ROCKWOOL Foundation Berlin
Institute for the Economy and the Future of Work (RFBerlin)

DISCUSSION PAPER SERIES 196/26

Was Your Degree Worth It? Heterogeneous Returns to Higher Education, Fields of Study and Skill Mismatch

Lorenzo Navarini, Dieter Verhaest

www.rfberlin.com JULY 2026

Was Your Degree Worth It? Heterogeneous Returns to Higher Education, Fields of Study and Skill Mismatch

Authors

Lorenzo Navarini, Dieter Verhaest

Reference

JEL Codes: I23; I26; J24

Keywords: Returns to higher education; fields of study; skill mismatch; occupational sorting; heterogeneous returns

Recommended Citation: Lorenzo Navarini, Dieter Verhaest (2026): Was Your Degree Worth It? Heterogeneous Returns to Higher Education, Fields of Study and Skill Mismatch. RFBerlin Discussion Paper No. 196/26

Access

Papers can be downloaded free of charge from the RFBerlin website: https://www.rfberlin.com/discussion-papers

Discussion Papers of RFBerlin are indexed on RePEc: https://ideas.repec.org/s/crm/wpaper.html

Disclaimer

Imprint

RFBerlin
ROCKWOOL Foundation Berlin –
Institute for the Economy
and the Future of Work

Gormannstrasse 22, 10119 Berlin
Tel: +49 (0) 151 143 444 67
E-mail: info@rfberlin.com
Web: www.rfberlin.com

Was Your Degree Worth It?
Heterogeneous Returns to Higher Education, Fields of Study and Skill Mismatch*

LORENZO NAVARINI† DIETER VERHAEST‡

(University of Vienna, RFBerlin) (KU Leuven)

July, 2026

Abstract

Returns to higher education vary substantially between and within fields of study. This paper studies whether occupational sorting at labor market entry contributes to this heterogeneity in early-career realized returns. We estimate a generalized sequential Roy model of yearly higher education enrollment choices, skill mismatch at entry, and subsequent labor market outcomes. Identification combines persistent latent heterogeneity with exclusion restrictions based on distance to programs and residual variation in graduation timing. Individuals with a higher probability of enrolling in higher education obtain higher returns, but also experience the largest losses in realized returns when they start in mismatched occupations. In counterfactual decompositions, entry mismatch accounts for a substantial share of low, and in some cases negative, early-career realized wage returns.

Keywords: Returns to higher education; fields of study; skill mismatch; occupational sorting; heterogeneous returns.

JEL classification: I23; I26; J24.

---

*This paper benefited from helpful comments at various stages from Olivier De Groote, Christophe Bruneel, Edwin Leuven, Jo Van Biesebroeck, Koen Declercq, Costas Meghir, Philipp Schmidt-Dengler, Philip Oreopoulos, Amanda Pallais, Suphanit Piyapromdee, Elena Mattana and several audiences at KU Leuven and the University of Vienna. It also benefited from discussions during and after presentations at the 2023 TiY Workshop, LEER 2023, the Vienna Applied Micro Workshop, the UCL-IFS Human Capital and Labor Markets Seminar, SOLE 2024, Statistics Norway, University of Oslo, the 1st Aarhus Workshop on Labor Markets, LESE 2026, SOLE 2026, and the University of Trieste. Funding for this project was generously provided by the Research Foundation Flanders (FWO) - G079420N.

†University of Vienna, Department of Economics; ROCKWOOL Foundation Berlin; KU Leuven, Department of Economics; Leuven Economics of Education (LEER); Address: 1090 Wien, Oskar-Morgenstern-Platz 1, 05.612, Email: lorenzo.navarini@univie.ac.at (Corresponding author)

‡KU Leuven, Department of Economics; Leuven Economics of Education (LEER); GLO; Address: Warmoesberg 26, 1000 Brussel, Belgium, Email: dieter.verhaest@kuleuven.be

1 Introduction

As higher education continues to expand, the question "Was your degree worth it?" has become increasingly common (Webber, 2016). Although returns to higher education are positive on average (Oreopoulos and Petronijevic, 2013), they vary substantially both between and within fields of study (Altonji et al., 2016; Kirkebøen et al., 2016; Patnaik et al., 2020; Borgen and Reimer, 2025). Therefore, to evaluate the consequences of further expanding access in higher education and to specific programs, it is crucial to understand the sources of this heterogeneity and how it relates to selection into these programs.

A potentially important but often overlooked source of heterogeneity is occupational sorting (Altonji et al., 2016; Patnaik et al., 2020). Indeed, starting a career in an occupation unrelated to one's education and skills is associated with lower wages (Robst, 2007; Kinsler and Pavan, 2015; Eckardt, 2026). Moreover, because early labor market conditions can have persistent effects, this initial sorting may shape long-run earnings trajectories (Oreopoulos et al., 2012; Baert et al., 2013). This occupational sorting may generate heterogeneous returns along two distinct margins. Students with weaker academic preparation may be more likely to enter unrelated occupations (Agopsowicz et al., 2020). At the same time, stronger students may have more to lose if they fail to enter occupations where degree-specific skills are rewarded.

This paper estimates heterogeneous early-career returns both between and within higher education programs and examines how these returns vary with first-job occupational match quality and individuals' likelihood of selection into tertiary education. To this end, we estimate a sequential Roy (1951) model with three main stages: higher education choices, selection into skill mismatch in the first job, and subsequent labor market outcomes through age 29 (Heckman et al., 2018; Humphries et al., 2025). We estimate the model based on detailed individual-level data from Belgium, where access to higher education programs is largely open, but progression and completion depend strongly on academic performance after enrollment (Declercq and Verboven, 2018).

In contrast to most of the existing literature, we proxy the unobserved first-job match quality using a latent index that combines information from expert-based assessments of occupational requirements, workers' self-reported mismatch, and the distribution of self-reported educational requirements by occupation and field of study. Relative to measures based on a single source of information, such as self-reports (Kinsler and Pavan, 2015; Agopsowicz et al., 2020) or occupation-training correspondence (Eckardt, 2026), this approach allows us to compare results across several sources of mismatch information rather than relying on a single proxy (Navarini and Verhaest, 2024).

Quantifying the importance of occupational sorting in determining heterogeneous returns is empirically challenging because higher education program choice, completion, and first-job match quality are jointly endogenous (Leuven and Oosterbeek, 2011). Among other factors, unobserved preferences, information, ability, and comparative advantage may influence each stage of this process (Agopsowicz et al., 2020; Eckardt, 2026). To address non-random selection into fields of study and skill mismatch, we combine a rich set of observed controls with a persistent latent factor that jointly governs higher education choices and grades, occupational sorting, and subsequent labor market outcomes (Heckman et al., 2018).

For identification, we exploit the sequential structure of choices and the panel dimension of the data, combined with exclusion restrictions at the key decision nodes of the model. First, we use distance to the nearest institution offering a given program, defined by field of study and institution type, as a cost shifter for enrollment and higher education choice (Declercq and Verboven, 2018). Second, we use variation in graduation timing induced by Belgium's exam-retake system as a shifter for the probability of entering a mismatched occupation. We do not require graduation timing to be as-good-as-random; instead, the model exploits variation in labor-market entry timing among students with similar academic histories and latent type. In the paper, we discuss the identifying assumptions underlying these exclusion restrictions in detail and provide a range of supporting validity checks.

The estimates yield three main findings. First, model-implied returns are substantially lower when graduates enter through a mismatched first job, and this difference is concentrated among students with high predicted gains from higher education. Indeed, the mismatch penalty is largest for individuals with a high propensity to enroll in tertiary education. For these individuals, adequate matches are associated with especially high wage potential, so entering through a low-quality match substantially reduces realized returns. For individuals with a lower propensity to enroll, potential wages in mismatched and adequately matched first jobs are not statistically different. Our findings show that, among individuals most likely to enroll in higher education, early-career occupational sorting is an important source of heterogeneity in realized returns to education (Carneiro et al., 2003; Rodríguez et al., 2016).

Second, a non-trivial share of graduates have negative early-career returns, especially in certain programs. When modelling counterfactuals that vary first-job match status while holding education choices and latent types fixed, the share of negative returns for Bachelor's graduates in Social Sciences rises from 28.0% in the well-matched counterfactual to 51.4% in the mismatched counterfactual. Within the model, these results imply that mismatch contributes substantially to negative early-career returns, especially if graduates have not obtained an MA degree.

Third, the estimated mismatch penalty varies systematically across fields. This penalty reaches up to 9.0 log points (10.3 log points) for a Bachelor's (Master's) degree in Health, but it is smaller for Business and Law degrees, at 1.6 log points (2.9 log points). The pattern across fields and programs is consistent with larger losses where program-specific skills are more tightly linked to occupation-specific tasks (Eckardt, 2026). These results are robust to alternative mismatch definitions, alternative latent-type specifications, and specifications that vary the wage and employment-state processes.

These findings have important policy implications. They do not suggest that low returns arise primarily from the enrollment margin alone. Instead, they point to the school-to-work transition and field of study choices as important margins in this setting: interventions that improve information, guidance, and the probability of obtaining a well-matched first job may affect how much of the private return to higher education is realized in the early career. Moreover, rather than focusing exclusively on who enrolls, substantial gains may still be realized by helping prospective students sort into fields of study with stronger labor market demand.

This paper relates to several literatures. First, it contributes to the literature on returns to different fields of study and higher education programs (see also Altonji et al., 2016; Patnaik et al., 2020). A growing body of work identifies causal returns using admission cutoffs or lotteries (Hastings et al., 2013; Kirkebøen et al., 2016; Ketel et al., 2016; Bleemer and Mehta, 2022; Mountjoy, 2026), typically estimating local average treatment effects for over-demanded programs. Other papers have used variation in distance to higher education institutions to estimate returns beyond marginal students (Mountjoy, 2022; Braccioli et al., 2023). Our approach is complementary to both: it studies an open-access system, incorporates the enrollment and completion margins, and estimates heterogeneity across a broad set of programs, while accounting for occupational sorting at the start of one's career. This allows us to estimate how heterogeneity in returns depends on educational choices or occupational sorting, while allowing for selection on observables and unobservables with exclusion restrictions at key decision nodes, including distance to higher education institutions.

Second, our paper contributes to the literature on heterogeneous returns to higher education and selection on gains. Prior work documents substantial heterogeneity in returns to post-secondary education and fields of study (Nybom, 2017), including negative returns for a non-trivial share of individuals (Rodríguez et al., 2016; Andrews et al., 2016, 2024), as well as substantial heterogeneity in earnings trajectories (Leighton and Speer, 2023). We build on this literature by estimating a sequential Roy model that accounts for both observed and unobserved determinants of educational choices and later earnings. Relative to structural work on heterogeneous returns and selection on gains (Arcidiacono, 2004; Beffy et al., 2012; Kinsler and Pavan, 2015), we explicitly model first-job match quality as an endogenous labor-market-entry state and include exclusion restrictions to separate selection into mismatch from persistent unobserved differences in wage potential (Heckman et al., 2018; Humphries et al., 2025).

Third, the paper contributes to the literature on skill mismatch and occupational sorting. Previous work shows that graduates earn higher wages when employed in occupations that are better matched to their field of study, and that mismatch probabilities vary substantially across fields (Robst, 2007; Nordin et al., 2010; Chevalier, 2011; Lemieux, 2014; Verhaest et al., 2017). Relative to this literature, we model mismatch as an endogenous early-career outcome and estimate how the wage consequences of mismatch vary between and within programs, rather than treating mismatch as an isolated post-schooling outcome. Our work is most closely related to Kinsler and Pavan (2015), who estimate a dynamic model to show that the returns to science majors disappear when workers sort into non-science occupations. We extend this framework by examining heterogeneity across and within a broader set of STEM and non-STEM programs, by estimating realized returns to college rather than wage differences alone (which also allows us to identify negative returns), and by studying how these patterns vary with one's likelihood of enrolling in higher education. Our results show that match quality at labor-market entry is an important component of model-implied differences in realized returns, particularly for individuals with high potential gains from enrollment. In this sense, our findings complement Agopsowicz et al. (2020), who show that vertical mismatch is strongly related to human-capital proxies such as GPA and major.

Our paper also complements recent work linking training, occupations, and tasks (Eckardt, 2026). While Eckardt (2026) studies how apprenticeship programs map into occupations, we study when and for whom the mapping between higher education programs and first occupations affects early-career returns. The results highlight the persistent role of the initial occupational match in shaping realized returns to higher education. Finally, our study is also connected to Navarini and Verhaest (2024), which examines how vertical educational mismatch contributes to differences in returns across educational levels. Our focus in the present study is not on the educational attainment margin, but on heterogeneity in realized returns across and within different higher education programs, while also incorporating exclusion restrictions at the key nodes of the model and considering a more general definition of skill mismatch.

2 Institutional setting and data

Institutional setting Belgium provides an interesting setting for studying the relationship between tertiary education choices, skill mismatch and returns to higher education. It combines an open-access higher education system with a high share of tertiary education graduates. Tertiary education in Belgium is considered universally accessible due to the absence of formal entry barriers, no ex ante selection and the relatively low tuition fees, with programs in medicine constituting an important exception (Declercq and Verboven, 2018). Students who obtain a high school diploma are eligible to enroll in most higher education programs, regardless of their specific secondary school track.

As of 2022, 51.36% of the population aged 25-34 in Belgium held a tertiary degree, a figure well above the OECD average. This represents a substantial increase from 40.61% in 2005 and 32.94% in 1995, both of which were already significantly higher than the OECD average at the time (OECD, 2026). The rapid expansion of higher education attainment has generated growing concern over a potential "oversupply" of graduates and the associated risk of labor market mismatches, attracting increasing attention from researchers and policymakers (Navarini and Verhaest, 2024).

SONAR dataset We analyze this setting using the SONAR dataset.[1] These data provide representative samples of about 3000 individuals from three birth cohorts (born in 1976, 1978, and 1980) in Flanders, the northern Dutch-speaking region of Belgium. The survey was conducted when participants were 23 years old, and follow-up surveys were completed at ages 26 and 29 for different cohorts (1976 and 1978 at age 26, and 1976 and 1980 at age 29), with response rates ranging from 60% to 70%. The dataset includes detailed information on education and labor market outcomes, including educational choices made from age six onwards and core labor market history every month. It also includes a range of indicators related to family background, skill mismatch status and wages at the start of the first job and at the time of the various surveys.[2]

Exogenous variables We include the following exogenous variables in our model: gender (as a dummy variable), number of siblings, foreign origin (as a dummy variable), years of education

[1] Data are proprietary and sponsored by the Flemish Government in the framework of the Flemish Policy Research Centre on Educational and School Careers (SSL). To get access to the data, users have to send a motivated request to the Policy Research Centre (Contact: Elsy.Verhofstadt@UGent.be).

[2] To ensure the model is tractable, we exclude individuals with (i) a delay of more than one year in starting primary education (76 individuals), (ii) special needs requiring care in schools (124 individuals), and (iii) inconsistent, erroneous, or incomplete data on the exogenous variables and educational career (638 individuals). After these exclusions, we estimate the equations related to educational outcomes using a final sample of 8,189 individuals.

of both the mother and the father (beyond primary education), day of birth within the calendar year, and cohort.[3] Descriptive statistics of these variables are reported in Table 1.

Table 1: Descriptive statistics: observables and initial conditions

	Mean	SD	Min	Max
Female	0.493	0.500	0.000	1.000
Number of siblings	1.672	1.426	0.000	18.000
Foreign origin	0.057	0.232	0.000	1.000
Father years of education	5.734	3.436	1.000	13.000
Mother years of education	6.214	3.675	1.000	13.000
Day of birth	171.756	100.195	1.000	365.000
Cohort 1976	0.319	0.466	0.000	1.000
Cohort 1978	0.338	0.473	0.000	1.000
Cohort 1980	0.344	0.475	0.000	1.000
Delay in primary education	0.015	0.123	0.000	1.000
Delay in secondary education	0.103	0.303	0.000	1.000
HS grades - 1st Q	0.052	0.223	0.000	1.000
HS grades - 2nd Q	0.117	0.321	0.000	1.000
HS grades - 3rd Q	0.391	0.488	0.000	1.000
HS grades - 4th Q	0.440	0.496	0.000	1.000
HS track - dropout	0.115	0.319	0.000	1.000
HS track - vocational	0.168	0.374	0.000	1.000
HS track - technical	0.294	0.456	0.000	1.000
HS track - general	0.423	0.494	0.000	1.000

NOTE.– Summary statistics of 8,189 observations from the SONAR data (cohorts: 1976, 1978, 1980). Delay in primary and secondary education includes information about grade retention based on the age of individuals. Higher secondary (HS) education grades are self-reported grades and provide information about the position of individuals relative to their peers in higher secondary education, expressed in quartiles (where 1st Q is the best quartile and 4th Q the worst).

Tertiary education Tertiary education in Belgium operates under an open-access system with low tuition fees, implying that financial constraints play a limited role in program choice. Since universities and colleges lack the autonomy to screen students prior to admission, selection occurs ex post through the awarding of credits based on academic performance during the early years of higher education (Declercq and Verboven, 2018).

[3]These variables are standard background characteristics that are typically included in dynamic discrete choice models on educational choices. See, for instance: Cameron and Heckman (1998, 2001); Heckman et al. (2016, 2018); Neyt et al. (2022).

We model higher education choices for up to six academic years. This horizon captures the period during which individuals make the relevant higher education decisions, including program choice, continuation, completion, or exit from higher education.[4] We define 11 higher education programs, as included in Table 2. These are combinations of 6 fields of study offered at 2 types of tertiary education institutions: an academic track in university (Univ) and a non-academic track at vocationally oriented colleges (Col).[5]

We choose to differentiate between STEM and Health degrees because previous research suggests that Health degrees perform much better regarding avoiding skill mismatch (Verhaest et al., 2017; Chevalier, 2017). We also include Education as a distinct program because of the institutional setting of the Belgian system.

Table 2: Descriptive statistics: higher education program and 1st year success rate

1st year success rate	Failed	Passed(s)	Passed(d)	Passed(h)	Total
Humanities and Arts (Col)	50.0	35.7	12.6	1.7	100.0
Humanities and Arts (Univ)	52.5	31.3	12.7	3.5	100.0
Business and Law (Col)	50.6	38.2	10.1	1.1	100.0
Business and Law (Univ)	51.4	35.4	10.5	2.7	100.0
Social sciences (Col)	52.8	37.7	9.2	0.3	100.0
Social sciences (Univ)	49.5	35.4	12.2	2.9	100.0
Health(Col)	41.7	35.8	18.9	3.6	100.0
Health(Univ)	44.0	33.9	12.9	9.3	100.0
STEM(Col)	51.9	31.3	13.4	3.5	100.0
STEM(Univ)	51.4	30.0	14.3	4.3	100.0
Education	48.3	39.9	10.7	1.1	100.0
Total	49.7	35.3	12.4	2.7	100.0

NOTE.– The fields of study are the following: Humanities and arts (HUMA), Business and Law (BULA), Social sciences (SSOC), Health and biomedical sciences (HEA), Science, technology, engineering and mathematics (STEM), Education (EDU). (Univ) stands for academic degree in university, (Col) stands for non-academic track at vocationally oriented colleges. The columns represent: (i) Passed (s) - Passed satisfactorily, (ii) Passed (d) - Passed with distinction, (iii) Passed (h) - Passed with highest distinction.

