosen HEU and the field of study. HEUs are aggregated depending on the number of excellence departments in 3 categories (Low, Medium, High). Fields are aggregated based on their disciplinary contents in three categories: Science, Technology, Engineering, and Mathematics (STEM); Economic, Law, and Social Sciences (ELSS); Humanities. Column 1 refers to the scenario No Places in which the supply of places for eligibles is reduced to 0 in each HEU. Columns 2 and 3 refer to the scenarios in which the number of places increases according to PNRR prevision. In Column 2 the places are distributed according to students' applications in all HEUs. In Column 3 the places are distributed only in Southern regions according to students' applications.

subset of the broader set of factors influencing high school graduates' university enrolment decisions.

Our results underline the particular importance of policies that expand dormitory capacity, especially for students who meet the means-test criteria. We estimate that an increase of 100 dormitory places would attract between 19 and 34 additional students to a given HEU, corresponding to an enrolment increase of 5.3% to 9.6% for an average-sized institution. In contrast, monetary tools do not appear to play a significant role overall. This finding, which somewhat diverges from the evidence from other countries, likely reflects specific features of the Italian higher education system, where relatively low tuition fees coexist with a chronic shortage of student housing. In such a context, financial aid alone cannot offset the indirect costs associated with relocation and accommodation. Regarding heterogeneity in student preferences, the effect of dormitory availability is stronger for male students and those without a university in their hometown. The latter group, in particular, emerges as the most in need of expanded dormitory provision, as they must relocate or commute to physically reach any university.

To summarise the effects of alternative configurations in the supply of student housing, we conducted a series of simulations to assess the mobility patterns induced by hypothetical policy changes. Given that a substantial expansion in dormitory capacity is currently at the centre of the policy debate, we simulated an expansive scenario aligned with the Italian NRRP, adding 60,000 new dormitory places across Italian universities, proportionally to the current unmet demand. The expected outcome is a strong geographical polarisation of student flows, with enrolments concentrating in a limited number of major university cities. In contrast, a policy aimed at addressing dormitory shortages exclusively in Southern regions would only partially mitigate student out-migration from these areas. This limited effect is due to the influence of other structural factors, such as local economic conditions, which also shape students' choices. This targeted policy would have a disproportionate impact on high-achieving students, who are overrepresented among those who would relocate in response to the improved housing provision.

These findings bring us back to the initial considerations in the Introduction. DSU services expand the range of opportunities for less-advantaged students and serve as a strategic tool for local areas competing to attract and retain human capital. As often happens, pursuing two policy goals with a single instrument is problematic. In this case, a stronger provision of student housing would certainly broaden the options available to highly motivated students, especially those from poorer areas. However, better DSU services alone are unlikely to halt the substantial brain drain affecting these regions.

A key constraint of this analysis is its reliance on cross-sectional data, which inherently limits the ability to capture temporal dynamics and adopt more rigorous identification strategies. As such, the strength of the methodological adjustments introduced should be interpreted in light of this structural limitation. A further and arguably more substantial limitation concerns the lack of data on students' eligibility for DSU policies under the EES rules, as well as on their actual uptake of support measures. Access to national-level eligibility data would significantly enhance the analysis. In particular, it would allow for a more precise assessment of how support policies shape access to tertiary education among students who are undecided about whether to enrol at university, or are currently unable to do so.

CRediT authorship contribution statement

Cristian Usala: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rinaldo Brau:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are grateful to Mariano Porcu for granting us access to the MOBYSU.IT database. We also thank Marco Nieddu, Claudio Deiana, Emanuela Marrocu, Erica Delugas, and participants at the Workshop on Student Mobility, University and Post-University Choices organised at the University of Cagliari, the 9th ICEEE conference, the Annual CRENoS Workshops, the 21 LAGV conference, the CISEPS annual workshop on Tackling Inequality (2023) and the XXXV SIEP Conference for insightful comments.

Appendix A

A.1. Higher Education Units' characteristics

USTAT provides information on universities' characteristics, including whether institutions are public or private, the number of scholars, their nationality, and research fields.

We have also collected information regarding the quality of researchers employed at the universities, namely the number of departments that were awarded in the *Dipartimenti di Eccellenza* (departments of excellence) project. This project, managed by the National Agency for the Evaluation of Universities and Research Institutes (ANVUR), consists of a standardised assessment of the research's quality of Italian departments and is based on the results of the third Italian Research Evaluation Exercise (VQR) referred to the period 2011–2014. To account for the resources available in each university, we have gathered data on the amount of public funding each institution received in 2018 from the MUR. Additionally, we control for students' enrolment costs related to university fees by using the information on the average tax revenues collected by universities.

