Self-Selection, University Courses and Returns to Advanced Degrees

Eleonora Brandimarti*

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Abstract

Higher education often requires choosing a bachelor's and a master's degree, yet we know little about the returns of these combined choices and the role of courses in different disciplines. This paper addresses this gap using detailed data on Italian graduates and university programs. I study the labor market returns to combinations of bachelor's and master's degrees and investigate how the characteristics of the curriculum affect outcomes. I exploit exogenous variation in access to bachelor's and master's degrees to causally estimate the returns to 43 combinations of degrees. I organize the data in a nested model with exogenous variation in admission requirements and investigate the preference profile of the sample through policy simulations that shift such requirements. I then relate the estimated returns to the academic curriculum of degrees to examine the role of quantitative education. I contribute to the literature on returns to advanced degrees by incorporating master's degrees in the discussion on how higher education affects outcomes and providing evidence on the characteristics of curricula that are positively related to labor market returns. I find that returns to degree combinations vary substantially even for combinations of degrees with the same bachelor's, suggesting that both types of programs require consideration. Combinations of degrees in different disciplines relate positively to economic outcomes, while combinations in the same field perform worse. Successful combinations have little non-quantitative education in the master's, and quantitative courses alone do not explain higher returns.

Keywords: Graduate earnings, returns to degrees, returns to courses, degree design, STEM.
JEL: C35, C36, I21, I23, I26, I28, J24

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1 Introduction

The literature on the returns to education is currently active on the issue of university degrees. Recent evidence suggests that alternative choices of degrees can have significant implications on labor market outcomes (Altonji and Zimmerman, 2018; Hastings et al., 2013; Kirkeboen et al., 2016; Altonji et al., 2016, 2012). A critical element in this debate that has so far gone rather unnoticed is that, within degrees, there is substantial heterogeneity in the amount of instruction across different disciplines. For example, a typical degree in economics requires a sizable number of classes in law, statistics, and math in addition to courses in economics. In this paper, I investigate the labor market value of university degrees by combining administrative data covering almost the entire universe of university graduates in Italy with purposely collected detailed information on the disciplinary content of all university programs. The data contains information on the number of compulsory classes required in each program and each class is associated with one discipline. I develop a methodology to causally estimate the labor market returns to each university program and I analyze the disciplinary content of programs with high and low returns.

I carry out the empirical exercise in the context of Italy, where most students enroll in a 2-year master's program after a 3-year bachelor's. Since the early 2000s, this is the harmonized structure of university programs across the European Union. Compared to other studies estimating the returns to degrees, this setting poses the additional empirical challenge of modeling the sequential choice of bachelor's and master's, both of which can be in several disciplines. I develop a novel methodology to estimate the returns to any combination of bachelor's and master's programs using the information on the strictness of entry requirements at both levels. In particular, for master's degrees, I have collected information about the credit requirements to enroll in any master's conditional on the previous bachelor's. For example, accessing an engineering master's from a literature bachelor's requires the acquisition of additional credits in math. I exploit this information to generate variation in the choices of bachelor's and master's that is plausibly exogenous to labor market outcomes. I organize it in a nested model in which agents first choose a bachelor's program, then, conditional on the bachelor's, choose a master's. Of course, I also allow for the choice of not doing a master's.

Several findings emerge from the analysis of 43 labor market returns to combinations of bachelor's and master's degrees. First, master's choices matter for outcomes. Returns vary substantially even for combinations of bachelors' and masters' with the same choice of bachelor's. Second, combining degrees from different disciplines can improve outcomes, compared to situations where individuals specialize in the same field throughout the bachelor's and master's. All the combinations of degrees associated with the best labor market returns exhibit master's degrees in different fields than the bachelor's, while not having a master's is generally associated with worse labor market outcomes. I then investigate two features of the combinations of degrees to inform on the characteristics that relate to higher payoffs. First, I measure the amount of quantitative education in each combination of degrees and find that the relationship between labor market returns and quantitative courses is slightly U-shaped. In fact, both low- and high-earning combinations of degrees exhibit high shares of quantitative education. This finding challenges the widespread belief that degrees with more STEM (Science, Technology, Engineering, and Mathematics) education benefit students and indicates one dimension to consider when analyzing policies that incentivize enrollment in STEM. Finally, I observe that high-return combinations of degrees exhibit low shares of non-quantitative education in the master's (humanities, law, education) and relatively higher shares of non-quantitative courses in the bachelor's. This breakdown by degree level (bachelor's or master's) sheds light on the importance of the timing of courses, further corroborating the centrality of master's degrees in the analysis of returns to higher education.

My findings help us better understand how university program design affects outcomes. In particular, they contribute to the policy discussion on STEM degrees by highlighting the potential pitfalls of degrees that do not appropriately balance quantitative and non-quantitative education. Crucially, my analysis establishes the importance of advanced degrees in connection to labor market outcomes and informs on their relation to undergraduate degrees. The share of the population worldwide with a master's degree has increased steadily over the past few decades. In the U.S., the number of adults with a master's degree has more than doubled since 2000, and approximately 42% of European students and 27% of U.S. students embark on a master's degree every year (EuroStat, 2022; Hanson, 2022; US Census Bureau, 2019). Furthermore, as the U.S. higher education system allows more flexibility in the choice of classes than in Europe, the central feature of this paper – that students cover a wide range of knowledge at university – is likely to be even more relevant in the U.S. Unlike Europe, where students enroll in degrees with little flexibility, students in the U.S. can wait up to two years before declaring a major.

I contribute to the literature on returns to higher education in four directions. Altonji et al. (2012, 2016); Oreopoulos and Petronijevic (2013), and Patnaik et al. (2020) review the literature. First, I propose an identification strategy that incorporates information about the sequential structure of the choice of degrees to causally estimate labor market returns to combinations of bachelor's and master's. Recent advancements concentrate on the limitations of using OLS and assuming selection on observables. Kirkeboen et al. (2016) exploit information on applications to higher education in Norway to account for partial rankings and estimate ex-post local heterogeneous returns to undergraduate degrees. Similarly, Hastings et al. (2013) employ a research discontinuity design that exploits threshold-crossing admissions in Chile to compute local returns that account for university reputation. Both papers use the information on private rankings of fields of study to identify the causal effect of bachelor's degrees at the margin. More recently, Bleemer and Mehta (2022) use a similar regression discontinuity approach to estimate returns to economics majors, and more selective colleges (Bleemer, 2021). Structural approaches pioneered by Arcidiacono (2004) have also been used to estimate returns to bachelor's degrees. By imposing structure on decision-making, methods relying on dynamic choice modeling can elicit ex-ante returns and incorporate introspective behaviors such as switching majors and non-pecuniary factors that can only be rationalized with error terms revealed in multiple stages. Arcidiacono et al. (2011) offer an overview of the main methods.[1] Malamud (2011, 2010) focuses on timing of specialization in higher education and its related probability of switching. He finds that early specialization in higher education is related to more costly switching. Montmarquette et al. (2002) research how students choose their majors by incorporating idiosyncratic expected earnings and heterogeneous probabilities of success and find

[1] Structural approaches have also been used to identify the effect of attending selective institutions (Brewer et al., 1999) and the evolution of wage returns to education over time (Ashworth et al., 2021). d'Haultfoeuille and Maurel (2013) show that non-pecuniary factors are key ex-ante determinants of higher education attendance.

that ex-ante expected earnings are powerful determinants of choice. Beffy et al. (2012) conversely attribute most sorting to non-pecuniary factors. I contribute to this literature by proposing an identification strategy that exploits the timing of choices and exogenous variation at different stages to retrieve labor market outcomes of combinations of degrees.

Second, I contribute to the literature on advanced degrees by incorporating them in my analysis and shedding light on the labor market enhancing features of degree combinations. Altonji and Zhong (2021) analyze the returns to detailed types of graduate programs by comparing pre- and post-graduate earnings, accounting for preferences, ability, and previous college choices. They find considerable variations in returns that are strongly related to undergraduate choices. Similarly, Arcidiacono et al. (2008) estimate returns to MBAs by taking advantage of the fact that admission into such programs requires previous work experience. Altonji (1993) estimates the returns to the highest degree obtained, including five aggregated graduate school categories, and assuming that only the highest degree matters. A few papers provide estimates of the returns to graduate degrees for specific groups of fields of study: Black et al. (2003) for individuals with economics undergraduate majors, and Bhattacharya (2005); Chen and Chevalier (2012); Ketel et al. (2016) for medical degrees. Ketel et al. (2016) is the only paper on advanced degrees not to use US data, focusing on the Netherlands. This article complements this body of work by focusing on returns for individuals who immediately enroll in a master's degree, which account for about 75% of master's graduates in Italy and 15% in the US, previously excluded from Altonji and Zhong (2021)'s analysis (AlmaLaurea, 2021b). I also exploit variation in admission eligibility to master's programs to causally estimate the returns to the complete set of bachelor's and master's combinations. The additional structure and availability of exogenous variation in incentives strengthen Altonji and Zhong (2021)'s results as they allow for rich counterfactual patterns and direct estimates of returns to degree combinations.

Third, this paper relates to the growing literature on unordered treatment effects, for which returns to university degrees are a compelling application (Bhuller and Sigstad, 2022; Heckman and Pinto, 2018; Kirkeboen et al., 2016; Mountjoy, 2022). These authors realized that when choices are unordered, the treatment effect depends on individual preferences over the choice set, even if properly accounting for self-selection. In practice, unordered settings lead to multiple contrasting margins of treatment that grow exponentially with the choice set. The large number of combinations of degrees considered in this application renders the estimation of heterogeneous margins of treatment both intractable and difficult to interpret. Bhuller and Sigstad (2022) propose an IV method to obtain economically relevant treatment effects that are averages across all heterogeneous margins.[2] This project is uniquely affected by a weak instrument problem that emerges in 2SLS estimation and that stems from the large number of endogenous regressors – the combination of undergraduate and graduate degrees – that are instrumented with the predicted probabilities of enrollment obtained with the nested model (Phillips and Gao, 2017). While the setup is close in spirit to Bhuller and Sigstad (2022), identification requires a reduced form solution to avoid using the information about

[2]Bhuller and Sigstad (2022) propose an average monotonicity condition that requires instruments to increase the probability of treatment on average. Joint with a cross-effects condition that guarantees that instruments uniquely affect treatments, average monotonicity identifies properly estimated average treatment effects with multiple unordered treatments in 2SLS. In practice, their model exploits a modified first stage where each instrument affects the treatment separately.

the correlation between the endogenous regressors and the instruments (Chernozhukov and Hansen, 2008).

Lastly, I contribute to the literature on degree characteristics. Despite the consensus that higher education is essential to labor market success beyond ability signaling, the evidence on how degrees affect outcomes lacks a systematic approach. Biasi and Ma (2022) focus on the coverage of frontier knowledge in higher education. They find that instructors play a central role in surmounting the education-innovation gap and that students with access to such knowledge earn more after graduation. Braga et al. (2016) investigate the impact of instructors in college on labor market outcomes and conversely discover a mild effect. Deming and Noray (2020) look at the skill decay of college graduates and find that earning premia decline faster for graduates in technology-intensive fields. Acemoglu et al. (2022) find that CEOs in Denmark and the US with business education are responsible for less profit sharing with employees and claim that practices and values acquired in business school are responsible. STEM degrees, characterized by quantitative and technical education, have received considerable attention. However, even within this group of degrees, there is a lack of consensus in the characteristics that are important for labor market outcomes (Xie et al., 2015). Table 9 in appendix A.1 substantiates this claim by comparing STEM definitions in the literature. By analyzing the impact of university courses by field of study on labor market returns, I contribute with the first systematic review of labor-enhancing degree characteristics across disciplines.

The rest of the paper is organized as follows. Section 2 summarizes the relevant features of the Italian higher education system and discusses its similarities with the European and U.S. context. Section 3 describes the theoretical framework of the analysis. It presents the stages of the model and the empirical challenges in close relation to the available data. Section 4 describes the main data sources on Italian graduates and university programs. Section 5 presents the results of all the stages of the model to obtain the labor market returns to 43 degree combinations. It also presents a policy simulation that shifts admission requirements to investigate how preferences affect enrollment at the intensive margin. Section 6 relates the estimated returns to program characteristics such as timing, quantitativeness, and multidisciplinarity to elicit labor market enhancing characteristics. Together, these results provide the basis for the discussion on program characteristics. Section 7 concludes.

2 Institutional Background

Italy adheres to the Bologna process (1999) that ensures comparability in higher education standards across the European Higher Education Area (EHEA), which comprises 48 European and Central Asian countries. Notably, this means that degrees are organized as bachelor's (three years) and master's (two years) with comparable workloads as measured by credits, the unit of academic work. According to the European Credit Transfer and Accumulation System (ECTS), one credit corresponds to 25 hours of academic work, divided between classes and individual study. One year of higher education consists of 60 credits. Admission into a master's degree is conditional upon completing a bachelor's, and students apply for admission into programs with different fields of study. Additional objectives of the Bologna process are the automatic recognition of degrees throughout the EHEA and the promotion of international student mobility.

Throughout the paper, I will use the following terminology: a *degree* is the university program that students choose to enroll in and can refer to either a bachelor's or a master's program, a *university career* is the joint choice of a bachelor's (undergraduate) and master's (graduate) degree. A university *course* is a portion of what is studied in a degree and covers an individual subject, and its unit is one *credit*. Both degrees and courses vary as several choices of *fields of study* (disciplines) are available, and the same university course can be studied across several degrees. The *academic curriculum* refers to the prescription of courses and credits that describes a degree.

For a degree to be legally recognized, it must meet considerable requirements that govern its curriculum and are expressed in terms of course content and credit amounts. During the period of the analysis that considers graduates from 2007 to 2014, there were 47 bachelor's and 99 master's degrees.[3] Some degrees are exceptionally organized as single-cycle degrees that last five or six years and confer a master's degree without there being a corresponding bachelor degree. These include medicine, veterinary, dentistry, architecture, law, chemical and pharmaceutical technologies, and primary education.

The academic curriculum of each degree can be described along two dimensions: the number of credits to be allocated to each course and the course content. Course content is coded homogeneously across degrees and universities for a total of 370 possible disciplines (CUN, 2000). This means that all the courses offered in higher education belong to one of the codified fields. Then, the academic curriculum of each degree further prescribes how many credits to give to each course. For example, the code MAT-5 corresponds to calculus. A course in calculus with this code can be found in 23 bachelor's degrees and 12 master's degrees, but different credits can be associated with these courses. For each degree, more than 50% of course content and number of credits is fixed. Students can freely allocate only 10% of all credits, equivalent to approximately one class per year. The remaining credits are divided between any compulsory internships and thesis periods in varying proportions. Hence, a degree is fully described by the vector of courses and credits in each discipline. Importantly, students choose degrees with a predefined curriculum rather than courses.

For statistical precision, I group bachelor's and master's degrees into ten fields of study, described in table 1. The grouping is consistent with the data provider's aggregation, with slight adjustments for comparability across data sources and is further discussed in section 4. A detailed list of which degrees belong to which group can be found in appendix A.5.2. Throughout the paper, I will focus on university careers rather than degrees, that is, a joint choice of bachelor's and master's degree. For example, a career in economics implies both a bachelor's and master's in economics, while a career in economics and law indicates a bachelor's in economics and a master's in law.

Students with any secondary education diploma can access university.[4] Admission into a bachelor degree can either be regulated at the national level – as it is the case with all health-related degrees, veterinary, architecture, and primary education – or at the university level. As universities cannot

[3]The Italian higher education system also includes academic diplomas, one-year master's, doctoral programs, and vocational degrees. Only academic diplomas which have equal legal standing to a bachelor's degree are considered.

[4]Until the late 1960s, only students with the most academic-oriented with high-school diplomas could access university. See Bianchi (2020) and Bianchi and Giorcelli (2020) for the evaluation of the reforms that expanded access to higher education to all high-school graduates.

Table 1: Fields of study description

Code	**Abbreviation**	**Description**
1	Agr.Vet.Geo.Bio.	Agriculture and veterinarian sciences, geology and biology
2	Arch.Eng.	Architecture and Engineering
3	Chem.Pharm.	Chemistry and Pharmacy
4	Econ.Mgmt.	Economics and Management
5	Educ.Psy.	Physical education, Teaching, Psychology
6	Law	Law
7	Lit.Lang.	Literature, Languages and Humanities
8	Health	Medicine and Health-related studies
9	Pol.Soc.	Political Sciences, Sociology and Communication
10	Sci.Stat.	Math, Physics, Natural Sciences and Statistics

significantly differentiate their programs in terms of content, when possible they use selection criteria to attract students. This characteristic will be exploited for identification, as explained in sections 3 and 4. Admission into a master's degree is conditional on having completed a bachelor's and it also typically requires the fulfillment of curricular prerequisites, conditions on the bachelor's graduation grade, and interviews. Curricular prerequisites are defined as credits in mandated courses. For example, to enroll in a master's in economics, a student must have completed 53 credits in economics, statistics, and other social sciences during the bachelor's. Tuition varies depending on the degree, the university, and family income. About one third of students do not pay any tuition because of low family income. The average annual fee for the other students is around 1,500 euros (1,628 euros in 2019. Commission/EACEA/Eurydice (2020)). Other benefits, such as housing and meal vouchers, are allocated at the regional level depending on income and merit. Private universities charge higher tuition, usually between 10 and 15 thousand euros per year for an undergraduate program, and they govern their own merit- and need-based grants. All higher education regulations in terms of degree types, academic curricula, and admission apply to both private and public institutions. In years 2011 and 2012, only 8.17% of all university students were enrolled in private institutions (ISTAT, 2021).

3 Theoretical Framework

The empirical exercise in this paper consists of two stages. First, I estimate labor market returns to university careers. This is done through a nested random utility model that accounts for timing of choices and self-selection. In fact, not accounting for the choice structure leads to biased results as students self-select into careers based on observed and unobserved characteristics, and choices are unordered. Then, I use the information about the disciplinary content of degrees to investigate various policy-relevant questions on degree design. I ask whether the academic careers with the highest labor market returns are also the ones with the most quantitative or STEM content. Moreover, I check whether specializing early (during the bachelor's) or late (during the master's) in a given discipline is associated with high labor market returns. Finally, I also study whether multidisciplinarity, i.e. doing a master's in a different discipline from one's bachelor's, pays off in terms of outcomes.

This section focuses on the first part of the empirical exercise and illustrates how I retrieve the labor market returns to university careers. Section 3.1 lays out the methods used to obtain the probabilities of enrollment into any university career that exploit the timing of choices and exclusion restrictions. Section 3.2 illustrates how the probabilities of enrollment engage with a simple function of labor market outcomes (employment and wages) to obtain causal returns to university careers. The theoretical framework is set up in close relation with the available data, discussed in section 4.

3.1 Sequential Choices of Bachelor's and Master's

Here, I discuss the estimation procedure that leverages a nested logit model and exclusion restrictions to identify the individual probability of enrolling in any university career. The modeling choice stems from its choice-theoretic connection to dynamic discrete choice problems, where the intuition of these methods is that conditional on observed state variables, one can express future utility terms as functions of the probabilities that such choices occur (Hotz and Miller, 1993). Sequential choice problems with discrete unordered choices can be estimated with conditional choice probability (CCP) estimators that are brought to the data with nested logit models under the assumption of generalized extreme valued (GEV) distributed errors (Arcidiacono et al., 2011). The model allows for unobserved determinants of the choices to be correlated across nests (Hoffman and Duncan, 1988; McFadden, 1974; Montmarquette et al., 2002; Bamberger, 1987) and is implemented sequentially for tractability (McFadden, 1984; Amemiya, 1985).

One important feature of my analysis - contrary for example to Montmarquette et al. (2002) - is that I do not model the alternative outcome of not choosing a bachelor's degree. Thus, the underlying assumption is that a student who is not admitted to their preferred degree will opt for another one, rather than not studying at university. This assumption is mostly dictated by the nature of my data but it is reasonable in a public, geographically widespread, and inexpensive higher education system such as the Italian one.

Let $i \in I$ denote individuals, $j \in B$ denote a choice of bachelor's degree with $\dim(B) = L \in \mathbb{N}$, $m \in M$ denote a choice of master's degree or no master with $\dim(M) = L+1$, such that $jm \in B \times M$ denotes a university career and $\dim(B \times M) = L(L+1)$. The timing is as follows: in the first period, the individual must choose a bachelor's degree; in the second period, they must choose a master's degree conditional on their choice of bachelor's; ultimately, the student enters the labor market where outcomes will depend on her choice of education. In the second period, students may additionally choose not to enroll in a master's degree, thus entering the labor market directly.

In the first period, a student $i \in I$ chooses a bachelor $j \in B$. The choice will depend on characteristics that vary with the student, as well as characteristics that vary with the choice. The probability that a student i chooses a bachelor j is given by

$$P_{ij} = \frac{\exp\{X_i\beta_j + Z_{ij}\lambda_j\}}{\sum_{k=1}^{B} \exp\{X_i\beta_k + Z_{ik}\lambda_k\}} \tag{1}$$

where X_i is a matrix of characteristics that vary with the individual (gender, family background, general ability) and Z_{ij} is a matrix of characteristics that vary both with the individual and the choice of bachelor's (a composite measure of selectivity of admission requirements and distance to college for all bachelors'). The variation in Z_{ij} ensures that the vector of probabilities for every counterfactual bachelor degree and individual $P_{ij}\ \forall\ j \in B$ can be computed.[5]

The second nest of the model captures the choice of master's degree $m \in M$ conditional on a previous choice of bachelor's j, where M also includes the choice of not enrolling in a master's and entering the labor market directly. Similar to the choice of bachelor's, the probability that a student i chooses master m conditional on bachelor j is given by

$$[P_{im} \mid j] \;=\; \frac{\exp\{X_i\beta_m + Z_{im}\lambda_m\}}{\sum\limits_{n=1}^{M}\exp\{X_i\beta_n + Z_{in}\lambda_n\}} \tag{2}$$

where X_i is defined as before and Z_{im} is a matrix of characteristics that vary both with the individual and the choice of master (factors that determine the individual's eligibility for enrollment into each master's degree), conditional on the previous choice of bachelor's j. In practice, I observe enrollment constraints for each master's that vary with the previous choice of bachelor's and can be reconstructed for each jm pair. Once again, the variation in Z_{im} ensures that the probability of choosing every counterfactual master's degree can be computed, $P_{im} \mid j\ \forall\ j \in B,\ m \in M$.
Then, the probability of enrolling in any career accounting for self-selection follows from equations (1) and (2) is given by

$$P_{ijm} = P_{ij} \times [P_{im} \mid j] \quad \forall\ j \in B,\ m \in M \tag{3}$$

where

$$\sum_{j=1}^{B}\sum_{m=1}^{M} P_{ijm} = 1 \quad \forall\ i.$$

P_{ijm} is the predicted probability of enrollment into degree combination jm that credibly accounts for self-selection since equations (1) and (2) account for general ability and family background inter alia, as well as exogenous variation in the ease of access into degrees. Importantly, the variation in matrices Z_{ij} and Z_{im} allows for the computation of the probability of choosing every counterfactual degree-pair, overcoming the main problem in the computation of returns to degrees, which is the lack of sufficient instrumental variables to account for all possible (endogenous) choices. In principle, any number of returns to degree-pairs can be computed with this approach, as long as there is sufficient variation in Z_{ij} and Z_{im}. In practice, the estimation of the nonlinear equations (1) and (2) with maximum likelihood and the relatively high dimensionality of X_i, Z_{ij} and Z_{im} imposes constraints on the number of probabilities P_{ijm} that can be estimated. This means that university careers which are infrequently chosen may be difficult to estimate.

[5]For clarity, I omit additional covariates throughout this section such as cohort and geography fixed effects and other controls. Section 5 addresses them in detail.