In Table 2, we highlight the low success rates in the first year, a key feature of the Belgian higher education system. Only about 50% of students successfully complete the required coursework in their first year. This period is marked by high rates of dropout and program reorientation. Our data track student performance at the end of each academic year, categorizing outcomes as

[4]In the calendar data, 311 individuals, or 5.6 percent of higher-education entrants, are observed making higher-education choices beyond the sixth academic year.

[5]Because the observed cohorts graduated before the Bologna reform, BA and MA refer to bachelor-equivalent and master-equivalent attainment categories constructed from program type and completed duration.

follows: failed, passed satisfactorily (Passed (s)), passed with distinction (Passed (d)), and passed with high or highest distinction (Passed (h)). These classifications apply consistently throughout all years of higher education, including both bachelor's and master's programs completion. This allows us to observe the full academic trajectory of each student, including annual grades and the final grade obtained upon completion of a degree. Moreover, it allows us to track students who fail or switch programs.

Among students who fail their first year, a large fraction (47%) drops out of higher education entirely (see Appendix Table A1). There is substantial heterogeneity across programs: the drop-out rate reaches 60.9% in college Business and Law programs, compared with around 23% in university STEM and Health programs. Drop-out rates are substantially larger for individuals who do not pass the first year in college programs. However, despite a failed first year, other individuals attain a Bachelor's degree in a different field of study (26%) or in the same program (27%). Switching rates are larger for individuals who do not pass the first year in university programs. These ability sorting patterns reflect a "cascade effect" (Declercq and Verboven, 2018): students start in the more difficult programs (in university) and update their choices depending on their grades (Arcidiacono et al., 2025).

For those who pass the first year, the large majority (87.4%) attain a Bachelor's degree in the same program (see Appendix Table A2). Only a small percentage choose to drop out later on (9.5%). However, this average masks substantial heterogeneity between programs: drop out rates range from 4.4% in a university program in Humanities and arts to 19.4% in a university program in Health. A residual proportion of students choose to earn a Bachelor's degree in a different program despite a successful first year.[6]

Occupational sorting We summarize occupational sorting at labor market entry with a binary treatment for mismatch in the first job after leaving education. This approach serves two purposes. First, it avoids modeling occupational choice over a high-dimensional set of alternatives while retaining an economically meaningful measure of job–education alignment. Second, it allows us to study the consequences of mismatch for subsequent wages, employment, and work experience, and to conduct counterfactual analyses. We use a broad set of alternative mismatch measures to reduce sensitivity to any single classification rule and to assess the robustness of our

[6]Appendix Table A3 shows the completion rate at the Bachelor's level for different choices in the first year of higher education. Relative to Declercq and Verboven (2018), we find similar rates of enrollment and reorientation. For individuals starting in a university (college) program, the probability of obtaining a Bachelor's degree is 60% (50%).

results across definitions.[7]

For vertical mismatch, we follow Navarini and Verhaest (2024) and measure it using a composite measure based on a latent factor approach, which includes a job-analysis (JA) measure, a direct self-assessment (DSA) measure, and an indirect self-assessment (ISA) measure. The JA measure is determined by comparing job requirements with the level of education. Jobs are classified based on the Standard Occupation Classification of Statistics Netherlands. The classification groups jobs based on five required educational levels. The DSA measure is derived from the survey question: “According to your opinion, do you have a level of education that is too high, too low or appropriate for your job?". The ISA measure is based on the survey question: “What is (was), in your opinion, the most appropriate educational level to execute your first job?".[8] Furthermore, we rely on two related measures for horizontal mismatch: job analysis (JA) and direct self-assessment (DSA). Each horizontal mismatch measure includes three possible outcomes: complete mismatch, somewhat match, or complete match (see Appendix Table A6).

Relying on these measures, we construct a latent factor measure, which controls for measurement error (see Navarini and Verhaest, 2024). We assume these five measures capture a continuous latent skill mismatch factor, ϕ_i. Because our observed measures are discrete, we model them using a system of discrete choice equations. For the three vertical mismatch indicators, we collapse the categories into a binary mismatch indicator and model the probability of mismatch using a standard logit specification, $\Pr(y_{iq} = 1 \mid \phi_i) = \Lambda(a_q + \lambda_q \phi_i)$, where Λ is the logistic cumulative distribution function. For the two horizontal mismatch indicators, which are ordered across three categories from complete match to complete mismatch, we use an ordered logit specification where a latent propensity $y^*_{iq} = a_q + \lambda_q \phi_i + \varepsilon_{iq}$ is mapped to the observed ordered categories via estimated threshold parameters, assuming ε_{iq} follows a logistic distribution.

For tractability in the treatment equation, we discretize the latent mismatch factor into a binary indicator, while treating the underlying continuous factor as our more primitive measure of low match quality at entry (see Appendix Table A5).[9] In this context, a higher value of the latent

[7] We refer to skill mismatch, rather than educational mismatch, because the sample consists of individuals observed at first labor market entry, with no accumulated work experience. In this setting, workers' productive skills are expected to be acquired primarily through their attained education and field of study, although they may also embody more general pre-market abilities.

[8] As this question was not included in the survey for the 1976 cohort, we implemented a modified procedure following Baert et al. (2013). First, we calculate each occupation's mean self-assessed required level based on the available information. To do this, we rely on the aforementioned five categories of education levels. Second, we extrapolate this mean to all jobs in each occupation. Third, we classify an individual as being overeducated if their attained level of education exceeds the mean required level within their occupation.

[9] The latent mismatch score is identified only up to a normalization, so its absolute scale is not substantively meaningful. We therefore choose a cutoff to convert the continuous index into a binary indicator and set it at 0.35. The cutoff yields a mismatch prevalence of approximately 38.1% in the full first-job sample, as reported in

mismatch factor increases the likelihood of both vertical and horizontal mismatch. Throughout the paper, the baseline skill-mismatch treatment refers to this latent-factor threshold. When reporting counterfactuals, “full mismatch" denotes the imposed regime $D_i = 1$ for this baseline indicator, not the logical union or intersection of observed vertical and horizontal mismatch indicators. We also conduct a rich set of robustness checks to confirm that our results hold when using single indicators such as JA or DSA.[10]

Our mismatch measure should be interpreted as an ex post measure of low match quality at labor market entry. It is not a direct measure of ex ante optimality, nor a life-cycle measure of eventual occupational fit after subsequent rematching. The latent factor combines several indicators that condition on different objects and uses their common component to summarize the extent to which education-acquired human capital is not well aligned with the requirements of the first job. This interpretation is best suited to labor-market entry, where occupational assignment is less likely to reflect substantial post-school labor market experience, firm-specific human capital, or post-school training. Our binary mismatch indicator should be interpreted as a tractable discretization of a continuous latent low-match-quality index.

As we do not make claims about the reason why individuals start in a low-quality first match, we treat it as a selection-into-treatment equation (Aakvik et al., 2005). In the spirit of Heckman et al. (2018), the model remains agnostic about the precise decision rules and expectation-formation process generating initial occupational sorting. Our framework can accommodate several mechanisms emphasized in the literature (Leuven and Oosterbeek, 2011). In our model, individuals may sort into low-quality first matches because they might expect steeper wage growth in subsequent spells, because search frictions make such jobs preferable to non-employment, or because they differ in preferences, in the information available when education is chosen (Eckardt, 2026), or in dimensions of comparative advantage not observed by the econometrician.

Labor market outcomes Our data enable us to analyze the impact of higher education choices and occupational sorting on log-hourly wages up to age 29 (see Appendix Table A7). The timing is consistent with influential studies employing similar models to estimate returns to education, e.g., Heckman et al. (2018). The effect of occupational sorting and mismatch includes the probability of persistent skill mismatch after the first job, but, potentially, also the scarring effect on subsequent wages even if the individuals find an adequately matched job.

Appendix Table A5. This threshold aligns closely with a majority-rule classification based on the five observed mismatch indicators: individuals above the cutoff are typically classified as mismatched on at least three of the five underlying measures.

[10] Occupations with the highest rates of simultaneous vertical and horizontal mismatch are primarily low-skilled

Table 3: Descriptive statistics: labor market outcomes

	Mean	SD	Min	Max
Potential experience at age 23	2.117	1.680	0.000	6.000
Non-employment at age 23	0.428	0.495	0.000	1.000
Wage observed at age 23	0.747	0.435	0.000	1.000
Hourly wage at age 23	7.354	1.590	2.791	19.963
Potential experience at age 26	4.367	2.115	0.000	9.000
Non-employment at age 26	0.215	0.411	0.000	1.000
Wage observed at age 26	0.894	0.308	0.000	1.000
Hourly wage at age 26	8.126	1.859	2.927	19.493
Potential experience at age 29	7.462	2.163	0.000	12.000
Non-employment at age 29	0.104	0.305	0.000	1.000
Wage observed at age 29	0.982	0.134	0.000	1.000
Hourly wage at age 29	8.563	1.855	2.853	20.007

NOTES.— Summary statistics for 8,189 observations from the SONAR data, covering the 1976, 1978, and 1980 cohorts. Wages are real hourly wages. Potential experience is measured as years since labor-market entry, following Adda and Dustmann (2023). At each age, individuals may be non-employed; among those employed, wages may be unobserved. We account for both non-employment and wage non-observation in the model.

Along with log-hourly wages, we include the relevant labor market outcomes to improve the identification of unobserved factors. We report descriptive statistics for each of these outcomes in Table 3. First, we include potential experience at ages 23, 26 and 29. We follow Adda and Dustmann (2023) and construct potential experience by considering the age of entry in the labor market of each individual. This captures the late entry into the labor market of individuals with a degree, but also of individuals who dropped out of higher education. On average, at age 23, individuals have 2.117 years of potential experience. This means that the average individual enters the labor market at around age 21. This increases to 4.367 years of potential experience at 26 and 7.462 at 29.

Second, we include the non-employment rate at ages 23, 26 and 29. For those with employment information, the non-employment rate is as high as 42.8% at age 23 and it decreases to 21.5% at 26 and 10.4% at 29. This accounts for differences between matched and mismatched individuals in their career and in the probability of finding a job. Finally, we also include an indicator for whether wages are observed at ages 23, 26, and 29, respectively. Of those employed, we observe 74.7% of the wages at age 23, 89.4% at age 26 and 98.2% at age 29.

occupations, such as shop sales assistants, waiters or mail carriers (see Table A8).

3 Empirical framework

We present a generalized sequential Roy (1951) model with endogenous selection on observables and unobservables into higher education programs and skill mismatch (Heckman and Navarro, 2007; Heckman et al., 2018; Walters, 2018; Humphries et al., 2025; Eckardt, 2026).

Our main interest is in the effect on hourly wages of two endogenous objects: final educational attainment E_i and mismatch at labor market entry D_i. E_i is the outcome of a dynamic selection process driven by yearly higher education enrollment decisions and academic progression, consistent with the Belgian institutional setting. Mismatch D_i is realized after exit from education in the first job and is defined relative to E_i.

Our empirical framework is a semi-structural sequential model that approximates an underlying dynamic decision problem (Humphries et al., 2025). We do not solve or estimate the full dynamic programming problem. Instead, we model the sequence of educational choices, state transitions, mismatch assignment, and labor market outcomes directly, while allowing for persistent latent heterogeneity. This approach is designed to recover ex post dynamic treatment effects of final education states and entry mismatch without imposing a fully specified solution to the agents' optimization problem (Heckman et al., 2018; Humphries et al., 2025).

The remainder of this section proceeds as follows. Section 3.1 presents the model. Section 3.2 discusses identification. Section 3.3 outlines estimation. Then, Section 3.4 reports the estimates and the evidence supporting the identifying assumptions.

3.1 Model

Overview The model is composed of three main stages: (i) higher education, (ii) labor market entry, and (iii) post-entry labor market outcomes. Individual i is endowed with observed characteristics X_i and a latent component θ_i, observed by i but not by the econometrician, which may affect all the stages of the model.

After graduating from high school, at the beginning of each year a, i chooses an enrollment option

$$C_{ia} \in \{0, 1, \ldots, J\},$$

where $C_{ia} = 0$ denotes non-enrollment and $C_{ia} = j \geq 1$ denotes enrollment in higher education program j.[11] Conditional on enrollment, the student receives a grade Q_{ia}, which determines credit accumulation and academic progression. Higher education continues until the student

[11] Programs are defined as field-of-study by institution-type pairs during yearly enrollment choices.

either exits without completing a tertiary program or satisfies the credit requirement for program completion.

When individuals collect enough credits, let $E_i \in \{0, 1, \ldots, J\}$ denote the final attained education, where $E_i = 0$ indicates individuals without a tertiary degree and $E_i = j \geq 1$ indicates completion of program j.[12] In our application, the final education state combines field of study, institution type, and highest completed degree level. Consistent with the Belgian context, completion of three years of tertiary study is classified as Bachelor (BA) attainment, while attainment beyond that threshold is classified as Master (MA) attainment. For individuals with $E_i \geq 1$, let $G_i \in \{0, 1\}$ denote graduation timing, where $G_i = 1$ indicates graduation in the second examination period and $G_i = 0$ indicates graduation in the regular examination period.

After leaving higher education, individuals enter the labor market. Let $D_i \in \{0, 1\}$ denote skill mismatch at labor market entry in the first occupation. Mismatch is defined relative to the individual's final education state E_i, so that D_i is observed for all individuals, including those who leave higher education without a tertiary degree. At ages $t \in \{23, 26, 29\}$, we observe accumulated experience since leaving education exp_{it}, employment status W_{it}, wage observability R_{it}, and log-hourly wages Y_{it}. Wages are observed only when an individual is employed, $W_{it} = 1$, and is present in the survey, $R_{it} = 1$.

Selection in higher education First, we model selection into E_i through yearly enrollment choices C_{ia} and grades Q_{ia}, following Arcidiacono (2004) and Declercq and Verboven (2018). Enrollment choices are represented by the maximization of a latent choice index

$$C_{ia} = \arg \max_{j \in \{0,1,\cdots,\mathrm{J}\}} v^c_{iaj}(S^c_{iaj}, \theta_i) + \varepsilon^c_{iaj},$$

where the utility of non-enrollment is normalized to zero.[13]

The observed state vector includes individual- and alternative-specific components

$$S^c_{iaj} = (X_i, \delta_a, Z^c_{ia}, H_{ia}, dist_{ij}),$$

where X_i collects exogenous individual characteristics, δ_a denotes academic year fixed effects,

[12]For notational brevity, we reuse the index J here to denote the set of final education states. Note that the actual empirical state space for final attainment is larger than the yearly enrollment choice set because it additionally distinguishes between the highest completed degree levels (BA versus MA).

[13]The non-enrollment option is absorbing: once $C_{ia} = 0$ is chosen, the individual permanently exits higher education and enters the labor market. This assumption is standard in dynamic discrete choice models of higher education (Arcidiacono, 2004; Declercq and Verboven, 2018).

and Z_{ia}^{c} includes additional observed determinants of enrollment, such as local labor market conditions (Heckman et al., 2018). The term H_{ia} summarizes higher education history: it includes lagged choices $C_{i,a-1}$, which capture switching costs, and accumulated credits at the beginning of year a. The variable $dist_{ij}$ measures the distance in kilometers between individual i's residence postal code and the location postal code of the chosen program j (see also Arcidiacono, 2004; Declercq and Verboven, 2018; De Groote, 2025).

Conditional on enrollment, $C_{ia} \neq 0$, academic performance at the end of academic year a is represented by the latent index

$$Q_{ia}^{*} = \mu_{ia}^{q} + \varepsilon_{ia}^{q},$$

where

$$\mu_{ia}^{q} = v^{q}\left(X_i, \delta_a, Z_{ia}^{q}, H_{ia}, C_{ia}\right) + h_{F(C_{ia})}^{q}(X_i, \theta_i).$$

Here, $F(C_{ia})$ denotes the broad field associated with the program in which individual i is enrolled. To limit dimensionality, we allow type effects to vary by broad field group rather than by detailed program, grouping Humanities and Arts with Education, Business and Law with Social Sciences, and STEM with Health.

The observed academic result is generated from Q_{ia}^{*} through an ordered logit specification:

$$Q_{ia} = \begin{cases} 0, & Q_{ia}^{*} \leq \kappa_0, \\ 1, & \kappa_0 < Q_{ia}^{*} \leq \kappa_1, \\ 2, & \kappa_1 < Q_{ia}^{*} \leq \kappa_2, \\ 3, & Q_{ia}^{*} > \kappa_2, \end{cases} \qquad \kappa_0 < \kappa_1 < \kappa_2.$$

The categories $Q_{ia} = 0$, $Q_{ia} = 1$, $Q_{ia} = 2$, and $Q_{ia} = 3$ respectively denote failure, passing satisfactorily, passing with distinction, and passing with high or highest distinction.[14]

Credits accumulate deterministically after passing within the same program:

$$H_{i,a+1}^{\text{cr}} = \mathbf{1}\{C_{i,a+1} = C_{ia}\}\left[H_{ia}^{\text{cr}} + \mathbf{1}\{Q_{ia} > 0\}\right]. \tag{1}$$

For individuals who collect enough credits and with $E_i \geq 1$, graduation timing is summarized

[14] Assuming that ε_{ia}^{q} follows a standard logistic distribution, the corresponding grade probabilities are

$$\Pr\left(Q_{ia} = q \mid X_i, \delta_a, Z_{ia}^{q}, H_{ia}, C_{ia}, \theta_i\right) = \Lambda\left(\kappa_q - \mu_{ia}^{q}\right) - \Lambda\left(\kappa_{q-1} - \mu_{ia}^{q}\right), \qquad q \in \{0,1,2,3\},$$

with the conventions $\kappa_{-1} = -\infty$ and $\kappa_3 = +\infty$. Hence, higher values of Q_{ia}^{*} correspond to better academic performance.

by $G_i \in \{0,1\}$, where $G_i = 1$ denotes graduation in the second examination period (August–September) and $G_i = 0$ denotes graduation in the regular examination period (June). Graduation timing is governed by the latent index

$$G_i = \mathbf{1}\{I_i^g(S_i^g, \theta_i, \varepsilon_i^g) > 0\}, \qquad I_i^g(S_i^g, \theta_i, \varepsilon_i^g) = v^g(X_i, E_i, Z_i^g) + h_{F_i}^g(X_i, \theta_i) + \varepsilon_i^g, \tag{2}$$

where Z_i^g collects observed determinants of graduation timing and $F_i \equiv f(E_i)$ denotes the broad field of study associated with completed program E_i. This specification allows latent heterogeneity to affect academic performance, graduation timing, occupational sorting, and later labor-market outcomes differently across these broad fields.