The relationship between the high school of origin and the chosen university is another important factor influencing students' decisions (see, e.g. Usala et al., 2023). High schools may recommend specific institutions, and students may be more likely to choose universities with a strong presence of peers from their own school. To account for

Table A.1
Definition and descriptive statistics of variables used in estimation.

Variable	Definition	Average	Std Dev
HEU and hosting areas characteristics:			
Grants : Expenditures (Mill.)	Expenditures for DSU grants in millions of Euros.	9.23	8.44
Places for eligible/100	Number of places in the city × share of places provided to eligible students.	3.64	4.15
Places for non-eligible/100	Number of places in the city × share of places provided to non-eligible students.	0.566	1.52
Rent support: Eligible/100	Number of policies of rent support provided to DSU eligible students.	0.413	1.06
Rent support: Non-eligible/100	Number of policies of rent support provided to students who do not meet DSU eligibility requirements.	0.322	1.30
Places in colleges/100	Number of places provided in colleges according to college eligibility requirements.	1.30	2.37
Non-DSU scholarships	Number of scholarships provided outside the DSU program.	3.15	4.06
Distance	Minutes of travel by car between students' city of residence and HEU's hosting city.	61.10	43.33
$\text{Distance}^2/100$	$\text{Distance}^2/100$	17 010	22 118
Lag HighSchool students	Average number of students coming from the same High-School between 2015 and 2017.	35.92	27.79
Excellence departments	Number of department of excellence.	0.690	1.03
Private	1 if the HEU is a private institute.	0.123	0.328
Field of study scholars	Number of professors and researchers employed in the field of study considered.	90.04	85.09
Share of foreign scholars	Share of foreigner professors and researchers.	0.014	0.018
Scholars/100	Number of professors and researchers employed by the HEU.	9.56	7.59
Public funding (Mill.)	Amount of public funding received by the HEU in millions of Euro in 2018.	117	104
Average fee/1000	University enrolment tax revenues/Total number of students who have paid taxes	2.14	1.69
Destination Prov. unemployment	Average provincial unemployment rate between 2015 and 2017 in HEU's hosting province.	12.18	5.78
Destination regional GDP	Regional GDP per capita in 2017 in HEU's hosting region.	0.026	0.007
Destination housing price	Average provincial housing purchase price per ^{2} in 2013 in HEU's hosting city.	1186	414
Nesting structure:			
$\ln(K_j)$	Logarithm of the number of programs $provided in HEU$	0.631	0.670
Commuting area	1 if the HEU is in student's commuting area as defined by DSU offices.	0.567	
Law	Law	0.116	
Education	Education	0.058	
Languages	Languages	0.082	
Humanities	Humanities	0.096	
Math & Physical Sciences	Math & Physical Sciences	0.071	
Psychology	Psychology	0.055	
Life & Natural Sciences	Life & Natural Sciences	0.088	
Chemistry & Pharmacy	Chemistry & Pharmacy	0.068	
Engineering	Engineering	0.102	
Social & Political Sciences	Social & Political Sciences	0.124	
Individual characteristics:			
Male	1 if student is male	0.449	0.497
Origin Prov. unemployment	Average provincial unemployment rate between 2015 and 2017 in student's province.	12.59	6.10
NorthWest	1 if the student resides in a region in the North-West of Italy	0.248	
NorthEast	1 if the student resides in a region in the North-East of Italy	0.180	
Centre	1 if the student resides in a region in the Centre of Italy	0.204	
Islands	1 if the student resides in Sicily or Sardinia (Islands)	0.102	
High school graduation mark	High school diploma grade.	81.31	11.73
On Site	1 if the student is on-site for at least one HEU.	0.407	
Commuter	1 if the student is a commuting students for at least one HEU.	0.566	
Origin regional GDP	Regional GDP per capita in 2017 in student's region.	25.28	6.99

Notes: The table reports the definitions of the variables used in estimation. If not specified, all the variables are observed in 2017.

Table A.2
First stage regression of the control function model.