3.2 Returns to University Careers

I exploit probabilities P_{ijm} to identify the effect of career (j, m) on labor market outcomes in a simple function

$$y_i = X_i\beta + \sum_{j=1}^{B}\sum_{m=1}^{M} P_{ijm}\alpha_{jm} + \epsilon_i \tag{4}$$

where y_i is the labor market outcome of interest (log wages, employment), X_i is a vector of individual characteristics and controls (gender, family background, high school grades), and α_{jm} denotes the effect of the potential treatment (careers) on outcomes. I interpret α_{jm} as the effect of university career jm on the labor market outcome y_i. These coefficients represent my object of interest as they will then be used to investigate the relationship between degree characteristics and economic outcomes in section 6. The empirical specification will additionally include rich sets of fixed effects (cohort, geography), detailed in section 5. I resort to this functional form to address three challenges to identification: self-selection on unobserved characteristics, the unordered nature of university careers, and the considerable number of choices.

To best understand the implications of these three challenges, I compare equation (4) with the extreme case of no-self selection into university careers on unobserved characteristics. In this case, the simple OLS regression

$$y_i = X_i\beta + \sum_{j=1}^{B}\sum_{m=1}^{M} D_{ijm}\gamma_{jm} + u_i \tag{5}$$

would return the effect γ_{jm} of career (treatment) D_{ijm} on outcome y_i relative to some excluded category D_{i0}, conditional on observed individual characteristics X_i, and γ_{jm} and α_{jm} would coincide. Clearly, any attempt to estimate equation (5) directly will result in strongly biased results as we expect students to enroll in careers based on unobserved characteristics. I address self-selection in equation (4) by leveraging exclusion restrictions Z_{ij} and Z_{im} in equations (1)-(3) to compute P_{ijm}.[6]

The second – more nuanced – challenge stems from the unordered nature of university careers. This equally affects equations (4) and (5) as it concerns the identification of counterfactuals, that is, the benchmark (omitted) choice against which I measure the effect of each career. Importantly, when choices are unordered, the omitted category is non-neutral and should represent at least the second preferred option or lack of treatment (Kirkeboen et al., 2016; Bhuller and Sigstad, 2022; Heckman and Pinto, 2018). To illustrate this point, consider a simplified setting with only three choices – math (M), humanities (H), and economics (E) – and two observationally identical students who enroll in economics. In this case, the effect of studying economics may not be identifiable without further information on partial rankings if absent the choice of economics, the two students choose to enroll in different degrees. To address this issue, I assume that the excluded category D_{i0} (and consequently P_{i0}) is a good proxy of lack of treatment. Section 5 describes the omitted category and its implications. In the example, the effect of studying economics may be heterogeneous or even contrasting depending on the choices the students would make if their preferred option were not available. A student who alternatively chooses humanities might benefit from studying economics if

[6] As equations (1)-(4) are estimated sequentially, I obtain the standard errors of α_{jm} through pairwise bootstrapping, further discussed in section 5.

$y_E > y_H$, ceteris paribus, while a student who alternatively chooses math might suffer if $y_E < y_M$.[7] This is the case in all unordered settings, with the number of heterogeneous margins of treatment increasing with the number of options. Given the high number of combinations of bachelor's and master's degrees, this setting allows for up to $L^4 + 2L^3 - L$ margins of treatment, which are unlikely to be of economic relevance.[8] The aggregation of the numerous heterogeneous margins to obtain meaningful effects requires proper weighting, which relies on two conditions: that the instruments affect choices monotonically on average, and that they do not cross-contaminate choices (Bhuller and Sigstad, 2022). Lack of cross-contamination implies that given a university career jm', any instrument $P_{jm'}$ is uniquely relevant for treatment $D_{jm'}$. This means that if instrument $P_{jm'}$ does not induce agent i into treatment jm', it cannot impact treatment $jm'' \neq jm'$ in any way that changes behavior.[9] The stepwise estimation of P_{ijm} with equations (1)-(3) allows for rich substitution patterns within which it is reasonable to assume average monotonicity of Z_{ij} and Z_{im} with respect to choices j and m (i.e. marginally shifting the admission requirements to one degree j affects choices monotonically on average within each career jm). The nested setup also reduces the chances of cross-contamination between P_{ijm} and D_{ijm} as variation in admission requirements is allowed to simultaneously affect many outcomes. Taken together, these conditions are necessary to ensure that instruments induce changes in treatment uptake in a single, threshold-crossing manner even in an unordered setting (Vytlacil, 2002; Heckman and Pinto, 2018).

The third challenge addressed by equation (4) pertains to the number of career effects α_{jm} of interest which can be as high as $L(L+1)$. By exploiting the reduced form, I do not need to leverage the correlation between P_{ijm} and D_{ijm} for identification, as would be the case in a two-staged least squares setting where P_{ijm} serves as an instrument for treatment D_{ijm} (Chernozhukov and Hansen, 2008). To understand why the dimension of α_{jm} can be an issue, consider the following modified 2SLS with a simplified first stage regression proposed by Bhuller and Sigstad (2022) to ensure the proper weighting of heterogeneous margins

$$D_{ijm'} = X_i\beta_{jm'} + P_{ijm'}\varphi_{jm'} + v_{ijm'} \tag{6}$$

for any arbitrary treatment $jm' \in B \times M$, such that treatment effects ψ_{jm} are calculated as

$$y_i = X_i\beta + \sum_{j=1}^{B}\sum_{m=1}^{M} \hat{D}_{ijm}\psi_{jm} + u_i.$$

Equation 6 differs from the first-stage equation in a standard 2SLS framework because only the

[7]See Mountjoy (2022) for a thorough discussion on contrasting margins of treatment.

[8]$\dim(B \times M) = L(L+1)$. Then, the number of possible margins of treatment is equal to $L(L+1)\cdot(L(L+1)-1) = L^4 + 2L^3 - L$. In comparison, Mountjoy (2022) focuses on three possible treatments and six contrasting margins. Similarly, a practical application of Heckman and Pinto (2018) who also focuses on unordered treatments identifies a subset of interesting margins (Braccioli et al., 2022). Heckman et al. (2006); Heckman and Urzua (2010) also investigate the constraints imposed by settings with unordered treatments.

[9]Lack of proper weighting due to cross-contamination of instruments may lead to severe misrepresentation of the treatment effects. In extreme cases, cross-contamination of instruments may result in a negative average treatment effect of career jm even if all heterogeneous margins of treatment are positive (Bhuller and Sigstad, 2022).

instrument pertaining to the treatment on the left-hand side is included, i.e., $\varphi_{jm'}$ is a scalar.[10] As the number of endogenous choices increases, it becomes increasingly plausible that at least some instrument P_{ijm} is not sufficiently correlated with treatment D_{ijm} even when it is relevant, thus incurring a weak instrument problem. When probabilities P_{ijm} are jointly strongly relevant, the reduced form coefficients α_{jm} asymptotically identify treatment effects ψ_{jm} (Chernozhukov and Hansen, 2008; Phillips and Gao, 2017; Crudu et al., 2021; Mikusheva and Sun, 2022). I discuss the implications of this assumption in section 5.1.1.

By addressing these three empirical challenges, I can interpret α_{jm} as the average treatment effect of enrolling in career jm. One alternative interpretation of α_{jm} that does not require the IV-equivalence assumptions on single threshold-crossing to hold relies on the structural interpretation of the nested model in section 3.1 as a dynamic discrete choice model (Arcidiacono et al., 2011). In this case, α_{jm} is the future utility term of a particular choice or the ex-ante treatment effect. The assumptions that support this interpretation require us to believe equations (1) and (2) accurately incorporate the determinants of the decision-making process of university career. Indeed, a wealth of sophisticated structural models has exploited this type of information to understand how students make schooling decisions (Arcidiacono, 2004; Ashworth et al., 2021; d'Haultfoeuille and Maurel, 2013). Lastly, α_{jm} can always be interpreted as the labor market effect of shifts in the potential treatment driven by changes in the admission requirements Z_{ij} and Z_{im}. In this setting, all instruments are jointly strongly relevant, increases in instruments P_{ijm} increase the probability of treatment D_{ijm} for all careers jm, and the nested model suggests that P_{ijm} should only affect D_{ijm}. For these reasons, I interpret α_{jm} as equivalent to IV estimates.

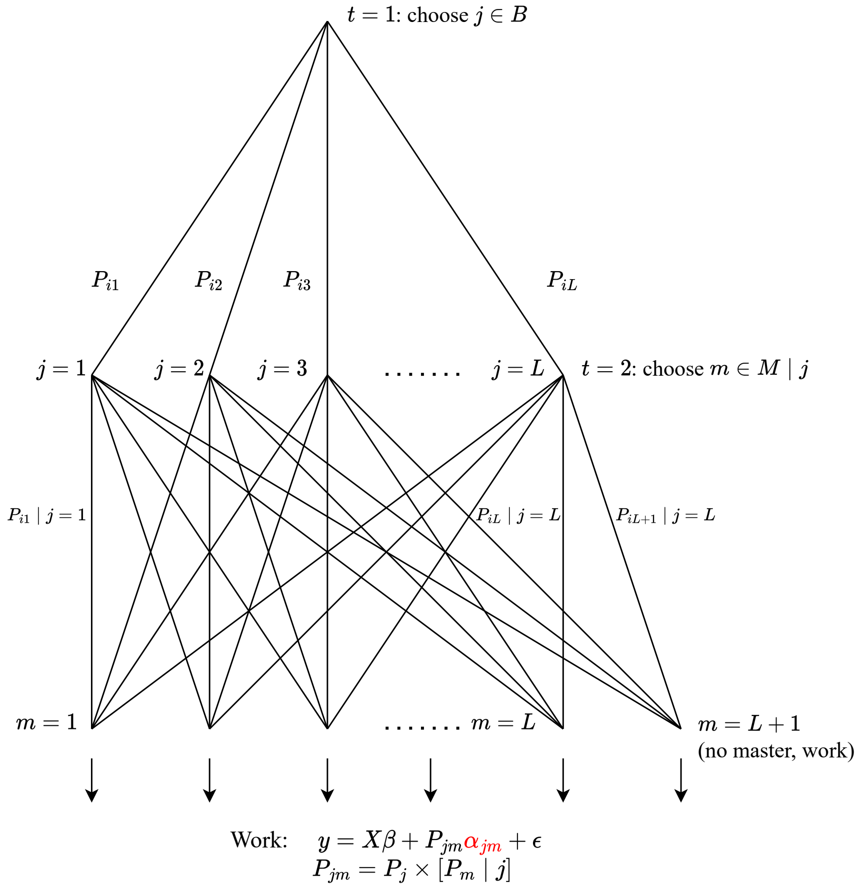
Figure 1 summarizes the timing and structure of the choice of university careers and how it integrates with the estimation of labor market outcomes α_{jm}. Exclusion restrictions that mimic admission procedures at each stage allow for the computation of counterfactual probabilities of choosing any alternative university career, partialling out the self-selection due to preferences, ability, and family background. Such counterfactual probabilities are then used as instruments for university career treatments to retrieve the causal effect of the choice of bachelor's and master's on labor market outcomes. The exploitation of timing to retrieve valid instruments allows for rich substitution patterns. An additional advantage of modeling the decision-making process explicitly is that, unlike standard 2SLS settings, it allows for students to be both forward-looking and introspective in their choices. In fact, by allowing for correlation between nests, the error term ϵ_i is allowed to be realized in multiple stages. Even though the equations of the model could be jointly estimated, the lack of certain degree combinations warrants that they be estimated sequentially. This implies that all standard errors must be bootstrapped to account for the method's sequential structure.

Finally, it is worth underscoring why standard 2SLS does not produce appropriate treatment effects. Not only does it allow for instruments to cross-contaminate treatments, it also imposes

[10] Standard 2SLS requires the estimation of $B \times M$ first stage equations for every career (j, m):

$$D_{ijm} = X_i\beta_{jm} + \sum_{k=1}^{B}\sum_{n=1}^{M} P_{ikn}\varphi_{kn} + \nu_{ijm}.$$

Figure 1: Model representation



the estimation of a large number of irrelevant parameters which introduce significant strain on the estimator. Including irrelevant instruments on the right-hand side of the first-stage regression will decrease the precision of the estimate of the treatment effect in the second stage because it will lead to possible collinearity between instruments and inflate the standard errors of the first-stage predictions. This is especially true if – as it is the case – certain probabilities $P_{ijm'}$ are close to zero for individuals who are observed to choose $jm'' \neq jm'$.[11]

[11] Let us consider a simplified framework for presentation purposes where there are only two possible choices in each set $B = \{H, S\}$ and $M = \{H, S\}$, with H denoting "humanities" and S "science". Then $jm \in B \times M = \{HH, HS, SH, SS\}$ and the "standard" first-stage regressions of a 2SLS model become

$$\begin{aligned}
D_{iHH} &= X_i\varphi_X^{HH} + P_{iHH}\varphi_{HH}^{HH} + P_{iHS}\varphi_{HS}^{HH} + P_{iSH}\varphi_{SH}^{HH} + P_{iSS}\varphi_{SS}^{HH} + u_{iHH} \\
D_{iHS} &= X_i\varphi_X^{HS} + P_{iHH}\varphi_{HH}^{HS} + P_{iHS}\varphi_{HS}^{HS} + P_{iSH}\varphi_{SH}^{HS} + P_{iSS}\varphi_{SS}^{HS} + u_{iHS} \\
D_{iSH} &= X_i\varphi_X^{SH} + P_{iHH}\varphi_{HH}^{SH} + P_{iHS}\varphi_{HS}^{SH} + P_{iSH}\varphi_{SH}^{SH} + P_{iSS}\varphi_{SS}^{SH} + u_{iSH} \\
D_{iSS} &= X_i\varphi_X^{SS} + P_{iHH}\varphi_{HH}^{SS} + P_{iHS}\varphi_{HS}^{SS} + P_{iSH}\varphi_{SH}^{SS} + P_{iSS}\varphi_{SS}^{SS} + u_{iSS}.
\end{aligned}$$

As this approach forces the estimation of $(B \times M - 1)^2$ irrelevant parameters, there is a serious concern of overidentification in the first stage, which is exacerbated if some P_{ijm} is small and aggravates any weak instrument bias.

4 Data Sources and Summary Statistics

For my empirical analysis, I combine three data sources. The first is an administrative student-level database covering the universe of all graduates from both bachelor's and master's programs at most Italian universities, both public and private. A consortium of universities maintains this administrative archive by combining and harmonizing the original student records shared by each university. The same consortium administers surveys to all the graduates in their archives at the time of graduation and one, three, and five years later. This is my second source of data and it is individually (but anonymously) linked to the administrative records.[12] The third data source is a novel archive of administrative information about the detailed content of all university programs in Italy, including admission requirements for all bachelor's and master's programs.

4.1 University Graduates

My working sample considers all the individuals who graduated from 2007 to 2014, such that I observe the most recent outcomes in 2019. Eventually, I have information on 655 847 students. According to a comparison with the National Statistical Institute's (ISTAT) records, the raw sample covers between 62% and 76% of all graduates in the years of interest.[13] Several analyses carried out by the consortium suggest that the composition of their sample accurately reflects the national population of graduates over time (AlmaLaurea, 2020, 2021a). The survey data is collected online and through phone interviews. Response rates are extremely high (91%) for the first survey, administered before graduation, but remain high also for the later ones (88% across cohorts one year after graduation, 81% after three years, and 75% after five years). The surveys provide information about socio-economic characteristics and labor market outcomes.

Two limitations are intrinsic to the setup. First, I only observe students who complete at least a bachelor's degree. Hence, any conclusion from the empirical analysis should be interpreted at the intensive margin. Second, I do not observe university dropouts. This is relevant for master's graduates, as it is impossible to distinguish between outmigration of bachelor's graduates to institutions outside of the consortium, and master's students who drop out. To avoid confusing the two, among bachelor's graduates without a master's degree, I only keep those who report no intention of enrolling in a master's program.[14] Second, ancillary information on local labor market conditions is not available for international students who are dropped from the main analysis. They account for less than 2% of the dataset, as most international mobility occurs through Erasmus and similar short-term exchange programs.[15]

[12] The AlmaLaurea Inter-University Consortium collaborates with Italian universities and the Ministry of University and Research (MUR) to monitor the labor market outcomes of Italian graduates and help match graduates with employers. Universities adhere to the consortium in different years, with 80 out of 96 universities participating in 2022. The full list of participating universities can be found in appendix A.5. Access to their resources is restricted.

[13] In 2007, only 46 universities of all 96 adhered to the consortium, while 64 were participating by 2014. I do not consider earlier cohorts since they only include students who graduate in July of each year, university participation was lower, and a different university system was still fading away.

[14] The survey asks bachelor's graduates whether they intend to enroll in a master's degree abroad, enroll in a different type of program (e.g. one-year master's), or not enroll. In addition to master's graduates, I only keep bachelor's graduates who do not intend to further enroll in higher education. Fortunately, attrition due to outmigration seems low, as only 1.4% state an intention to enroll in a master's that is not observed by the consortium.

[15] The employment rate for individuals 25-34 years old in the province of birth before enrollment into univer-

Table 2 presents the distribution of individuals across university careers. Groups with fewer than 100 observations (in red) are dropped to ensure sufficient power during estimation for a total of 1 325 observations. 56 groups out of 110 contain sufficient records. 60.8% of graduates complete both a bachelor's and a master's degree. 24 433 (6.1%) of master's graduates switch disciplines after the bachelor's. This value is very conservative as it depends on the grouping of degrees in broad fields. Less conservative groupings observe switching in up to 15% of cases. Section 4.2 elaborates on the grouping rule.

Table 2: Frequency of graduates in all university careers

		Master's											
		No Master	AVGB	Arc.Eng.	Chem.Ph.	Ec.Mg.	Ed.Psy.	Law	Lit.Lan.	Health	Pol.Soc.	Sci.Stat.	Total
Bachelor's	AVGB	8,387	26,316	219	59	19	180	*	41	622	29	932	36,656
	Arc.Eng.	22,285	87	79,827	776	84	18	*	287	10	91	251	103,426
	Chem.Ph.	3,902	118	11	20,643	*	*	*	*	260	*	18	24,923
	Ec.Mg.	27,806	23	16	*	46244	123	208	67	31	1,153	459	75,993
	Ed.Psy.	28,530	26	*	*	16	46,085	18	250	125	537	11	75,527
	Law	8,054	*	27	*	1,466	127	46,766	84	24	1,101	13	57,514
	Lit.Lan.	38,343	76	122	27	693	595	55	44,974	27	5,788	166	90,681
	Health	75,743	403	29	*	16	313	*	11	28,056	50	*	104,515
	Pol.Soc.	35,003	*	65	*	1,562	599	1,342	1,949	24	25,324	112	65,891
	Sci.Stat.	8,597	1,014	115	183	123	15	*	60	*	160	10,529	20,721
	Total	256,650	27,851	80,283	21,602	50,088	48,022	48,316	47,460	29,063	34,063	12,449	655,847

Frequencies in red denote careers that are observed for less than 100 individuals. Asterisks indicate groups with fewer than 10 individuals. All groups except 3 are chosen at least once. Total amounts do not include the less frequent choices in red. AVGB – Life Sciences, Arc.Eng. – Architecture and Engineering, Chem.Ph. – Chemistry and Pharmacy, Ec.Mg. – Economics and Management, Ed.Psy. – Education and Psychology, Lit.Lan. – Humanities, Literature and Languages, Law – Law, Health – Medicine and Health, Pol.Soc. Political and Social Sciences, Sci.Stat. – Math, Physics and Statistics.

Table 3 presents the descriptive statistics of the main individual characteristics, summarized by bachelor's degree. The characteristics that vary the most across fields are gender and high school type. Even though there are 62% of women in the sample, female students are under-represented in architecture and engineering (34%) and science and statistics (35%), and are over-represented in education and psychology (83%) and humanities (78%). High school types are grouped into three main categories: sciences, humanities, and other high schools, including languages, social sciences, and vocational schools. Although no high school type precludes enrollment into any degree, we remark more students with a humanities high school in literature and languages (23%) and law (34%). Students from science high schools are over-represented in life sciences, engineering, chemistry and hard sciences. I include two measures of family background: parent education, measured as at least one parent with a college degree, and parent occupation, that is, at least one parent in a high-ranked profession, such as executive, entrepreneur, professional, or academic. Neither of these measures varies dramatically across fields. One exception is law degrees, where

sity summarizes local labor market conditions. The information is obtained from the National Statistical Institute (ISTAT).

relatively more individuals have parents with college degrees (36%) and in high-ranked occupations (30%). I standardize high school final grades by province to account for differences in grading standards across school districts. Relatively more students with above-average high school grades enroll in engineering (62%) and hard sciences (58%). Below-average high school grades are observed in education (37%), social sciences (41%) and healthcare (42%).

Table 3: Description of the main individual characteristics by bachelor's field of study.

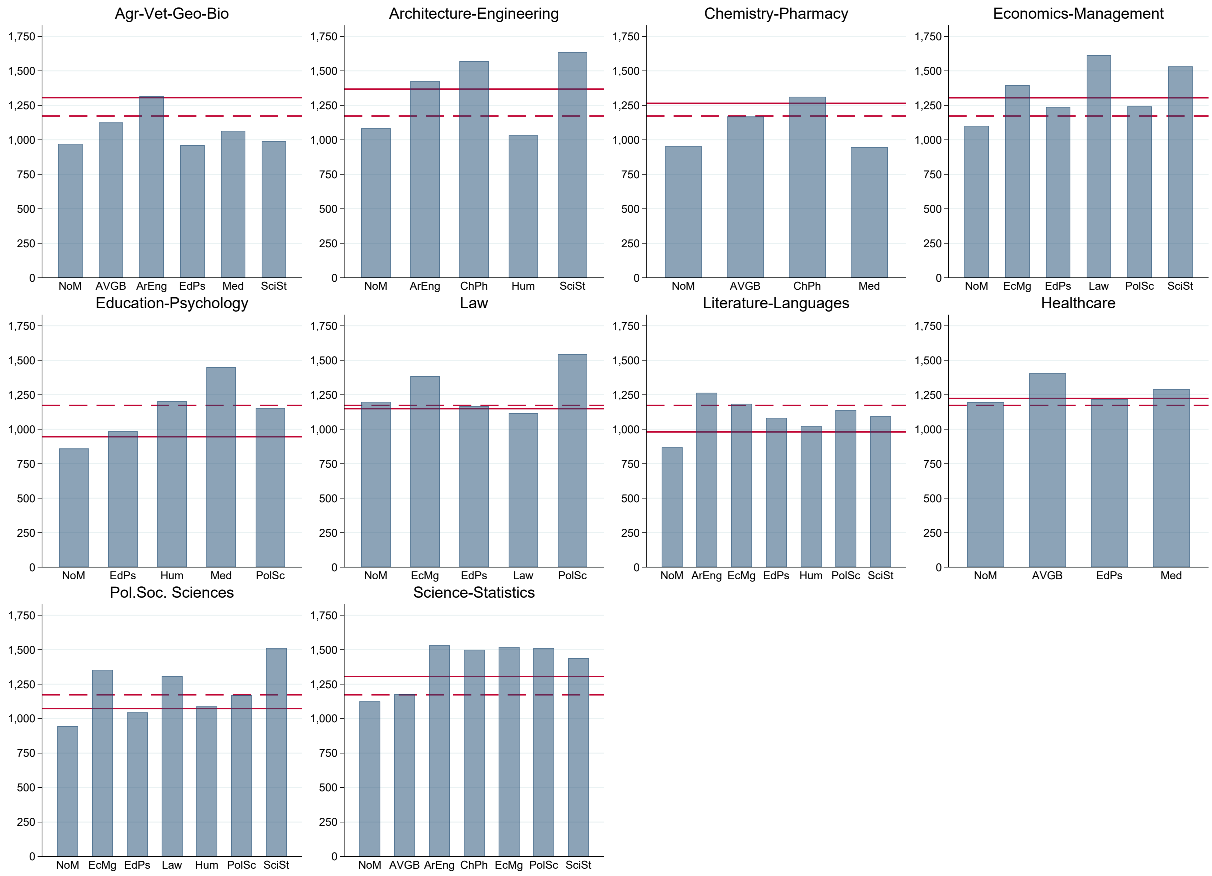
Variables	All (1)	AVGB (2)	Arch.Eng. (3)	Chem.Ph. (4)	Econ.Mg. (5)	Educ.Psy. (6)	Law (7)	Lit.Lan. (8)	Med. (9)	Pol.Soc. (10)	Sci.Stat. (11)
High School: grade (st.)	0.00	0.04	0.30	0.11	0.04	-0.30	0.08	0.10	-0.19	-0.20	0.22
	(1.000)	(0.969)	(0.954)	(0.955)	(0.991)	(0.954)	(0.981)	(0.984)	(1.021)	(0.979)	(0.997)
High School: humanities	0.15	0.13	0.08	0.18	0.07	0.13	0.34	0.23	0.14	0.16	0.06
	(0.359)	(0.337)	(0.271)	(0.380)	(0.258)	(0.342)	(0.474)	(0.423)	(0.344)	(0.365)	(0.241)
High School: science	0.39	0.52	0.55	0.57	0.36	0.27	0.32	0.26	0.42	0.29	0.52
	(0.487)	(0.499)	(0.498)	(0.495)	(0.481)	(0.445)	(0.468)	(0.441)	(0.494)	(0.452)	(0.500)
Gender (1=female)	0.62	0.60	0.34	0.69	0.54	0.83	0.63	0.78	0.68	0.69	0.36
	(0.485)	(0.490)	(0.474)	(0.463)	(0.499)	(0.378)	(0.483)	(0.414)	(0.468)	(0.464)	(0.479)
Parents: graduate	0.26	0.27	0.31	0.33	0.22	0.18	0.36	0.26	0.23	0.22	0.27
	(0.438)	(0.444)	(0.463)	(0.472)	(0.416)	(0.384)	(0.481)	(0.439)	(0.420)	(0.415)	(0.442)
Parents: high-rank occ.	0.21	0.21	0.25	0.26	0.22	0.16	0.30	0.21	0.18	0.20	0.18
	(0.410)	(0.405)	(0.431)	(0.440)	(0.411)	(0.368)	(0.459)	(0.404)	(0.388)	(0.400)	(0.383)
Observations	655847	36656	103426	24923	75993	75527	57514	90681	104515	65891	20721

Column labels: AVGB – Life Sciences, Arch.Eng. – Architecture and Engineering, Chem.Ph. – Chemistry and Pharmacy, Econ.Mg. – Economics and Management, Educ.Psy. – Education and Psychology, Lit.Lan. – Humanities, Literature and Languages, Law – Law, Med. – Medicine and Health, Pol.Soc – Political and Social Sciences, Sci.Stat. – Math, Physics and Statistics.