Selection into entry mismatch Second, we model selection into entry mismatch for all individuals, including those with a high-school degree. Following the selection framework of Heckman et al. (2018), we treat mismatch as an endogenous treatment assigned through a threshold-crossing rule. The latent index governing mismatch at labor-market entry is

$$D_i = \mathbf{1}\{I_i^d(S_i^d, \theta_i, \varepsilon_i^d) > 0\}, \qquad I_i^d(S_i^d, \theta_i, \varepsilon_i^d) = v^d(X_i, E_i, G_i, Z_i^d) + h_{F_i}^d(X_i, \theta_i) + \varepsilon_i^d, \tag{3}$$

where ε_i^d is an unobserved match-quality shock, assumed to follow a standard logistic distribution. The state vector $S_i^d = (X_i, E_i, G_i, Z_i^d)$ includes earlier educational outcomes, such as grades obtained in Bachelor's and Master's[15] programs, as well as district-level unemployment rates. The term $h_{F_i}^d(X_i, \theta_i)$ allows the effect of persistent unobserved heterogeneity and observed characteristics to vary across broad field groups, with high-school graduates as the omitted reference category.

Labor market outcomes Conditional on educational attainment E_i and entry mismatch D_i, we model labor-market outcomes at ages $t \in \{23, 26, 29\}$. Wages conditional on mismatch status are specified as

$$Y_{it}(d) = \phi_t^d + \alpha_{E_i}^d + g_d\left(Z_{it}^y\right) + h_{dF_i}^y(X_i, \theta_i) + \varepsilon_{it}^y(d), \tag{4}$$

[15] The final program indicator is set equal to the Bachelor's completed program for individuals whose highest degree is a BA, and to the Master's completed program for individuals who progress beyond the BA threshold. Bachelor's effects therefore enter through the completed program indicators and through dummies for BA performance, with the lowest passing BA grade as the reference category among completers. Master's attainment enters as an additional indicator, together with dummies for MA performance, so the MA coefficients should be interpreted as the incremental effect of progressing beyond the BA threshold within the completed field-by-type program.

where ϕ_t^d captures mismatch-specific age effects, and $g_d(\cdot)$ is allowed to vary with mismatch status, thereby capturing common returns to experience and other observed and unobserved characteristics. Completed educational attainment E_i affects wages through an attainment-specific intercept $\alpha_{E_i}^d$ and through the term $h_{dF_i}^y(X_i, \theta_i)$, which allows returns to vary across broad fields of study, exogenous variables, and unobserved heterogeneity. The vector Z_{it}^y includes educational histories determined earlier in the model, accumulated experience since leaving education, and district-level unemployment rates.

We additionally model employment, wage observability, and experience accumulation jointly, so wages enter the likelihood only when $W_{it} = 1$ and $R_{it} = 1$, such that observed wages are:

$$Y_{it} = D_i Y_{it}(1) + (1 - D_i) Y_{it}(0), \tag{5}$$

and we control for potential working experience, exp_{it}. This separates the effect of mismatch from mechanical differences in time since labor-market entry.

Forward-looking behavior Our model can be rationalized by an underlying dynamic discrete choice model (Humphries et al., 2025). Individuals choose educational programs taking into account both current payoffs and the expected continuation value associated with future educational and labor-market outcomes, conditional on the observed state space and their persistent unobserved endowment θ_i. We do not solve or estimate this dynamic optimization problem directly. Instead, the empirical specification should be interpreted as a reduced-form approximation of this environment.

To fix ideas, consider the initial enrollment decision. We could write the latent choice index for enrollment choices in the first academic year as

$$\begin{aligned} v_{i1j}^c(S_{i1j}^c, \theta_i) = u_{i1j}(S_{i1j}^c, \theta_i) + \\ \beta\, \mathbb{E}\Big[U_i\Big(\{C_{ia}, Q_{ia}\}_{a=1}^{A_i}, E_i, G_i, D_i, \{exp_{it}, R_{it}, W_{it}, Y_{it}\}_{t \in T}\Big) \,\Big|\, S_{i1j}^c, C_{i1} = j,\, \theta_i\Big]. \end{aligned} \tag{6}$$

Here, $U_i(\cdot)$ denotes the continuation payoff from the realized future path of educational and labor-market outcomes, conditional on choosing higher education program j. This continuation value depends on the probability of success and persistence in higher education, final educational attainment E_i, graduation timing G_i, entry mismatch D_i, and subsequent labor-market realizations, $\{exp_{it}, R_{it}, W_{it}, Y_{it}\}_{t \in T}$.

Dynamic treatment effects Rather than fully specifying the forward-looking behavior of individuals, as in Equation 6, we follow the dynamic treatment effects literature (Heckman and Navarro, 2007; Heckman et al., 2018; Humphries et al., 2025). This approach allows us to remain agnostic about expectation formation, information sets, and learning dynamics, while still capturing forward-looking behavior in reduced form (Heckman et al., 2016, 2018). Estimating the dynamic optimization problem would require strong assumptions on agents' information sets, belief formation and learning dynamics (Wiswall and Zafar, 2014; Patnaik et al., 2020; Arcidiacono et al., 2020).

We make the following assumptions, standard in the dynamic discrete choice literature (Heckman and Navarro, 2007; Humphries et al., 2025): (A1) there exists a time-invariant unobserved component θ_i such that, conditional on θ_i, the idiosyncratic shocks entering the different stages of the model are independent across stages, periods, and individuals; (A2) conditional on θ_i, the current observed state, and the current decision, the distribution of next period's observed state does not depend on earlier history or on current-period idiosyncratic shocks.

While we recognize that these assumptions are strong, they are more credible in our setting because of the detailed data. We observe pre-tertiary characteristics, the full tertiary trajectory, and rich labor market outcomes, so many of the factors that could otherwise induce persistence across stages are directly measured. A limitation is that some shocks may be specific to later labor market stages, such as dimensions of labor market productivity that are distinct from tertiary education ability. To address this, we model residual unobserved heterogeneity using a finite mixture of persistent latent types. If type effects are allowed to differ across equations, a given latent type may be more strongly associated with higher education choices, while another may be more strongly associated with labor-market outcomes. In this sense, the finite-mixture structure reduces the need to force all cross-stage dependence through a single scalar latent component. At the same time, its credibility still relies on the assumption that the remaining dependence is sufficiently low-dimensional to be approximated by a finite number of persistent types.

Under these assumptions, the model can be represented by a sequence of semi-parametric reduced-form components that are sufficient to recover expected payoffs along realized paths, without imposing a full parametric solution to the dynamic problem (Heckman and Navarro, 2007; Heckman et al., 2018; Walters, 2018; Humphries et al., 2025).

The main limitation of this approach is that it is not suited to counterfactuals that require modeling a time-varying θ_{it} or how agents learn about θ_i, form expectations, or re-optimize under alternative expected environments (Stinebrickner and Stinebrickner, 2012; Wiswall and Zafar, 2014; Arcidiacono et al., 2025). As a result, the model does not generally deliver welfare evaluations or policy counterfactuals that depend on expectation formation. It is, however, well suited to estimating ex post dynamic treatment effects along alternative realized paths (Heckman et al., 2018; Humphries et al., 2025). In particular, it supports counterfactual outcome distributions under alternative higher education choices or alternative mismatch realizations at labor market entry.

3.2 Identification

Identification relies on three ingredients: (i) persistence in latent heterogeneity revealed through joint educational and labor-market histories; (ii) excluded cost shifters for higher education choices and (iii) excluded shifters of entry mismatch.

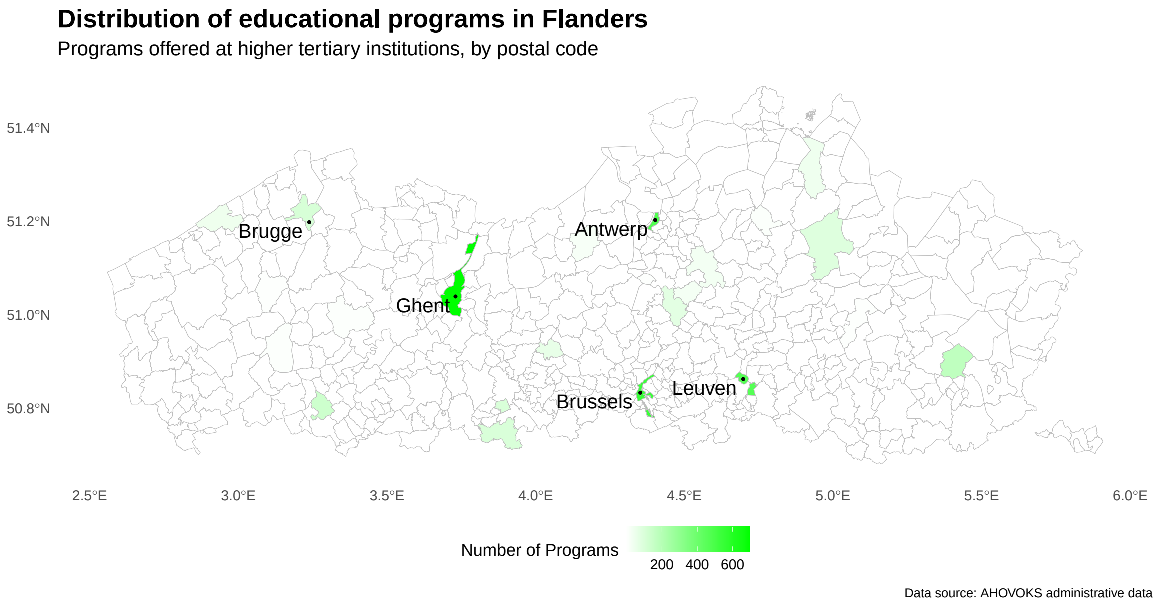
Unobserved heterogeneity We model unobserved heterogeneity using discrete type random effects, following the finite-mixture approach commonly employed in dynamic discrete choice models (Heckman and Singer, 1984; Arcidiacono, 2004). We allow for an a priori unknown number M of latent types, each characterized by type-specific parameters across model components. With an appropriate number of mass points, mixture models of this form can accurately approximate arbitrary distributions of unobserved heterogeneity (Heckman and Singer, 1984; Cameron and Heckman, 1998; Walters, 2018).

Unobserved heterogeneity is identified from the joint persistence and cross-equation dependence of educational choices, educational outcomes, occupational mismatch, and labor market trajectories over time, conditional on observed state variables (Heckman and Navarro, 2007). Individuals with similar observed histories who subsequently make different choices or experience different outcomes reveal the presence of latent, persistent traits that shape both educational decisions and labor market performance (Aakvik et al., 2005). Exploiting this joint variation allows the model to disentangle true state dependence from selection driven by unobserved characteristics.

Distance to higher education programs Following the literature (Card, 1995; Declercq and Verboven, 2018; Walters, 2018; De Groote and Declercq, 2021; Mountjoy, 2022), we exploit distance as a source of plausibly exogenous variation in the costs of educational choices. In our context, distance affects program choice through commuting and relocation costs, while, conditional on observed background characteristics, geographic characteristics, and unobserved heterogeneity, it does not directly enter later labor market outcomes.

We measure distance (in kilometers) as the geographic distance between the individual's residence postal code and the postal code of the nearest higher education program, defined at the level of field of study and type of institution.[16] As discussed in Declercq and Verboven (2018), distance is a key determinant of enrollment decisions in Belgium. In the Belgian system, geographic proximity primarily shifts enrollment costs rather than program quality. Figure 1 illustrates the spatial distribution of higher education programs in Flanders.

Figure 1: Distribution of educational programs in Flanders



We assess the identifying assumptions underlying the use of distance by examining both its relevance for higher education choices and its conditional independence from labor market outcomes. Appendix Table A11 reports first-stage estimates of the effect of relative distance on higher education program choice under alternative specifications.[17] Estimated effects are stable across specifications and change little when controlling for observed student characteristics, such as grades, consistent with distance operating primarily as a cost shifter rather than proxying for unobserved ability.

In Appendix Table A12, we also report balance tests relating high school grades to dis-

[16] Information on the universe of officially recognized programs is obtained from administrative records provided by AHOVOKS, the Flemish government agency for Higher Education, Adult Education, Qualifications, and Study Grants.

[17] In odd columns, distance enters with a single coefficient for each program, while in even columns coefficients are allowed to vary across higher education programs.

tance, progressively adding controls for local labor market conditions, urbanization, neighborhood characteristics, and student background. Across specifications, we find no systematic relationship between grades in secondary education and distance. We further regress relative distance on a rich set of observed background characteristics and find no systematic correlation (Appendix Table A14). Finally, Appendix Table A13 shows that relative distance is not directly associated with labor market outcomes once educational choices are controlled for. Taken together, these results are consistent with interpreting distance as an exogenous shifter of higher education choices in our setting, operating through educational decisions rather than directly affecting subsequent labor market outcomes.

Graduation timing and skill mismatch To identify the causal effect of skill mismatch in the first job on early-career wages, we exploit variation in labor market entry timing generated by the institutional structure of Belgian higher education institutions. Students who fail one or more exams during the regular academic year can retake them in a second examination period held in August–September. While this allows students to graduate within the same academic year, it delays labor market entry by several months relative to peers who complete all requirements in June.

In our framework, late graduation is not assumed to be exogenous. Because the same persistent latent component θ_i enters the graduation, mismatch, and wage equations, graduation timing may be correlated with unobserved determinants of both mismatch and wages. Hence, a standard instrumental variables interpretation of late graduation would generally fail.

Identification instead relies on a weaker structural restriction. Conditional on observed characteristics, completed education, and latent type θ_i, the remaining variation in graduation timing is driven by a transitory shock that is assumed to be orthogonal to the transitory unobservables governing mismatch and wages (i.e. Assumption A1). Thus, we do not require graduation timing itself to be independent of ability or preferences. Rather, after conditioning on θ_i and the relevant observed states, only the residual component of graduation timing provides identifying variation.

Our wage specification targets the direct effect of mismatch conditional on post-entry labor market states, including potential experience since graduation. Accordingly, our identifying restriction is that, once entry mismatch status, persistent unobserved heterogeneity, and the realized post-entry states included in the wage equation are held fixed, graduation timing does not exert an additional direct effect on wages. Under this restriction, graduation timing may still affect wages indirectly by changing the probability of entering a mismatched occupation, but it does not shift wages within cells defined by mismatch status, latent type, and post-entry states.

Identification further requires a relevance condition: conditional on observed characteristics, completed education, and latent type, late graduation must shift the probability of entering a mismatched occupation. Under these assumptions, individuals with the same observed state space may nevertheless differ in mismatch status because of transitory variation in graduation timing. In that case, this variation can be used to identify the direct effect of mismatch on wages, conditional on realized post-entry labor-market histories. Appendix Table A18 provides evidence on the relevance condition, showing that late graduation significantly increases the probability of entering a mismatched occupation, conditional on a rich set of educational and demographic controls.[18]

This argument is plausible in our setting for two reasons. First, at labor market entry, wages are likely to be determined primarily by observable characteristics, such as completed education, field of study, degree level, and the occupation in which the individual starts working, rather than by employers' assessments of individual productivity. Second, the Belgian labor market is characterized by relatively rigid wage-setting institutions, including collective agreements and wage schedules that limit the scope for firms to flexibly adjust entry wages to individual signals such as delayed graduation (Fuss, 2009; Du Caju et al., 2012). As a result, once we condition on educational qualifications, grades, mismatch status, latent type, and post-entry labor market states, it is unlikely that late graduation has an independent effect on wages within these cells. The main channel through which late graduation can affect early-career wages is therefore through its effect on the type of occupation entered, and in particular on the probability of starting in a mismatched job. Appendix Table A21 examines this implication directly. In the baseline first-job wage specification, late graduation is associated with 2.3 log points lower wages. Adding first-job occupation fixed effects further weakens the association, and in the wage panel with occupation fixed effects the coefficient falls to -0.007.

A potential concern is that delayed graduation proxies for prior labor market attachment. This concern appears unlikely in our context. During the observation period (graduation cohorts 1997–2004, prior to the Bologna reform), 95% of bachelor's graduates and 97% of master's graduates report no prior work experience, and more than 98% report no prior full-time employment. These patterns indicate that labor market entry typically occurs after graduation and that delayed graduation is unlikely to reflect pre-existing employment relationships.

Finally, we further support these arguments with additional tests that assess the correlation of late graduation within estimated types of individuals with similar unobservables. These results are reported and discussed in Section 3.4.

[18] In Appendix Table A4, we show the prevalence of late graduation by field of study.

3.3 Estimation

We estimate the model by maximum likelihood, allowing for persistent unobserved heterogeneity θ_i approximated by a finite mixture of M mass points $\{\theta_m\}_{m=1}^M$. Let $\pi_m(Z_i^0) \equiv \Pr(\theta_i = \theta_m \mid Z_i^0)$ denote the type probability conditional on initial conditions Z_i^0, with $\sum_{m=1}^M \pi_m(Z_i^0) = 1$.[19] This specification allows θ to be correlated with predetermined characteristics and addresses the initial conditions problem (Keane and Wolpin, 1997). We include the high-school track diploma Z_i^0.

The individual likelihood contribution is a mixture over types m,

$$\mathscr{L}_i(\Theta) = \sum_{m=1}^{M} \pi_m(Z_i^0)\,\mathscr{L}_i(\Theta \mid \theta_m), \qquad \hat{\Theta} = \arg\max_{\Theta} \sum_{i=1}^{N} \log \mathscr{L}_i(\Theta),$$

where Θ collects all model parameters.