	Places with grant/100	
Gvt's matching grants for dormitories (Mill.)	0.0706***	(0.0141)
Grants : Expenditures (Mill.)	0.214***	(0.0318)
Rent support: Eligible/100	1.016***	(0.147)
Rent support: Non-eligible/100	0.114*	(0.0506)
Places for Non-eligible/100	0.764***	(0.0960)
Places in colleges/100	0.102*	(0.0490)
Scholars/100	−0.0708	(0.0562)
Share of foreign scholars	−35.24***	(5.460)
Field of study scholars	0.000201	(0.00198)
Public funding (Mill.)	−0.00855	(0.00438)
Private	0.232	(0.430)
Non-DSU scholarships	0.0204	(0.0320)
Average fee/1000	−0.415***	(0.108)
$\ln(K_j)$	0.636**	(0.207)
Destination regional GDP	−52.46	(32.61)
Destination Prov. unemployment	−0.0460	(0.0317)
Destination housing price	0.000955**	(0.000366)
Distance^2/100	−0.000132***	(0.0000250)
Distance	0.0882***	(0.0140)
Lag HighSchool students	0.0640***	(0.00516)
Excellence departments	0.00643	(0.140)
Commuting area	2.083*	(0.816)
Chemistry & Pharmacy	−0.463	(0.571)
Business & Statistics	−0.321	(0.506)
Life & Natural Sciences	−0.685	(0.536)
Law	−0.128	(0.483)
Engineering	−0.999	(0.548)
Education	0.648	(0.600)
Humanities	−0.213	(0.521)
Languages	0.199	(0.540)
Social & Political Sciences	−0.0902	(0.515)
Psychology (baseline)	0	–
Math & Physical Sciences	−0.0731	(0.596)
Constant	−2.672	(1.390)
Observations	636	
R^2	0.703	
Adjusted R^2	0.688	

Notes: The table shows the result of the first stage regression in which the number of places for eligibles is regressed against all the regressors used in estimation and the amount of Public dormitory investment (the instrument). See Section 4.1 for more details on the control function approach. Variable definitions are reported in Table A.1. Standard errors are reported in parentheses:
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

this, we computed, for each student/HEU pair, the average number of students from the same high school over 2015–2017.

Additional controls aim to capture the economic conditions of the hosting areas. We collected data on regional GDP per capita in 2017 and the average provincial unemployment rate between 2015 and 2017 from ISTAT. Furthermore, to account for living costs in university towns, we included the average purchase price per square meter in 2013, obtained from the Real Market Observatory (OMI) database.

Finally, USTAT allows us to account for financial and in-kind support measures not included in the DSU program. In particular, we observe the number of non-DSU grants provided by universities and the number of places provided by colleges.[41]

A.2. Details on students' utilities approximation

The semi-parametric approximation of students' preference distribution is implemented by estimating a class-specific deterministic utility $V_{nj|q}$ and letting class-membership probability depend on students' characteristics. This allows us to approximate the distribution of students' preference parameters by accounting for the influence related to students' observables. Following Greene and Hensher (2003), the class-membership probability is defined as:

$$H_{nq}(\gamma_q) = \frac{exp(z_n'\gamma_q)}{\sum_{s=1}^{Q} exp(z_n'\gamma_s)} \tag{A.1}$$

where z_n is the vector of individual characteristics of student n that enters in the class membership probability model and γ_q are the parameters that link z_n to H_{nq}.

Overall, for each class, we will have two vectors of parameters, a first one containing the taste parameters associated with j's attributes (β_q) that enter into students' utilities defined in Eq. (4), and a second one, related to students' characteristics (γ_q), that defines their class-membership probabilities in Eq. (A.1).

The probabilities defined in Eqs. (7) and (A.1), along with the information on students' observed choices, can be used to estimate the posterior class membership probability:

$$\hat{H}_{q|n}(\beta_q,\gamma_q) = \frac{P_{nq}(\beta_q)H_{nq}(\gamma_q)}{\sum_{q=1}^{Q} P_{nq}(\beta_q)H_{nq}(\gamma_q)} \tag{A.2}$$

where P_{nq} denotes the probability to predict the observed choice of student n according to class q estimates. Thus, the posterior class probability is computed by assigning higher weights to classes that better predict the observed choices. This measure weights class-specific estimates of students' utilities $V_{nj|q}$ by their probability of belonging to class q.

A.3. Computation of individual marginal effects

We use the posterior class probability $\hat{H}_{q|n}$ in Eq. (A.3) to derive the set of individual marginal effects. Following Train (2009), we define a student's n individual AME with respect to an attribute of a generic HEU as:

$$\sigma_n = \sum_{q=1}^{Q} \hat{H}_{nq}\sigma_{n|q} = \sum_{q=1}^{Q} \hat{H}_{nq} \sum_{j=1}^{J} P_{nj|q}(1-P_{nj|q})\frac{\partial V_{nj|q}}{\partial x_{nj}}. \tag{A.3}$$

$V_{nj|q}$ is the deterministic part of utility in class q, x_{nj} is the attribute of HEU j observed by student n, and $P_{nj|q}$ is the probability of student n to choose the HEU j given class q estimates. Thus, $\sigma_{n|q}$ is the class-specific marginal effect, and σ_n is computed by weighting these with the student's posterior class membership probabilities $\hat{H}_{q|n}$. These probabilities allow AMEs to reflect individual characteristics and observed choices.