The main empirical analysis focuses on two labor market outcomes: log wages and employment five years after graduation.[16] Figure 2 presents average wages in levels reported to 2015 Euros for the sample of the employed, which tallies 508 242 records (77%), for each academic career. Figure 3 shows similar summary statistics for average employment levels over the whole sample of 655 847 graduates. Both figures 2 and 3 display differences in labor market outcomes by undergraduate choice of major by comparing the solid and dashed red lines. The figures also point to large differences in outcomes by combinations of undergraduate and graduate majors, visible by comparing the vertical bars within each subgraph. Overall, individuals without a master's degree experience worse labor market outcomes on average (first column of each subgraph). Even though these figures present unconditional means, they suggest that outcomes vary substantially across masters' choices also conditional on bachelors'.

[16]When the outcomes are not available five years after graduation, they are imputed using the one- and three-year survey waves. The main empirical analysis includes survey-wave fixed effects to account for these differences.

Figure 2: Description of wages in 2015 Euros by academic career.



Sub-graph titles indicate the bachelor's choice, while the fields of study on the horizontal axis refer to master's choices. The solid red line represents the average wage in 2015 Euros for the subsample of individuals who share the same bachelor's choice. The dotted red line indicates the sample average. NoM – No Master, AVGB – Life Sciences, ArEng – Architecture and Engineering, ChPh – Chemistry and Pharmacy, EcMg – Economics and Management, EdPs – Education and Psychology, Hum – Humanities, Literature and Languages, Law – Law, Med – Medicine and Health, PolSc Political and Social Sciences, SciSt – Math, Physics and Statistics.

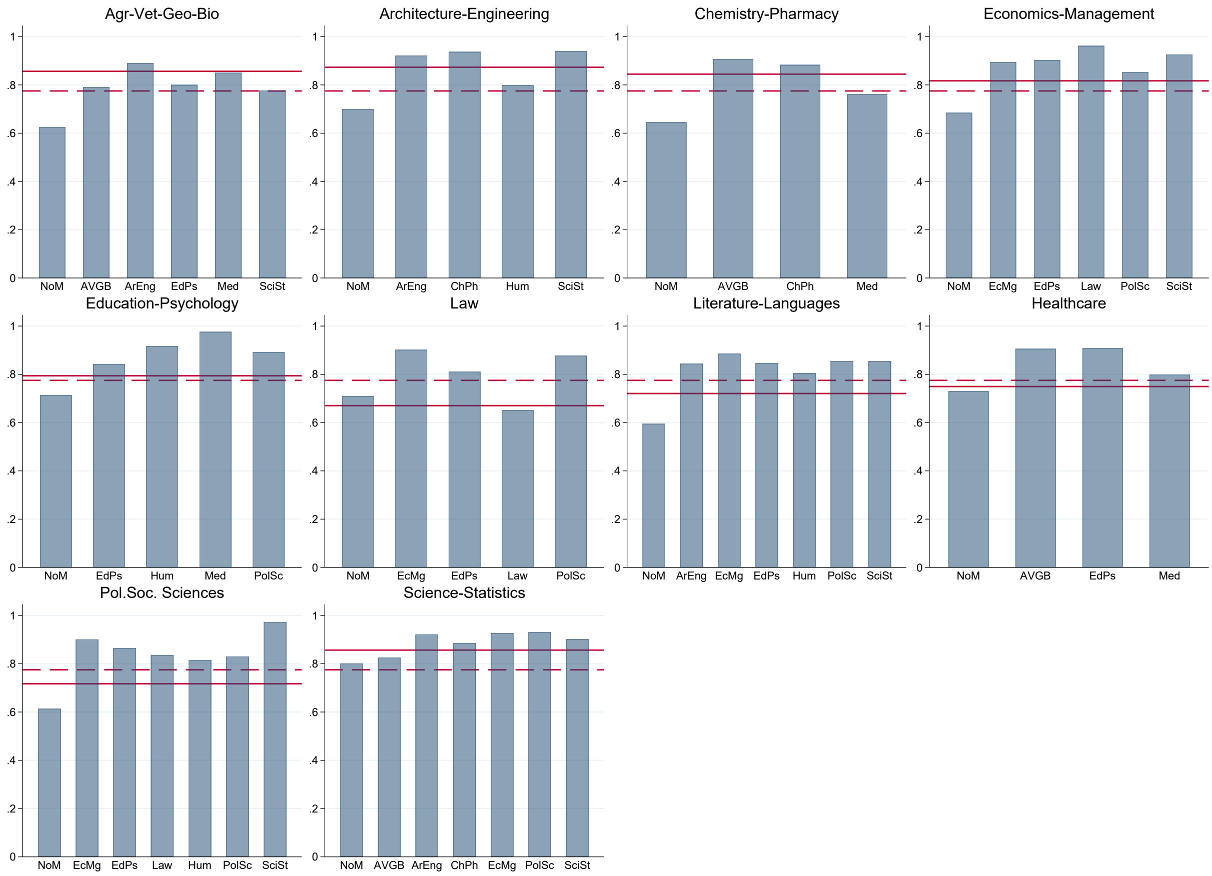
4.2 University Programs

I complement the student records with detailed information about the content and structure of all academic programs. The data on the content of programs combines various legal sources to reconstruct the compulsory features of degrees. The data on the structure of programs focuses on admission practices and results from a survey of all programs offered in Italy.

The data on the content of academic programs comes from two sources: the content requirements in terms of credits and courses of all 47 legally recognized bachelor's programs and 99 master's programs, and the official codes and description of 370 available disciplines.[17] Crucially, I observe the disciplinary content of any university course independently of the institution or the degree in which it is taught. Furthermore, for each course I observe the number of credits that must be

[17]Law 270/2004 provides detailed information on the legal requirements that degrees must meet. Addenda to the law have been exceptionally published over the years and are considered when relevant. The list of scientific disciplines (*settori scientifico-disciplinari*) is maintained by the Italian National University Council (CUN). The total number of disciplines has increased since the years under consideration to 384.

Figure 3: Description of employment by academic career.



Sub-graph titles indicate the bachelor's choice, while the fields of study on the horizontal axis refer to master's choices. The solid red line represents the average level of employment for the subsample of individuals who share the same bachelor's choice. The dotted red line indicates the sample average. NoM – No Master, AVGB – Life Sciences, ArEng – Architecture and Engineering, ChPh – Chemistry and Pharmacy, EcMg – Economics and Management, EdPs – Education and Psychology, Hum – Humanities, Literature and Languages, Law – Law, Med – Medicine and Health, PolSc Political and Social Sciences, SciSt – Math, Physics and Statistics.

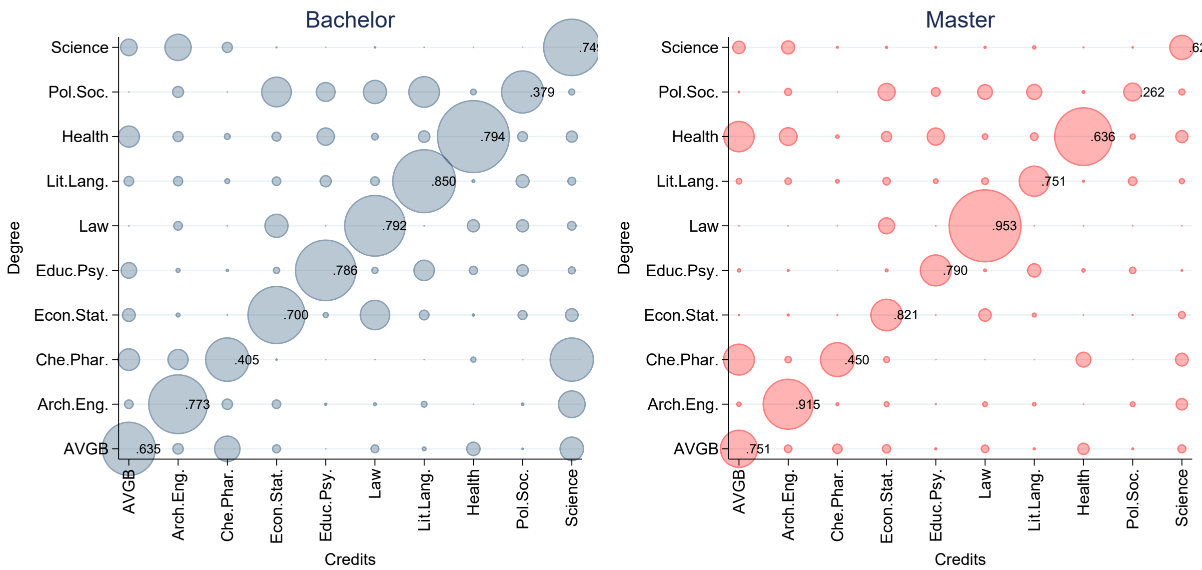
obtained to meet the program's legal requirements. I use this information to account for different levels of specialization across degrees. For example, a course in applied economics is present in 17 bachelor's programs and 33 master's programs. However, the number of required credits varies greatly, from 4 credits in a master's program in architecture to 32 credits in a bachelor's in economics.

Figure 4 presents a complete description of the content of bachelor's (left) and master's (right) degrees at the relevant level of aggregation, by plotting them against their academic curriculum, with the total percentage of required credits in the degree's main field of study on the diagonal. Each line represents a degree by averaging the content of each program that belongs to the degree grouping.[18] Indeed, there is significant off-diagonal variation, with two degrees – chemistry and pharmacy, and political and social sciences – requiring less than 50% of time studying the main discipline both at the undergraduate and graduate level. While degrees specialize slightly during the master's, with more credits in the main domain, there still is substantial education in off-diagonal

[18] Table 1 describes the disciplines in each group.

fields. The grouping of degrees, described in table 1, serves two objectives: yield statistical precision and economically interesting results. I primarily base the grouping on that of the data provider and the Italian ministry of higher education. Infrequently chosen groups are further grouped according to the literature (table 9 overviews some of the papers that were used) to maintain proximity in content. To further validate this approach, I check that the content of the degrees is close within group. For example, even though teaching and psychology lead to different occupations, they are grouped together for statistical precision and because a comparison of their curricula showed several similarities. This approach is justified by the ultimate interest of this paper in understanding the role of the content of degrees.

Figure 4: Breakdown of fields of study taught in degrees



The figure presents groups of degrees on the vertical axis plotted against the content in each degree. Larger bubbles indicate that more credits (ECTSs) in a given group of university courses are taught in a given degree. The percentages on the diagonal refer to the time spent studying the main field of study of the degree. Off-diagonal bubbles represent the credits spent studying field of study x in degree y. A row fully describes a university degree. The left (blue) panel refers to bachelor's degrees, while the right (red) panel to master's degrees. The groups of degrees are provided by AlmaLaurea and further aggregated for statistical precision, the full description is available in appendix A.5.2. The groups of university courses are provided by MIUR and further aggregated by myself. A description of the labels is summarized in table 1. The unit that defines the bubble size is one ECTS (university credit).

In addition to information about disciplinary content, I also collected information about admission requirements. I do this differently for bachelor's and master's programs to account for differences in enrollment procedures.

For bachelors', I survey the admission procedures to 2296 undergraduate programs in Italy by codifying the following information: presence of a entry exam, type of exam (standardized test, multiple choice, open-end exam, knowledge assessment), number of spots, number of applicants, and application windows.[19] I use this information to construct an indicator of binding admission restrictions for each bachelor's program. Specifically, I construct a dummy for each program that

[19]The information on admission procedures is only widely available for the years 2018 to 2021. However, all the additional evidence that I could procure points toward high persistence in enrollment practices and admission rates.

is equal to 1 if the bachelor's features fewer spots than applicants in the first round of admissions. For some programs the number of applicants is not available. In these cases, I use information on the dates of opening and closing of the application phase to infer whether the selection process is competitive. Application calls that are reopened several times or that remain open well into the beginning of the program suggest that the selection process is not too stringent. Hence, in the absence of information on applicants, I classify programs with entry exams as not having binding admission restrictions in the cases where the call has been reopened or where the exam consists of a low-stakes knowledge assessment.

Admission into the master's in most instances depends on a student's ability to meet eligibility requirements in terms credits acquired during one's bachelor's. Additional criteria include bachelor's grades and interviews. Entry exams are rare, but may be in place for healthcare-related fields and psychology. Even in these cases, students must meet curricular criteria. I collect information on all eligibility requirements by surveying all public university master's programs in 2020 and 2021.[20] This information is then matched with the previously collected data on academic curricula to calculate the number of credits that must be acquired beyond those already contained in the bachelor's for each pair of undergraduate and graduate degrees. For example, a student with a bachelor's degree in economics meets all the requirements for enrollment in a master's in economics. However, she must acquire 41 additional credits to be eligible for enrollment in a master's in statistics. Conversely, any student who wants to enroll in a master's in economics must have acquired 53 credits in economics, statistics, and other social sciences. The exact number of additional credits that the student must earn will depend on the content covered in her bachelor's. When a bachelor's does not meet any eligibility criteria, the number of necessary credits is set to 180, equivalent to starting over another bachelor's degree. This is the case for access into many degrees that only admit a subset of bachelor's or single-cycle master's degrees such as law or medicine which prevent students from transferring.

The vector of exclusion restrictions Z_{ij} that regulates access into the bachelor's is built based on the previously described data on admission criteria into undergraduate programs. I build a measure of the percentage of bachelor's degrees for which the admission criterion is binding for each aggregated category of degrees as described in appendix A.5.2 and university, and merge it with the administrative data for each individual and closest public institution. There are thus ten variables, one for each group of bachelor's degrees, that measure the share of degrees within a group with a binding admission requirements in the institution closest to the individual's place of birth. As not all universities offer all groups of degrees and programs in different universities vary in their admission restrictions, this information will vary with the individual and the degree. Vector Z_{ij} is clearly exogenous since students cannot influence the level of applicants. Panel A in table 4 summarizes these ten variables, one for each bachelor's degree, that vary between 0 and 1, with 1 indicating that all degrees in a given group and institution present binding admission requirements and 0 indicating that none do. On average, the presence of binding admission requirements is lowest in humanities and highest in medicine and healthcare degrees.

The vector of exclusion restrictions Z_{im} that governs admission into master's degrees includes the measures on the differences between each undergraduate's curriculum and the enrollment re-

[20] Again, admission criteria are highly persistent in time such that the collected information is strongly relevant even if the years of enrollment do not match the years in which the requirements were collected.

Table 4: Descriptive statistics for the exclusion restriction variables Z_{ij} and Z_{im}

Variable	Mean	Std. Dev.	Min	Max
A. Z_{ij}: *Entry Exams*				
EE (AVGB)	0.492	0.183	0.100	0.883
EE (Arch.Eng.)	0.417	0.196	0	0.889
EE (Chem.Pharm.)	0.634	0.258	0	1
EE (Econ.Mgmt.)	0.453	0.377	0	1
EE (Ed.Psy.)	0.769	0.234	0.130	1
EE (Law)	0.172	0.235	0	0.759
EE (Lit.Lang.)	0.165	0.126	0.001	0.672
EE (Health)	0.939	0.068	0.791	1
EE (Pol.Soc.)	0.299	0.238	0	0.852
EE (Sci.Stat.)	0.308	0.273	0	1
B. Z_{im}: *Constrained number of credits*				
Cred. (AVGB)	60.987	17.616	0	69.874
Cred. (Arch.Eng.)	86.927	20.680	0	96.249
Cred. (Chem.Pharm.)	84.485	22.110	0	95.891
Cred. (Econ.Mgmt.)	50.539	18.686	0	58.404
Cred. (Ed.Psy.)	65.998	22.539	0	82.778
Cred. (Law)	91.487	38.442	0	114.910
Cred. (Lit.Lang.)	65.866	5.802	48.790	69.000
Cred. (Health)	146.272	33.683	0	163.571
Cred. (Pol.Soc.)	41.140	20.475	0	62.066
Cred. (Sci.Stat.)	76.325	9.041	40.040	86.584
C. Z_{im}: *Constrained number of credits (standardized)*				
Cred. (AVGB)	-0.766	0.843	-3.683	-0.341
Cred. (Arch.Eng.)	0.475	0.989	-3.683	0.921
Cred. (Chem.Pharm.)	0.358	1.058	-3.683	0.903
Cred. (Econ.Mgmt.)	-1.266	0.894	-3.683	-0.890
Cred. (Ed.Psy.)	-0.526	1.078	-3.683	0.276
Cred. (Law)	0.693	1.839	-3.683	1.813
Cred. (Lit.Lang.)	-0.533	0.278	-1.349	-0.383
Cred. (Health)	3.313	1.611	-3.683	4.141
Cred. (Pol.Soc.)	-1.715	0.979	-3.683	-0.714
Cred. (Sci.Stat.)	-0.032	0.432	-1.768	0.458

Total number of observations: 655 847; global average of constrained credits across degrees: 77.003. AVGB – Life Sciences, ArEn – Architecture and Engineering, ChPh – Chemistry and Pharmacy, EcMg – Economics and Management, EdPs – Education and Psychology, Hum – Humanities, Literature and Languages, Law – Law, Med – Medicine and Health, PlSc Political and Social Sciences, Sci – Math, Physics and Statistics.

quirements for all master's programs. There are ten variables, one for every master's program, that vary at the individual and program level. Panels B and C in table 4 summarize these ten variables, one for each master's degree, where panel B presents the average values in terms of credits, and panel C transforms the variables in panel B by standardizing them. On average, students must acquire 77 constrained credits to enter a master's program. Once again, there is substantial variation across fields of study.[21] Average admission requirements are highest for healthcare degrees and lowest for political and social sciences. I additionally include the log distance to the closest public university to instrument the choice not to enroll in a graduate program.

5 Returns to University Careers

This section discusses the implementation of the model outlined in section 3 to obtain labor market returns to combinations of undergraduate and graduate degrees. I discuss the relevant steps of the estimation procedure sequentially to highlight the information available at each stage as summarized in figure 1.

5.1 Choice of Bachelor's and Master's Degrees

Equations (1) and (2) are brought to the data sequentially even though in principle it should be possible to estimate them simultaneously through a nested logit model. However, several considerations about the data – mostly empty cell problems due to not all combinations existing and large differences in the size of degree combinations – make it more convenient to estimate the equations separately in the order presented in section 3.1 as multinomial logit models (equations 1 and 2).

Here and throughout this section, the vector of observed individual characteristics X_i will include high school grade, standardized at the province level to account for regional differences in grading standards, high school type (humanities, scientific or other – baseline category), gender, parents' education (at least one parent with a college degree), and parents' occupation (at least one parent in a high-ranked occupation: academics, liberal professionals, entrepreneurs, executives). Summary statistics for these variables were reported in section 4.1. Additional controls include information on local labor markets (employment rate for 25-34 year olds in the province of birth at the time of enrollment) and an index of university quality from Censis, an independent research center, standardized to improve model fit. The battery of fixed effects Θ includes fixed effects for the year of graduation θ^{year}, macro-region θ^{geo}, and years since graduation θ^{exper}.[22] The choice set of bachelors' B is described in table 1 and includes ten aggregated fields of study. The variables belonging to vector Z_{ij} are the share of binding entry exams for each group of degrees in the public university closest to the student's province of birth previously described in section 4.2 and summarized in panel A of table 4.

Table 5 presents the results for equation (1). The excluded category is the choice of bachelor in humanities as it is the bachelor with the lowest average value of the instrument on the share of bind-

[21] These variables are standardized in the empirical analysis to improve model fit.

[22] I use the standard definition of macro-regions from the National Statistical Institute (ISTAT): North-East, North-West, Center, South, Islands.

ing entry exams. The exclusion restrictions are jointly strongly significant with $\chi^2(90) = 46572.60$.[23] Clearly, rich substitution patterns emerge. Increasing the share of programs with binding entry exams in law and health increases the probability of enrollment in all degrees with respect to the baseline category (humanities), entry exams in other degrees have more nuanced effects. Interestingly, coefficients λ_j are positive along the diagonal for degrees in engineering, education, law, health and political sciences, such that decreasing the selectivity of these degrees decreases the relative probability of enrollment. This suggests that positive signaling through selectiveness may be an attribute of these degrees. Table 10 in appendix A.2 additionally presents the marginal effects of coefficients λ, estimated at the mean of the right-hand variables of equation 1. Shifts in the share of degree programs with binding entry exams lead to substantial changes in the probability of enrolling in different degrees, along rich substitution patterns. Just like the coefficients in table 5, the marginal effects contained in table 10 suggest that marginally changing the bindingness of entry exams leads to significant shifts in the probability of enrolling into different degrees at the average values of the sample. Even though on average the net shift of each instrument is close to 0, the variance of the marginal effects is highest for the entry exam variables in literature and languages and health, suggesting that students are particularly reactive to the admission policies of these degrees in their decision to enroll in higher education. I offer an additional discussion on the magnitude of the effects of the exclusion restrictions in section 5.1.1. Figure 5 shows how the model fits the data. As the estimator used to fit equation (1) is based on maximum likelihood, it matched group averages. To show how accurate the predictions are, I fit the model using cohorts 2007-2011 and present the average data and predictions for cohorts 2012-2014. Indeed, the model seems to match the observed choices on average quite well when I do not require matching on group averages, with differences in enrollment being less that 2 percentage points. The coefficients of equation (1) are eventually used to estimate the probability P_{ij} of enrolling in any bachelor's for all individuals.

Estimating the probability of enrolling in a master's degree is slightly more cumbersome as it is conditional on the choice of bachelor's degree. I estimate ten separate multinomial logit models (equations 2) on the subsample of students in each bachelor's.[24] I then predict the probability of choosing any master's for all conditional choices of bachelor's $P_{im} \mid j \; \forall \; j \in B, \, i \in I$.