Under (A1)–(A2), the type-specific likelihood contribution of individual i factorizes as

$$\begin{aligned}
\mathscr{L}_i(\Theta \mid \theta_m) = & \left[\prod_{a=1}^{A_i} p_a^c\big(C_{ia} \mid S_{iaj}^c, \theta_m\big) \cdot \Big(p_a^q\big(Q_{ia} \mid S_{ia}^q, C_{ia}, \theta_m\big) \Big)^{\mathbf{1}\{C_{ia} \neq 0\}} \right] \\
& \cdot \Big(p^g\big(G_i \mid S_i^g, \theta_m\big) \Big)^{\mathbf{1}\{E_i > 0\}} \cdot p^d\Big(D_i \mid S_i^d, \theta_m\Big) \\
& \cdot \Bigg[\prod_{t \in \{23,26,29\}} f_t^{exp}\big(exp_{it} \mid S_{it}^{exp}, \theta_m\big) \cdot p_t^w(W_{it} \mid S_{it}^w, \theta_m) \cdot \Big(p_t^r(R_{it} \mid S_{it}^r, \theta_m) \Big)^{\mathbf{1}\{W_{it}=1\}} \\
& \cdot \Big(f_{1t}^y\big(Y_{it} \mid S_{it}^y, \theta_m\big) \Big)^{\mathbf{1}\{W_{it}=1, R_{it}=1\} D_i} \cdot \Big(f_{0t}^y\big(Y_{it} \mid S_{it}^y, \theta_m\big) \Big)^{\mathbf{1}\{W_{it}=1, R_{it}=1\}(1-D_i)} \Bigg],
\end{aligned}$$

where each state vector collects the stage-specific observed determinants for the corresponding outcome.[20] In particular, S_{it}^{exp}, S_{it}^w, S_{it}^r are defined analogously to S_i^d, where the latter two also include exp_{it}.[21]

We estimate the model using an Expectation–Maximization (EM) algorithm. Let $\mathscr{O}_i$ denote the observed data for individual i. In the E-step, we compute posterior type probabilities

$$\tau_{im}^{(r)} \equiv \Pr(\theta_i = \theta_m \mid \mathscr{O}_i, Z_i^0; \Theta^{(r)}) = \frac{\pi_m(Z_i^0; \Theta^{(r)})\,\mathscr{L}_i(\Theta^{(r)} \mid \theta_m)}{\sum_{k=1}^{M} \pi_k(Z_i^0; \Theta^{(r)})\,\mathscr{L}_i(\Theta^{(r)} \mid \theta_k)}. \tag{7}$$

[19] In our full specification, Z_i^0 includes an indicator for high-school track diploma.

[20] S_{ia}^q includes X_i, local labor market conditions, delays, high-school track, high-school grades, academic year fixed effects, number of accumulated credits and the current enrollment choice.

[21] The assumptions on the unobservables imply closed-form expressions for the stage-specific choice probabilities: multinomial logit for p_a^c, ordered logit for p_a^q, and binary logit for p^g, p^d, p_t^w, and p_t^r. The continuous outcomes are modeled using linear regressions.

In the M-step, we update parameters by maximizing the weighted log-likelihood treating $\tau_{im}^{(r)}$ as observed (Arcidiacono and Jones, 2003):

$$\hat{\Theta}^{(r+1)} = \arg\max_{\Theta} \sum_{i=1}^{N} \sum_{m=1}^{M} \tau_{im}^{(r)} \log \mathscr{L}_i(\Theta \mid \theta_m). \tag{8}$$

We iterate E- and M-steps until convergence. We select the number of types by estimating specifications with one, two, and three latent types and by using multiple starting values for each specification (Appendix Table A22). Among the estimated models, AIC and BIC select the specification with three unobserved types, which we use as the benchmark model.[22]

3.4 Model estimates and identification assumptions

Initial conditions The correlations between types and initial conditions are reported in Appendix Table A23. Because finite-mixture labels are arbitrary, we interpret the types through their correlations with pre-tertiary characteristics. Type 1 is most strongly associated with the academic high-school track, although it is also positively associated with the lower grade quartiles and high-school dropout. Type 2 is most strongly associated with the vocational track and secondary-school delay, but is positively correlated with the highest grade quartile. Type 3 is primarily associated with the technical track. These descriptive correlations guide the interpretation of the type coefficients below.

Higher education choice model estimates Table 4 reports the raw coefficient estimates from the higher education choice model estimated using a multinomial logit specification in six panels (A–F).[23] Panel (A) shows that earning an additional academic credit is positively associated with persisting in tertiary education. Panel (B) indicates that delays in secondary education are negatively associated with both enrollment and persistence across all tertiary programs.[24] Having followed an academic track in secondary school is strongly associated with enrollment and persistence in every tertiary program. Finally, grades at the end of upper-secondary education

[22] We estimate specifications with one, two, and three latent types using multiple starting values. We first restrict attention to admissible runs, defined as estimates that satisfy the numerical convergence criterion and yield a valid covariance matrix with finite standard errors for all estimated parameters. Among these admissible estimates, both AIC and BIC select the three-type specification reported as our benchmark. Appendix Table A22 reports the negative log likelihood, information criteria, maximum standard error, filter status, and preferred run for each specification.

[23] Appendix Table A10 reports the raw coefficient estimates on the exogenous variables for each stage of the model.

[24] Conditional on other factors, individuals who repeated a grade in primary school exhibit a higher propensity to enroll and persist in certain college programs.

Table 4: Tertiary education choice model

	University programs					College programs					
	HUMA	BUL	SSOC	HEA	STEM	HUMA	BUL	SSOC	HEA	STEM	EDU
(A) Common utility parameters											
Credits	10.462***										
	(0.323)										
(B) Primary and secondary education											
Delay in primary education	0.082	0.430	1.009**	0.974**	1.086**	0.585*	0.202	0.243	0.444	-1.155**	0.049
	(0.490)	(0.395)	(0.412)	(0.488)	(0.428)	(0.340)	(0.288)	(0.407)	(0.327)	(0.454)	(0.349)
Delay in secondary education	-0.896***	-1.586***	-1.590***	-1.981***	-1.831***	-0.889***	-0.983***	-1.244***	-0.710***	-1.034***	-1.197***
	(0.285)	(0.278)	(0.352)	(0.483)	(0.389)	(0.182)	(0.130)	(0.209)	(0.161)	(0.137)	(0.162)
Academic track in HS	5.394***	5.858***	5.532***	6.094***	6.013***	3.592***	3.568***	3.267***	3.189***	3.035***	3.123***
	(0.151)	(0.147)	(0.158)	(0.222)	(0.172)	(0.099)	(0.078)	(0.101)	(0.098)	(0.083)	(0.087)
HS grades - 4th Q	-1.064***	-0.789***	-1.238***	1.779*	-0.618**	-0.523**	-0.318	-0.373	-0.321	-0.515***	0.011
	(0.300)	(0.275)	(0.275)	(1.071)	(0.297)	(0.264)	(0.199)	(0.262)	(0.307)	(0.194)	(0.252)
HS grades - 3rd Q	-0.732***	-0.207	-0.848***	2.109**	-0.336	-0.309	-0.173	-0.384	-0.029	-0.345**	0.071
	(0.263)	(0.243)	(0.240)	(1.059)	(0.266)	(0.240)	(0.183)	(0.243)	(0.287)	(0.175)	(0.238)
HS grades - 2nd Q	0.204	0.629***	-0.178	3.050***	0.723***	0.107	-0.059	-0.440*	0.100	-0.145	0.221
	(0.258)	(0.241)	(0.237)	(1.057)	(0.261)	(0.239)	(0.184)	(0.245)	(0.287)	(0.175)	(0.238)
(C) Switching costs (field of study)											
HUMA (a-1)		-3.344***	-3.555***	-4.507***	-3.896***		-3.344***	-3.555***	-4.507***	-3.896***	-3.339***
		(0.112)	(0.169)	(0.256)	(0.157)		(0.112)	(0.169)	(0.256)	(0.157)	(0.141)
BUL (a-1)	-4.104***		-3.220***	-4.322***	-4.027***	-4.104***		-3.220***	-4.322***	-4.027***	-3.731***
	(0.180)		(0.128)	(0.205)	(0.145)	(0.180)		(0.128)	(0.205)	(0.145)	(0.149)
SSOC (a-1)	-3.947***	-3.296***		-4.076***	-5.114***	-3.947***	-3.296***		-4.076***	-5.114***	-3.452***
	(0.194)	(0.112)		(0.208)	(0.295)	(0.194)	(0.112)		(0.208)	(0.295)	(0.150)
HEA (a-1)	-4.867***	-4.132***	-4.024***		-4.230***	-4.867***	-4.132***	-4.024***		-4.230***	-4.032***
	(0.283)	(0.151)	(0.197)		(0.184)	(0.283)	(0.151)	(0.197)		(0.184)	(0.183)
STEM (a-1)	-4.075***	-3.893***	-4.335***	-3.779***		-4.075***	-3.893***	-4.335***	-3.779***		-3.782***
	(0.184)	(0.129)	(0.225)	(0.172)		(0.184)	(0.129)	(0.225)	(0.172)		(0.161)
EDU (a-1)	-3.819***	-3.552***	-2.744***	-3.723***	-3.774***	-3.819***	-3.552***	-2.744***	-3.723***	-3.774***	
	(0.246)	(0.175)	(0.152)	(0.246)	(0.220)	(0.246)	(0.175)	(0.152)	(0.246)	(0.220)	
(D) Switching costs (type of institution)											
College program (a-1)	-3.317***										
	(0.079)										
University program (a-1)						-1.817***					
						(0.053)					
(E) Alternative-specific distance cost											
Distance to program j	-0.015***	-0.010**	-0.010*	-0.009	-0.010*	-0.018***	-0.013***	-0.001	0.000	-0.004	-0.001
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
(F) Alternative-specific constants and types											
Constant	-11.346***	-11.548***	-11.303***	-15.769***	-12.227***	-9.666***	-8.420***	-9.591***	-9.610***	-7.846***	-9.561***
	(0.360)	(0.333)	(0.345)	(1.104)	(0.371)	(0.317)	(0.251)	(0.321)	(0.353)	(0.249)	(0.301)
Type 2	-0.357***	-0.283***	-0.356***	-0.322***	-0.311***	-0.409***	-0.352***	-0.398***	-0.350***	-0.396***	-0.385***
	(0.113)	(0.096)	(0.108)	(0.120)	(0.106)	(0.108)	(0.086)	(0.114)	(0.113)	(0.094)	(0.097)
Type 3	-0.155	-0.093	-0.199	-0.123	-0.110	-0.176	-0.138	-0.216*	-0.139	-0.200**	-0.198*
	(0.130)	(0.110)	(0.126)	(0.140)	(0.122)	(0.119)	(0.093)	(0.125)	(0.122)	(0.101)	(0.105)
Estimated type probabilities	Type 1: 0.203 Type 2: 0.485 Type 3: 0.312										

NOTE.- See Table A9 for the full set of estimated choice parameters. The tertiary education programs are the following: Humanities and Arts (HUMA), Business, Economics and Law (BUL), Social Sciences (SSOC), Health (HEA), Science, Technology, Engineering and Mathematics (STEM) and Education (EDU). HS denotes higher secondary education. HS grades report the estimated coefficients relative to receiving a grade in the first quarter (highest grades). Distance always refers to alternative-specific distance to program j. Panel (A) reports the common utility parameters, where coefficients are constrained to be equal across all alternatives. Panel (B) reports the alternative-specific coefficients for primary and secondary education variables. Panel (C) presents the estimated field-specific switching costs, following Declercq and Verboven (2018), which capture the penalty from choosing a major different from the one taken in the previous academic year. Panel (D) reports analogous switching costs for changes in institution type (College vs. University). Panel (E) presents the effects of alternative-specific distance to program j, where coefficients are restricted to enter only the utility of the corresponding alternative. Panel (F) includes the alternative-specific constants and the coefficients on the unobserved type, which equal 1 if the student belongs to type 2 or 3 rather than type 1. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

are generally positively associated with enrolling and persisting in each program j.

In Panels (C) and (D) of Table 4, we include the switching cost coefficients for changing field of study or type of institution relative to the current choice. These estimates are consistently large and negative across all alternatives and are all statistically significant. Consistent with the descriptives, individuals face lower switching costs when moving from a university program to a college program, relative to the opposite direction.

In Panel (E), we find that a higher distance has a significant and negative association with enrolling and persisting in higher education. As discussed in Section 3.2, this source of spatial variation is central to our identification strategy. Across programs, the alternative-specific distance coefficients are generally negative, consistent with the idea that greater distance lowers both enrollment and persistence. The strength of this relationship, however, is heterogeneous: distance strongly predicts choices in several programs, while in others the point estimates are small and statistically insignificant. One notable institutional exception is enrollment in Health at university, the only program with a selective entrance exam, where geography may play a more limited role in shaping enrollment.

Unobserved types In Panel (F) of Table 4, we show that the unobserved types are strongly related to tertiary education choices. The type coefficients are large and often statistically significant, indicating that persistent latent heterogeneity matters for program choice and continuation.

Table 5 reports the estimated unobserved type parameters in each stage of the model, with Type 1 as the reference category. The estimates indicate that the model recovers meaningful latent types that are strongly related to educational trajectories and early labor market outcomes. The latent types capture persistent traits related both to field of study choices, where the majority of type coefficients are significant in Table 4, and to post-graduation outcomes such as mismatch and graduation timing. This suggests that the types reflect underlying differences in ability, preferences, or constraints that jointly shape educational trajectories and labor market outcomes.

Any causal interpretation of our results relies on the ability of the latent types to capture persistent, unobserved heterogeneity affecting higher education choices, subsequent skill mismatch, and labor market outcomes, while mitigating dynamic selection bias (Heckman et al., 2018). The identifying assumption is that, conditional on observed covariates and latent type membership, the remaining variation is orthogonal to unobserved determinants of outcomes.[25]

Identifying assumptions We conduct a series of additional analyses to assess the role of unobserved heterogeneity using the posterior probabilities from our estimated model as weights in a

[25] Appendix Table A15 re-estimates the first-stage field of study choice model using posterior probabilities of latent types as weights. The results show that distance to tertiary program j significantly affects field of study choice and persistence *within* latent types, indicating that identification is not driven by compositional differences across types.

Table 5: Unobserved heterogeneity coefficients from the model stages

Type	Field of study	Results higher tertiary	Graduation (second sit)	Skill mismatch	Log-hourly wage matched (ages 23, 26, 29)	Log-hourly wage mismatched (ages 23, 26, 29)
Type 2		0.018	6.595***	-2.682***	-0.003	-0.013
		(0.068)	(2.493)	(0.212)	(0.029)	(0.013)
	× Humanities and Arts			2.523***	0.002	-0.038
				(0.388)	(0.032)	(0.049)
	× Business and Law	-0.066	-2.578	4.406***	0.002	-0.001
		(0.084)	(2.626)	(0.276)	(0.031)	(0.028)
	× Social Sciences	-0.066	-2.578	4.406***	0.002	-0.001
		(0.084)	(2.626)	(0.276)	(0.031)	(0.028)
	× STEM	-0.003	-9.935***	3.473***	0.007	0.015
		(0.087)	(2.545)	(0.287)	(0.031)	(0.030)
	× Health	-0.003	-9.935***	3.473***	0.007	0.015
		(0.087)	(2.545)	(0.287)	(0.031)	(0.030)
	× Education			2.523***	0.002	-0.038
				(0.388)	(0.032)	(0.049)
Type 3		0.068	6.013**	-2.940***	-0.001	-0.011
		(0.076)	(2.498)	(0.216)	(0.029)	(0.014)
	× Humanities and Arts			9.723***	0.004	-0.014
				(1.255)	(0.034)	(0.045)
	× Business and Law	-0.131	-0.577	2.827***	-0.004	-0.018
		(0.094)	(2.631)	(0.311)	(0.031)	(0.035)
	× Social Sciences	-0.131	-0.577	2.827***	-0.004	-0.018
		(0.094)	(2.631)	(0.311)	(0.031)	(0.035)
	× STEM	-0.063	-5.611**	2.872***	0.005	0.007
		(0.096)	(2.506)	(0.309)	(0.032)	(0.035)
	× Health	-0.063	-5.611**	2.872***	0.005	0.007
		(0.096)	(2.506)	(0.309)	(0.032)	(0.035)
	× Education			9.723***	0.004	-0.014
				(1.255)	(0.034)	(0.045)

Notes: Type 1 is the reference latent type. Rows "Type 2" and "Type 3" report the common type component in each equation. Rows labeled × field report the additional field-specific type component relative to the omitted field group for that latent type; they are not total type effects. The total type effect for a non-omitted field is obtained by adding the common type component to the corresponding type–field interaction. Blank cells indicate that no separate field interaction is estimated in that equation, so the omitted field-group interaction is zero and the total effect for that omitted field group is given by the type row. In the Results higher tertiary and Graduation (second sit) equations, Humanities and Arts and Education are the omitted field group. Field interactions are constrained to be common for Humanities and Arts/Education, Business and Law/Social Sciences, and STEM/Health. Coefficients are index coefficients from the corresponding model equations, not marginal effects. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

set of regressions.[26] First, Appendix Table A16 presents placebo regressions relating distance to tertiary program j to a comprehensive set of pre-tertiary outcomes.[27] For each outcome, we report estimates for the full sample and separately by latent type. Across all panels, the coefficient on distance is close to zero and statistically insignificant in nearly all specifications, implying that geographic proximity to a specific higher education program is not systematically related to prior academic performance, school delay, track placement, or dropout risk.

Appendix Table A17 further evaluates the exclusion restrictions by examining whether dis-

[26] These probabilities are the model-implied probabilities that individual i belongs to latent type m.

[27] These include initial conditions such as delay in primary or secondary school, high-school dropout, vocational, technical, and academic track choice, and high-school grades.

tance predicts post-tertiary outcomes that may proxy for unobserved heterogeneity. Each panel reports estimates for the full sample and by latent type, conditioning on the full set of exogenous controls as well as for province and cohort fixed effects. Panel A shows that distance to program j has a coefficient that is essentially zero and statistically insignificant for log-hourly wages. Panel B similarly indicates no systematic association between distance and skill mismatch in the first occupation. Panels C and D consider late graduation. As expected, late graduation is positively correlated with subsequent mismatch both in the aggregate and within latent types. Moreover, late graduation is negatively correlated with wages in the aggregate. The type-specific wage estimates, meanwhile, are imprecise, heterogeneous, and modest in magnitude. This pattern is consistent with late graduation being uncorrelated with wages once latent types are controlled for.

Finally, in our full model with three unobserved types (see Appendix Table A19), late graduation strongly predicts entry mismatch under both linear and flexible experience controls, and the pattern is similar under the K=2 latent-type specification. Together with the evidence on limited pre-graduation labor-market attachment and the controls for local labor-market conditions, this pattern supports the view that residual shocks to graduation timing affect early-career outcomes mainly through occupational assignment at entry, rather than through a direct wage-setting channel. Once latent types are included, this variation is decomposed into within-type components, such that the effect of late graduation is identified solely from deviations within a given latent class. Consequently, late graduation no longer proxies for global unobserved heterogeneity but instead captures idiosyncratic shocks conditional on type membership.

We therefore conclude that distance to tertiary education program j is plausibly excluded from both log-hourly wages and skill mismatch in the first occupation. Moreover, conditioning on latent types clarifies the roles of our two sources of variation: relative distance instruments enrollment and field of study choices, while residual variation in late graduation captures within-type shocks that shift mismatch at entry.

4 Results

In this section, we present the main results of the paper. Section 4.1 reports aggregate wage returns to higher education by propensity to enroll and skill mismatch status. Section 4.2 then examines average and heterogeneous returns between and within fields of study. Finally, Section 4.3 and Section 4.4 report results with respect to a potential mechanism and a set of robustness checks.