A.4. Additional material

See Tables A.1–A.3 and Fig. A.1.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2026.104232.

Data availability

We will be able to share our data set on student supports services for university students in Italy based on the USTAT portal. We will be unable to share the microdata from the Database MOBYSU.IT (Mobilità degli Studi Universitari in Italia) (2023). The data used in this study have been processed in accordance with the RESEARCH PROTOCOL FOR THE STUDY 'From high school to the job placement: analysis of university careers and university mobility from Southern to Northern Italy' among the Ministry of University and Research, the Ministry of Education and Merit, the University of Palermo as the lead institution, and the INVALSI Institute. The reference researcher is Mariano Porcu.

[41] Colleges provide places in dormitories based on specific criteria such as students' sex or high school graduation marks. To account for these services, we have assigned each student the number of places available in each HEU according to their characteristics.

Table A.3
Latent class logit results.

	*Class*1	*Class*2	*Class*3	*Class*4	*Mean*
Random utility parameters					
Places for eligible/100	0.03814***	0.06892***	0.16812***	0.04506***	0.07194
	(0.00379)	(0.00390)	(0.00817)	(0.00313)	
Places for non-eligible/100	0.04529***	0.01969**	0.18077***	−0.04544***	0.02888
	(0.00666)	(0.00795)	(0.01467)	(0.00849)	
Grants : Expenditures (Mill.)	0.00749***	0.00408	−0.03025***	−0.00460**	−0.00371
	(0.00271)	(0.00261)	(0.00650)	(0.00222)	
Rent support: Eligible/100	−0.07971***	0.00897	−0.17320***	−0.03598***	−0.05020
	(0.01164)	(0.01394)	(0.01810)	(0.01260)	
Rent support: Non-eligible/100	−0.43807***	0.14526***	0.42086***	0.08615***	0.07116
	(0.01694)	(0.01611)	(0.01960)	(0.01411)	
Places in colleges/100	0.06635***	0.01069**	−0.02245**	−0.04567***	−0.00352
	(0.00515)	(0.00521)	(0.01051)	(0.00433)	
Distance	−0.01193***	−0.05249***	−0.01043***	−0.04656***	−0.03685
	(0.00024)	(0.00059)	(0.00043)	(0.00051)	
Distance^2/100	0.00001***	0.00002***	0.00001***	0.00002***	0.00002
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	
Lag HighSchool students	0.00469***	0.01815***	0.12435***	0.00983***	0.03030
	(0.00031)	(0.00032)	(0.00184)	(0.00024)	
Scholars/100	0.04015***	0.05183***	0.06597***	0.01192**	0.03914
	(0.00554)	(0.00551)	(0.01488)	(0.00483)	
Field of study scholars	0.00473***	0.00066***	0.00137***	−0.00087***	0.00097
	(0.00016)	(0.00013)	(0.00034)	(0.00018)	
Share of foreign scholars	6.75508***	5.14926***	−215.05634***	9.06094***	−28.87933
	(0.66382)	(0.74458)	(5.03942)	(0.67842)	
$\ln(K_j)$	1.01673***	0.74129***	0.65354***	0.81534***	0.79814
	(0.02273)	(0.01674)	(0.03560)	(0.01426)	
Excellence departments	0.10768***	0.00993	0.58001***	−0.03154***	0.10519
	(0.01225)	(0.00949)	(0.01537)	(0.00847)	
Average fee/1000	0.05352***	−0.05871***	0.52913***	−0.10015***	0.04190
	(0.00896)	(0.01118)	(0.03922)	(0.01094)	
Non-DSU scholarships	−0.03520***	−0.00234	−0.05971***	−0.00648**	−0.01856
	(0.00299)	(0.00275)	(0.00588)	(0.00313)	
Public funding (Mill.)	−0.00322***	−0.00559***	−0.00976***	−0.00019	−0.00411
	(0.00044)	(0.00043)	(0.00118)	(0.00036)	
Private	−0.24318***	−0.67214***	−4.14968***	−0.20331***	−1.00831
	(0.06302)	(0.06876)	(0.19557)	(0.04999)	
Destination housing price	0.00072***	0.00011***	−0.00053***	−0.00013***	0.00003
	(0.00004)	(0.00004)	(0.00010)	(0.00003)	
Destination regional GDP	0.01032**	−0.03437***	0.02683***	−0.00001	−0.00569
	(0.00507)	(0.00502)	(0.00726)	(0.00384)	
Destination Prov. unemployment	−0.05296***	−0.02739***	−0.21147***	0.03727***	−0.04045
	(0.00584)	(0.00515)	(0.00962)	(0.00397)	
Nesting structure parameters					
Commuting area	2.00067***	0.48697***	3.08871***	0.22070***	1.07856
	(0.04834)	(0.03185)	(0.07847)	(0.02610)	
Chemistry & Pharmacy	−0.32543***	−1.57541***	−0.65799***	−0.21673***	−0.77213
	(0.05316)	(0.03559)	(0.05323)	(0.03250)	
Life & Natural Sciences	−0.99976***	−1.51432***	−0.66051***	0.20186***	−0.73030
	(0.05836)	(0.03266)	(0.04839)	(0.02960)	
Law	0.80004***	−1.12935***	−0.74539***	0.36990***	−0.25076
	(0.03940)	(0.03287)	(0.05861)	(0.02973)	
Engineering	−0.48947***	0.18387***	−0.93577***	−2.01057***	−0.82577
	(0.04164)	(0.02359)	(0.05586)	(0.29883)	
Education	−1.83283***	−18.20455**	−1.91998	1.16265***	−6.48254
	(0.13921)	(7.63851)	(3.30182)	(0.03432)	
Humanities	−0.08436**	−1.62090***	−1.14422***	0.17167***	−0.69882
	(0.04156)	(0.03300)	(0.05930)	(0.02852)	
Languages	1.02354***	−2.25844	−0.63693	1.16635***	−0.32292
	(0.04364)	(1.71803)	(3.42555)	(0.03037)	
Social & Political Sciences	0.42309***	−1.38596***	−0.67048***	0.40663***	−0.37887
	(0.03974)	(0.03216)	(0.06174)	(0.02897)	
Psychology	0.75368***	−2.39348	−3.21967***	0.78338***	−0.95704
	(0.05439)	(5.19461)	(0.28423)	(0.03554)	
Math & Physical Sciences	−0.50903***	−0.41376***	−2.03533***	−2.36014***	−1.32527
	(0.04780)	(0.02304)	(0.07463)	(0.81348)	