While the possible fields of study coincide between bachelor and master, the set of choices of master's M is different from B as it also includes the possibility of no master at all, that is, entering directly the labor market after the bachelor's. X and the fixed effects are defined as before and only vary at the individual level.[25] The omitted category is always the choice of not pursuing a master's. The choice-theoretic characterization is that not pursuing a master's is equivalent to a lack of treatment conditional on the choice of bachelor's, thus always at least the second best option. Furthermore, the option is always available. $Z_{im|j}$ is a rich set of exclusion restrictions

[23] Each element of Z_j is also individually strongly significant with $p = 0$. AVGB: $\chi^2(9) = 3557.03$, Arc.Eng.: $\chi^2(9) = 2672.36$, Chem.Pharm.: $\chi^2(9) = 9441.17$, Econ. Mgmt.: $\chi^2(9) = 3155.64$, Educ.Psy.: $\chi^2(9) = 5385.44$, Hum.: $\chi^2(9) = 2613.46$, Law: $\chi^2(9) = 7722.88$, Health: $\chi^2(9) = 6836.68$, Pol.Soc.: $\chi^2(9) = 2787.76$, Sci.Stat.: $\chi^2(9) = 1857.02$.

[24] Only students who are not enrolled in a single cycle degree are used to fit the model as they have to make a choice. The prediction uses the whole sample. This should not matter as the offer of single cycle degrees is plausibly exogenous to the choice and to labor market outcomes.

[25] Fixed effects for years since graduation are omitted due to collinearity with other covariates or lack of variation in certain subsamples.

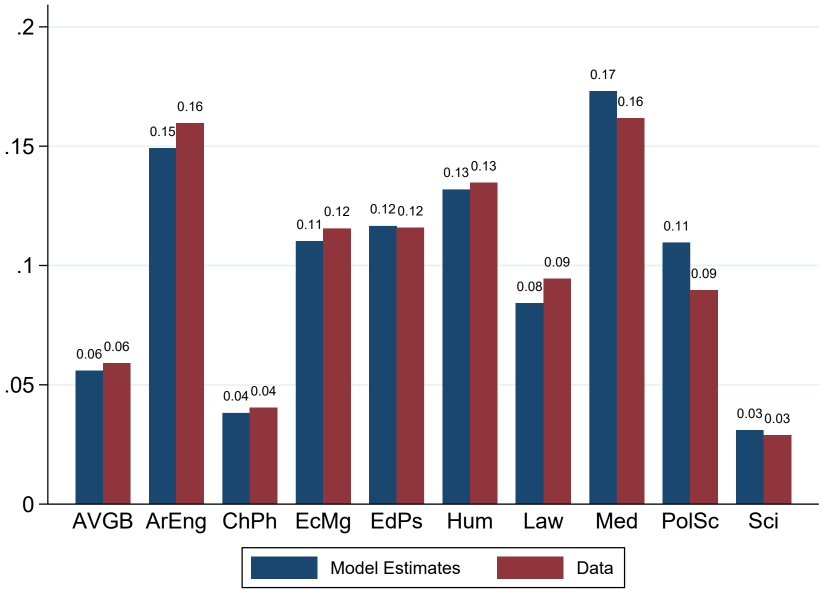
Table 5: Period 1 – Choice of Bachelor

VARIABLES	AVGB (1)	Arc.Eng. (2)	Chem.Ph. (3)	Econ.Mg. (4)	Ed.Psy. (5)	Law (6)	Health (7)	Pol.Soc. (8)	Sci.Stat. (9)
Z_j: *Entry Exams*									
AVGB	-0.527***	-0.461***	-0.145**	-1.331***	0.807***	0.539***	0.526***	0.300***	0.332***
	(0.053)	(0.038)	(0.063)	(0.039)	(0.041)	(0.045)	(0.040)	(0.041)	(0.064)
Arc.Eng.	0.320***	0.637***	1.454***	-0.831***	-0.629***	-0.158***	1.428***	0.375***	1.141***
	(0.073)	(0.054)	(0.085)	(0.055)	(0.056)	(0.061)	(0.054)	(0.058)	(0.094)
Chem.Ph.	0.282***	0.501***	-0.737***	-0.015	-0.890***	-0.301***	-2.508***	-0.333***	-1.444***
	(0.047)	(0.034)	(0.056)	(0.034)	(0.036)	(0.039)	(0.035)	(0.037)	(0.057)
Econ.Mg.	-0.109***	-0.186***	-0.677***	-0.271***	-0.180***	-0.308***	-1.212***	-0.442***	-0.143***
	(0.035)	(0.026)	(0.041)	(0.026)	(0.028)	(0.031)	(0.025)	(0.028)	(0.044)
Ed.Psy.	0.329***	0.924***	-0.145***	0.325***	0.887***	-0.103***	1.853***	0.020	0.848***
	(0.043)	(0.031)	(0.050)	(0.033)	(0.032)	(0.034)	(0.032)	(0.032)	(0.055)
Law	1.848***	1.378***	1.043***	1.244***	0.813***	1.244***	1.873***	0.458***	0.736***
	(0.059)	(0.044)	(0.066)	(0.046)	(0.047)	(0.050)	(0.044)	(0.047)	(0.071)
Hum	-4.569***	-0.499***	-2.914***	0.580***	-3.077***	-2.332***	-3.874***	-2.064***	-1.658***
	(0.096)	(0.064)	(0.103)	(0.064)	(0.068)	(0.073)	(0.071)	(0.068)	(0.100)
Health	6.876***	2.693***	7.326***	4.235***	3.999***	2.987***	6.855***	1.795***	4.261***
	(0.138)	(0.102)	(0.163)	(0.103)	(0.105)	(0.113)	(0.101)	(0.108)	(0.175)
Pol.Soc.	-1.297***	-2.262***	0.893***	0.130*	-0.888***	-0.188**	0.967***	0.674***	0.373***
	(0.101)	(0.073)	(0.113)	(0.073)	(0.078)	(0.085)	(0.073)	(0.079)	(0.121)
Sci.Stat.	0.864***	-0.060	0.543***	-0.256***	1.245***	0.599***	-1.171***	0.436***	0.045
	(0.085)	(0.062)	(0.096)	(0.062)	(0.064)	(0.072)	(0.060)	(0.066)	(0.102)
X					Yes				
FE					Yes				
Observations	655,847	655,847	655,847	655,847	655,847	655,847	655,847	655,847	655,847

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Pseudo $R^2 = 0.103$.

Excluded category: humanities. Joint test of exclusion restrictions Z_j: $\chi^2(90) = 46572.60$, p-value=0. X: gender, high school grade, high school type, parent occupation, parent education, local labor market, and university quality controls. Θ: Macro-region, experience and year fixed effects.

Figure 5: Comparison of model and data - choice of bachelor



Model fitted on cohorts 2007-2011, predictions and data plotted for 2012-2014. Description of titles: the title refers to the previous bachelor choice on which the model is fitted. AVGB – Life Sciences, ArEng – Architecture and Engineering, ChPh – Chemistry and Pharmacy, EcMg – Economics and Management, EdPs – Education and Psychology, Hum – Humanities, Literature and Languages, Law – Law, Med – Medicine and Health, PolSc – Political and Social Sciences, Sci – Math, Physics and Statistics.

that regulate access to the master's program and vary with the previous choice of bachelor's. It includes the standardized credit requirements for enrollment into each master's that vary at the individual and program level described in table 4 panel B, and log distance to the closest public university. Not all degree combinations can be estimated since some are not observed in the data (table 2 summarizes the available groups). Hence, only the credit requirements relevant to the possible choices are included.

Tables 11 to 20 in appendix A.3 present the results of these estimations. In all cases, the baseline category is to not enroll in a master's degree. Some exclusion restrictions on credit requirements may be dropped for collinearity or lack of variation within certain subgroups. For instance, this may occur if all students with the same bachelor face the same credit requirements for a given master's. Joint tests of the exclusion restrictions are presented in table 6 and indicate that the exclusion restrictions are valid within each conditional choice of bachelor's. Again, rich substitution patterns emerge. In all cases except one, increasing the credit requirement in the master's with the same discipline as the bachelor's decreases the probability of enrolling in that master's. Positive coefficients indicate that the probability of enrollment increases with increases in the credit requirement with respect to the choice of not enrolling in a master's. This suggests that for certain degree combinations, the probability of enrollment increases with the additional (relative) work that the student must do. Students with graduate parents are more likely to enroll in a master's degree, with very few exceptions. Gender does not seem to systematically generate sorting into more (less) quantitative fields during the master, even though it does increase the probability of enrolling in masters' in education and psychology.[26] The model fit is presented in figure 6 by comparing average predicted probabilities and observed enrollment. As before, equations (2) are estimated on cohorts 2007-2012 and the comparison between data and estimates is presented for years 2012-2014; the model seems to predict the conditional probability of enrolling in a master well.

Table 6: Test of exclusion restrictions for equations (2)

	All Z_m		Credit Requirements			
Conditional Choice of Bachelor	D.f.	χ^2	D.f.	χ^2	Observations	Table
Agr.Vet.Geo.Bio.	25	3725.9	20	3691.69	32,494	A.3.11
Architecture and Engineering	20	6572.69	16	6570.72	79,817	A.3.12
Chemistry and Pharmacy	6	277.14	3	273.37	7,398	A.3.13
Economics and Management	10	14011.08	5	13977.24	75,993	A.3.14
P.E., Teaching and Psychology	12	10142.09	8	10106.78	62,741	A.3.15
Law	8	1089.64	4	1076.1	10,882	A.3.16
Literature and Languages	30	3083.15	24	3048.16	90,681	A.3.17
Healthcare and Medicine	6	861.1	3	855.77	81,883	A.3.18
Political and Social Sciences	36	7988.74	30	7974.45	65,798	A.3.19
Science and Statistics	18	1045.78	12	1040.46	20,721	A.3.20

Joint test of all exclusion restrictions for each conditional bachelor choice, d.f. denotes degrees of freedom. All reported χ^2 have p-values equal to 0. Z_m includes bachelor final grade (standardized), credit requirement (standardized) and distance to closest public university. Students who previously enrolled in single-cycle degrees are not used for inference.

Lastly, I estimate the probability of enrolling in any combination of degrees $P_{ijm} = P_{ij} \times [P_{m_i} \mid j]$ for all $i \in I$, $j \in B$ and $m \in M$. For the special case of students who end up in single-cycle degrees, $P_{ijm} = P_{ij}$ if $j = m$. I am left with the choice probabilities for 56 combinations of degrees.[27] On average, probabilities P_{jm} match observed treatments D_{jm}. Their difference across all degree combinations is 7.14×10^{-9}. Importantly, since P_{jm} is the product of two probabilities, the observed maximum values are strictly lower than 1, ranging from 0.012 for (Econ.Mgmt, Educ.Psy.) to 0.748 for (Healthcare, No Master), with degree combinations chosen less frequently presenting lower ranges of probabilities of enrollment. Additional summary statistics for the treatments D_{jm} and probabilities P_{jm} can be found in table 21 in appendix A.3.

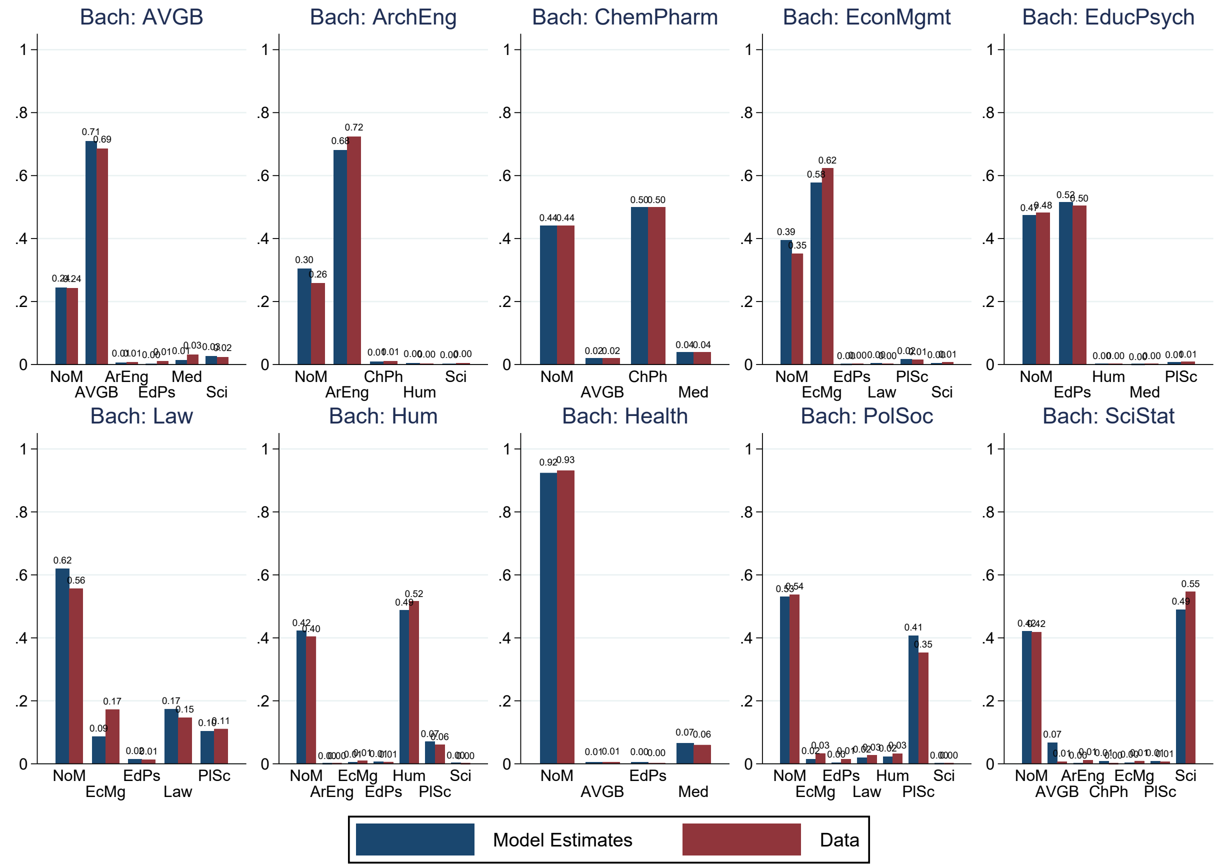
5.1.1 Exclusion Restrictions Z_{ij} and Simulations

I present two policy simulations that investigate different admission policies in the bachelor's to elicit how sorting at the margin responds to shifts in entry restrictions. The focus will be on entry into bachelor degrees as it leads to remarkable shifts in the student body composition. Using the choice model set up in section 3, I shift the values of Z_j in equation (1) to understand how students react to entry exams. Figure 5 has previously justified the appropriateness of the model to predict the distribution of students across degrees. As the available data is not appropriate to understand

[26]Marginal effects for the exclusion restriction variables, estimated at the means of the sample are available upon request.

[27]In practice, I can only retrieve 43 returns to combinations of degrees ex post. The rationale is explained in sections 5.2 and 6. A priori, all the data from 56 combinations of degrees is used.

Figure 6: Comparison of model and data - choice of master



Model fitted on cohorts 2007-2011, predictions and data presented for cohorts 2012-2014. Students who enroll in single-cycle degrees (e.g. architecture, medicine, law) are not considered here as they do not make a schooling choice. The title of each histogram refers to the previous bachelor choice on which the model is fitted. Description of labels: AVGB – Agriculture, Veterinary, Geology, Biology; ArEn – Architecture and Engineering; ChPh – Chemistry and Pharmacy; EcMg – Economics and Management; EdPs – P.E., Teaching and Psychology; Law – Law; Hum – Literature and Languages; Med – Health; PlSc – Political and Social Sciences; Sci – Science and Statistics; NoM – No Master.

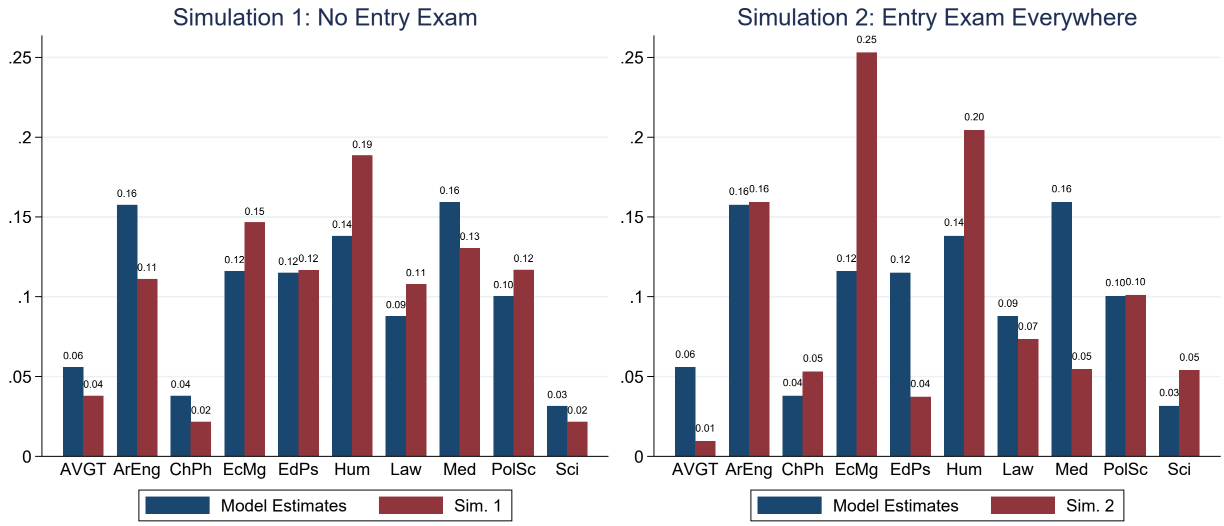
the labor market outcomes of individuals who did not attend college, I am unable to assess the inbound shift that might occur if admission policies were to change substantially. For these reasons, these simulations should be interpreted as shifts in enrollment at the intensive margin.

In the first simulation, all variables in Z_j are set to their minimum and new probabilities of enrollment in each degree are estimated using equation (1).[28] The global effect of this policy is shown in the left panel of figure 7 and suggests that relaxing entry barriers would increase enrollment in economics and management, humanities (literature and languages), law, and political and social sciences, while decreasing enrollment in all the other degrees. This may be rationalized by considering that enrollment in the former is bound by entry exams, while demand for the latter may not be determined by it. This means that if there were fewer entry exams, enrollment would

[28]Values of Z_j are set to their observed minimum rather than 0 for all degrees because certain degrees such as healthcare have minimum values which are very high (78%), otherwise resulting in out-of-sample predictions.

increase by 35.7% in humanities (5 p.p.) and 20% (3 p.p.) in economics and management. The largest decrease would occur in engineering, with a 31% decrease in enrollment (5 p.p.). Figure 18 in the appendix presents the results of this simulation decomposed across several individual characteristics: gender, parental occupation, education, and high school grades. While sorting into degrees varies along these dimensions, reducing entry barriers does not produce additional patterns.

Figure 7: Period 1: Policy Simulations on Entry Exams



An alternative simulation where entry exams are imposed everywhere is presented in the right panel of figure 7. Here, all variables in Z_j are set to 1 (i.e., all bachelor's programs have binding admission requirements) and new probabilities of enrollment in each degree are estimated using equation (1). Once again, enrollment in economics and humanities increases, as well as enrollment in chemistry and science. The comparison of the two simulations in figure 7 showcases the nonlinear substitution patterns that are possible due to the rich set of information on selective entry admissions Z_j.

Simulation 1 in figure 7 suggests that the existing entry exams mostly serve the purpose of managing excess demand into less quantitative fields such as economics or humanities. In fact, if students have lower preferences for quantitative studies even after controlling for rich individual characteristics (Rask, 2010; Mann and DiPrete, 2013; Fricke et al., 2018), it is not surprising that removing entry barriers does not increase enrollment into such degrees. On the other hand, simulation 2 indicates the degrees where selectiveness at the margin is positively related to enrollment. One interpretation of these results is that students derive a net benefit at the margin of increasing selectiveness in economics, humanities, chemistry, and science. I rationalize the decrease in enrollment in medicine in simulation 2 by noting that entry exams are so ubiquitously present that the signal of selectiveness is saturated at the margin. Jointly, these simulations illustrate the richness of the substitution patterns allowed by the model and suggest that settings where admission requirements are assumed to relate monotonically with preferences on enrollment do not fit real world situations.[29]

[29]Importantly, the assumption that the instrument P_{ijm} monotonically increases the take up of the treatment D_{ijm} stands.

Both of the proposed policies (elimination and imposition of binding entry exams) will reasonably induce reactions at the extensive margin as well as the intensive margin. Since individuals with no college are not observed, these results should not be interpreted as informative of global shifts in enrollment. However, they underline that when faced with multiple choices, several contrasting margins matter for sorting. In both cases, varying the values of the exclusion restrictions induces substantial shifts in enrollment across degrees. This suggests that one of the necessary conditions for identification in the reduced form presented in section 3 – that the exclusion restrictions be strongly relevant – is satisfied.

5.2 Returns to university careers

The probabilities P_{ijm} estimated in the previous section enter the reduced form equation (4) which is estimated with the previously described vector x and fixed effects, where the labor market outcomes of interest are log wages and employment, and jm only refers to combinations that are observed in the data.

To ensure that the coefficients α_{jm} can be interpreted as causal effects, I choose the combination of degrees (Lit.Lang., No Master) as the excluded category to proxy lack of treatment. Undergraduate degrees in humanities exhibit the lowest levels of binding entry exams and are available in 54 out of 67 public universities. Combined with "No Master", this university career serves as the most credible benchmark.

The results for the vector of coefficients β are presented in table 7.[30] All of the equations' standard errors are bootstrapped using full iterations of the entire model to account for the probabilities being predicted (equations (1)-(4)). For comparison, I also present OLS results where treatments D_{jm} substitute probabilities P_{jm}, thus not controlling for self-selection (equation (5)).

The reduced form coefficients in columns (2) and (4) of table 7 follow the sign and significance level of the OLS coefficients (columns 1 and 3) for almost all the main explanatory variables, where the magnitude of the effects increases. This is likely driven by the correction for endogeneity in the observed choices of university careers. Higher grades are strongly positively related to higher chances of being employed, whereby they do not improve wages (conditional on employment). Similarly, having a science high school degree improves outcomes in terms of employment, but not wages conditional on working. Surprisingly, once we control for university careers, women are more likely to be employed than men, even though they experience lower wages. This is likely due to selection on gender into different university careers.

Coefficients α cannot be interpreted as causal treatment effects without taking into account that the probabilities P_{jm} vary along a scale that is strictly smaller than one, as discussed in section 5.1. By rescaling the coefficient by the maximum observed probability of choosing a given career (j, m), the effect becomes

$$\tilde{\alpha}_{jm} = \alpha_{jm} \cdot \max_{I}(P_{jm}) \tag{7}$$

which can be interpreted as a shift in labor market outcomes induced by an increase in the probability

[30] Table 8 in section A.1 reports the differences in observed characteristics X between the sample of employed and unemployed to assist the interpretation of the results on log wages conditional on employment.

of choosing said career from 0 to the sample's maximum, ceteris paribus.[31] In the end, I obtain 43 credible TEs for both log wages and employment.

Table 7: β coefficients for labor market outcomes.