4.1 Heterogeneous returns to higher education

We begin by documenting heterogeneity in returns along the enrollment margin. In Belgium, this margin is policy-relevant: around 70% of individuals enroll in higher education after completing secondary school (Declercq and Verboven, 2018). Given the absence of selective entrance examinations for most programs, enrollment choices are largely unrestricted. This makes the enrollment margin particularly relevant for policy: if low realized returns and high mismatch rates were concentrated among marginal enrollees, restricting access could, in principle, improve educational and labor market outcomes for these individuals.

We define the individual's propensity to enroll in tertiary education as

$$p_i = \Pr(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i) = \sum_j^J \Pr(C_{i1} = j \mid S^c_{i1}, \theta_i),$$

where higher values of p_i indicate a greater likelihood of enrollment. This scalar index summarizes selection on the extensive margin into higher education, driven by observed exogenous characteristics, pre-tertiary educational choices and outcomes, and latent type.[28]

We compute the difference in log-hourly wages under enrollment and non-enrollment as a function of p:

$$\text{TE}(p) = \mathbb{E}\left[Y_1 - Y_0 \,\middle|\, \Pr(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i) = p\right],$$

where Y_1 and Y_0 denote potential wage outcomes under enrollment and non-enrollment in the first period, respectively.[29] These potential outcomes are recovered by simulating full educational and labor market trajectories under each counterfactual regime.[30] We also compute the same objects conditional on degree completion, by removing the contribution of dropout risk and switching costs.

[28] Here, $C_{i1} = 0$ denotes the outside option (non-enrollment) at $t = 1$, while $C_{i1} \neq 0$ denotes enrollment in tertiary education.

[29] The estimated returns to enrollment capture the entire subsequent educational path, including program choice, switching, academic failure, dropout, degree completion, and post-graduation labor market outcomes. They should therefore be interpreted as total returns to enrollment, reflecting both direct effects and indirect effects operating through educational progression and occupational sorting.

[30] To construct the counterfactual Y_1, we simulate first-period choice probabilities over $C_{i1} = j$. If the predicted choice is $j = 0$ (non-enrollment), we instead assign the second-most preferred alternative and simulate the full subsequent education path, including progression, grades, and degree completion. This yields a simulated Y_1, which we compare to $Y_0 = Y(C_{i1} = 0)$. In the wage equations, potential experience is treated as an endogenous state variable. In the counterfactual simulations, I replace this state with the experience implied by the simulated education path: for the higher-education counterfactual, individuals are assigned 0, 3, and 6 years of potential experience at ages 23, 26, and 29, respectively; for the non-enrollment counterfactual, they are assigned 5, 8, and 11 years. Thus, the estimated return to enrollment incorporates the foregone labor-market experience generated by delayed entry into work, rather than holding experience fixed across counterfactual regimes.

Figure 2 organizes the TE estimates by outcome and estimand. The first column reports results with respect to higher education enrollment, while the second column with respect to higher education completion. The first row reports average returns, the second row conditions returns on mismatch status in the first job, and the third row reports the estimated mismatch penalty. The top row shows that the TE curve for higher education enrollment is positive across the entire distribution, but substantially lower than the TE curve for completion. Within our early-career horizon, the potential benefits of enrollment are offset by delays in educational progression and, as a consequence, by later entry into the labor market. Even individuals with a high propensity to enroll, who are more likely to complete the first year and less likely to drop out, still have relatively low BA degree completion rates within 3 years (see Appendix Table A31) and accumulate less potential work experience by ages 23 to 29 (see Appendix Table A32). Although they also experience a reduction in skill mismatch rates, this gain is not large enough to compensate for the loss in labor market experience associated with delayed entry.

The TE curves are upward sloping, indicating selection on gains: individuals with a higher propensity to enroll obtain the largest returns to tertiary education, exceeding 10 log points for completion. This suggests that lower early-career wage returns to enrollment are mainly driven by delays and frictions during higher education rather than by low returns to degree completion per se. Once these frictions are removed through degree completion, the returns to tertiary education rise substantially across the distribution. Although completion is still associated with higher non-employment rates and lower potential work experience accumulation for some individuals, these costs are no longer large enough to offset the benefits of obtaining the degree (see Appendix Table A32).[31]

We next extend the analysis by conditioning on skill mismatch status in the first job. Let $d \in \{0,1\}$ denote mismatch status, and let $Y_1(d)$ denote the potential wage outcome under a mismatch regime d. We then estimate

$$\mathrm{TE}(d,p) = \mathbb{E}\left[Y_1(d) - Y_0 \,\middle|\, \Pr(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i) = p\right].$$

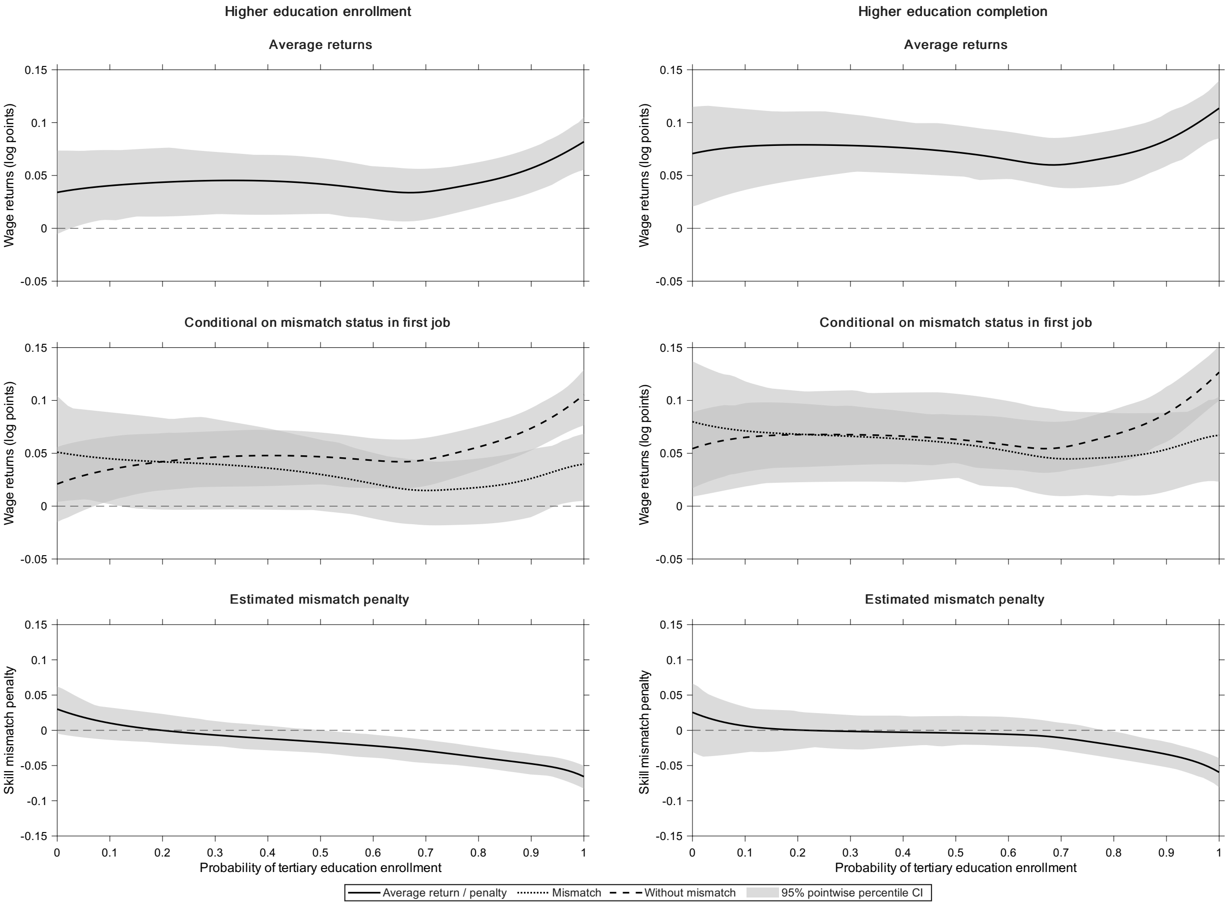
The second row of Figure 2 reports these curves separately for matched and mismatched first-job outcomes, while the third row plots the implied mismatch penalty.[32]

This analysis yields three important findings, with each being robust across alternative mismatch measures (see, for instance, Figure 8). First, the no-mismatch TE curve lies above the

[31] In Appendix Table A33, we report the different composition at each propensity score bin based on observed and unobserved characteristics.

[32] Thus, the treatment effects share the same simulated non-enrollment benchmark and differ only in the mismatch status imposed under enrollment.

Figure 2: Treatment Effect (TE) curves and mismatch penalties for tertiary education enrollment and completion



NOTE.– The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, computed from the higher education choice model as $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$. Higher values therefore indicate higher enrollment likelihood. Columns distinguish higher education enrollment and higher education completion. Rows report, respectively, average wage returns, wage returns by first-job mismatch status, and the estimated mismatch penalty. In the second row, "mismatch" and "without mismatch" refer to counterfactual first-job mismatch regimes. In the third row, the mismatch penalty is defined as the return under mismatch minus the return without mismatch, so negative values indicate wage losses from entering a mismatched job. To construct the enrolled counterfactual outcome, if the simulated first-period choice is non-enrollment we assign the second-highest alternative and simulate the full subsequent education path, including field, progression, grades, and completion, yielding Y_1; this is compared with the non-enrollment counterfactual Y_0. The completion column conditions on degree completion, removing uncertainty about dropout and subsequent educational progression. TE curves are estimated by local-linear smoothing over a grid of $u \in [0,1]$, following `mtefe` (Andresen, 2018). Shaded bands are 95% pointwise percentile confidence intervals based on parameter draws from the asymptotic distribution.

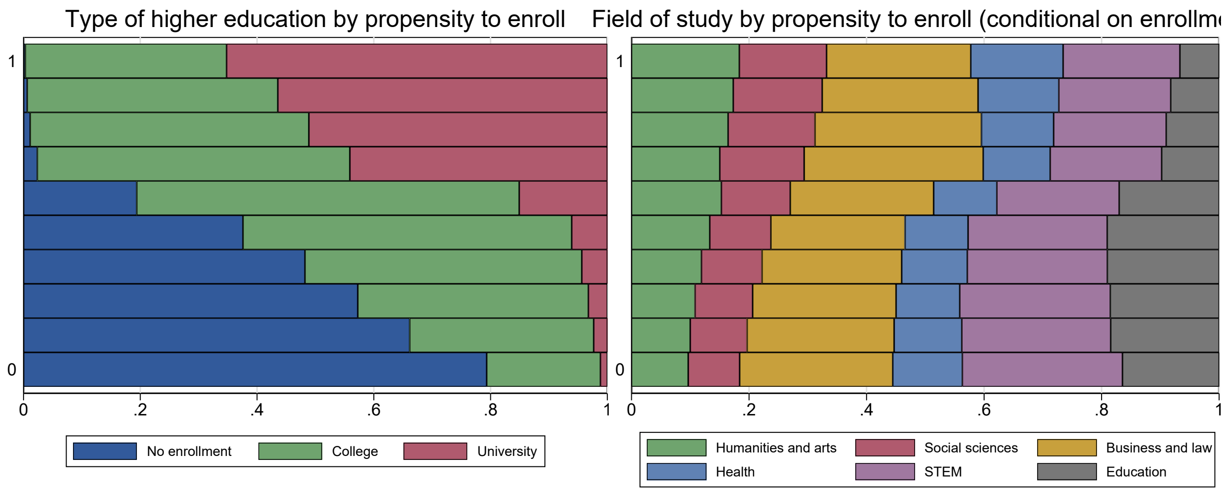
overall TE curve over most of the distribution of the enrollment propensity, both for enrollment and completion. For individuals with the highest likelihood of enrolling in tertiary education, the estimated return under no mismatch is close to 10 log points. More generally, most individuals benefit from tertiary education enrollment when they subsequently enter a well-matched job.

Second, for both enrollment and completion, the return to TE remains positive in the case of a skill mismatch in the first job, but it is statistically lower for individuals with the highest probability of self-selecting into higher education. For enrollment, this means that, among those who end up in a mismatched occupation, the wage advantage over high-school graduates is relatively small. The same is not true for completion: although the returns are lower for those with the highest probability of self-selection, they remain statistically and economically significant.

Third, the gap between the mismatch and no-mismatch return is largest for individuals with a high propensity to enroll. These individuals have the most to gain from tertiary education when they are well matched, whereas the return in case of a mismatch is substantially lower, around 5 log points. As the propensity to enroll decreases, the no-mismatch returns decline and become statistically indistinguishable from the returns in the case of mismatch.[33]

Taken together, these results indicate that early-career wage returns to tertiary education completion are generally positive in our simulations, while mismatch penalties are concentrated among high-propensity individuals: those who benefit the most from tertiary education when well matched also incur the largest wage losses when they enter mismatched jobs.[34]

Figure 3: Allocation to higher education programs by probability of tertiary education enrollment



NOTE.– The horizontal axis is the predicted probability of tertiary enrollment in period 1. The vertical axis reports the model-implied share allocated to each institution type or field of study. In the right panel, shares are conditional on tertiary enrollment.

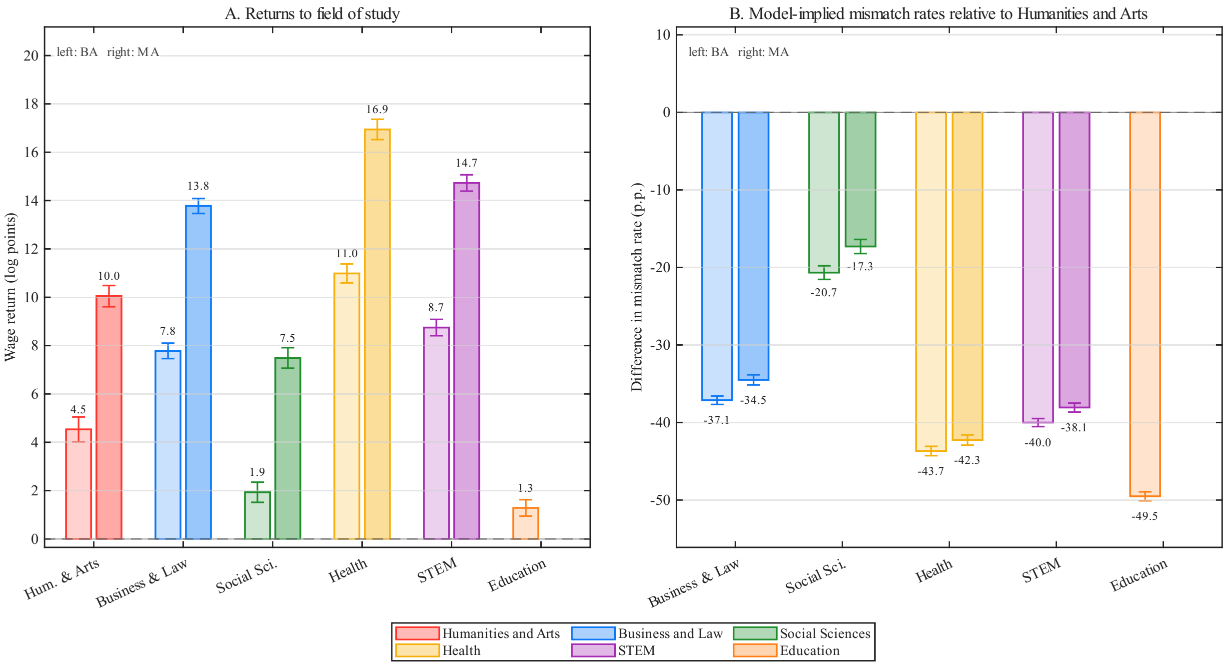
Figure 3 further reveals that individuals with the highest propensity to enroll are more likely

[33]Appendix Figure A4 further shows that, in most fields of study, high-propensity individuals face both larger mismatch penalties and larger returns, with Health as the main exception.

[34]To separate selection on gains from geographic proximity, Appendix Figure A15 reports an alternative version of the TE curves in which the horizontal axis is recomputed after fixing the program-distance vector at its sample mean.

to sort into Humanities and Arts and Social Sciences, fields that are often thought to be associated with low average returns. Our estimates point in the same direction. As shown in Figure 4 and Appendix Table A24, average returns to higher education completion are positive across all fields of study, but vary substantially. Degrees in Business and Law, STEM, and Health yield average wage gains above 5 log points, whereas Humanities and Arts and Social Sciences yield substantially lower returns.[35]

Figure 4: Benchmark Model: Field Returns and Field Mismatch



NOTE.– The figure reports benchmark-model estimates by field of study. Panel A shows mean wage returns to BA and MA attainment relative to high-school completion. Panel B shows aggregate field-level model-implied counterfactual mismatch-rate differences relative to Humanities and Arts under assignment to field j, following the mismatch-sorting construction used in the benchmark tables. Panel A reports log-wage points; Panel B reports percentage-point differences in mismatch rates. For fields offered in both vocational college and university tracks, estimates are weighted averages using simulated enrollment probabilities. Education has no MA/university counterpart in the Belgian higher-education system.

Counterfactual mismatch rates also differ systematically across fields. As shown in Figure 4 and Appendix Table A27, these rates compare the simulated probability of entering a mismatched first job under assignment to field j with the corresponding probability under Humanities and Arts. Relative to Humanities and Arts, Social Sciences has lower mismatch exposure, by about 21 percentage points for BA graduates and 17 percentage points for MA graduates, but remains

[35] Appendix Table A25 reports estimated field of study premia using Humanities and Arts as the reference category within each degree level. Health and STEM are the highest-paying fields by more than 3 log points.

higher than other fields. Business and Law, Health, STEM, and Education display much larger reductions in BA mismatch rates, of approximately 37, 44, 40, and 50 percentage points, respectively. Thus, individuals with the highest propensity to enroll are more likely to choose fields with lower average wage returns and relatively high model-implied mismatch exposure, especially Humanities and Arts and Social Sciences.

From a policy perspective, this suggests that restricting access to higher education is unlikely, by itself, to reduce mismatch rates or mismatch penalties. Moreover, in settings like ours, policies operating on the field-of-study margin may warrant at least as much attention as policies that tighten access to tertiary education as a whole.

4.2 Heterogeneous returns within fields of study

We now move beyond the enrollment margin and study heterogeneous returns within different fields of study. By combining the parametric structure of the higher education choice model with the selection equation for skill mismatch, and under our assumptions on unobserved heterogeneity, we recover the distribution of potential wages under alternative education and mismatch states (Carneiro et al., 2003; Aakvik et al., 2005; Abbring and Heckman, 2007; De Groote and Declercq, 2021).