(*continued on next page*)

Table A.3 (*continued*).

Class probability parameters				
Cons.	−6.22873***	−5.77762***	−5.13116***	Fixed
	(0.20242)	(0.23219)	(0.22764)	Fixed
NorthWest	−1.30848***	0.39391***	−1.67669***	Fixed
	(0.09546)	(0.10625)	(0.10779)	Fixed
NorthEast	−0.79379***	0.33905***	−2.01882***	Fixed
	(0.08981)	(0.10272)	(0.10361)	Fixed
Centre	−0.90033***	0.21491***	−1.05194***	Fixed
	(0.07033)	(0.08303)	(0.08124)	Fixed
Islands	−0.24347***	−0.06938	0.37585***	Fixed
	(0.04335)	(0.05305)	(0.04795)	Fixed
High school graduation mark	0.06908***	0.05439***	0.03028***	Fixed
	(0.00128)	(0.00143)	(0.00135)	Fixed
On site	0.31821***	0.24787***	−0.20148***	Fixed
	(0.03069)	(0.03291)	(0.03566)	Fixed
Commuter	−0.08563***	0.01900	−0.18928***	Fixed
	(0.02995)	(0.03382)	(0.03371)	Fixed
Origin Prov. unemployment	−0.04049***	−0.02026***	−0.00460	Fixed
	(0.00493)	(0.00582)	(0.00538)	Fixed
Origin regional GDP	0.01222*	−0.02087***	0.10629***	Fixed
	(0.00643)	(0.00705)	(0.00723)	Fixed
Male	2.89124***	4.66993***	2.36123***	Fixed
	(0.05691)	(0.06270)	(0.05712)	Fixed
Class membership prob.	0.170	0.343	0.162	0.325
Choice makers	187 067			
Log likelihood	−419 388.1			
BIC	840 730.7			

Notes: Latent Class Logit estimated considering, for each student, a choice set composed by the chosen alternative and 129 random alternatives. With respect to nesting structure parameters related to fields of study, we consider the field as the baseline. For each latent class, the table reports the set of class-specific parameters related to students' utility, the nesting structure and the class membership probability model. The mean parameter is computed as the average of class-specific parameters weighted for the class membership probability. Variable definitions are reported in Table A.1. The first stage regression results are shown in Table A.2.