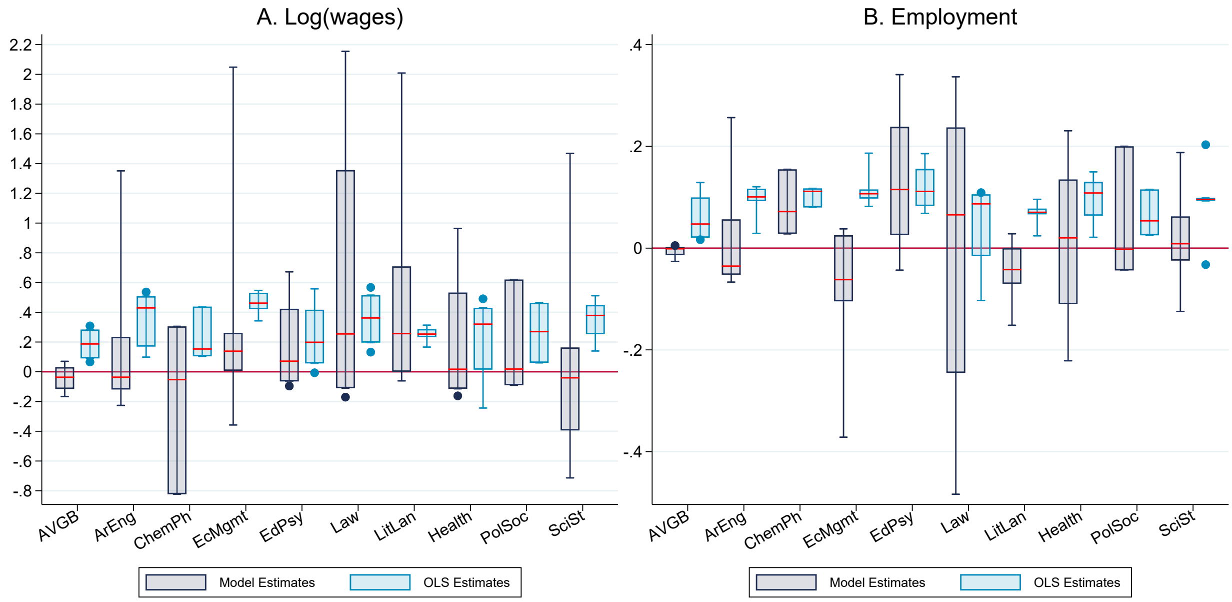
	log(wage)| employed		employment	
VARIABLES	OLS (1)	Red. Form (2)	OLS (3)	Red. Form (4)
X				
High School: grade (st.)	-0.018***	-0.937***	0.004***	3.670***
	(0.001)	(0.178)	(0.001)	(0.210)
High School: humanities	-0.079***	-1.067***	-0.032***	-0.128
	(0.003)	(0.376)	(0.002)	(0.197)
High School: science	-0.048***	-2.744***	-0.020***	15.052***
	(0.002)	(0.647)	(0.001)	(0.888)
Gender (1=female)	-0.154***	-1.956***	0.009***	3.257***
	(0.003)	(0.644)	(0.001)	(0.373)
Parents: graduate	-0.042***	-1.016***	-0.027***	4.431***
	(0.003)	(0.184)	(0.001)	(0.285)
Parents: high-ranked occup.	0.004	-0.072	0.002	1.584***
	(0.003)	(0.196)	(0.001)	(0.108)
Additional controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
D_{jm}	Yes		Yes	
P_{jm}		Yes		Yes
Observations	508,242	508,242	655,847	655,847
R-squared	0.101		0.125	
Mean y	6.887	6.887	0.775	0.775

Reduced form results from equation (4), OLS results from equation (5). Columns (2) and (4) feature bootstrapped standard errors with 104 iterations. Additional controls for local labor markets and university quality.

Figure 8 compares the distributions of treatment effects α_{jm} and OLS coefficients γ_{jm} for university careers and both labor market outcomes and emphasizes three main findings. Notably, this comparison makes use of the strong assumptions discussed in section 3 that justify the IV-equivalence result of equation (6). OLS and reduced form results are statistically different in 84% of cases for log(wages) and in 64% of cases for employment, such that any method that does not

[31] In this setting, the causal effect of university careers (j, m) is driven by several potentially small subsamples which may display different observed characteristics, both in X and in covariate patterns of P_{jm}. Hence, when treatment effects are abnormally large (or small), it is difficult to distinguish between non-credible estimates which are not estimated precisely and credible estimates with large magnitudes due to strong self-selection. I introduce a regulating criterion to rule out treatment effects with excessive magnitudes. For employment, I ensure that all treatment effects, summed with the average predicted probability of the baseline are constrained between 0 and 1. I obtain the boundaries $\tilde{\alpha}(\text{empl}) \in [-0.62, 0.38]$ and disregard treatment effects that exhibit larger magnitudes. For log(wages), I compare the treatment effect obtained in (7) with the maximum (minimum) deviations from the baseline predicted in the sample. Similarly, I disregard treatment effects beyond boundaries $\tilde{\alpha}(\ln(\text{wage})) \in [-1.04, 2.27]$, in levels, this corresponds to monthly salaries between 187 and 7186 Euros. I further correct the out of sample estimated treatment effects by weighting them by the 95% percentile of P_{jm} and drop the rest.

Figure 8: Comparison the distributions of OLS coefficients γ_{jm} and reduced form treatment effects α_{jm}



Generalized box plots for the distribution of returns by bachelor's. Dark blue markers denote reduced form (RF) coefficients α_{jm} (4), light blue markers denote OLS coefficients γ_{jm} (5). Red markers denote medians. The baseline is (Lit.Lang., No Master).

account for self-selection into university careers is highly misleading (to compare the returns one-to-one, refer to figure 15). Secondly, substantial variation is present when we compare the effect of university careers with the same undergraduate choice, which underscores the importance of accounting for advanced degrees in the discussion on returns to higher education. For example, log wage returns to undergraduate programs in chemistry and pharmacy vary greatly depending on the advanced degree. By plotting the distribution of the labor market returns by undergraduate choice, it is apparent that in almost all instances, the interquartile range of the conditional distribution spans positive and negative values with respect to the excluded category. Thirdly, OLS estimates more positive effects for 29 out of 43 log wage returns and 33 out of 43 returns to employment. This suggests that students self-select into degrees based on comparative advantage. Under the OLS equivalence assumptions, OLS coefficients overestimate on average the returns to university careers by 7.2pp (employment) and 0.26 log points (log wages). It also emphasizes the validity of exclusion restrictions Z_j and Z_m to partial out individual sorting. Another interpretation of these effects is thus the average returns to degree combinations enjoyed by individuals if they were randomly allocated to them. With this interpretation, it is perhaps not surprising that the average return to a career in engineering (Arch.Eng., Arch.Eng.) shifts from strictly positive when not accounting for self-selection to slightly negative when I do.

6 Results on Academic Curricula

Here I exploit the information on academic curricula to shed light on outcome-enhancing characteristics of university careers. I focus on how the composition of the curriculum affects returns with interest in market responses to multidisciplinary careers, quantitative courses, and the timing of degrees and courses. To facilitate the understanding of the results, I refer to careers with $j = m$ as *specialized careers*, such as (Econ.Mgmt., Econ.Mgmt.), careers with $j \neq m$ and $m \neq 0$ as *multidisciplinary careers*, for example (Econ.Mgmt., Sci.Stat.), and careers with $m = 0$ as *no master careers*, for example (Econ.Mgmt., No Master).

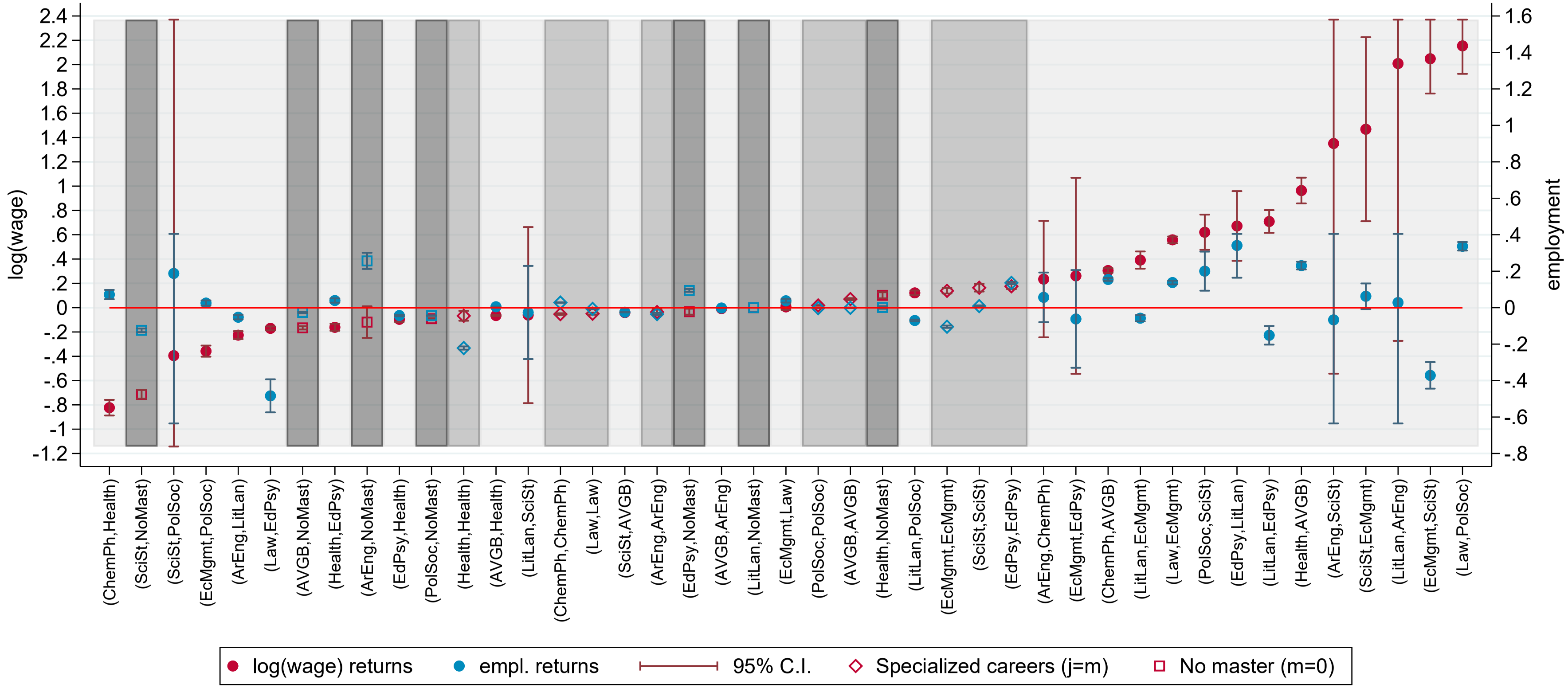
6.1 Academic Curricula and Degree Composition

Figure 9 directly compares the estimated returns to log wages and employment and orders careers by increasing returns to log wages. Both outcomes are significantly and positively correlated once we account for the precision of the estimates ($\rho(\tilde{\alpha}^{\text{lnwage}}, \tilde{\alpha}^{\text{empl}}) = 0.37$, $p = 0.015$), although the relationship does not hold at the tails of the distribution of log wage returns. Especially for very high log wage returns, there seems to be a trade-off between higher pecuniary outcomes and a lower probability of employment. In the extreme case of (Ec.Mgmt., Sci.Stat.), the estimated return to log wages is 2.05 (average monthly wage of 5 784 Euros), however, the return to employment is extremely low (-0.37), resulting in a probability of employment of 24.5%. The career with the best overall outcome is (Law, Pol.Soc.), with an estimated log wage return of 2.15 (6 393 Euros) and return to employment of 0.35 (0.95 probability of employment). More generally, only 7 of the 10 careers with the highest log wage returns display positive returns to employment with respect to the excluded career (Lit.Lang., No Master). On the opposite end of the distribution, the worst overall labor market returns are associated with career (Sci.St., No Master) which features a log wage return of -0.71 (366 Euros) and return to employment of -0.12 (0.49 probability of employment).[32] These results might be partially driven by different timelines that affect entry into the profession. The pathway to employment might be more complicated for individuals with peculiar university careers, for example, because of additional requirements regarding certification, training, or difficulty in building a client base. Certain careers require long apprenticeship periods after graduation (teachers, lawyers, doctors). In other instances, differences between wages and employment may reflect the riskiness of the career, whereby few individuals reap substantial benefits (creative careers, policy). Similarly, low-earning careers with relatively high levels of employment might reflect lower riskiness of the career, which is often the case for careers with no master.[33] These low-earning careers also exhibit differences in the sign of the two labor market returns, with 5 out of the 10 lowest earning careers displaying positive returns to employment with respect to the excluded career. Figure 17 in the appendix concentrates on careers with no master's and specialized careers that mostly populate the central part of figure 9. By considering the returns as a whole, I note that

[32] In terms of employment, the worst performing university career is (Law, Ed.Psy.), with an employment coefficient of -0.48 (13.5 probability of employment on average) and a -0.17 log wage coefficient (628 Euros).

[33] The magnitude of the estimates is obtained by comparing the returns to the predicted outcomes for the excluded career (Lit.Lang., No Master) at sample averages of the observed characteristics. Value in levels (Euros) of log wage return $\tilde{\alpha}_{jm}^{\text{lnwage}}$ is $\exp(6.614 + \tilde{\alpha}_{jm}^{\text{lnwage}})$, probability of employment for return to employment $\tilde{\alpha}_{jm}^{\text{empl}}$ is $0.615 + \tilde{\alpha}_{jm}^{\text{empl}}$.

Figure 9: Comparison of log wage and employment returns for all careers



Comparison of log wage returns (red, left vertical axis) and returns to employment (blue, right vertical axis). Axes are centered around 0. Full-circle symbol markers indicate multidisciplinary careers $j \neq m$ (light gray shading), hollow diamond symbols indicate specialized careers $j = m$ (mid-gray shading), and hollow square symbols indicate careers with no master $m = 0$ (dark gray shading). Careers are ordered by increasing returns to log wages. Only careers for which both labor market outcomes were estimated are displayed.

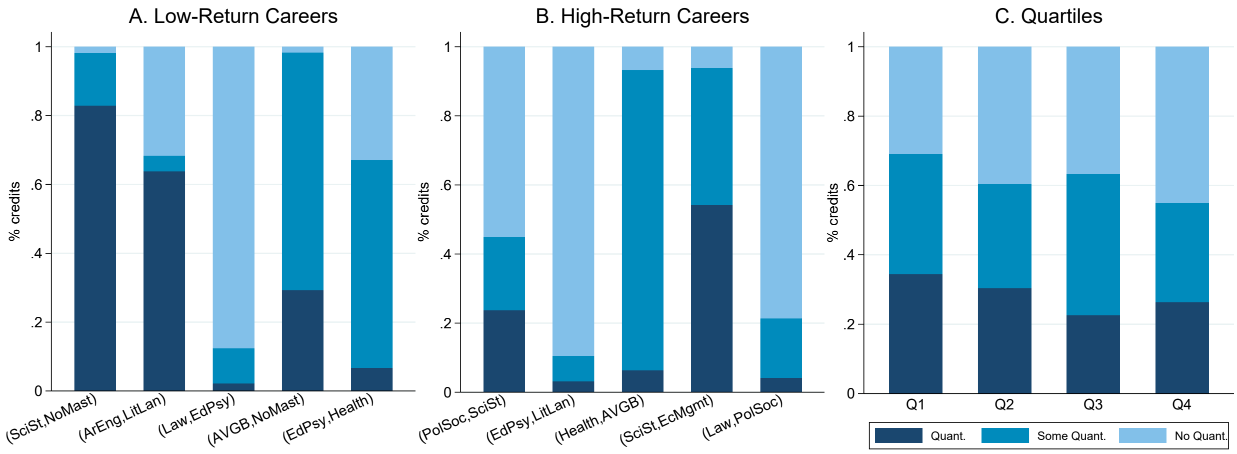
the returns to combinations with no master are ranked towards the bottom of the distribution of wage returns (dark gray shading), suggesting that in most instances there is a premium to having a master's degree. Specialized careers are bunched towards the middle of the distribution in mid-gray shading with sensible rankings (science ranks better than economics which ranks better than law), while the top of the distribution is exclusively populated by multidisciplinary careers (light gray shading).[34] Out of 43 estimated returns to careers, the 14 highest log wage returns are all multidisciplinary careers with $j \neq m$ and $m \neq 0$ (top third of the distribution), while the 10 lowest log wage returns are associated with no master careers in 3 cases and multidisciplinary careers in the other 7. These findings suggest that enrolling in a multidisciplinary career can substantially boost labor market outcomes if chosen well. Even though career (Econ.Mgmt., Econ.Mgmt.) yields the third highest log wage returns among specialized careers ($\tilde{\alpha}^{\text{lnwage}}_{(\text{EcMg,EcMg})} = 0.14$), returns can be up to fourteen times higher if combined with other degrees such as (Econ.Mgmt., Educ.Psy.), (Law, Econ.Mgmt.), or (Econ.Mgmt., Sci.Stat.), yielding $\tilde{\alpha}^{\text{lnwage}}_{(\text{EcMg,EdPs})} = 0.26$, $\tilde{\alpha}^{\text{lnwage}}_{(\text{Law,EcMg})} = 0.56$, $\tilde{\alpha}^{\text{lnwage}}_{(\text{EcMg,Sci})} = 2.05$, respectively. At the same time, multidisciplinarity can lead to drastically lower returns. For example, log wage returns to (Econ.Mgmt., Pol.Soc.) are equal to -0.36, or 1.4 times lower than the specialized career.

While figure 9 highlights the importance of the joint choice of bachelor's and master's beyond undergraduate majors, it does not reveal which characteristics of the careers are informative about outcomes. I investigate the composition of the curriculum of the best- and worst-performing careers to elicit any patterns in the type of knowledge that is covered. In order to avoid considerations on the trade off between employment and wages, I focus on the five best-performing careers – compared to the benchmark – which display the highest log wage returns as well as positive returns to employment. Similarly, the five worst-performing careers are selected such that they display negative returns to both outcomes.

Panels A and B of figure 10 present the academic curricula of the selected high- and low-performing careers. The curricula are summarized as the share of credits in courses with different levels of quantitative content. Following the agreement among scholars in the categorization of STEM disciplines (table 9), I group university courses according to their quantitative content. Quantitative courses include science and statistics, architecture and engineering, and chemistry and pharmacy. These are the fields of study that most scholars agree can be defined as STEM. Courses with some quantitative component include life sciences (agriculture, veterinary, geology and biology), economics and management, and healthcare. These are more technical fields of study over which researchers disagree on whether they should belong to STEM education (I will alternatively refer to these disciplines as "technical"). Non-quantitative courses include education and psychology, law, humanities (literature and languages), and political and other social sciences. Most scholars agree that these fields of study do not fit the STEM definition. The ordering along the horizontal axis reflects increasing log wage returns. Figure 10 shows that quantitativeness alone does not explain

[34] Indeed, some specialized careers result in surprising results: the best-ranking specialized career is education and psychology, while the worst one is healthcare. The ones reported as sensible rankings remain stable throughout versions of this paper, while the ones cited in this note change (previous versions of this paper are available upon request). Furthermore, healthcare requires extensive training after the degree such that potential long term returns are not captured in this framework, and overall the returns to specialized careers are close to each other in magnitude, leading to variations in rankings even without substantial changes in the estimated.

Figure 10: Comparison of academic curricula and log wage returns for selected careers

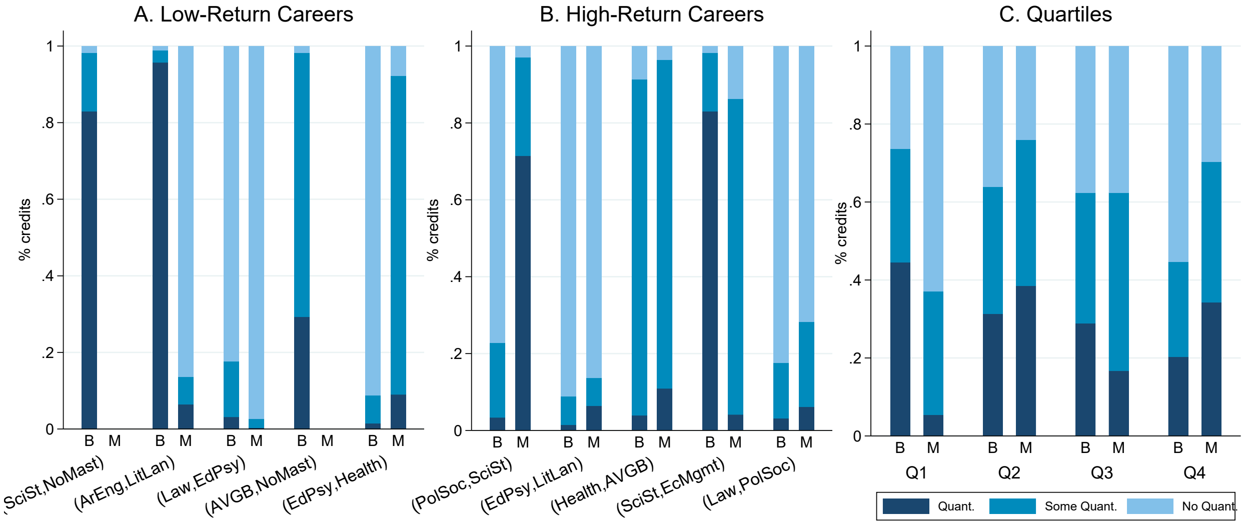


Quantitative courses (dark blue): science and statistics, architecture and engineering, and chemistry and pharmacy. Some quantitative (technical) courses (blue): life sciences (agriculture, veterinary, geology and biology), economics and management, and healthcare. Non-quantitative courses (light blue): education and psychology, law, humanities (literature and languages), and political and social sciences. The total percentage of credits in each grouping is plotted on the vertical axis. The order of degrees follows the ranking of log-wage returns, increasing from left to right within each panel.

the higher returns of certain careers. In fact, careers with high shares of credits in quantitative courses are represented both among the worst- and best-performing careers. Panel C presents the average composition of careers by quartiles of the distribution of log wage returns. This ensures that the lack of relationship between the share of quantitative credits and returns is not driven by the choice of low- and high-return careers. Indeed, the share of quantitative courses displays a slight U-shape relationship with log wage returns. The overall share of non-quantitative courses tends to increase along the distribution of log wage returns. Panel A in figure 12 presents the same decomposition of academic curricula for the distribution of returns to employment. Increasing the share of quantitative courses only improves outcomes up to the third quartile, whereby the fourth quartile has the highest share of non-quantitative courses.

I report the curriculum composition for the same groups of careers separately for the bachelor's and the master's degrees to elicit patterns in the timing of courses in figure 11. The most striking difference between low- and high-earning degrees in terms of curriculum that emerges once courses are plotted separately by bachelor's and master's is that degrees with low returns have a low share of technical courses in the bachelor's (panel A and quartile 1 of panel C). Conversely, high-return careers have a low share of non-quantitative credits in the master's (panel B and quartile 4 of panel C). Once again, a U-shaped relationship between the share of quantitative courses and log wage returns emerges, reiterating that quantitativeness alone does not explain higher returns, even when I account for timing. Panel B in figure 12 presents the same decomposition of academic curricula for the distribution of returns to employment. In this case, high-performing degrees spend more time in more general type of courses in the bachelor's (non-quantitative and quantitative) while they invest substantially more in technical courses in the master's (quartile 4). These results are consistent with the paradigms of education, whereby more general education should be approached earlier and more vocational education later.[35]

Figure 11: Comparison of academic curricula for selected careers



Quantitative courses (dark blue): science and statistics, architecture and engineering, and chemistry and pharmacy. Some quantitative (technical) courses (blue): life sciences (agriculture, veterinary, geology and biology), economics and management, and healthcare. Non-quantitative courses (light blue): education and psychology, law, humanities (literature and languages), and political and social sciences. The total percentage of credits in each grouping is plotted on the vertical axis. The order of degrees follows the ranking of log-wage returns, increasing from left to right within each panel. Column labels B and M denote bachelor's and master's, respectively.