This framework allows us to move beyond average treatment effects and characterize heterogeneity in returns to higher education within fields of study under strict assumptions. While some individuals may realize returns well above the average, others may experience low or even negative early-career returns. For these individuals, the model implies that entering the labor market directly after high school would have yielded higher wage realizations through age 29 than completing tertiary education in a given field.

Let $R_{ij}(d)$ denote the return to higher education for individual i in field of study j under mismatch status $d \in \{0,1\}$. Let $p_j \equiv \Pr(D_i = 1 \mid j)$ denote the field-specific absolute mismatch probability. We define the unconditional share of negative returns in field j as

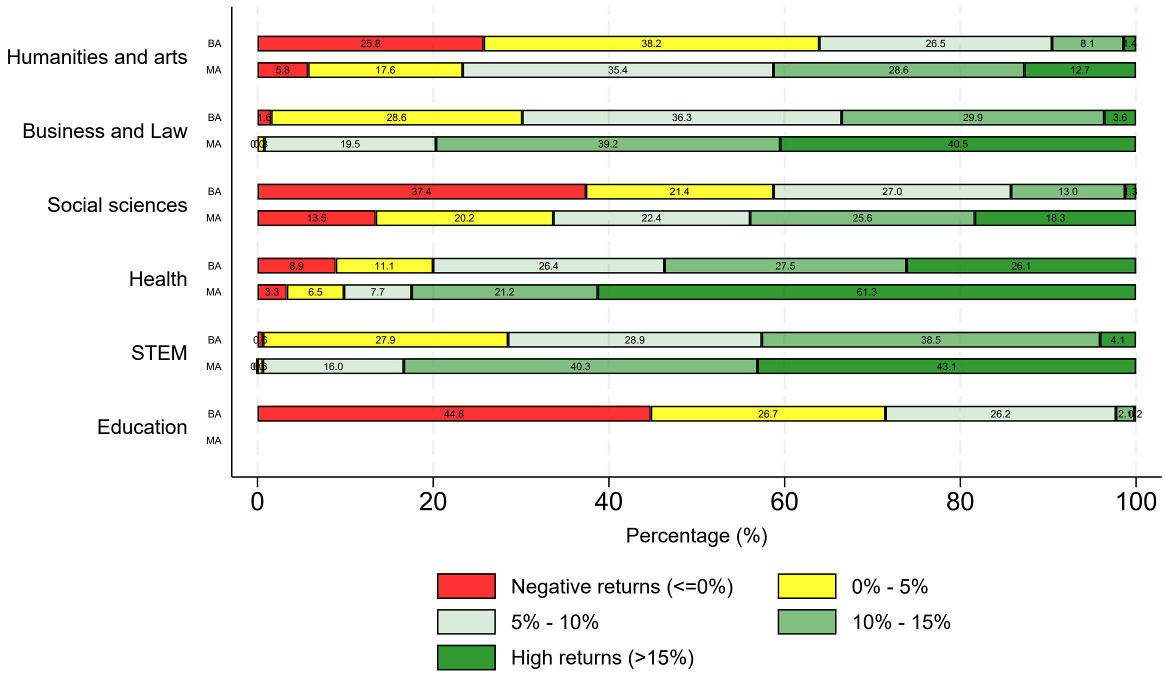
$$s_j^U = p_j \Pr\big(R_{ij}(1) \le 0 \mid j\big) + (1 - p_j) \Pr\big(R_{ij}(0) \le 0 \mid j\big),$$

which averages over the absolute mismatch distribution within the field; this p_j is not the relative mismatch-rate difference reported in Appendix Table A27. By contrast, the mismatch-specific counterfactual share of negative returns is

$$s_j(d) = \Pr\big(R_{ij}(d) \le 0 \mid j\big), \qquad d \in \{0,1\},$$

so that $s_j(0)$ corresponds to the no-mismatch scenario and $s_j(1)$ to the full-mismatch scenario.

Figure 5: Fraction of negative returns to higher education programs



NOTE.– BA and MA denote Bachelor's and Master's degrees. In Belgium there is no MA in Education. The figure reports individual returns to enrolling in and completing BA or MA programs in higher education program j. The fraction of individuals earning: (a) negative returns ($\leq 0\%$), (b) returns between 0 and 5%, (c) between 5 and 10%, (d) between 10 and 15% and, (e) high returns ($>15\%$). These are the results for the aggregate programs. We include the results separately for universities and college programs in Appendix Figure A1 and A2.

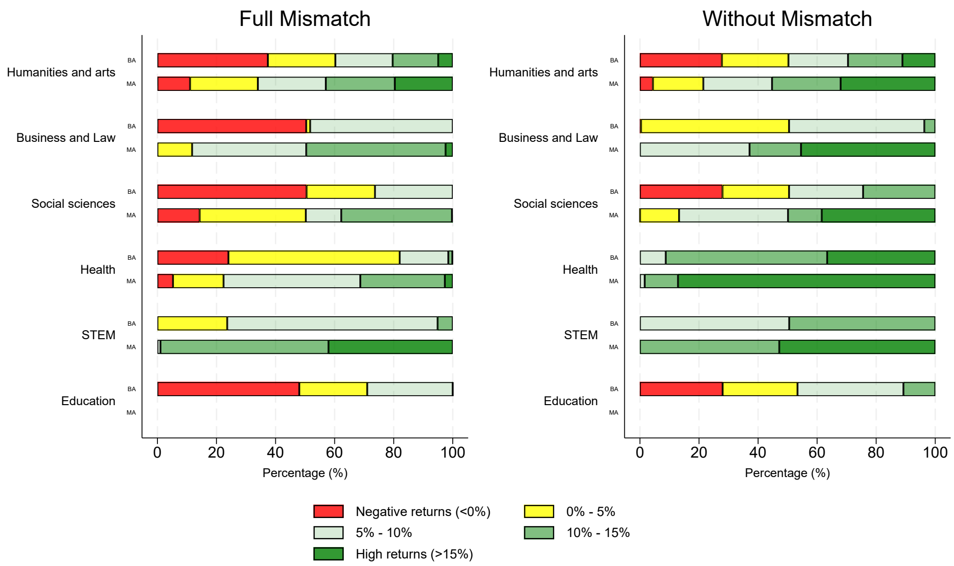
Figure 5 reports that a substantial fraction of individuals experience negative returns to higher education, consistent with previous evidence (see Rodríguez et al., 2016 for Chile).[36] At the BA level, Social Sciences and Education stand out, with more than 30% of individuals experiencing negative returns. Humanities and Arts also display high shares of negative returns at the BA level with 25.8%. By contrast, STEM and Health consistently show the lowest incidence of negative returns, often below 10%. At the MA level, the incidence of negative returns is generally lower across fields. Social Sciences remain the most affected by skill mismatch, with negative return

[36] Appendix Table A26 reports the share of individuals with negative returns by education level (BA vs. MA) and mismatch counterfactual. Average mismatch corresponds to the unconditional measure. Without mismatch and full mismatch, meanwhile, correspond to conditional measures computed under counterfactual states in which all individuals are, respectively, well matched or mismatched.

rates for 13.5% of all individuals. By contrast, we find no negative returns at the Master's level in STEM and Business and Law. This suggests that further educational investments are generally less risky in more applied and technical fields.

Differences in returns both between and within fields of study (i.e. variation in the incidence of low and negative returns) may arise from occupational sorting at labor market entry, as shown in Figure 2. If graduates enter occupations requiring a high school diploma, completing a BA or MA in field j yields only limited wage gains. At the same time, tertiary education entails opportunity costs through delayed labor-market entry and lower accumulated experience.

Figure 6: The role of skill mismatch



NOTE.– BA and MA denote Bachelor's and Master's degrees. In Belgium, an MA Degree in Education does not exist. The figure includes the individual return to enrolling and obtaining a BA or an MA in higher education program j. These are the results for the aggregate programs.

Figure 6 complements Figure 5 by moving from unconditional to conditional returns, and reports the corresponding conditional shares under counterfactual mismatch states. Across most fields of study, the conditional incidence of negative or very low returns is much higher under full mismatch than under well-matched employment, showing that low returns may be largely driven by occupational sorting at entry. Conversely, when mismatch is ruled out, the conditional share of negative returns declines substantially in several fields, although it remains high for BA Social Sciences and changes little for Education. Taken together, the two figures show that the unconditional distribution of returns reflects both the mismatch penalty itself and the field-specific probability of entering a mismatched occupation at labor market entry. Under full mismatch, the conditional share of BA graduates with negative returns rises to nearly one half in Social Sciences, Health, and Education.

Appendix Table A28 quantifies these patterns by reporting conditional average returns by field and degree under well-matched employment and under full mismatch. Under full mismatch, conditional average returns to a BA are close to zero in most fields, with the exception of Business and Law, Health, and STEM. Conditional average returns to an MA remain positive, but are substantially lower under mismatch. The implied mismatch penalty—defined as the difference between conditional returns in matched and mismatched employment—ranges, for BA (MA) degrees, from -9.0 log points (-10.3 log points) in Health to -1.6 log points (-2.9 log points) in Business and Law. Overall, the table shows that skill mismatch largely eliminates the average payoff to a BA in most fields, whereas MA degrees still yield positive conditional returns, albeit at substantially lower levels under mismatch.[37]

Appendix Tables A34, A35, A36, and A37 further report average returns and mismatch penalties separately by unobserved type, documenting substantial heterogeneity in the payoff to higher education across latent groups.

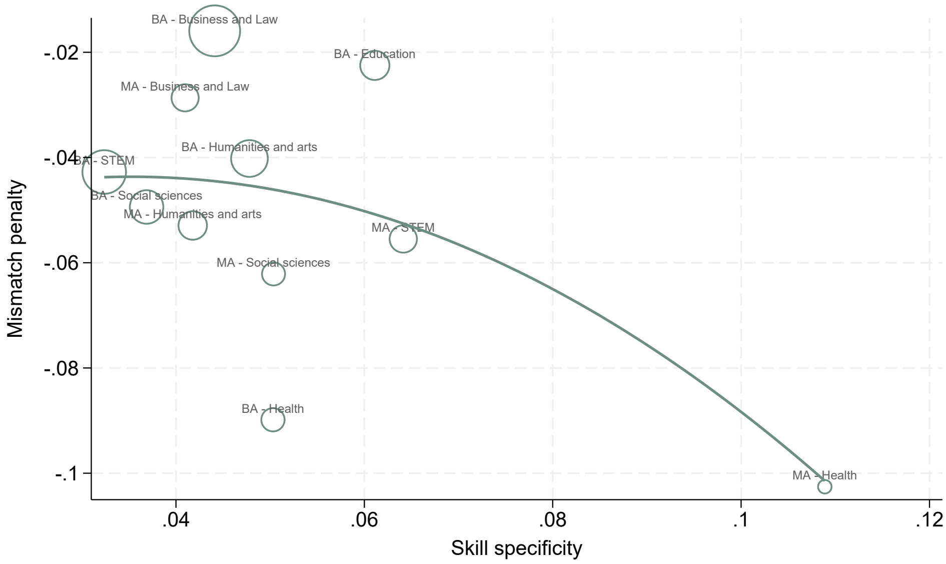
4.3 Mechanism: skill specificity

We next present suggestive evidence linking mismatch penalties to the degree of skill specificity embodied in the human capital accumulated during higher education (Kinsler and Pavan, 2015; Eckardt, 2026). Highly specialized programs (e.g. Health) may generate high average returns and lower mismatch incidence, but also imply larger wage losses when graduates are employed outside their domain. In contrast, broader programs (e.g. Social Sciences) may be associated with higher mismatch rates and lower average returns, yet smaller mismatch penalties due to greater skill transferability across occupations.

To examine this mechanism, we proxy skill specificity by the concentration of a program in occupations conditional on being well-matched. Figure 7 documents a negative correlation between the mismatch penalty and this HHI-based measure of specificity across fields of study (see Appendix Figure A3 for alternative ISCO-08 aggregation levels). This pattern is consistent with the interpretation that mismatch is more costly in programs whose matched graduates are

[37] When distinguishing by type of institution, mismatch penalties tend to be larger for college degrees in Health and Humanities and Arts, and larger for university degrees in Social Sciences and STEM (see Appendix Tables A29 and A30). More generally, advanced degrees (MA) yield higher returns than bachelor's degrees (BA) in matched employment, but this advantage narrows substantially, and may disappear, under skill mismatch. Additional heterogeneity in treatment effects, including differences by unobserved type, is discussed in Appendix Section C.

Figure 7: Mismatch penalty and skill specificity (3-digit ISCO-08)



NOTE.– Skill specificity is measured by the concentration of occupations among matched graduates. Each point is a field of study × degree (BA/MA), aggregating over college and university programs. The horizontal axis reports a Herfindahl–Hirschman Index (HHI) computed over the distribution of 3-digit ISCO-08 occupations among matched graduates: $\text{HHI}_{gd} = \sum_o s_{ogd}^2$, where s_{ogd} is the share of matched graduates in occupation o within field g and degree d. The vertical axis reports the estimated mismatch penalty for the same group. Marker size is proportional to the number of matched graduates in the group. The solid curve is a quadratic fit. Appendix Figure A3 reports the same relationship using alternative ISCO-08 aggregation levels.

concentrated in a relatively narrow set of occupations, as would be expected when field-specific skills are less transferable. While purely descriptive, this evidence supports the hypothesis that greater specialization amplifies the wage cost of entering a mismatched job.

4.4 Robustness checks

We assess the robustness of the main results along two dimensions: the inclusion of unobserved heterogeneity and the definition of skill mismatch. Additional robustness results are discussed in Appendix Section D.

Selection on observables and unobservables Appendix Tables A38 and A39 compare estimates from a linear wage regression with those from the model. Overall, accounting for selection on unobservables matters for both the estimated returns to field of study and the estimated skill mismatch penalty.

First, estimated returns to completed fields of study are generally lower in the full model than in a standard linear regression. This suggests that standard Mincerian wage regressions overstate returns because they do not account for selection on unobserved characteristics. For example, the estimated return to a BA degree in Humanities and Arts falls from 11.1 log points in OLS to 4.5 log points in the full model, indicating that part of the wage premium captured by standard regressions reflects positive selection.

Second, the estimated mismatch penalty also changes once unobserved heterogeneity is taken into account, but the adjustment is not uniform across fields. Table A39 shows that adding observed controls to the standard regression changes the estimates only partially, whereas the full model produces larger changes. In some fields, the mismatch penalty becomes more negative in the full model — such as programs in BA Social Sciences, BA Health, and MA Health — while in others it becomes less negative, as in Business and Law, Education, and most MA fields. These patterns indicate that selection on unobservables affects not only average returns to education, but also the estimated wage losses associated with entering a mismatched occupation.

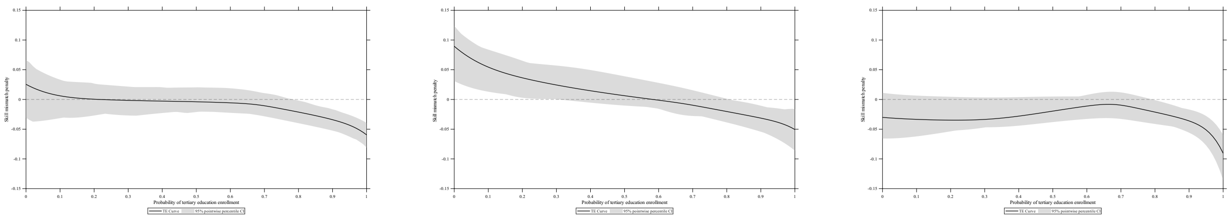
Heterogeneous returns to higher education and skill mismatch Appendix Figures A13 and A14 replicate the results on heterogeneous returns to higher education enrollment and completion using alternative measures of skill mismatch, including heterogeneous mismatch penalties. The DSA- and JA-based measures preserve the broad qualitative pattern, although the level of the penalty varies across single-indicator definitions. Figure 8 reports the TE curve for the skill mismatch penalty in the baseline model and compares it with the corresponding curves obtained using the JA and DSA measures. Across all specifications, individuals with a higher propensity to self-select into higher education experience larger wage losses from entering a mismatched occupation.

As a robustness check, Appendix Figure A16 reconstructs potential experience from the simulated education path of each individual and parameter draw, so that early dropouts enter the labor market earlier and delayed BA/MA paths enter later. The resulting TE curves provide a check that the estimated enrollment and completion patterns are not mechanically driven by a fixed experience assignment.

Heterogeneous returns to field of study The estimated returns to fields of study from the benchmark model are also robust to alternative measures of skill mismatch, as shown in Appendix Table A40. Across all specifications, Social Sciences and Education continue to have the lowest estimated returns, regardless of the mismatch measure employed. By contrast, Master's

Figure 8: TE curve for skill mismatch penalty (completion)

(a) Baseline **(b)** DSA **(c)** JA



NOTE.– See Figures A13 and A14 for the robustness checks on enrollment TE curves. The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, computed from the higher education choice model as $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$. Higher values therefore indicate higher enrollment likelihood. To construct the enrolled counterfactual outcome, if the simulated first-period choice is non-enrollment we assign the second-highest alternative and simulate the full subsequent education path (field, progression, grades, completion), yielding Y_1; this is compared with the non-enrollment counterfactual Y_0. TE curves are estimated following the package `mtefe` by local-linear smoothing over a grid of $u \in [0,1]$ (Andresen, 2018). Shaded bands are 95% *pointwise percentile* confidence intervals: at each u, the 2.5th and 97.5th percentiles of the simulated TE, based on parameter draws from the asymptotic distribution. DSA = Direct Self-Assessment; JA = Job Analysis.

degrees in Health consistently yield the highest returns, with estimated effects around 17% in all models. Overall, the estimated field-specific returns are remarkably stable across alternative mismatch definitions.

The same conclusion applies to the mismatch penalty, with more variation across single-indicator definitions. Appendix Table A41 summarizes the comparison across all specifications. We continue to find economically meaningful and statistically significant mismatch penalties at both the BA and MA levels in the benchmark and K=2 specifications. The DSA specification is reported for vocational colleges only and the JA specification changes some field-degree estimates, including MA Business and Law and MA Health. Health programs display large mismatch penalties in the benchmark and DSA specifications, although the estimates become less precise and less stable when the model relies on a single mismatch indicator. Taken together, these results suggest that the latent-factor approach improves precision relative to single indicators by combining information across measures, while still leaving open the broader conceptual question of how best to define mismatch.[38]

Finally, the evidence on low and negative returns is also robust to alternative definitions of skill mismatch (see Appendix Table A42), but comparability is limited for DSA because those columns are vocational-college only. The broad concentration of negative returns in Social Sciences, Humanities and Arts, and Education remains visible across the benchmark, JA, and K=2 specifications, while DSA changes the ordering for some vocational-college fields, most notably

[38] Appendix Table A43 reports the robustness checks relative to skill mismatch sorting.