Standard errors in parenthesis:

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

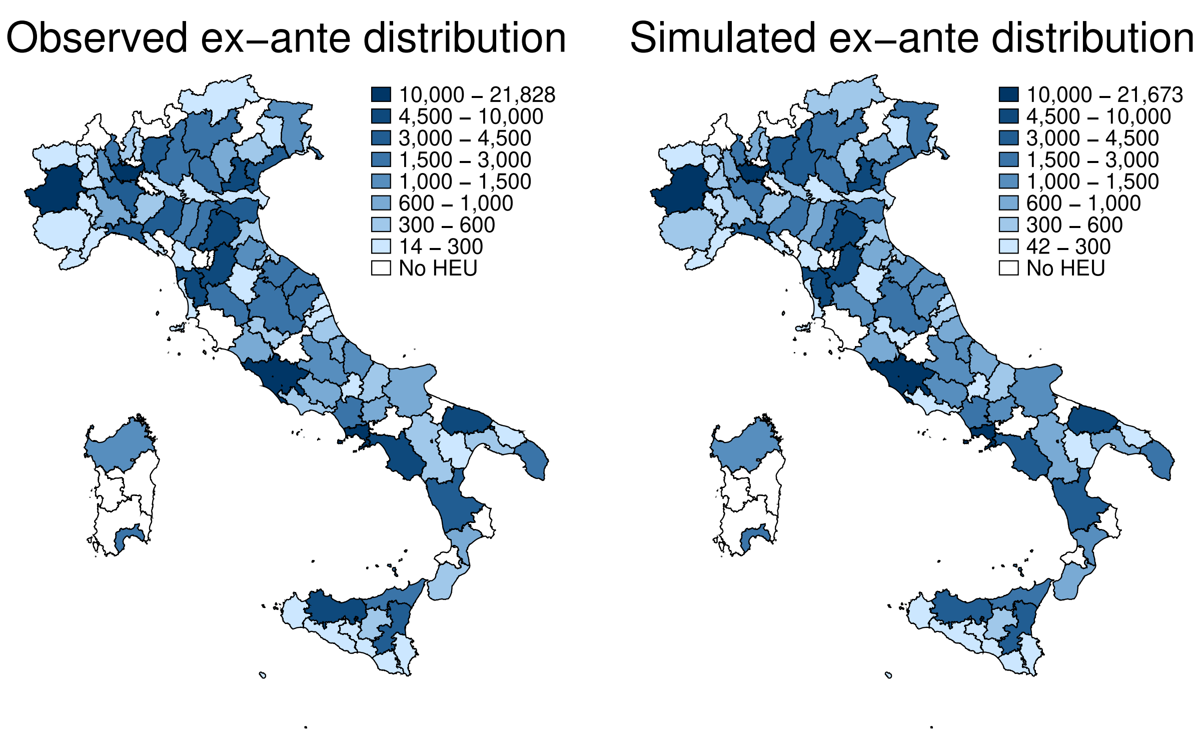

Fig. A.1. Students' population in Italian provinces.

Notes: The figure reports students' observed (left) and simulated (right) ex-ante distribution. The ex-ante simulated distribution was computed by letting the DSU indicators be at the observed values. Provinces with few students are shown in light blue, while areas with many are in dark blue. White provinces are those that do not host any HEU. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

References

Aina, C., Baici, E., Casalone, G., Pastore, F., 2022. The determinants of university dropout: A review of the socio-economic literature. Socio-Econ. Plan. Sci. 79, 101102.

ANVUR, 2023. Italian National Agency for the evaluation of universities and research institutes - Rapporto sul sistema della formazione superiore e della ricerca.

Attanasio, M., Enea, M., 2019. La mobilitá degli studenti universitari nell'ultimo decennio in Italia. In: Santis, G.D., Pirani, E., Porcu, M. (Eds.), Rapporto Sulla Popolazione. L'Istruzione in Italia. Il Mulino, Bologna, pp. 43–58.

Bellemare, M.F., Masaki, T., Pepinsky, T.B., 2017. Lagged explanatory variables and the estimation of causal effect. J. Politics 79 (3), 949–963.

Bernal, G.L., Abadia, L.K., Arango, S., De Witte, K., 2024. Can information change preferences for higher education? Evidence from a randomised experiment in Colombia. Int. J. Educ. Res. 127, 102417.

Bhat, C.R., 1997. An endogenous segmentation mode choice model with an application to intercity travel. Transp. Sci. 31 (1), 34–48.

Biancardi, D., Bratti, M., 2019. The effect of introducing a Research Evaluation Exercise on student enrolment: Evidence from Italy. Econ. Educ. Rev. 69, 73–93.

Bowman, N.A., Bastedo, M.N., 2009. Getting on the front page: Organizational reputation, status signals, and the impact of 'U.S. news and world report' on student decisions. Res. High. Educ. 50, 415–436.