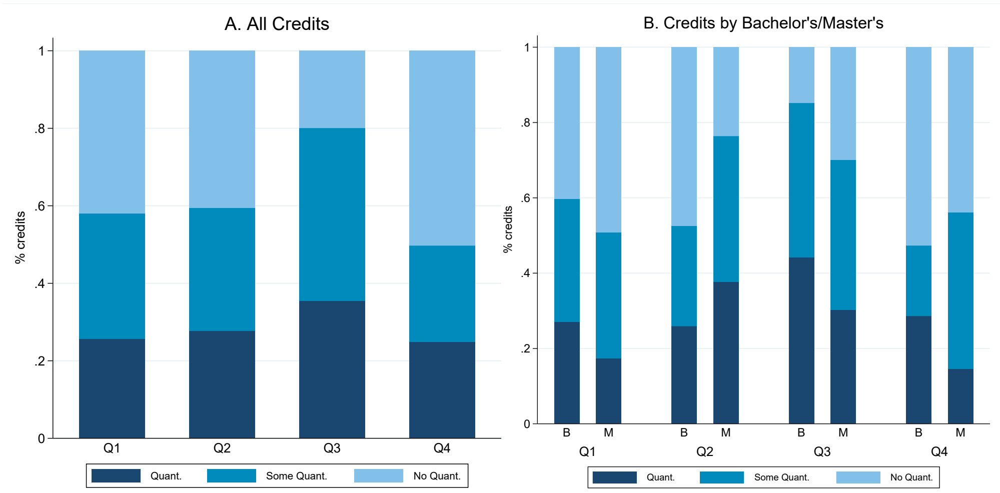
To further understand how the timing of degrees affects returns, I compare the returns and career composition for symmetric multidisciplinary careers, that is, given two fields of study x and y, the returns to career (x, y) compared with career (y, x). Complete returns for both sets of outcomes are available for seven pairs of reciprocal degrees: (AVGB, Health), (Econ. Mgmt., Law), (Educ. Psyc., Health), (Pol. Soc., Sci. Stat.), (Ec.Mgmt., Sci.Stat.), (Arch.Eng., Lit.Lang.), (Ed.Psy., Lit.Lang.), and the reciprocals of these groups. Figure 13 presents the composition of these careers by degrees and the labor market returns, where each reciprocal is ordered such that the more quantitative group of the two is studied in the master's. Even though the composition of symmetric careers is comparable, the log wage returns vary substantially. In particular, log wage returns are higher when the more quantitative of the degrees is studied later, consistent with the findings of figure 11.[36] This trend in log wage returns is only partially carried across returns to employment.

The analysis on the composition of curricula suggests that multidisciplinary careers can substantially increase or decrease labor market returns. While there is no clear recipe for a successful university career, several clues guide indicate best practices in the design of university programs. Quantitative courses are connected to log wage returns by a U-shaped relationship, whereby both low- and high-performing careers display relatively high shares of quantitative courses, and returns to employment increase with the share of quantitative courses only up to the third quartile. The

[35] Neal (2018) on optimal life cycle investments in skills, "*learn to learn, learn to earn, earn*" (Appendix I.5).

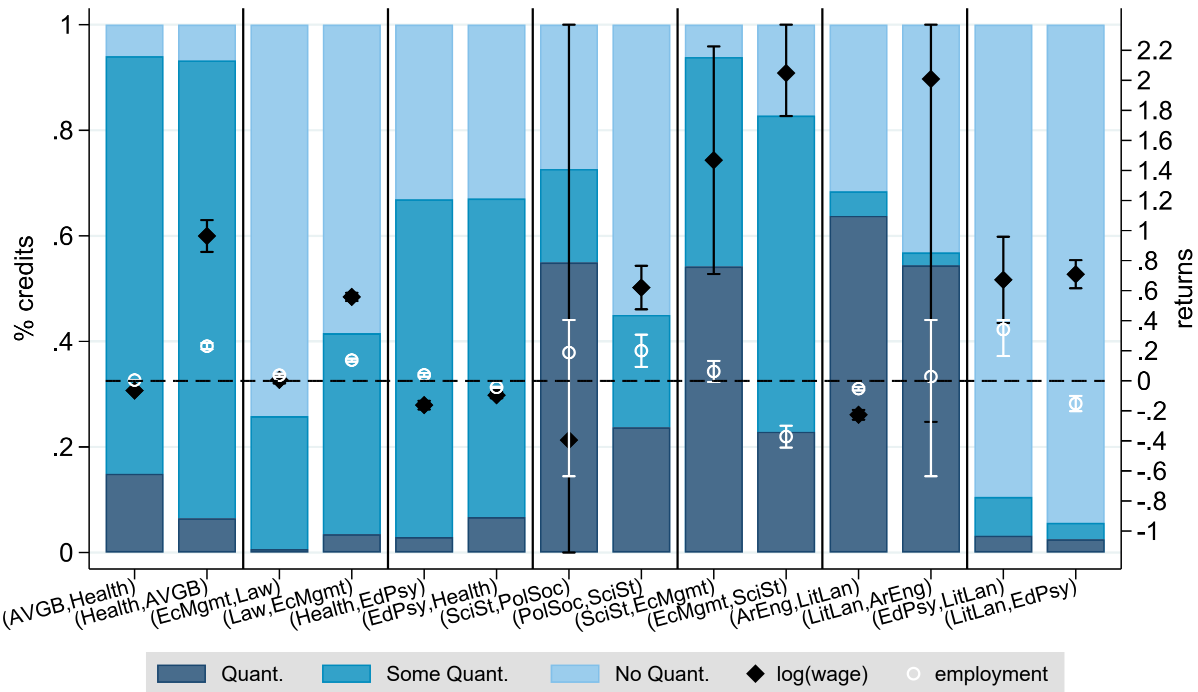
[36] A degree in Agr.Vet.Geo.Bio. contains more quantitative courses (e.g. math, chemistry) than a degree in Health. Similarly, a degree in Health contains more quantitative courses than a degree in Education and Psychology and so on.

Figure 12: Comparison of academic curricula along quartiles of the distribution of employment



Quantitative courses (dark blue): science and statistics, architecture and engineering, and chemistry and pharmacy. Some quantitative (technical) courses (blue): life sciences (agriculture, veterinary, geology and biology), economics and management, and healthcare. Non-quantitative courses (light blue): education and psychology, law, humanities (literature and languages), and political and social sciences. The total percentage of credits in each grouping is plotted on the vertical axis. The order of degrees follows the ranking of returns to employment, increasing from left to right within each panel. Panel B further decomposes by bachelor's (B) and master's (M).

Figure 13: Differences in returns for symmetric careers



Symmetric careers are grouped next to eachother. The share of courses by quantitativeness are plotted on the left vertical axis, while the estimated returns to log wages (black diamonds) and employment (white circles) follow the right vertical axis.

timing of courses matters with higher shares of non-quantitative courses in the master's being related to lower returns. All high earning careers are characterized by relatively more general education early on (especially non-quantitative), and more technical courses in the master's. This is consistent with the comparison of symmetric multidisciplinary careers. It suggests that returns are different even when the overall structure of the curriculum is similar, with the returns being higher for careers with the most quantitative and technical degree studied later, even if globally it may result in less time spent in these subjects.

Even though these results should not be regarded as conclusive insights on the role of timing, multidisciplinarity and quantitativeness on labor market outcomes, they do suggest that these characteristics strongly affect outcomes and call for a deeper understanding of synergies across courses. When optimally designing a degree, additional constraints on total credits, substitution patterns and complementarities between courses should be considered, as well as measuring skill acquisition at university and skill use during the job, which are not observed in this setting. While this project does not allow for an in-depth discussion of how to increase the labor market returns of existing university careers, it does suggest that the combination of quantitative and technical courses is important for labor market outcomes, that well-thought multidisciplinary careers can lead to impressive labor market outcomes, and that timing of courses matters. In particular, it does seem that specializing in quantitative degrees in graduate school is positively associated with outcomes. Indeed, the signaling component of the degree might play a role in these results, so further research is needed to corroborate the role of timing.

7 Conclusions

This article proposes a new method to causally estimate the returns to many combinations of bachelor's and master's degrees. It then leverages information on the course content of programs to investigate how multidisciplinarity, quantitativeness, and timing affect returns. I find that considering the joint choices of bachelor's and master's degrees is crucial to truthfully evaluate the effect of higher education on outcomes. Combining degrees in different fields can boost labor market returns, although there is no unique pattern of quantitative course content and timing that explains the success of certain careers. In fact, a U-shaped relationship between labor market returns and the share of quantitative courses emerges. The breakdown of this relationship by bachelor's and master's suggests that successful careers have little non-quantitative education in the master's, but a deeper understanding of the complementarities between courses acquired early and late in the career is necessary. Finally, policy simulations that remove entry barriers in the bachelor's suggest that students have preferences for non-quantitative degrees.

These results suggest that policies that incentivize enrollment in STEM education without considering nonlinearities in the relationship between quantitative education and outcomes might not benefit students. Furthermore, policies that incentivize STEM education through a reduction in entry barriers might be ineffective due to individual preferences, and unable to affect the composition of the student body, for example by increasing female enrollment. The results point to the importance of covering multiple disciplines throughout higher education with surprising effects on wages, challenging the prejudice that extreme specialization is profitable. This suggests that policies that ease switching from one field to another may be extremely beneficial to students. Caution is nonetheless advised, as certain combinations that encompass multiple fields can be nefarious.

One limitation of this setup is that it does not consider students' reactions to enrollment policies at the extensive margin. Indeed, the negative effects of policies that incentivize STEM enrollment through reductions in entry barriers might be attenuated if they generate a sufficient influx of students who would otherwise not obtain a degree. Furthermore, it does not incorporate the signaling component of degrees. If employers only observe the highest level of education (as assumed by Altonji (1993)), master's degrees might be weighted disproportionately by the employer, thus partially explaining the results on timing. Lastly, while the policy simulations hint at preferences towards non-quantitative studies out-weighting quantitative preferences, the model does not isolate the effect. Non-pecuniary returns not captured by the model might explain some features of the sorting, in which case policies that affect enrollment could have a greater impact if they can incorporate these amenities.

This paper reveals two potential venues for future research that would improve our understanding of how knowledge acquired at university plays into the labor market. Skills are acquired during university and vary across fields, but I do not observe them in this setting. In particular, the results on the content of degrees signal the importance of the time spent in technical courses, such as medicine or management, which typically involve the acquisition of practical knowledge. We can speculate that part of the commonly observed success of STEM can be explained by the successful integration of quantitative and technical education that interplay with skills. Similarly, the concept of quantitativeness remains elusive and we can expect high returns to specific types of quantitative education. Understanding how specialized knowledge in quantitative fields and how the mathematical language spills over into different courses – for example through enhanced problem solving ability – might be critical to optimally designing university degrees.

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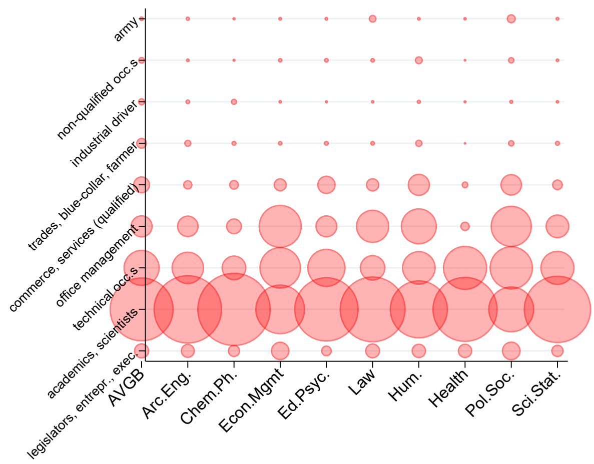
A Appendix

A.1 Additional Descriptive Results

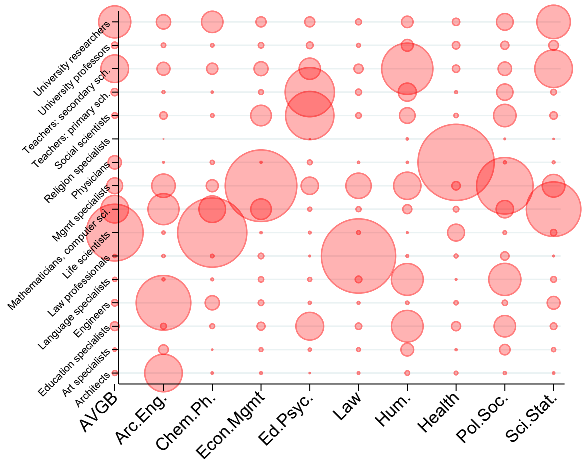
Table 8: Differences in X for the sample of employed and unemployed.

	All	Employed	Unemployed
High School: grade (st.)	0.00	0.03	-0.11
	(1.000)	(0.998)	(0.998)
High School: humanities	0.15	0.14	0.18
	(0.359)	(0.352)	(0.384)
High School: science	0.39	0.40	0.36
	(0.487)	(0.489)	(0.479)
Gender (1=female)	0.62	0.60	0.68
	(0.485)	(0.489)	(0.466)
Parents: graduate	0.26	0.26	0.26
	(0.438)	(0.437)	(0.439)
Parents: high-ranked occ.	0.21	0.22	0.21
	(0.410)	(0.412)	(0.406)
Employment	0.77	1.00	0.00
	(0.418)	(0)	(0)
Observations	655 847	508 242	147 605

Figure 14: Occupation sectors by master degree's (ISTAT codes)



(a) Share of master graduates in one-digit occupations.



(b) Two-digit occupations for master graduates employed in sector "academics and scientists".

Panel 14a presents one-digit occupation sectors for all master graduates as defined by ISTAT's 2011 classification of occupations (in turn based on ILO's 2008 *International Standard Classification of Occupations*). This information is available for 209 906 individuals. Panel 14b focuses on two-digit occupation sectors for master graduates employed in sector "academics and scientists" (intellectual and highly specialized occupations), for a total of 126 166 observations. In both instances, occupation codes are only available for individuals who complete a master degree and are not available for students who start working after their bachelor. Both panels show that labor markets are segregated along specialized skill sets.

Table 9: Comparison of STEM classification methods in Economics papers

Paper	Classification	Groups of Degrees Classified as STEM									
		Science	Arch. Eng.	Chem. Pharm.	Agr.Vet. Geo.Bio.	Econ. Stat.	Health	Educ. Psy.	Law	Lit. Lang.	Pol. Soc.
Adams and Kirchmaier (2016)	O*NET, authors	All	Most	Most	Some	Most	None	None	None	None	None
Ahn et al. (2019)	author	All	Most	Most	Some	All	None	None	None	None	None
Altonji et al. (2016)	author	All	All	All	All	All	All	None	None	None	None
Altonji and Zhong (2021)	author, NSCG, NSRCG	All	Most	None	All	None	None	None	None	None	None
Arcidiacono et al. (2016b)	author	All	All	All	Most	Some	None	Some	None	None	None
Arcidiacono et al. (2016a)	author	All	All	Most	All	None	Some	None	None	None	None
Bianchi and Giorcelli (2020)	author	All	Most	Most	Most	Some	None	None	None	None	None
Biasi and Ma (2022)	ARC 2016	All	All	All	All	None	All	None	None	None	None
Buffington et al. (2016)	author	All	Most	All	Most	None	All	None	None	None	None
Canaan and Mouganie (2018)	author	All	All	All	All	Most	Most	None	None	None	None
Chise et al. (2021)	ISCED, MIUR, author	All	All	Most	Some	Some	None	None	None	None	None
Delaney and Devereux (2019)	ISCED, authors	All	All	All	Some	Some	All	None	None	None	None
Delaney and Devereux (2021)	ISCED, authors	All	All	All	Some	Some	All	None	None	None	None
Deming (2017)	Autor and Dorn (2013)	All	All	Some	Some	Some	Some	None	None	None	None
Granato (2018)	MIUR	All	All	All	Some	Some	None	None	None	None	None
Kahn and Ginther (2017)	author	All	Most	All	Most	Most	None	Some	None	None	None
Maple and Stage (1991)	author	All	Most	None	None	None	None	None	None	None	None
Ng and Riehl (2020)	author	All	Most	Most	Most	Some	None	None	None	None	None
Porter and Serra (2020)	author	All	All	All	None	All	None	None	None	None	None
Rask (2010)	Anon. data provider	All	NA	All	Most	Some	None	Some	None	None	None
Schmeiser et al. (2016)	author	All	All	All	All	Some	Most	None	None	None	None
Uddin et al. (2021)	ARC 2016	All	All	All	All	None	All	None	None	None	None
Webber (2016)	author, NLSY, NSCG, ACS	All	Most	Most	Some	None	None	None	None	None	None
Winters (2014)	U.S. ICE	All	All	All	All	Some	Some	Some	None	None	None

The table presents a non-exhaustive review of the methods used to classify STEM fields in the literature. All possible degrees are grouped into ten categories: Science, Architecture and Engineering, Chemistry and Pharmacy, Agriculture Veterinary Geology and Biology, Economics and Statistics, Education and Psychology, Law, Literature and Languages, Political sciences and social sciences. The full list of degrees belonging to each group according to the Italian classification can be found in appendix A.5.2. The grouping and the comparison across papers is inherently lax as not all degrees are available across countries. The label "Most" indicates that almost all the degrees in the group according to my grouping are defined as STEM in the authors' paper. "Some" indicates that only a few of them are defined as STEM. "All" and "None" should be self-explanatory.

A.2 Marginal Effects of Main Regressions

Table 10: $t = 1$: Marginal Effects at Means of exclusion restrictions on choice of bachelor

Z_j: *Entry Exams*	AVGB (1)	Ar.Eng. (2)	Ch.Pharm. (3)	Ec.Mgmt. (4)	Ed.Psy. (5)	Law (6)	Lit.Lan. (7)	Health (8)	Pol.Soc. (9)	Sci.Stat. (10)
Outcomes										
Pr(AVGB)	-0.031***	0.004	0.048***	0.016***	-0.014***	0.049***	-0.170***	0.196***	-0.065***	0.046***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.007)	(0.005)	(0.004)
Pr(ArEng)	-0.061***	0.053***	0.138***	0.025***	0.049***	0.046***	0.173***	-0.127***	-0.280***	-0.022***
	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)	(0.009)	(0.007)	(0.006)
Pr(ChPh)	-0.005**	0.044***	-0.009***	-0.011***	-0.026***	0.000	-0.043***	0.137***	0.041***	0.016***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)
Pr(EcMg)	-0.171***	-0.141***	0.064***	0.013***	-0.031***	0.026***	0.305***	0.080***	0.046***	-0.047***
	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)	(0.009)	(0.006)	(0.005)
Pr(EdPsy)	0.091***	-0.097***	-0.042***	0.021***	0.035***	-0.025***	-0.145***	0.042***	-0.073***	0.125***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.006)	(0.005)
Pr(Law)	0.049***	-0.036***	0.018***	0.005**	-0.059***	0.018***	-0.050***	-0.056***	0.003	0.044***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.008)	(0.006)	(0.005)
Pr(LitLan)	0.003	-0.037***	0.076***	0.055***	-0.085***	-0.156***	0.264***	-0.543***	0.034***	-0.016***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.010)	(0.007)	(0.006)
Pr(Health)	0.078***	0.168***	-0.286***	-0.121***	0.184***	0.119***	-0.302***	0.462***	0.171***	-0.182***
	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)	(0.010)	(0.007)	(0.006)
Pr(PolSoc)	0.037***	0.014***	0.020***	-0.009***	-0.063***	-0.067***	-0.035***	-0.210***	0.104***	0.038***
	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)	(0.009)	(0.007)	(0.005)
Pr(SciSt)	0.010***	0.026***	-0.027***	0.007***	0.008***	-0.009***	0.003	0.019***	0.017***	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)
Observations	655,847	655,847	655,847	655,847	655,847	655,847	655,847	655,847	655,847	655,847

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

A.3 Choice of Master Degree – Regression Tables

Table 11: Choice of master conditional on bachelor in Agriculture, Veterinary, Geology, Biology

VARIABLES	(1) AVGB	(2) Arc.Eng.	(3) Ed.Psy.	(4) Health	(5) Sci.Stat.
Z_m					
Credit req. (st.): AVGB	1.141***	-1.191**	1.727	-6.138***	6.461***
	(0.114)	(0.530)	(1.472)	(0.777)	(0.251)
Credit req. (st.): ArEn	3.897***	2.266*	13.779***	17.824***	1.226
	(0.323)	(1.242)	(4.057)	(1.164)	(1.031)
Credit req. (st.): Med	-2.667***	7.017***	-8.738***	2.887***	-1.746***
	(0.132)	(0.932)	(1.467)	(0.472)	(0.450)
Credit req. (st.): Sci	-1.668***	0.931	-15.627***	-6.154***	-9.848***
	(0.140)	(0.863)	(3.481)	(0.596)	(1.024)
log(distance)	0.006	-0.166***	0.043	-0.012	-0.016
	(0.007)	(0.029)	(0.041)	(0.021)	(0.018)
X					
HS: grade (st.)	0.538***	0.237***	0.124	0.314***	0.454***
	(0.016)	(0.076)	(0.090)	(0.048)	(0.041)
HS: humanities	0.872***	0.402	0.638***	0.547***	1.121***
	(0.055)	(0.277)	(0.225)	(0.141)	(0.135)
HS: science	0.867***	0.140	-0.390**	0.488***	0.860***
	(0.032)	(0.163)	(0.191)	(0.102)	(0.088)
Gender (1=female)	-0.451***	-0.097	0.667***	0.077	0.252**
	(0.041)	(0.205)	(0.252)	(0.134)	(0.107)
Parents: graduate	0.366***	0.387**	0.361*	0.406***	0.468***
	(0.040)	(0.185)	(0.202)	(0.114)	(0.095)
Parents: high-rank occ.	-0.033	0.198	0.209	0.089	-0.126
	(0.042)	(0.191)	(0.208)	(0.124)	(0.106)
Additional Controls			Yes		
Θ			Yes		
Constant	10.364***	-34.833***	17.671**	-41.140***	13.965***
	(0.909)	(5.033)	(7.548)	(3.938)	(2.570)
Observations	32,494	32,494	32,494	32,494	32,494
Pseudo R2	0.211	0.211	0.211	0.211	0.211

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 12: Choice of master conditional on bachelor in Architecture and Engineering

VARIABLES	(1) Arc.Eng.	(2) Chem.Pharm.	(3) Lit.Lang.	(4) Sci.Stat.
Z_m				
Credit req. (st.): ArEn	-0.053**	-2.726***	-6.861***	-0.268*
	(0.024)	(0.144)	(0.687)	(0.143)
Credit req. (st.): ChPh	-6.053***	-1.743*	23.136***	-5.426***
	(0.127)	(0.977)	(2.300)	(1.132)
Credit req. (st.): Hum	-0.734***	15.535***	14.477***	8.470***
	(0.127)	(2.934)	(2.252)	(2.453)
Credit req. (st.): Sci	0.649***	0.239	5.577***	-1.262*
	(0.053)	(0.729)	(0.521)	(0.754)
log(distance)	-0.015***	0.005	0.004	0.005
	(0.005)	(0.022)	(0.028)	(0.037)
X				
HS: grade (st.)	0.737***	0.742***	0.634***	0.808***
	(0.010)	(0.045)	(0.072)	(0.079)
HS: humanities	0.900***	1.340***	1.124***	0.849***
	(0.044)	(0.170)	(0.192)	(0.302)
HS: science	1.023***	1.425***	0.564***	1.273***
	(0.021)	(0.098)	(0.148)	(0.164)
Gender (1=female)	-0.253***	0.208*	0.549***	0.604***
	(0.030)	(0.113)	(0.194)	(0.179)
Parents: graduate	0.368***	0.385***	0.517***	0.544***
	(0.025)	(0.089)	(0.151)	(0.150)
Parents: high-rank occ.	0.074***	-0.033	-0.029	0.015
	(0.026)	(0.097)	(0.160)	(0.162)
Additional Controls		Yes		
Θ		Yes		
Constant	4.078***	-2.262	-18.458***	-0.826
	(0.158)	(1.656)	(1.929)	(1.670)
Observations	79,817	79,817	79,817	79,817
Pseudo R2	0.241	0.241	0.241	0.241

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 13: Probability of choosing a master degree given a bachelor in Chemistry and Pharmacy

VARIABLES	(1) AVGB	(2) Chem.Pharm.	(3) Health
Z_m			
Credit req. (st.): ChPh	0.423***	-2.994***	7.038
	(0.125)	(0.186)	(293.390)
log(distance)	-0.072	-0.013	-0.037
	(0.044)	(0.021)	(0.037)
X			
HS: grade (st.)	0.688***	0.770***	0.779***
	(0.112)	(0.047)	(0.088)
HS: humanities	0.346	0.877***	0.864***
	(0.315)	(0.176)	(0.239)
HS: science	-0.049	0.866***	0.622***
	(0.217)	(0.093)	(0.167)
Gender (1=female)	0.300	-0.203	-0.781***
	(0.283)	(0.126)	(0.244)
Parents: graduate	0.464*	0.403***	-0.013
	(0.248)	(0.115)	(0.230)
Parents: high-rank occ.	0.197	0.080	-0.002
	(0.272)	(0.130)	(0.261)
Additional Controls		Yes	
Θ		Yes	
Constant	-3.444***	-5.804***	-23.672
	(0.911)	(0.580)	(1,430.729)
Observations	7,398	7,398	7,398
Pseudo R2	0.571	0.571	0.571