Business and Law. Although the exact magnitudes vary across measures, the central economic message remains the same: some fields are systematically more exposed to low or negative returns than others.

5 Conclusion

This paper starts from a broad question "was your degree worth it?" and studies how early-career wage returns vary with first-job sorting. While average returns to higher education are positive, our findings show that these averages mask substantial heterogeneity, much of which is shaped by occupational sorting at labor market entry.

By estimating a generalized Roy model that jointly accounts for selection on unobservables into fields of study, skill mismatch in the first job, and subsequent labor market outcomes, and by exploiting longitudinal Belgian data, we obtain three main findings. First, individuals with a high propensity to enroll in tertiary education obtain the largest returns, but only when they enter a well-matched occupation. When they instead start their careers in a mismatched job, they experience the largest mismatch penalty. By contrast, for individuals with a lower propensity to enroll, mismatch has no significant effects on potential wages.

Second, we find that a non-negligible fraction of graduates, especially in Social Sciences, Humanities, and Arts, experience negative early-career realized wage returns. These negative returns decline sharply when graduates are well-matched at labor market entry in several fields, although the decline is limited for Education and negative returns remain substantial for BA Social Sciences. This finding suggests that realized wage returns depend not only on the field of study and underlying human capital, but also on how graduates are allocated to occupations at the start of their careers.

Third, mismatch penalties are economically meaningful and vary substantially across programs. Some degrees, such as Health, both reduce the probability of mismatch and entail sizeable losses when mismatch occurs, whereas other programs are characterized by higher mismatch risk and more moderate penalties. More generally, mismatch reduces realized wage returns most strongly for those with the highest potential gains from higher education, thereby amplifying the private costs associated with low-quality initial occupational matches.

These findings carry important policy implications for open-access systems like the one we study. The value of higher education participation depends not only on obtaining a degree but also on how graduates are allocated across occupations, particularly at labor market entry. Policies that improve the school-to-work transition, through career guidance, better information on occupational prospects, structured internships, or stronger links between degree programs and labor market demand, may therefore generate substantial benefits. Moreover, policies that influence field-of-study choices, even among individuals who are highly likely to enroll in higher education, may be just as important in shaping subsequent match quality and labor market outcomes. Our findings therefore point to the school-to-work transition and the field-of-study margin as important policy levers, deserving at least as much attention as policies focused solely on regulating access to tertiary education or on average returns to educational attainment.

References

AAKVIK, A., J. J. HECKMAN, AND E. J. VYTLACIL (2005): "Estimating treatment effects for discrete outcomes when responses to treatment vary: an application to Norwegian vocational rehabilitation programs," *Journal of Econometrics*, 125(1), 15–51.

ABBRING, J. H., AND J. J. HECKMAN (2007): "Chapter 72 Econometric Evaluation of Social Programs, Part III: Distributional Treatment Effects, Dynamic Treatment Effects, Dynamic Discrete Choice, and General Equilibrium Policy Evaluation," in *Handbook of Econometrics*, ed. by J. J. Heckman, and E. E. Leamer, vol. 6 of *Handbook of Econometrics*, pp. 5145–5303. Elsevier.

ADDA, J., AND C. DUSTMANN (2023): "Sources of Wage Growth," *Journal of Political Economy*, 131(2), 456–503.

AGOPSOWICZ, A., C. ROBINSON, R. STINEBRICKNER, AND T. STINEBRICKNER (2020): "Careers and Mismatch for College Graduates: College and Noncollege Jobs," *The Journal of Human Resources*, 55(4), pp. 1194–1221.

ALTONJI, J., P. ARCIDIACONO, AND A. MAUREL (2016): "Chapter 7 - The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects," vol. 5 of *Handbook of the Economics of Education*, pp. 305–396. Elsevier.

ANDRESEN, M. E. (2018): "Exploring Marginal Treatment Effects: Flexible Estimation Using Stata," *The Stata Journal*, 18(1), 118–158.

ANDREWS, R. J., S. A. IMBERMAN, M. F. LOVENHEIM, AND K. STANGE (2024): "The Returns to College Major Choice: Average and Distributional Effects, Career Trajectories, and Earnings Variability," *The Review of Economics and Statistics*, pp. 1–45.

ANDREWS, R. J., J. LI, AND M. F. LOVENHEIM (2016): "Quantile Treatment Effects of College Quality on Earnings," *Journal of Human Resources*, 51(1), 200–238.

ARCIDIACONO, P. (2004): "Ability Sorting and the Returns to College Major," *Journal of Econometrics*, 121, 343–375.

ARCIDIACONO, P., E. AUCEJO, A. MAUREL, AND T. RANSOM (2025): "College Attrition and the Dynamics of Information Revelation," *Journal of Political Economy*, 133(1), 53–110.

ARCIDIACONO, P., V. J. HOTZ, A. MAUREL, AND T. ROMANO (2020): "Ex Ante Returns and Occupational Choice," *Journal of Political Economy*, 128(12), 4475–4522.

ARCIDIACONO, P., AND J. B. JONES (2003): "Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm," *Econometrica*, 71, 933–946.

BAERT, S., B. COCKX, AND D. VERHAEST (2013): "Overeducation at the Start of the Career: Stepping Stone or Trap?," *Labour Economics*, 25, 123–140.

BEFFY, M., D. FOUGERE, AND A. MAUREL (2012): "Choosing the Field of Study in Postsecondary Education: Do Expected Earnings Matter?," *The Review of Economics and Statistics*, 94(1), 334–347.

BLEEMER, Z., AND A. MEHTA (2022): "Will Studying Economics Make You Rich? A Regression Discontinuity Analysis of the Returns to College Major," *American Economic Journal: Applied Economics*, 14(2), 1–22.

BORGEN, N. T., AND D. REIMER (2025): "Field of Study Choice and Labor Market Outcomes," in *Handbook of Education and Work*, ed. by M. H. J. Wolbers, and D. Verhaest, chap. 4, pp. 52–74. Edward Elgar Publishing, Cheltenham, UK.

BRACCIOLI, F., P. GHINETTI, S. MORICONI, C. NAGUIB, AND M. PELLIZZARI (2023): "Education Expansion, College Choice and Labour Market Success," CEPR Discussion Paper 18712, CEPR Press, Paris & London.

CAMERON, S. V., AND J. J. HECKMAN (1998): "Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males," *Journal of Political Economy*, 106, 262–333.

——— (2001): "The Dynamics of Educational Attainment for Black, Hispanic, and White Males," *Journal of Political Economy*, 109, 455–499.

CARD, D. (1995): "Using Geographic Variation in College Proximity to Estimate the Return to Schooling," in *Aspects of Labour Market Behaviour: Essays in Honour of John Vanderkamp*, ed. by L. N. Christofides, E. K. Grant, and R. Swidinsky, pp. 201–222. University of Toronto Press, Toronto.

CARNEIRO, P., K. T. HANSEN, AND J. J. HECKMAN (2003): "2001 Lawrence R. Klein Lecture: Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice," *International Economic Review*, 44(2), 361–422.

CHEVALIER, A. (2011): "Subject Choice and Earnings of UK Graduates," *Economics of Education Review*, 30, 1187–1201.

——— (2017): "To Be or Not to Be a Scientist?," in *Skill Mismatch in Labor Markets*, vol. 45, pp. 1–39. Emerald Group Publishing Limited.

De Groote, O. (2025): “Dynamic Effort Choice in High School: Costs and Benefits of an Academic Track,” *Journal of Labor Economics*, 43(2), 467–502.

De Groote, O., and K. Declercq (2021): “Tracking and Specialization of High Schools: Heterogeneous Effects of School Choice,” *Journal of Applied Econometrics*, 36(7), 898–916.

Declercq, K., and F. Verboven (2018): “Enrollment and degree completion in higher education without admission standards,” *Economics of Education Review*, 66(C), 223–244.

Du Caju, P., C. Fuss, and L. Wintr (2012): “Downward Wage Rigidity for Different Workers and Firms,” *Brussels Economic Review*, 55(1), 5–32.

Eckardt, D. (2026): “Training Specificity and Occupational Mobility: Evidence From German Apprenticeships,” *Econometrica*, 94(3), 741–766.

Fuss, C. (2009): “What is the Most Flexible Component of Wage Bill Adjustment? Evidence from Belgium,” *Labour Economics*, 16(3), 320–329.

Hastings, J. S., C. A. Neilson, and S. D. Zimmerman (2013): “Are Some Degrees Worth More than Others? Evidence from college admission cutoffs in Chile,” NBER Working Papers 19241, National Bureau of Economic Research.

Heckman, J., and S. Navarro (2007): “Dynamic Discrete Choice and Dynamic Treatment Effects,” *Journal of Econometrics*, 136, 341–396.

Heckman, J., and B. Singer (1984): “A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data,” *Econometrica*, 52(2), 271–320.

Heckman, J. J., J. E. Humphries, and G. Veramendi (2016): “Dynamic Treatment Effects,” *Journal of Econometrics*, 191(2), 276–292.

——— (2018): “Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking,” *The Journal of Political Economy*, 126, S197–S246.

Humphries, J. E., J. S. Joensen, and G. F. Veramendi (2025): “Complementarities in High School and College Investments,” SSRN Working Paper 4560152, Social Science Research Network, Version dated June 17, 2025.

Keane, M. P., and K. I. Wolpin (1997): “The Career Decisions of Young Men,” *Journal of Political Economy*, 105, 473–522.

KETEL, N., E. LEUVEN, H. OOSTERBEEK, AND B. VAN DER KLAAUW (2016): "The Returns to Medical School: Evidence from Admission Lotteries," *American Economic Journal: Applied Economics*, 8(2), 225–54.

KINSLER, J., AND R. PAVAN (2015): "The Specificity of General Human Capital: Evidence from College Major Choice," *Journal of Labor Economics*, 33, 933–972.

KIRKEBØEN, L., E. LEUVEN, AND M. MOGSTAD (2016): "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics*, 131, 1057–1111.

LEIGHTON, M., AND J. SPEER (2023): "Rich Grad, Poor Grad: Family Background and College Major Choice," IZA Discussion Paper 16099, IZA Institute of Labor Economics, Last revised: May 7, 2025.

LEMIEUX, T. (2014): "Occupations, Fields of Study and Returns to Education," *Canadian Journal of Economics/Revue canadienne d'économique*, 47, 1047–1077.

LEUVEN, E., AND H. OOSTERBEEK (2011): "Overeducation and Mismatch in the Labor Market," IZA Discussion Papers 5523, Institute of Labor Economics (IZA).

MOUNTJOY, J. (2022): "Community Colleges and Upward Mobility," *American Economic Review*, 112(8), 2580–2630.

——— (2026): "Marginal Returns to Public Universities*," *The Quarterly Journal of Economics*, 141(1), 429–497.

NAVARINI, L., AND D. VERHAEST (2024): "Returns to Education and Overeducation Risk: A Dynamic Model," Discussion Paper Series 24.08, KU Leuven, Faculty of Economics and Business.

NEYT, B., D. VERHAEST, L. NAVARINI, AND S. BAERT (2022): "The Impact of Internship Experience on Schooling and Labour Market Outcomes," *CESifo Economic Studies*, 68, 127–154.

NORDIN, M., I. PERSSON, AND D.-O. ROOTH (2010): "Education-occupation mismatch: Is there an income penalty?," *Economics of Education Review*, 29(6), 1047–1059.

NYBOM, M. (2017): "The Distribution of Lifetime Earnings Returns to College," *Journal of Labor Economics*, 35(4), 903–952.

OECD (2026): "Population with Tertiary Education," OECD Data indicator, Accessed: 16 June 2026.

OREOPOULOS, P., AND U. PETRONIJEVIC (2013): "Making College Worth It: A Review of Research on the Returns to Higher Education," NBER Working Papers 19053, National Bureau of Economic Research, Inc.

OREOPOULOS, P., T. VON WACHTER, AND A. HEISZ (2012): "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 4(1), 1–29.

PATNAIK, A., M. J. WISWALL, AND B. ZAFAR (2020): "College Majors," NBER Working Papers 27645, National Bureau of Economic Research.

ROBST, J. (2007): "Education and Job Match: The Relatedness of College Major and Work," *Economics of Education Review*, 26(4), 397–407.

RODRÍGUEZ, J., S. URZÚA, AND L. REYES (2016): "Heterogeneous Economic Returns to Post-Secondary Degrees: Evidence from Chile," *Journal of Human Resources*, 51, 416–460.

ROY, A. D. (1951): "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 3(2), 135–146.

STINEBRICKNER, T. R., AND R. STINEBRICKNER (2012): "Learning about academic ability and the college dropout decision," *Journal of Labor Economics*, 30(4), 707–748.

VERHAEST, D., S. SELLAMI, AND R. VAN DER VELDEN (2017): "Differences in horizontal and vertical mismatches across countries and fields of study," *International Labour Review*, 156(1), 1–23.

WALTERS, C. R. (2018): "The Demand for Effective Charter Schools," *Journal of Political Economy*, 126(6), 2179–2223.

WEBBER, D. A. (2016): "Are college costs worth it? How ability, major, and debt affect the returns to schooling," *Economics of Education Review*, 53, 296–310.

WISWALL, M., AND B. ZAFAR (2014): "Determinants of College Major Choice: Identification using an Information Experiment," *The Review of Economic Studies*, 82(2), 791–824.

A Data and model

A.1 Higher education in Belgium

Table A1: Descriptive statistics: individuals who fail the first year

1st year program	Drop	Switch	Stay	Total
Humanities and Arts (Col)	45.6	34.0	20.4	100.0
Humanities and Arts (Univ)	33.6	36.9	29.5	100.0
Business and Law (Col)	60.9	9.9	29.2	100.0
Business and Law (Univ)	31.2	44.5	24.3	100.0
Social sciences (Col)	55.3	17.4	27.3	100.0
Social sciences (Univ)	27.9	51.9	20.1	100.0
Health(Col)	51.8	18.1	30.2	100.0
Health(Univ)	22.9	56.0	21.1	100.0
STEM(Col)	57.3	10.9	31.8	100.0
STEM(Univ)	23.9	46.9	29.1	100.0
Education	59.6	15.6	24.8	100.0
Total	47.0	26.0	27.0	100.0

NOTE.– The fields of study are the following: Humanities and arts (HUMA), Business and Law (BULA), Social sciences (SSOC), Health and biomedical sciences (HEA), Science, technology, engineering and mathematics (STEM), Education (EDU). (Univ) stands for academic degree in university, (Col) stands for non-academic track at vocationally oriented colleges.

Table A2: Descriptive statistics: individuals who pass the first year

1st year program	Drop	Switch	Stay	Total
HUMA(Col)	18.0	6.3	75.7	100.0
HUMA(Univ)	4.4	1.5	94.1	100.0
BULA(Col)	9.0	2.2	88.8	100.0
BULA(Univ)	9.6	2.8	87.6	100.0
SSOC(Col)	11.8	5.6	82.6	100.0
SSOC(Univ)	9.6	3.8	86.6	100.0
HEA(Col)	7.6	5.0	87.4	100.0
HEA(Univ)	19.4	2.9	77.7	100.0
STEM(Col)	7.0	2.0	91.0	100.0
STEM(Univ)	5.5	1.0	93.5	100.0
EDU	9.1	2.4	88.4	100.0
Total	9.5	3.1	87.4	100.0

NOTE.– The fields of study are the following: Humanities and arts (HUMA), Business and Law (BULA), Social sciences (SSOC), Health and biomedical sciences (HEA), Science, technology, engineering and mathematics (STEM), Education (EDU). (Univ) stands for academic degree in university, (Col) stands for non-academic track at vocationally oriented colleges. Columns include the information on: (i) Drop - if drop out and never attained a Bachelor's degree, (ii) Switch - attained a Bachelor's degree but in a different major, (iii) Stay - attained a Bachelor's degree in the same major.

Table A3: Descriptive statistics: reorientation and completion in higher education

Bachelor's Degree	HUMA(Col)	HUMA(Univ)	BULA(Col)	BULA(Univ)	SSOC(Col)	SSOC(Univ)	HEA(Col)	HEA(Univ)	STEM(Col)	STEM(Univ)	EDU	Total
No college	31.8	19.7	35.2	20.7	35.0	18.6	26.0	21.0	33.1	15.0	33.5	28.1
HUMA(Col)	48.1	2.1	0.0	0.6	0.3	0.6	0.2	0.8	0.6	1.2	0.3	4.2
HUMA(Univ)	0.0	60.2	0.0	0.2	1.0	0.0	0.2	0.0	0.0	0.5	0.3	3.4
BULA(Col)	10.4	6.3	58.7	15.6	2.0	9.0	2.5	4.4	1.9	2.4	1.1	14.2
BULA(Univ)	0.2	0.4	0.2	55.1	0.3	1.0	0.0	0.8	0.1	1.0	0.0	5.6
SSOC(Col)	1.7	1.4	0.7	2.7	53.3	7.7	1.0	1.6	0.2	0.0	3.6	4.7
SSOC(Univ)	0.2	0.7	0.6	0.8	1.6	53.7	0.0	0.8	0.1	1.2	0.2	3.6
HEA(Col)	1.0	1.1	0.7	0.8	1.6	1.9	63.5	8.5	1.1	0.7	1.6	7.0
HEA(Univ)	0.0	0.4	0.0	0.4	0.3	0.3	2.1	52.8	0.0	0.2	0.0	2.8
STEM(Col)	2.2	0.4	1.8	2.0	0.3	1.0	1.0	4.0	60.3	14.0	1.7	11.7
STEM(Univ)	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.5	60.4	0.0	4.8
EDU	4.1	7.4	2.2	1.2	4.2	6.1	3.4	4.4	2.0	3.4	57.7	9.8
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

NOTE.– The fields of study are the following: Humanities and arts (HUMA), Business and Law (BULA), Social sciences (SSOC), Health and biomedical sciences (HEA), Science, technology, engineering and mathematics (STEM), Education (EDU). (Univ) stands for academic degree in university, (Col) stands for non-academic track at vocationally oriented colleges. Columns include the information on: (i) Drop - if drop out and never attained a Bachelor's degree, (ii) Switch - attained a Bachelor's degree but in a different major, (iii) Stay - attained a Bachelor's degree in the same major.

Table A4: Second-sit graduation by field of study

	Mean	SD
Humanities and Arts	0.168	0.374
Business and Law	0.110	0.313
Social sciences	0.112	0.315
Health	0.057	0.232
STEM	0.075	0.263
Education	0.032	0.176
Total	0.090	0.286

NOTE.– This table reports descriptive statistics on second-sit (late) graduation by field of study. The reported moments are computed for the indicator of second-sit graduation (equal to one if the individual graduates in a second examination session and zero otherwise) within each field of study.