Bratti, M., Verzillo, S., 2019. The 'gravity' of quality: research quality and the attractiveness of universities in Italy. Reg. Stud. 53 (10), 1385–1396.

Burland, E., Dynarski, S., Michelmore, K., Owen, S., Raghuraman, S., 2023. The power of certainty: Experimental evidence on the effective design of free tuition programs. Am. Econ. Rev.: Insights 5 (3), 293–310.

Castleman, B.L., Long, B.T., 2016. Looking beyond enrollment: The causal effect of need-based grants on college access, persistence, and graduation. J. Labor Econ. 34, 1023–1073.

Cattaneo, M., Malighetti, P., Meoli, M., Paleari, S., 2017. University spatial competition for students: the Italian case. Reg. Stud. 51 (5), 750–764.

Cattaneo, M., Malighetti, P., Paleari, S., Redondi, R., 2016. The role of the air transport service in interregional long-distance students' mobility in Italy. Transp. Res. A 93, 66–82.

Checchi, D., Fiorio, C.V., Leonardi, M., 2014. Parents' risk aversion and children's educational attainment. Labour Econ. 30, 164–175.

Chevalier, A., Jia, X., 2016. Subject-specific leauge tables and students' application decisions. Manch. Sch. 84 (5), 600–620.

Ciriaci, D., 2014. Does university quality influence the interregional mobility of students and graduates? The Case of Italy. Reg. Stud. 48 (10), 1592–1608.

Columbu, S., Porcu, M., Sulis, I., 2021. University choice and the attractiveness of the study area: Insights on the differences amongst degree programmes in Italy based on generalised mixed-effect models. Socio-Econ. Plan. Sci. 74, 100926.

Contini, D., Cugnata, F., Scagni, A., 2018. Social selection in higher education. Enrolment, dropout and timely degree attainment in Italy. High. Educ. 75 (5), 785–808.

Council of European Union, 2023. Council implementing decision amending implementing decision of 13 July 2021 on the approval of the assessment of the recovery and resilience plan for Italy. Interinstitutional file: 2023/0295 (NLE).

D'Agostino, A., Ghellini, G., Longobardi, S., 2019. Out-migration of university enrolment: the mobility behaviour of Italian students. Int. J. Manpow. 40 (1), 56–72.

Declercq, K., Verboven, F., 2018. Enrollment and degree completion in higher education without admission standards. Econ. Educ. Rev. 66, 223–244.

Dillon, E.W., Smith, J.A., 2017. Determinants of the match between student ability and college quality. J. Labor Econ. 35 (1), 45–66.

Dynarski, S., 2002. The behavioral and distributional implications of aid for college. Am. Econ. Rev. 92 (2), 279–285.

Dynarski, S., Page, L., Scott-Clayton, J., 2023. Chapter 4 - College costs, financial aid, and student decisions. In: Hanushek, E.A., Machin, S., Woessmann, L. (Eds.), Handbook of the Economics of Education. Vol. 7, Elsevier, pp. 227–285.

Fack, G., Grenet, J., 2015. Improving college access and success for low-income students: Evidence from a large need-based grant program. Am. Econ. J.: Appl. Econ. 7 (2), 1–34.

Giambona, F., Porcu, M., Sulis, I., 2017. Students mobility: Assessing the determinants of attractiveness across Competing Territorial Areas. Soc. Indic. Res. 133 (3), 1105–1132.

Gibbons, S., Neumayer, E., Perkins, R., 2015. Student satisfaction, league tables and university applications: Evidence from Britain. Econ. Educ. Rev. 48, 148–164.

Gibbons, S., Vignoles, A., 2012. Geography, choice and participation in higher education in England. Reg. Sci. Urban Econ. 42 (1–2), 98–113.

Haapanen, M., Tervo, H., 2012. Migration of the highly educated: Evidence from residence spells of university graduates. J. Reg. Sci. 52 (4), 587–605.

Habibi, S., Frejinger, E., Sundberg, M., 2019. An empirical study on aggregation of alternatives and its influence on prediction in car type choice models. Transportation 46, 563–582.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015. Applied Choice Analysis: A Primer. Cambridge University Press.

Hess, S., 2014. Latent class structures: Taste heterogeneity and beyond. In: Hess, S., Daly, A. (Eds.), Handbook of Choice Modelling. Edward Elgar Publishing, pp. 311–330, Chapter 14.

Hübner, M., 2012. Do tuition fees affect enrollment behavior? Evidence from a 'natural experiment' in Germany. Econ. Educ. Rev. 31 (6), 949–960.

Kelchtermans, S., Verboven, F., 2010. Partecipation and study decisions in a public system of higher education. J. Appl. Econometrics 25, 255–391.