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 14: Probability of choosing a master degree given a bachelor in Economics and Management

VARIABLES	(1) Econ.Mgmt.	(2) Educ.Psy.	(3) Law	(4) Pol.Soc.	(5) Sci.Stat.
Z_m					
Credit req. (st.): PlSc	-18.471***	-15.756***	-13.175***	-18.097***	-13.711***
	(0.157)	(1.497)	(1.264)	(0.554)	(0.815)
log(distance)	0.012**	-0.125***	0.040**	-0.054***	-0.025
	(0.005)	(0.046)	(0.019)	(0.016)	(0.028)
X					
HS: grade (st.)	0.509***	0.027	-0.009	0.237***	0.515***
	(0.010)	(0.101)	(0.075)	(0.034)	(0.053)
HS: humanities	0.908***	1.391***	1.506***	1.160***	0.875***
	(0.041)	(0.282)	(0.211)	(0.105)	(0.206)
HS: science	0.763***	0.771***	-0.160	0.538***	1.128***
	(0.021)	(0.213)	(0.182)	(0.072)	(0.106)
Gender (1=female)	-0.393***	1.282***	-1.303***	-0.065	-0.432***
	(0.026)	(0.258)	(0.221)	(0.088)	(0.133)
Parents: graduate	0.377***	0.698***	-0.091	0.608***	0.442***
	(0.026)	(0.225)	(0.216)	(0.080)	(0.122)
Parents: high-rank occ.	0.076***	-0.392	-0.868***	-0.105	-0.194
	(0.025)	(0.248)	(0.261)	(0.085)	(0.130)
Additional Controls			Yes		
Θ			Yes		
Constant	-40.752***	-44.205***	-31.250***	-41.948***	-34.294***
	(0.365)	(3.554)	(2.950)	(1.284)	(1.900)
Observations	75,993	75,993	75,993	75,993	75,993
Pseudo R2	0.220	0.220	0.220	0.220	0.220

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 15: Probability of choosing a master degree given a bachelor in Physical Education, Teaching and Psychology

VARIABLES	(1) Educ.Psy.	(2) Lit.Lang.	(3) Health	(4) Pol.Soc.
Z_m				
Credit req. (st.): EdPsy	4.587***	-0.610***	0.610	-0.581***
	(0.081)	(0.137)	(0.573)	(0.094)
Credit req. (st.): PlSc	-1.547***	-0.731***	-0.842***	-0.512***
	(0.021)	(0.162)	(0.210)	(0.111)
log(distance)	-0.016***	-0.081***	-0.055	-0.031
	(0.004)	(0.028)	(0.035)	(0.019)
X				
HS: grade (st.)	0.365***	0.194***	0.018	0.312***
	(0.011)	(0.070)	(0.102)	(0.048)
HS: humanities	0.786***	0.878***	0.362	0.574***
	(0.032)	(0.182)	(0.298)	(0.136)
HS: science	0.670***	-0.055	-0.173	0.313***
	(0.023)	(0.170)	(0.237)	(0.107)
Gender (1=female)	-0.446***	-0.454**	-0.661**	-0.548***
	(0.032)	(0.199)	(0.270)	(0.140)
Parents: graduate	0.371***	0.344*	-0.123	0.417***
	(0.029)	(0.186)	(0.315)	(0.123)
Parents: high-rank occ.	0.105***	-0.168	-0.711*	0.185
	(0.029)	(0.203)	(0.367)	(0.128)
Additional Controls			Yes	
Θ			Yes	
Constant	3.314***	-4.234***	-5.255***	-2.900***
	(0.134)	(0.702)	(1.131)	(0.457)
Observations	62,741	62,741	62,741	62,741
Pseudo R2	0.223	0.223	0.223	0.223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 16: Probability of choosing a master degree given a bachelor in Law

VARIABLES	(1) Econ.Mgmt.	(2) Educ.Psy.	(3) Law	(4) Pol.Soc.
Z_m				
Credit req. (st.): PlSc	-3.800***	-2.129***	-5.008***	-2.087***
	(0.149)	(0.418)	(0.154)	(0.160)
log(distance)	-0.040***	0.032	0.012	-0.032*
	(0.013)	(0.057)	(0.010)	(0.017)
X				
HS: grade (st.)	0.540***	0.233**	0.270***	0.311***
	(0.034)	(0.098)	(0.033)	(0.037)
HS: humanities	0.166	1.392***	0.814***	0.893***
	(0.115)	(0.240)	(0.097)	(0.104)
HS: science	0.796***	0.755***	0.571***	0.592***
	(0.075)	(0.227)	(0.076)	(0.084)
Gender (1=female)	-0.137	0.078	-0.640***	-0.509***
	(0.088)	(0.257)	(0.088)	(0.095)
Parents: graduate	0.592***	0.669***	0.335***	0.404***
	(0.091)	(0.242)	(0.096)	(0.102)
Parents: high-rank occ.	0.411***	0.121	-0.042	-0.001
	(0.091)	(0.258)	(0.100)	(0.106)
Additional Controls		Yes		
Θ		Yes		
Constant	-13.281***	-28.260	-12.949***	-8.243***
	(0.567)	(374.262)	(0.494)	(0.551)
Observations	10,882	10,882	10,882	10,882
Pseudo R2	0.182	0.182	0.182	0.182

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 17: Probability of choosing a master degree given a bachelor in Literature and Languages

VARIABLES	(1) Arc.Eng.	(2) Econ.Mgmt.	(3) Educ.Psy.	(4) Lit.Lang.	(5) Pol.Soc.	(6) Sci.Stat.
Z_m						
Credit req. (st.): EdPs	3.252***	1.105***	-1.907***	-1.582***	0.219*	0.222
	(1.001)	(0.371)	(0.208)	(0.052)	(0.123)	(0.888)
Credit req. (st.): Hum	7.735***	-3.854***	0.118	-1.500***	-4.206***	0.931
	(0.970)	(0.611)	(0.513)	(0.089)	(0.207)	(0.845)
Credit req. (st.): PlSc	-1.525**	2.315***	-0.244	-0.122**	1.966***	-2.063***
	(0.633)	(0.412)	(0.330)	(0.057)	(0.138)	(0.543)
Credit req. (st.): Sci	-0.176	2.466***	-0.433	-2.117***	0.411**	-0.963
	(1.986)	(0.521)	(0.520)	(0.089)	(0.173)	(0.900)
log(distance)	-0.041	0.045**	-0.005	-0.008**	-0.030***	-0.037
	(0.042)	(0.022)	(0.015)	(0.004)	(0.006)	(0.038)
X						
HS: grade (st.)	0.580***	0.428***	-0.123***	0.565***	0.381***	0.251***
	(0.096)	(0.042)	(0.044)	(0.008)	(0.015)	(0.083)
HS: humanities	0.315	0.839***	0.367***	1.115***	0.846***	0.593***
	(0.288)	(0.108)	(0.115)	(0.021)	(0.040)	(0.224)
HS: science	0.615***	0.784***	0.250**	0.753***	0.836***	0.605***
	(0.213)	(0.093)	(0.102)	(0.019)	(0.035)	(0.187)
Gender (1=female)	-0.833***	-0.068	0.073	-0.393***	-0.740***	-1.032***
	(0.251)	(0.125)	(0.135)	(0.024)	(0.043)	(0.252)
Parents: graduate	0.769***	0.373***	0.136	0.403***	0.244***	0.439**
	(0.213)	(0.096)	(0.111)	(0.020)	(0.036)	(0.199)
Parents: high-rank occ.	0.189	0.020	-0.209*	-0.058***	0.052	-0.271
	(0.219)	(0.102)	(0.121)	(0.021)	(0.038)	(0.233)
Additional Controls			Yes			
Θ			Yes			
Constant	-3.131**	-6.094***	-1.798***	-0.913***	0.201	-7.927***
	(1.546)	(0.588)	(0.528)	(0.105)	(0.189)	(1.456)
Observations	90,681	90,681	90,681	90,681	90,681	90,681
Pseudo R2	0.108	0.108	0.108	0.108	0.108	0.108

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 18: Probability of choosing a master degree given a bachelor in Health

VARIABLES	(1) AVGB	(2) Educ.Psy.	(3) Health
Z_m			
Credit req. (st.): AVGB	-4.685***	9.015***	-4.584***
	(0.189)	(1.686)	(0.160)
log(distance)	-0.017	-0.033	0.011*
	(0.019)	(0.023)	(0.006)
X			
HS: grade (st.)	0.403***	-0.032	0.115***
	(0.054)	(0.062)	(0.015)
HS: humanities	0.205	-0.376*	0.147***
	(0.180)	(0.219)	(0.049)
HS: science	0.401***	-0.402***	-0.193***
	(0.109)	(0.132)	(0.032)
Gender (1=female)	-0.258*	-0.006	-0.027
	(0.142)	(0.164)	(0.040)
Parents: graduate	0.186	0.309*	-0.098**
	(0.143)	(0.174)	(0.047)
Parents: high-rank occ.	0.063	0.200	-0.070
	(0.157)	(0.183)	(0.050)
Additional Controls		Yes	
Θ		Yes	
Constant	-5.587***	-1.271	-4.954***
	(0.453)	(0.806)	(0.158)
Observations	81,883	81,883	81,883
Pseudo R2	0.0591	0.0591	0.0591

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 19: Probability of choosing a master degree given a bachelor in Political and Social Sciences

VARIABLES	(1) Econ.Mgmt.	(2) Educ.Psy.	(3) Law	(4) Lit.Lang.	(5) Pol.Soc.	(6) Sci.Stat.
Z_m						
Credit req. (st.): EcMg	-1.417**	4.024***	8.987***	1.368***	3.404***	4.183**
	(0.661)	(0.557)	(1.241)	(0.453)	(0.154)	(1.859)
Credit req. (st.): EdPs	-2.027***	-4.539***	-7.398***	-3.631***	-2.605***	-3.432***
	(0.733)	(0.345)	(0.867)	(0.681)	(0.086)	(1.207)
Credit req. (st.): Law	-1.630***	-3.461***	-7.974***	-2.296***	-2.837***	-3.141**
	(0.613)	(0.355)	(0.829)	(0.489)	(0.103)	(1.262)
Credit req. (st.): Hum	13.178***	-15.963***	-15.441***	-4.140**	-3.580***	-10.459
	(2.992)	(1.868)	(4.253)	(1.981)	(0.608)	(7.022)
Credit req. (st.): PlSc	6.158***	-8.130***	-7.197***	2.305***	-3.379***	-4.010
	(1.142)	(0.674)	(1.688)	(0.725)	(0.233)	(2.711)
log(distance)	-0.024**	-0.000	0.029***	-0.013	-0.003	0.104
	(0.011)	(0.018)	(0.010)	(0.009)	(0.004)	(0.066)
X						
HS: grade (st.)	0.433***	0.385***	0.228***	0.604***	0.468***	0.795***
	(0.029)	(0.049)	(0.031)	(0.026)	(0.010)	(0.104)
HS: humanities	0.342***	0.615***	0.053	0.864***	0.790***	-0.079
	(0.086)	(0.134)	(0.089)	(0.066)	(0.028)	(0.369)
HS: science	0.794***	0.646***	0.249***	0.483***	0.668***	0.610***
	(0.061)	(0.108)	(0.067)	(0.058)	(0.022)	(0.210)
Gender (1=female)	-0.192***	0.616***	-0.497***	-0.135**	-0.165***	-1.282***
	(0.073)	(0.145)	(0.083)	(0.067)	(0.027)	(0.266)
Parents: graduate	0.222***	0.398***	-0.015	0.467***	0.274***	0.210
	(0.068)	(0.118)	(0.082)	(0.059)	(0.025)	(0.247)
Parents: high-rank occ.	-0.070	0.039	-0.240***	-0.079	-0.078***	-0.260
	(0.072)	(0.124)	(0.089)	(0.063)	(0.026)	(0.267)
Additional Controls			Yes			
Θ			Yes			
Constant	20.289***	-29.793***	-11.597**	5.244**	-4.120***	-14.040*
	(3.374)	(1.974)	(4.706)	(2.182)	(0.667)	(7.746)
Observations	65,798	65,798	65,798	65,798	65,798	65,798
Pseudo R2	0.162	0.162	0.162	0.162	0.162	0.162

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

Table 20: Probability of choosing a master degree given a bachelor in Science and Statistics

VARIABLES	(1) AVGB	(2) Arc.Eng.	(3) Chem.Phar.	(4) Econ.Mgmt.	(5) Pol.Soc.	(6) Sci.Stat.
Z_m						
Credit req. (st.): ChPh	-14.708***	2.612***	-81.978	7.585***	1.568*	-4.359***
	(1.878)	(0.842)	(2,381.101)	(1.886)	(0.911)	(0.173)
Credit req. (st.): Sci	-0.320	1.618***	-21.711	0.989***	0.567*	-0.879***
	(1.022)	(0.272)	(709.538)	(0.279)	(0.335)	(0.062)
log(distance)	-0.042*	-0.021	-0.067	0.072	-0.006	-0.005
	(0.024)	(0.049)	(0.042)	(0.076)	(0.037)	(0.009)
X						
HS: grade (st.)	0.031	0.433***	0.386***	0.606***	0.183**	0.736***
	(0.052)	(0.102)	(0.090)	(0.100)	(0.086)	(0.019)
HS: humanities	1.326***	0.698*	0.271	0.928**	0.736**	0.829***
	(0.187)	(0.363)	(0.339)	(0.432)	(0.364)	(0.084)
HS: science	1.020***	-0.047	0.370**	1.046***	0.377**	0.955***
	(0.117)	(0.219)	(0.186)	(0.205)	(0.179)	(0.038)
Gender (1=female)	1.020***	-0.312	0.484*	0.197	-0.662***	0.140***
	(0.143)	(0.276)	(0.252)	(0.259)	(0.233)	(0.053)
Parents: graduate	-0.181	0.530**	0.316	0.140	0.110	0.365***
	(0.119)	(0.235)	(0.198)	(0.232)	(0.216)	(0.045)
Parents: high-rank occ.	0.021	0.610**	-0.110	0.252	0.019	0.008
	(0.131)	(0.239)	(0.227)	(0.243)	(0.231)	(0.050)
Additional Controls				Yes		
Θ				Yes		
Constant	9.007***	-4.773***	32.378	-13.920***	-1.120	2.247***
	(0.791)	(1.286)	(896.781)	(2.239)	(0.994)	(0.222)
Observations	20,721	20,721	20,721	20,721	20,721	20,721
Pseudo R2	0.300	0.300	0.300	0.300	0.300	0.300

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Excluded category: no master.

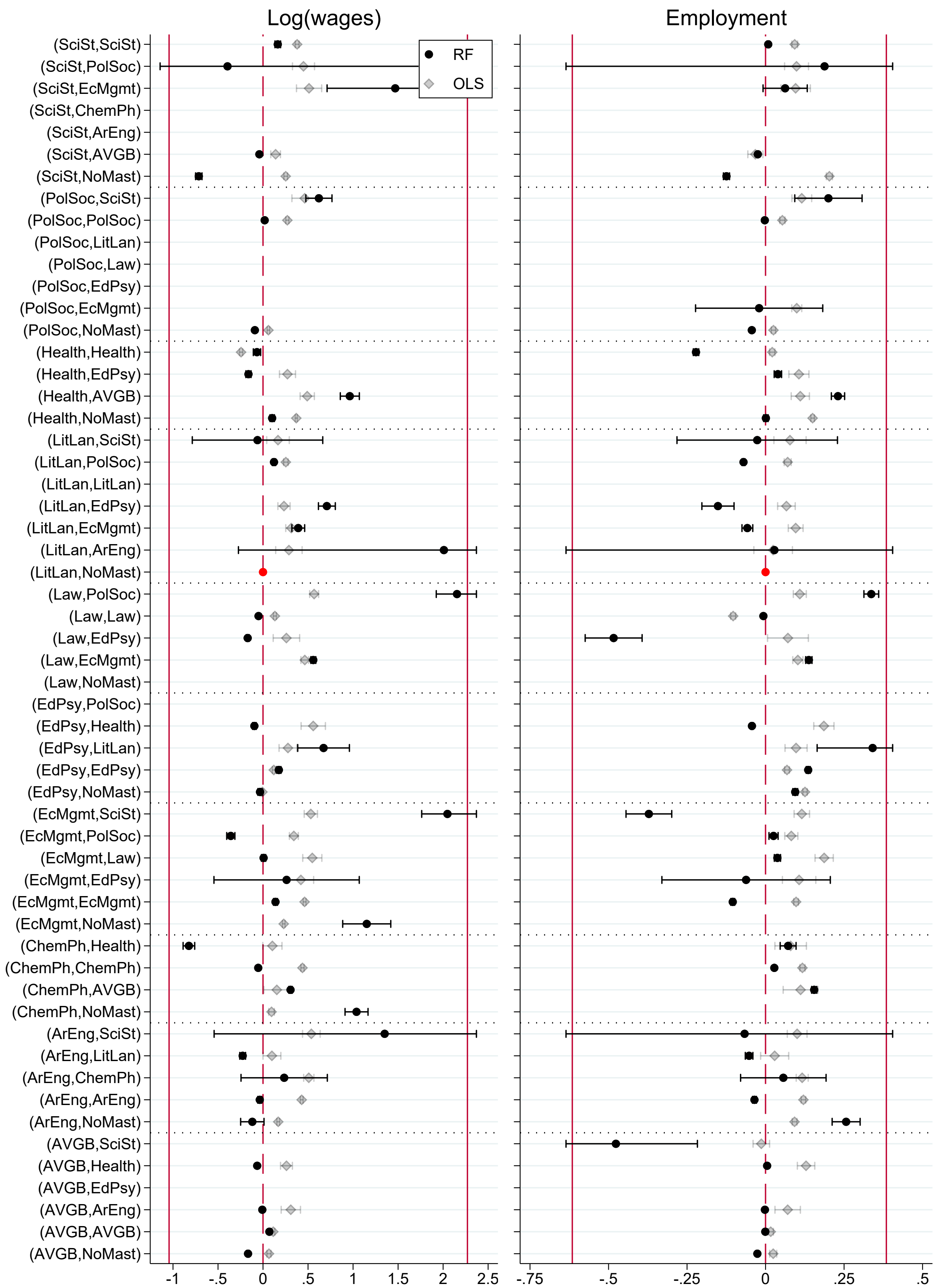
A.4 Additional Results

Table 21: Summary of treatments D_{jm} and probabilities P_{jm}

#	(j, m)	D_{jm}		P_{jm}			$P_{jm} - D_{jm}$
		Mean	Std. Dev.	Mean	Std. Dev.	Max	
1	(AVGB, No Master)	0.0128	(0.1124)	0.0019	(0.0057)	0.1613	-0.0109
2	(AVGB, AVGB)	0.0401	(0.1963)	0.0141	(0.023)	0.1944	-0.026
3	(AVGB, Arch.Eng.)	0.0003	(0.0183)	0	(0.0002)	0.0236	-0.0003
4	(AVGB, Educ.Psy.)	0.0003	(0.0166)	0.0071	(0.0205)	0.1911	0.0069
5	(AVGB, Pol.Soc.)	0.0009	(0.0308)	0.0001	(0.0008)	0.0586	-0.0009
6	(AVGB, Sci.Stat.)	0.0014	(0.0377)	0.0326	(0.0317)	0.2041	0.0312
7	(Arch.Eng., No Master)	0.034	(0.1812)	0.0631	(0.0722)	0.5837	0.0291
8	(Arch.Eng., Arch.Eng.)	0.1217	(0.327)	0.0939	(0.1237)	0.7117	-0.0278
9	(Arch.Eng., Chem.Pharm.)	0.0012	(0.0344)	0.0004	(0.0023)	0.066	-0.0008
10	(Arch.Eng., Lit.Lang.)	0.0004	(0.0209)	0.0001	(0.0009)	0.1028	-0.0004
11	(Arch.Eng., Sci.Stat.)	0.0004	(0.0196)	0.0002	(0.0012)	0.0995	-0.0002
12	(Chem.Pharm., No Master)	0.0059	(0.0769)	0.0264	(0.023)	0.2088	0.0204
13	(Chem.Pharm., AVGB)	0.0002	(0.0134)	0.0014	(0.0031)	0.0839	0.0012
14	(Chem.Pharm., Chem.Pharm.)	0.0315	(0.1746)	0.0085	(0.0216)	0.1834	-0.023
15	(Chem.Pharm., Health)	0.0004	(0.0199)	0.0017	(0.0057)	0.1438	0.0013
16	(Econ.Mgmt., No Master)	0.0424	(0.2015)	0.0724	(0.068)	0.5057	0.03
17	(Econ.Mgmt., Econ.Mgmt.)	0.0705	(0.256)	0.042	(0.0611)	0.462	-0.0285
18	(Econ.Mgmt., Educ.Psy.)	0.0002	(0.0137)	0.0001	(0.0002)	0.0115	-0.0001
19	(Econ.Mgmt., Law)	0.0003	(0.0178)	0.0001	(0.0006)	0.0641	-0.0002
20	(Econ.Mgmt., Pol.Soc.)	0.0018	(0.0419)	0.0011	(0.002)	0.0523	-0.0007
21	(Econ.Mgmt., Sci.Stat.)	0.0007	(0.0264)	0.0002	(0.0006)	0.0281	-0.0005
22	(Educ.Psy., No Master)	0.0435	(0.204)	0.0449	(0.0559)	0.5477	0.0014
23	(Educ.Psy., Educ.Psy.)	0.0703	(0.2556)	0.0547	(0.061)	0.5451	-0.0156
24	(Educ.Psy., Lit.Lang.)	0.0004	(0.0195)	0.0035	(0.0116)	0.313	0.0031
25	(Educ.Psy., Health)	0.0002	(0.0138)	0.0002	(0.0008)	0.0644	0
26	(Educ.Psy., Pol.Soc.)	0.0008	(0.0286)	0.0119	(0.0359)	0.4998	0.0111
27	(Law, No Master)	0.0123	(0.1101)	0.052	(0.0512)	0.5102	0.0398
28	(Law, Econ.Mgmt.)	0.0022	(0.0472)	0.0097	(0.0168)	0.3091	0.0074
29	(Law, Educ.Psy.)	0.0002	(0.0139)	0.0009	(0.0025)	0.0933	0.0007
30	(Law, Law)	0.0713	(0.2573)	0.0186	(0.0435)	0.4688	-0.0527
31	(Law, Pol.Soc.)	0.0017	(0.0409)	0.0065	(0.0121)	0.2348	0.0048
32	(Lit.Lang., No Master)	0.0585	(0.2346)	0.0649	(0.0539)	0.5661	0.0064
33	(Lit.Lang., Arch.Eng.)	0.0002	(0.0136)	0.0037	(0.0145)	0.5213	0.0035
34	(Lit.Lang., Econ.Mgmt.)	0.0011	(0.0325)	0.0007	(0.0019)	0.0706	-0.0004
35	(Lit.Lang., Educ.Psy.)	0.0009	(0.0301)	0.0027	(0.0058)	0.1723	0.0018
36	(Lit.Lang., Lit.Lang.)	0.0686	(0.2527)	0.0614	(0.0604)	0.6429	-0.0071
37	(Lit.Lang., Pol.Soc.)	0.0088	(0.0935)	0.0046	(0.0071)	0.1531	-0.0042
38	(Lit.Lang., Sci.Stat.)	0.0003	(0.0159)	0.0002	(0.0016)	0.1725	0
39	(Health, No Master)	0.1155	(0.3196)	0.1337	(0.1242)	0.7477	0.0183
40	(Health, AVGB)	0.0006	(0.0248)	0.0025	(0.0073)	0.3174	0.0018
41	(Health, Educ.Psy.)	0.0005	(0.0218)	0.0004	(0.0011)	0.0337	0
42	(Health, Health)	0.0428	(0.2024)	0.0227	(0.041)	0.6067	-0.0201
43	(Pol.Soc., No Master)	0.0534	(0.2248)	0.0124	(0.0309)	0.3077	-0.041
44	(Pol.Soc., Econ.Mgmt.)	0.0024	(0.0487)	0.0596	(0.0545)	0.3717	0.0572
45	(Pol.Soc., Educ.Psy.)	0.0009	(0.0302)	0.008	(0.0259)	0.2688	0.0071
46	(Pol.Soc., Law)	0.002	(0.0452)	0.0104	(0.0276)	0.3019	0.0083
47	(Pol.Soc., Lit.Lang.)	0.003	(0.0544)	0.0044	(0.0141)	0.2164	0.0014
48	(Pol.Soc., Pol.Soc.)	0.0386	(0.1927)	0.0054	(0.0155)	0.2249	-0.0332
49	(Pol.Soc., Sci.Stat.)	0.0002	(0.0131)	0.0003	(0.0015)	0.0539	0.0001
50	(Sci.Stat., No Master)	0.0131	(0.1137)	0.0132	(0.0174)	0.2344	0.0001
51	(Sci.Stat., AVGB)	0.0015	(0.0393)	0.0001	(0.0018)	0.0881	-0.0014
52	(Sci.Stat., Arch.Eng.)	0.0002	(0.0132)	0.0011	(0.0026)	0.0651	0.0009
53	(Sci.Stat., Chem.Pharm.)	0.0003	(0.0167)	0.0097	(0.0217)	0.2926	0.0094
54	(Sci.Stat., Econ.Mgmt.)	0.0002	(0.0137)	0.0006	(0.0014)	0.0462	0.0004
55	(Sci.Stat., Pol.Soc.)	0.0002	(0.0156)	0.0005	(0.0011)	0.055	0.0002
56	(Sci.Stat., Sci.Stat.)	0.0161	(0.1257)	0.0064	(0.0115)	0.218	-0.0096

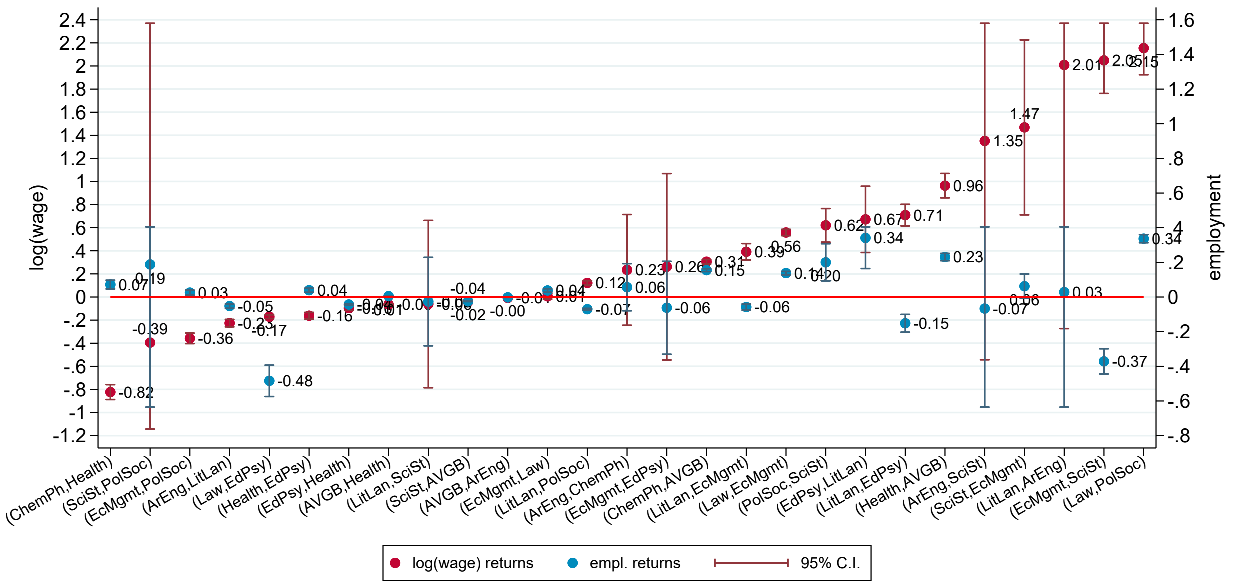
Summary statistics for the vector of treatments D_{jm} and probabilities P_{jm} for 56 combinations of bachelor's and master's degrees. Treatments D_{jm} take values 0 and 1. The minimum value for instruments P_{jm} is, hence the omission. Sums calculated on 655 847 observations.

Figure 15: Comparison of OLS coefficients γ and reduced form treatment effects



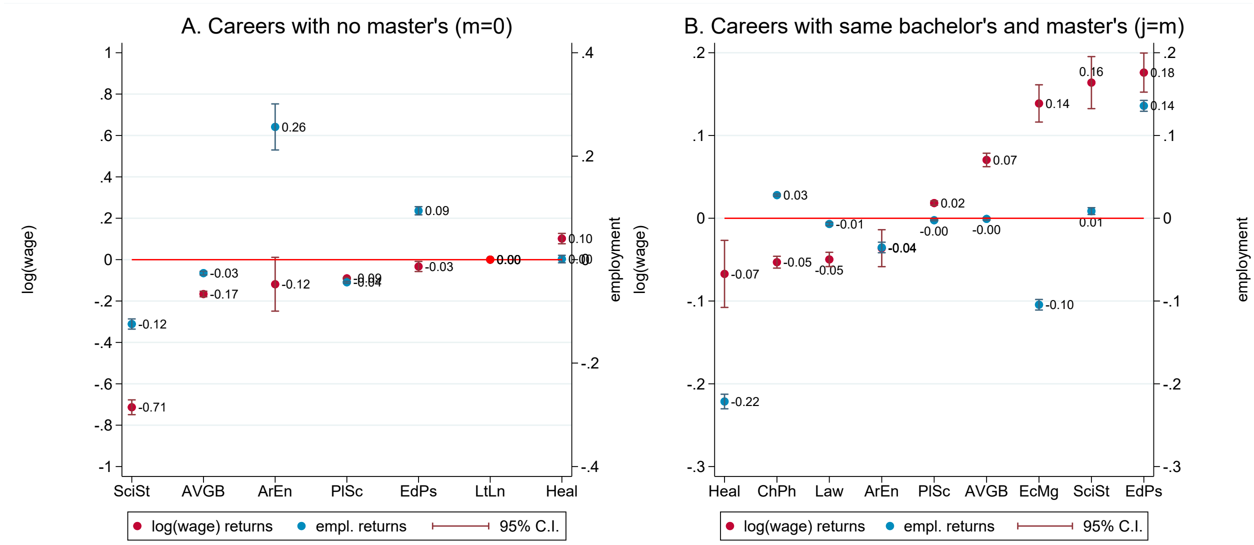
Black markers indicate reduced form (RF) results (4), grey markers indicate OLS results (5). Whiskers denote 95% CIs and the red dot denotes the baseline (Lit.Lang., No Master). Red lines denote credible boundaries for the treatment effects. $TE(\ln(\text{wage})) \in [-1.04, 2.27]$, employment: $TE(\text{employment}) \in [-0.62, 0.38]$.

Figure 16: Comparison of log wage and employment returns for all multidisciplinary careers



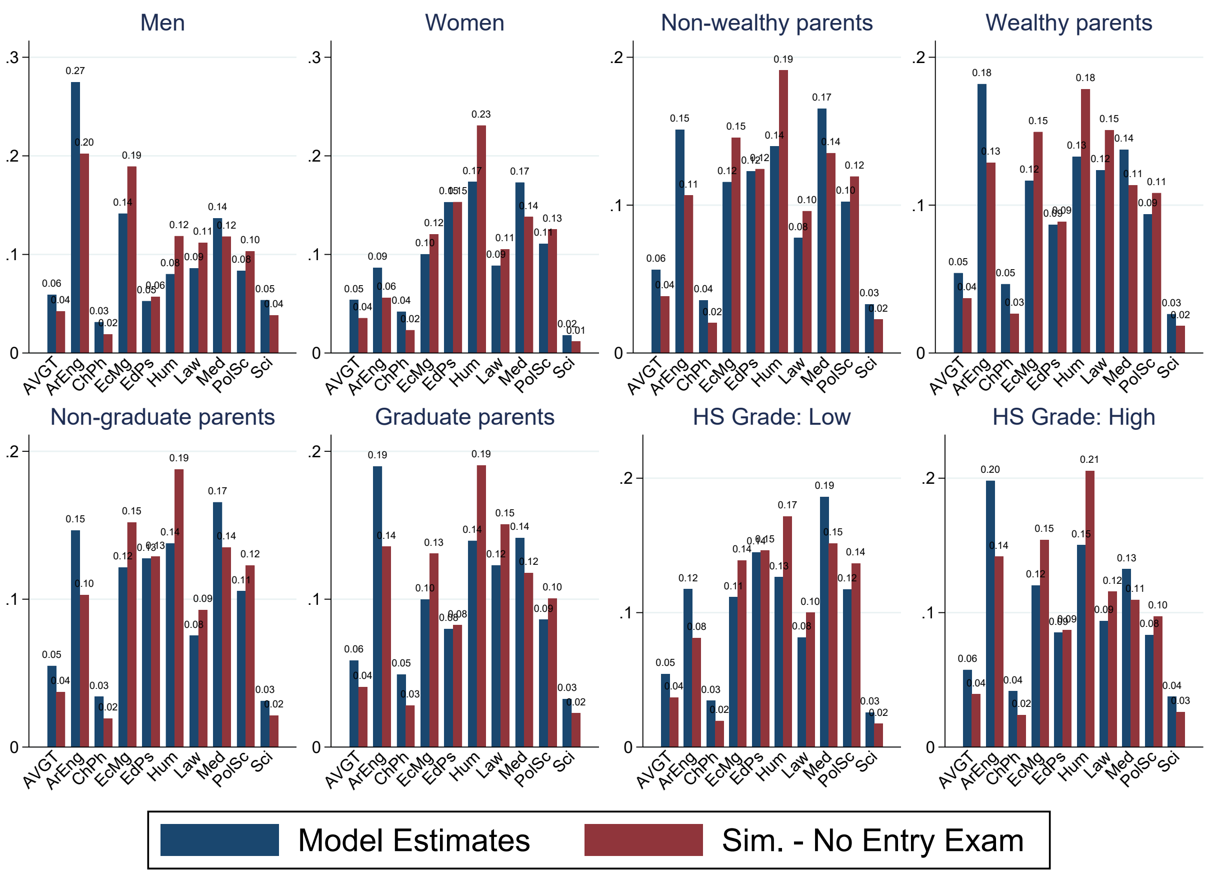
Comparison of log wage returns (red, left vertical axis) and returns to employment (blue, right vertical axis). Axes are centered around 0. The excluded category is (Lit.Lang., No Master) centered at 0. Any missing returns could not be estimated for both outcomes. Panel B presents returns to specialized careers with the same bachelor's and master's. The order follows the ranking of log wage returns from lowest to highest.

Figure 17: Comparison of log wage and employment returns for non-multidisciplinary careers



Comparison of log wage returns (red, left vertical axis) and returns to employment (blue, right vertical axis). Axes are centered around 0. Panel A presents labor market returns for careers with no master, where (Lit.Lang., No Master) denotes the excluded category centered at 0. Any missing returns could not be estimated for both outcomes. Panel B presents returns to specialized careers with the same bachelor's and masters. In both panels, the order follows the ranking of log wage returns from lowest to highest.

Figure 18: Simulation 1 – Decomposition by individual characteristics



A.5 Methodological notes

A.5.1 Universities

The universities that I consider are the following: Politecnico di Ancona, Bari, Politecnico di Bari, Basilicata, Bergamo, Bologna, Bolzano, Brescia, Cagliari, Calabria, Camerino, Campania - Luigi Vanvitelli, Cassino e Lazio Meridionale, Catania, Catanzaro, Chieti e Pescara, Enna Kore, Ferrara, Firenze, Foggia, Genova, Insubira, L'Aquila, LIUC Castellanza, Macerata, Messina, Milano Bicocca, Milano IULM, Milano Statale, Milano Vita-Salute S. Raffaele, Modena e Reggio Emilia, Molise, Napoli - Federico II, Napoli - Seconda Università, Napoli - L'Orientale, Napoli - Parthenope, Padova, Palermo, Parma, Pavia, Perugia, Università per Stranieri di Perugia, Piemonte Orientale, Pisa, Reggio Calabria Mediterranea, Roma - Campus Bio-Medico, Roma LUMSA, Roma Foro Italico, Roma Tre, Roma - La Sapienza, Roma - Tor Vergata, Salento, Salerno, Sannio e Benevento, Sassari, Siena, Università per Stranieri di Siena, Teramo, Torino, Politecnico di Torino, Trento, Trieste, Udine, Urbino, Viterbo Tuscia, Valle D'Aosta Venezia - Ca' Foscari, Venezia - IUAV, Verona.

Some universities which are not in this list may nonetheless appear in the dataset (e.g. Milano Bocconi). The reason is that students appear in the dataset if they graduated (master) from a university in the consortium, yet information is collected also for their bachelor which may differ. Only about 5% of students in the sample switches institution throughout their career.

A.5.2 Degrees and groups

Here, I present the exact pooling of degrees into groups. The allocation has been done by the AlmaLaurea consortium. A few groups of degrees were further grouped to improve estimation: agriculture and veterinary was grouped with geology and biology, architecture with engineering, teaching with physical education and psychology, and literature with languages. Information on an additional group – defense and security – was dropped as access into these degrees is managed differently from standard university degrees.

Table 22: Degree grouping

Code	**Description**
1. Agriculture, veterinarian sciences, geology, biology	
L-2	BIOTECNOLOGIE
L-13	SCIENZE BIOLOGICHE
L-25	SCIENZE E TECNOLOGIE AGRARIE E FORESTALI
L-26	SCIENZE E TECNOLOGIE AGRO-ALIMENTARI
L-32	SCIENZE E TECNOLOGIE PER L'AMBIENTE E LA NATURA
L-34	SCIENZE GEOLOGICHE
L-38	SCIENZE ZOOTECNICHE E TECNOLOGIE DELLE PRODUZIONI ANIMALI
LM-6	BIOLOGIA

Code	Description
LM-7	BIOTECNOLOGIE AGRARIE
LM-8	BIOTECNOLOGIE INDUSTRIALI
LM-9	BIOTECNOLOGIE MEDICHE, VETERINARIE E FARMACEUTICHE
LM-42	MEDICINA VETERINARIA
LM-69	SCIENZE E TECNOLOGIE AGRARIE
LM-70	SCIENZE E TECNOLOGIE ALIMENTARI
LM-73	SCIENZE E TECNOLOGIE FORESTALI ED AMBIENTALI
LM-74	SCIENZE E TECNOLOGIE GEOLOGICHE
LM-75	SCIENZE E TECNOLOGIE PER L'AMBIENTE E IL TERRITORIO
LM-86	SCIENZE ZOOTECNICHE E TECNOLOGIE ANIMALI
2. Architecture and Engineering	
L-4	DISEGNO INDUSTRIALE
L-7	INGEGNERIA CIVILE E AMBIENTALE
L-8	INGEGNERIA DELL'INFORMAZIONE
L-9	INGEGNERIA INDUSTRIALE
L-17	SCIENZE DELL'ARCHITETTURA
L-21	SCIENZE DELLA PIANIFICAZIONE TERRITORIALE, URBANISTICA, PAESAGGISTICA E AMBIENTALE
L-23	SCIENZE E TECNICHE DELL'EDILIZIA
LM-3	ARCHITETTURA DEL PAESAGGIO
LM-4	ARCHITETTURA E INGEGNERIA EDILE-ARCHITETTURA
LM-12	DESIGN
LM-20	INGEGNERIA AEROSPAZIALE E ASTRONAUTICA
LM-21	INGEGNERIA BIOMEDICA
LM-22	INGEGNERIA CHIMICA
LM-23	INGEGNERIA CIVILE
LM-24	INGEGNERIA DEI SISTEMI EDILIZI
LM-25	INGEGNERIA DELL'AUTOMAZIONE
LM-26	INGEGNERIA DELLA SICUREZZA
LM-27	INGEGNERIA DELLE TELECOMUNICAZIONI
LM-28	INGEGNERIA ELETTRICA
LM-29	INGEGNERIA ELETTRONICA
LM-30	INGEGNERIA ENERGETICA E NUCLEARE
LM-31	INGEGNERIA GESTIONALE
LM-32	INGEGNERIA INFORMATICA
LM-33	INGEGNERIA MECCANICA
LM-34	INGEGNERIA NAVALE
LM-35	INGEGNERIA PER L'AMBIENTE E IL TERRITORIO
LM-44	MODELLISTICA MATEMATICO-FISICA PER L'INGEGNERIA

Code	Description
LM-48	PIANIFICAZIONE TERRITORIALE URBANISTICA E AMBIENTALE
LM-53	SCIENZA E INGEGNERIA DEI MATERIALI
3. Chemistry and Pharmacy	
L-27	SCIENZE E TECNOLOGIE CHIMICHE
L-29	SCIENZE E TECNOLOGIE FARMACEUTICHE
LM-13	FARMACIA E FARMACIA INDUSTRIALE
LM-54	SCIENZE CHIMICHE
LM-71	SCIENZE E TECNOLOGIE DELLA CHIMICA INDUSTRIALE
4. Economics and Management	
L-15	SCIENZE DEL TURISMO
L-16	SCIENZE DELL'AMMINISTRAZIONE E DELL'ORGANIZZAZIONE
L-18	SCIENZE DELL'ECONOMIA E DELLA GESTIONE AZIENDALE
L-33	SCIENZE ECONOMICHE
LM-16	FINANZA
LM-56	SCIENZE DELL'ECONOMIA
LM-76	SCIENZE ECONOMICHE PER L'AMBIENTE E LA CULTURA
LM-77	SCIENZE ECONOMICO-AZIENDALI
5. Teaching, Physical Education and Psychology	
L-19	SCIENZE DELL'EDUCAZIONE E DELLA FORMAZIONE
L-22	SCIENZE DELLE ATTIVITA MOTORIE E SPORTIVE
L-24	SCIENZE E TECNICHE PSICOLOGICHE
LM-47	ORGANIZZAZIONE E GESTIONE DEI SERVIZI PER LO SPORT E LE ATTIVITA MOTORIE
LM-50	PROGRAMMAZIONE E GESTIONE DEI SERVIZI EDUCATIVI
LM-51	PSICOLOGIA
LM-55	SCIENZE COGNITIVE
LM-57	SCIENZE DELL'EDUCAZIONE DEGLI ADULTI E DELLA FORMAZIONE CONTINUA
LM-67	SCIENZE E TECNICHE DELLE ATTIVITA MOTORIE PREVENTIVE E ADATTATE
LM-68	SCIENZE E TECNICHE DELLO SPORT
LM-85	SCIENZE PEDAGOGICHE
LM-93	TEORIE E METODOLOGIE DELL'E-LEARNING E DELLA MEDIA EDUCATION
6. Law	
L-14	SCIENZE DEI SERVIZI GIURIDICI

Code	Description
LMG-1	GIURISPRUDENZA
7. Literature and Languages	
L-1	BENI CULTURALI
L-3	DISCIPLINE DELLE ARTI FIGURATIVE, DELLA MUSICA, DELLO SPETTACOLO E DELLA MODA (DAMS)
L-5	FILOSOFIA
L-6	GEOGRAFIA
L-10	LETTERE
L-11	LINGUE E CULTURE MODERNE
L-12	MEDIAZIONE LINGUISTICA
L-42	STORIA
L-43	TECNOLOGIE PER LA CONSERVAZIONE E IL RESTAURO DEI BENI CULTURALI
LM-1	ANTROPOLOGIA CULTURALE ED ETNOLOGIA
LM-2	ARCHEOLOGIA
LM-5	ARCHIVISTICA E BIBLIOTECONOMIA
LM-10	CONSERVAZIONE DEI BENI ARCHITETTONICI E AMBIENTALI
LM-11	CONSERVAZIONE E RESTAURO DEI BENI CULTURALI
LM-14	FILOLOGIA MODERNA
LM-15	FILOLOGIA, LETTERATURE E STORIA DELL'ANTICHITA
LM-36	LINGUE E LETTERATURE DELL'AFRICA E DELL'ASIA
LM-37	LINGUE E LETTERATURE MODERNE EUROPEE E AMERICANE
LM-38	LINGUE MODERNE PER LA COMUNICAZIONE E LA COOPERAZIONE
LM-39	LINGUISTICA
LM-45	MUSICOLOGIA E BENI MUSICALI
LM-65	SCIENZE DELLO SPETTACOLO E PRODUZIONE MULTIMEDIALE
LM-78	SCIENZE FILOSOFICHE
LM-80	SCIENZE GEOGRAFICHE
LM-84	SCIENZE STORICHE
LM-89	STORIA DELL'ARTE
LM-94	TRADUZIONE SPECIALISTICA E INTERPRETARIATO
8. Health and Medicine	
L/SNT-1	SCIENZE INFERMIERISTICHE E OSTETRICHE
L/SNT-2	SCIENZE RIABILITATIVE DELLE PROFESSIONI SANITARIE
L/SNT-3	SCIENZE DELLE PROFESSIONI SANITARIE TECNICHE
L/SNT-4	SCIENZE DELLE PROFESSIONI SANITARIE DELLA PREVENZIONE
LM/SNT-1	SCIENZE INFERMIERISTICHE E OSTETRICHE
LM/SNT-2	SCIENZE RIABILITATIVE DELLE PROFESSIONI SANITARIE

Code	Description
LM/SNT-3	SCIENZE DELLE PROFESSIONI SANITARIE TECNICHE
LM/SNT-4	SCIENZE DELLE PROFESSIONI SANITARIE DELLA PREVENZIONE
LM-41	MEDICINA E CHIRURGIA
LM-46	ODONTOIATRIA E PROTESI DENTARIA
LM-61	SCIENZE DELLA NUTRIZIONE UMANA
9. Political and social sciences	
L-20	SCIENZE DELLA COMUNICAZIONE
L-36	SCIENZE POLITICHE E DELLE RELAZIONI INTERNAZIONALI
L-37	SCIENZE SOCIALI PER LA COOPERAZIONE, LO SVILUPPO E LA PACE
L-39	SERVIZIO SOCIALE
L-40	SOCIOLOGIA
LM-19	INFORMAZIONE E SISTEMI EDITORIALI
LM-49	PROGETTAZIONE E GESTIONE DEI SISTEMI TURISTICI
LM-52	RELAZIONI INTERNAZIONALI
LM-59	SCIENZE DELLA COMUNICAZIONE PUBBLICA, D'IMPRESA E PUBBLICITÀ
LM-62	SCIENZE DELLA POLITICA
LM-63	SCIENZE DELLE PUBBLICHE AMMINISTRAZIONI
LM-81	SCIENZE PER LA COOPERAZIONE ALLO SVILUPPO
LM-87	SERVIZIO SOCIALE E POLITICHE SOCIALI
LM-88	SOCIOLOGIA E RICERCA SOCIALE
LM-90	STUDI EUROPEI
LM-91	TECNICHE E METODI PER LA SOCIETA DELL'INFORMAZIONE
LM-92	TEORIE DELLA COMUNICAZIONE
10. Science and Statistics	
L-28	SCIENZE E TECNOLOGIE DELLA NAVIGAZIONE
L-30	SCIENZE E TECNOLOGIE FISICHE
L-31	SCIENZE E TECNOLOGIE INFORMATICHE
L-35	SCIENZE MATEMATICHE
LM-17	FISICA
LM-18	INFORMATICA
LM-40	MATEMATICA
L-41	STATISTICA
LM-43	METODOLOGIE INFORMATICHE PER LE DISCIPLINE UMANISTICHE
LM-58	SCIENZE DELL'UNIVERSO
LM-60	SCIENZE DELLA NATURA
LM-66	SICUREZZA INFORMATICA
LM-72	SCIENZE E TECNOLOGIE DELLA NAVIGAZIONE

Code	Description
LM-82	SCIENZE STATISTICHE
LM-83	SCIENZE STATISTICHE ATTUARIALI E FINANZIARIE

Note: Prefix L- refers to bachelor degrees, LM- to master degrees.