Krugman, P., 1991. Increasing returns and economic geography. J. Political Econ. 99, 483–499.

Long, T.B., 2004. How have college decisions changed over time? An application of the conditional logistic choice model. J. Econometrics 121 (1–2), 271–296.

Lupi, C., Ordine, P., 2009. Family income and students' mobility. Giornale Degli Econ. E Ann. di Econ. 68 (1), 1–23.

Marrocu, E., Paci, R., Usai, S., 2022. Direct and indirect effects of universities on European regional productivity. Pap. Reg. Sci. 101 (5), 1105–1133.

Mcfadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Forntiers in Econometrics. pp. 105–142.

McFadden, D., 1978. Modeling the choice of residential location. In: Karlgvist, A., et al. (Eds.), Spatial Interaction and Planning Models. North-Holland, Amsterdam, pp. 72–77.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econometrics 15 (5), 447–470.

Minaya, V., Agasisti, T., Bratti, M., 2022. When need meets merit: The effect of increasing merit requirements in need-based student aid. Eur. Econ. Rev. 146, 104164.

Modena, F., Rettore, E., Tanzi, G.M., 2020. The effect of grants on university dropout rates: Evidence from the Italian case. J. Hum. Cap. 14 (3), 343–370.

Molina, T., Rivadeneyra, I., 2021. The schooling and labor market effects of eliminating university tuition in Ecuador. J. Public Econ. 196, 104383.

Murphy, R., Scott-Clayton, J., Wyness, G., 2019. The end of free college in England: Implications for enrolments, equity, and quality. Econ. Educ. Rev. 71, 7–22.

OECD, 2022. Education at a Glance 2022. p. 462.

Oggenfuss, C., Wolter, S.C., 2019. Are they coming back? The mobility of university graduates in switzerland. Rev. Reg. Res. 1–20.

Pacifico, D., Yoo, i.H., 2013. Lclogit: A stata command for fitting latent-class conditional logit models via the expectation-maximization algorithm. Stata J.: Promot. Commun. Stat. Stata 13 (3), 625–639.

Page, L.C., Scott-Clayton, J., 2016. Improving college access in the United States: Barriers and policy responses. Econ. Educ. Rev. 51, 4–22, Access to Higher Education.

Palmisano, F., Biagi, F., Peragine, V., 2022. Inequality of opportunity in tertiary education: Evidence from Europe. Res. High. Educ. 63 (3), 514–565.

Petrin, A., Train, K., 2010. A control function approach to endogeneity in consumer choice models. J. Mark. Res. 47 (1), 3–13.

Pigini, C., Staffolani, S., 2015. In: Mussida, C., Pastore, F. (Eds.), The Effect of University Costs and Institutional Incentives on Enrolments: Empirical Evidence for Italian Regions. In: AIEL Series in Labour Economics, pp. 261–282.

Spiess, C.K., Wrohlich, K., 2010. Does distance determine who attends a university in Germany? Econ. Educ. Rev. 29 (3), 470–479.

Suhonen, T., 2014. Field-of-study choice in higher education: Does distance matter? Spatial Econ. Anal. 9 (4), 355–375.

Türk, U., 2019. Socio-economic determinants of student mobility and inequality of access to higher education in Italy. Netw. Spat. Econ. 19 (1), 125–148.

Usala, C., Primerano, I., Santelli, F., Ragozini, G., 2024. The more the better? How degree programs' variety affects university students' churn risk. Socio-Econ. Plan. Sci. 101926.

Valero, A., Van Reenen, J., 2019. The economic impact of universities: Evidence from across the globe. Econ. Educ. Rev. 68, 53–67.

Vergolini, L., Zanini, N., 2015. Away, but not too far from home. The effects of financial aid on university enrolment decisions. Econ. Educ. Rev. 49, 91–109.

Von Haefen, R.H., Domanski, A., 2018. Estimation and welfare analysis from mixed logit models with large choice sets. J. Environ. Econ. Manag. 90, 101–118.

Appendix references

Database MOBYSU.IT (Mobilità degli Studi Universitari in Italia), 2023. Research protocol MUR - Universities of Cagliari, Palermo, Siena, Torino, Sassari, Firenze, Cattolica and Napoli Federico II, Scientific Coordinator Massimo Attanasio (UNIPA). Data Source ANS-MUR/CINECA.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transp. Res. B 37 (8), 681–698.

Train, K.E., 2009. Discrete Choice Methods with Simulation, second ed. Cambridge University Press.

Usala, C., Porcu, M., Sulis, I., 2023. The high school effect on students' mobility choices'. Stat. Methods Appl. 32, 1259–1293.