A.2 Skill mismatch, fields of study and occupations

Table A5: Descriptive statistics of field of study and mismatch rates

	Mean	SD	Min	Max
High school graduate	0.373	0.484	0.000	1.000
Humanities and Arts (Col)	0.581	0.494	0.000	1.000
Humanities and Arts (Univ)	0.478	0.501	0.000	1.000
Business and Law (Col)	0.465	0.499	0.000	1.000
Business and Law (Univ)	0.518	0.500	0.000	1.000
Social sciences (Col)	0.300	0.459	0.000	1.000
Social sciences (Univ)	0.650	0.478	0.000	1.000
Health(Col)	0.132	0.339	0.000	1.000
Health(Univ)	0.383	0.488	0.000	1.000
STEM(Col)	0.441	0.497	0.000	1.000
STEM(Univ)	0.423	0.495	0.000	1.000
Education	0.141	0.349	0.000	1.000
Total	0.381	0.486	0.000	1.000

NOTE.– The table reports descriptive statistics for the baseline skill-mismatch indicator by education group. Each row is computed within the corresponding group; because the variable is binary, the mean equals the mismatch rate. Field-of-study rows refer to tertiary graduates in the indicated field and institution type, where "Col" denotes vocational college and "Univ" denotes university. The high-school row refers to individuals whose highest completed degree is high school. The total row pools all groups.

Table A6: Comparison of horizontal mismatch measures

	JA				
	Complete mismatch	Somewhat match	Complete match	Missing	Total
DA					
Complete mismatch	1,765	221	394	90	2,470
Somewhat match	619	465	2,215	67	3,366
Complete match	557	274	716	45	1,592
Missing	26	4	31	673	734
Total	2,967	964	3,356	875	8,189

NOTE.– The table cross-tabulates the two categorical horizontal mismatch measures used in the analysis. JA denotes the job-analysis measure, based on the correspondence between the occupation and the field of study. DA denotes the direct-assessment measure, based on the respondent's self-assessed field match. Both measures classify jobs as complete mismatch, somewhat matched, or complete match. Missing values are shown in gray and are included in the row and column totals.

Table A7: Hourly wages by education group and skill mismatch

	Wage First Job	Wage Age 23	Wage Age 26	Wage Age 29
High-school graduate (Adequate match)	6.781	7.276	7.751	8.150
High-school graduate (Skill mismatch)	6.695	7.089	7.672	8.012
Humanities and Arts (Col) (Adequate match)	6.832	7.147	8.549	9.685
Humanities and Arts (Col) (Skill mismatch)	7.374	7.417	8.543	8.560
Humanities and Arts (Univ) (Adequate match)	8.384	8.442	8.595	9.512
Humanities and Arts (Univ) (Skill mismatch)	7.972	8.427	8.537	8.988
Business and Law (Col) (Adequate match)	7.204	7.381	8.310	8.530
Business and Law (Col) (Skill mismatch)	7.149	7.310	8.250	8.662
Business and Law (Univ) (Adequate match)	8.200	8.169	9.616	10.355
Business and Law (Univ) (Skill mismatch)	8.336	8.653	9.691	10.277
Social sciences (Col) (Adequate match)	7.322	7.413	7.738	8.199
Social sciences (Col) (Skill mismatch)	7.539	7.586	7.900	8.034
Social sciences (Univ) (Adequate match)	8.528	8.235	9.393	9.622
Social sciences (Univ) (Skill mismatch)	7.905	7.713	8.399	9.040
Health (Col) (Adequate match)	7.756	8.131	8.275	8.935
Health (Col) (Skill mismatch)	7.600	8.357	7.905	8.431
Health (Univ) (Adequate match)	9.338	9.341	9.936	9.968
Health (Univ) (Skill mismatch)	8.672	9.815	9.019	9.531
STEM (Col) (Adequate match)	7.883	8.068	8.619	9.680
STEM (Col) (Skill mismatch)	7.527	7.956	8.928	9.478
STEM (Univ) (Adequate match)	8.779	8.843	9.664	10.871
STEM (Univ) (Skill mismatch)	8.066	8.309	9.263	9.987
Education (Adequate match)	7.459	7.380	7.834	8.136
Education (Skill mismatch)	7.004	7.293	7.836	8.207
Total	7.130	7.354	8.126	8.563

NOTE.– The table reports mean hourly wages by completed education group and skill mismatch status. Field-of-study groups are based on the completed education; “Col” denotes vocational college and “Univ” denotes university. Skill mismatch is the baseline mismatch indicator, defined by the latent-factor threshold described in the text. Wage variables refer to the first job and to ages 23, 26, and 29. Zero wage entries are treated as missing. The total row pools all individuals with non-missing wages in the corresponding column.

Table A8: Skill mismatch rates by occupation

ISCO-08 Occupations	Vertical Mismatch	Horizontal Mismatch	Full Mismatch	HHI Index
Building Architects	0.136	0.068	0.000	0.421
Dentists	0.000	0.000	0.000	0.692
Optometrists and Ophthalmic Opticians	0.347	0.067	0.000	0.677
Special Needs Teachers	0.064	0.029	0.000	0.885
Lawyers	0.000	0.000	0.000	0.849
Nursing Associate Professionals	0.042	0.056	0.000	0.280
Accounting Associate Professionals	0.170	0.085	0.000	0.561
Nursing Professionals	0.037	0.025	0.006	0.641
Social Work and Counselling Professionals	0.208	0.110	0.013	0.503
Payroll Clerks	0.143	0.181	0.019	0.270
[...]				
Shop Sales Assistants	0.806	0.609	0.497	0.158
Waiters	0.782	0.683	0.542	0.151
Crane, hoist and related plant operators	0.680	0.900	0.620	0.147
Cashiers and Ticket Clerks	0.789	0.737	0.632	0.158
Hand Launderers and Pressers	0.828	0.776	0.672	0.137
Freight Handlers	0.798	0.854	0.692	0.141
Dairy Products Makers	0.818	0.849	0.698	0.141
Mail Carriers and Sorting Clerks	0.842	0.877	0.754	0.146
Hand Packers	0.841	0.885	0.758	0.141
Elementary Workers Not Elsewhere Classified	0.946	0.838	0.784	0.141

NOTE.– The table reports selected ISCO-08 occupations ranked by mismatch outcomes. Vertical mismatch, horizontal mismatch, and full mismatch are binary indicators; entries are occupation-level means and can therefore be interpreted as mismatch rates. In this descriptive occupation table only, full mismatch denotes simultaneous observed vertical and horizontal mismatch; the model's baseline mismatch treatment is the latent-factor threshold defined in the text. The HHI index measures the concentration of fields of study among workers in the occupation, with higher values indicating that the occupation draws from a narrower set of fields. The table reports occupations at the top and bottom of the distribution.

A.3 Model estimates

Table A9: Tertiary education choice model (full parameters)

	University programs					College programs					
	HUMA	BUL	SSOC	HEA	STEM	HUMA	BUL	SSOC	HEA	STEM	EDU
Female	0.401***	0.119	0.572***	0.845***	-0.424***	0.313***	0.340***	1.000***	1.281***	-1.212***	0.815***
	(0.092)	(0.076)	(0.090)	(0.104)	(0.088)	(0.080)	(0.060)	(0.088)	(0.087)	(0.073)	(0.070)
Foreign origin	-0.158	0.763***	0.199	0.497	-0.363	-0.221	0.533***	0.134	-0.026	0.051	-0.216
	(0.307)	(0.200)	(0.277)	(0.312)	(0.344)	(0.260)	(0.147)	(0.240)	(0.227)	(0.185)	(0.212)
Number of siblings	-0.015	-0.026	-0.022	-0.020	0.057	-0.031	-0.107***	0.004	-0.006	-0.020	0.011
	(0.039)	(0.032)	(0.037)	(0.043)	(0.037)	(0.033)	(0.025)	(0.032)	(0.031)	(0.026)	(0.026)
Father years of education	0.157***	0.146***	0.146***	0.223***	0.176***	0.156***	0.106***	0.094***	0.099***	0.117***	0.107***
	(0.015)	(0.012)	(0.014)	(0.017)	(0.014)	(0.013)	(0.010)	(0.014)	(0.013)	(0.011)	(0.011)
Mother years of education	0.100***	0.101***	0.124***	0.110***	0.101***	0.108***	0.060***	0.107***	0.076***	0.065***	0.104***
	(0.016)	(0.013)	(0.016)	(0.018)	(0.015)	(0.014)	(0.011)	(0.015)	(0.014)	(0.011)	(0.012)
Day of birth	0.109**	0.041	0.047	-0.026	0.103**	0.054	0.107***	0.046	0.005	0.049	0.047
	(0.047)	(0.038)	(0.045)	(0.050)	(0.043)	(0.040)	(0.030)	(0.041)	(0.040)	(0.031)	(0.034)
Cohort 1978	0.087	0.104	0.055	0.118	0.128	-0.001	0.047	-0.043	-0.289***	0.158**	-0.036
	(0.111)	(0.092)	(0.107)	(0.119)	(0.106)	(0.096)	(0.073)	(0.100)	(0.094)	(0.078)	(0.085)
Cohort 1980	-0.128	-0.111	-0.121	-0.117	0.060	-0.187*	-0.052	-0.114	-0.437***	0.130*	0.130
	(0.114)	(0.095)	(0.108)	(0.123)	(0.106)	(0.098)	(0.074)	(0.100)	(0.095)	(0.078)	(0.082)
Period 1						7.359***					
						(0.101)					
Period 2						6.880***					
						(0.096)					
Period 3						4.863***					
						(0.099)					
Period 4						3.014***					
						(0.101)					
Credits	10.462***										
	(0.323)										
Unemployment rate						-0.082***					
						(0.009)					
Delay in primary education	0.082	0.430	1.009**	0.974**	1.086**	0.585*	0.202	0.243	0.444	-1.155**	0.049
	(0.490)	(0.395)	(0.412)	(0.488)	(0.428)	(0.340)	(0.288)	(0.407)	(0.327)	(0.454)	(0.349)
Delay in secondary education	-0.896***	-1.586***	-1.590***	-1.981***	-1.831***	-0.889***	-0.983***	-1.244***	-0.710***	-1.034***	-1.197***
	(0.285)	(0.278)	(0.352)	(0.483)	(0.389)	(0.182)	(0.130)	(0.209)	(0.161)	(0.137)	(0.162)
Academic track in HS	5.394***	5.858***	5.532***	6.094***	6.013***	3.592***	3.568***	3.267***	3.189***	3.035***	3.123***
	(0.151)	(0.147)	(0.158)	(0.222)	(0.172)	(0.099)	(0.078)	(0.101)	(0.098)	(0.083)	(0.087)
HS grades - 4th Q	-1.064***	-0.789***	-1.238***	1.779*	-0.618**	-0.523**	-0.318	-0.373	-0.321	-0.515***	0.011
	(0.300)	(0.275)	(0.275)	(1.071)	(0.297)	(0.264)	(0.199)	(0.262)	(0.307)	(0.194)	(0.252)
HS grades - 3rd Q	-0.732***	-0.207	-0.848***	2.109**	-0.336	-0.309	-0.173	-0.384	-0.029	-0.345**	0.071
	(0.263)	(0.243)	(0.240)	(1.059)	(0.266)	(0.240)	(0.183)	(0.243)	(0.287)	(0.175)	(0.238)
HS grades - 2nd Q	0.204	0.629***	-0.178	3.050***	0.723***	0.107	-0.059	-0.440*	0.100	-0.145	0.221
	(0.258)	(0.241)	(0.237)	(1.057)	(0.261)	(0.239)	(0.184)	(0.245)	(0.287)	(0.175)	(0.238)
HUMA (a-1)		-3.344***	-3.555***	-4.507***	-3.896***		-3.344***	-3.555***	-4.507***	-3.896***	-3.339***
		(0.112)	(0.169)	(0.256)	(0.157)		(0.112)	(0.169)	(0.256)	(0.157)	(0.141)
BUL (a-1)	-4.104***		-3.220***	-4.322***	-4.027***	-4.104***		-3.220***	-4.322***	-4.027***	-3.731***
	(0.180)		(0.128)	(0.205)	(0.145)	(0.180)		(0.128)	(0.205)	(0.145)	(0.149)
SSOC (a-1)	-3.947***	-3.296***		-4.076***	-5.114***	-3.947***	-3.296***		-4.076***	-5.114***	-3.452***
	(0.194)	(0.112)		(0.208)	(0.295)	(0.194)	(0.112)		(0.208)	(0.295)	(0.150)
HEA (a-1)	-4.867***	-4.132***	-4.024***		-4.230***	-4.867***	-4.132***	-4.024***		-4.230***	-4.032***
	(0.283)	(0.151)	(0.197)		(0.184)	(0.283)	(0.151)	(0.197)		(0.184)	(0.183)
STEM (a-1)	-4.075***	-3.893***	-4.335***	-3.779***		-4.075***	-3.893***	-4.335***	-3.779***		-3.782***
	(0.184)	(0.129)	(0.225)	(0.172)		(0.184)	(0.129)	(0.225)	(0.172)		(0.161)
EDU (a-1)	-3.819***	-3.552***	-2.744***	-3.723***	-3.774***	-3.819***	-3.552***	-2.744***	-3.723***	-3.774***	
	(0.246)	(0.175)	(0.152)	(0.246)	(0.220)	(0.246)	(0.175)	(0.152)	(0.246)	(0.220)	
College program (a-1)	-3.317***										
	(0.079)										
University program (a-1)						-1.817***					
						(0.053)					
Distance to program j	-0.015***	-0.010**	-0.010*	-0.009	-0.010*	-0.018***	-0.013***	-0.001	0.000	-0.004	-0.001
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	-11.346***	-11.548***	-11.303***	-15.769***	-12.227***	-9.666***	-8.420***	-9.591***	-9.610***	-7.846***	-9.561***
	(0.360)	(0.333)	(0.345)	(1.104)	(0.371)	(0.317)	(0.251)	(0.321)	(0.353)	(0.249)	(0.301)
Type 2	-0.357***	-0.283***	-0.356***	-0.322***	-0.311***	-0.409***	-0.352***	-0.398***	-0.350***	-0.396***	-0.385***
	(0.113)	(0.096)	(0.108)	(0.120)	(0.106)	(0.108)	(0.086)	(0.114)	(0.113)	(0.094)	(0.097)
Type 3	-0.155	-0.093	-0.199	-0.123	-0.110	-0.176	-0.138	-0.216*	-0.139	-0.200**	-0.198*
	(0.130)	(0.110)	(0.126)	(0.140)	(0.122)	(0.119)	(0.093)	(0.125)	(0.122)	(0.101)	(0.105)

NOTE.- The tertiary education programs are the following: Humanities and Arts (HUMA), Business, Economics and Law (BUL), Social Sciences (SSOC), Health (HEA), Science, Technology, Engineering and Mathematics (STEM) and Education (EDU). HS denotes higher secondary education. HS grades reports the estimated coefficients relative to receiving a grade in the first quarter (highest grades). Distance always refers to alternative-specific distance to program j. Standard errors in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table A10: Exogenous variables parameters

	Female	Foreign	Number of siblings	Father education	Mother education	Day of birth	Cohort 1978	Cohort 1980
Results higher tertiary	0.333***	-0.571***	-0.023*	-0.005	0.017***	0.019	-0.080**	-0.177***
	(0.029)	(0.088)	(0.012)	(0.004)	(0.005)	(0.013)	(0.034)	(0.038)
Graduation (second sit)	-0.826***	1.151**	0.195***	-0.060***	0.014	0.065	0.836***	0.604***
	(0.154)	(0.449)	(0.063)	(0.023)	(0.025)	(0.071)	(0.191)	(0.185)
Skill mismatch	0.009	0.172	0.052**	-0.035**	0.007	0.005	-0.029	0.161**
	(0.079)	(0.155)	(0.023)	(0.014)	(0.015)	(0.030)	(0.076)	(0.078)
Potential experience (ages 23, 26, 29)	-0.027	-0.573***	-0.019**	-0.038***	-0.029***	-0.021**	0.117***	0.212***
	(0.020)	(0.052)	(0.008)	(0.003)	(0.003)	(0.009)	(0.024)	(0.024)
Unemployment (ages 23, 26, 29)	0.323***	0.418***	0.085***	0.009	-0.009	-0.048**	-0.289***	0.023
	(0.048)	(0.113)	(0.017)	(0.008)	(0.008)	(0.023)	(0.060)	(0.057)
Wage selection (ages 23, 26, 29)	-0.034	-0.237***	0.004	-0.010**	-0.014**	-0.005	-0.604***	-0.514***
	(0.032)	(0.084)	(0.012)	(0.005)	(0.005)	(0.015)	(0.038)	(0.038)
Log-hourly wage matched (ages 23, 26, 29)	-0.077***	0.026*	0.000	0.001	0.004***	-0.002	0.009	0.019***
	(0.007)	(0.015)	(0.002)	(0.001)	(0.001)	(0.002)	(0.006)	(0.006)
Log-hourly wage mismatched (ages 23, 26, 29)	-0.130***	0.001	-0.008***	0.001	-0.001	-0.004	0.000	0.020**
	(0.010)	(0.018)	(0.003)	(0.002)	(0.002)	(0.004)	(0.009)	(0.009)

NOTE.– The table reports estimated coefficients on observed exogenous individual characteristics in the model equations. Standard errors are in parentheses. Female, foreign origin, and cohort indicators are binary variables; number of siblings, parental education, and day of birth enter linearly. Rows that refer to ages 23, 26, and 29 pool the corresponding age-specific equations. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

A.4 Higher education model

Table A11: First stage estimates: distance and higher education program choice

	(1)	(2)	(3)	(4)	(5)	(6)
Humanities and Arts (Col)						
Distance to higher education program	-0.014***	-0.025***	-0.008***	-0.017***	-0.010***	-0.018***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)
Humanities and Arts (Univ)						
Distance to higher education program	-0.014***	-0.025***	-0.008***	-0.016***	-0.010***	-0.023***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Business and Law (Col)						
Distance to higher education program	-0.014***	-0.018***	-0.008***	-0.015***	-0.010***	-0.014***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Business and Law (Univ)						
Distance to higher education program	-0.014***	-0.021***	-0.008***	-0.011***	-0.010***	-0.012***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Social sciences (Col)						
Distance to higher education program	-0.014***	-0.002	-0.008***	0.002	-0.010***	-0.003
	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.004)
Social sciences (Univ)						
Distance to higher education program	-0.014***	-0.018***	-0.008***	-0.009**	-0.010***	-0.015***
	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.004)
Health (Col)						
Distance to higher education program	-0.014***	-0.003	-0.008***	-0.001	-0.010***	-0.006
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Health (Univ)						
Distance to higher education program	-0.014***	-0.028***	-0.008***	-0.014***	-0.010***	-0.019***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
STEM (Col)						
Distance to higher education program	-0.014***	-0.005*	-0.008***	-0.001	-0.010***	-0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)
STEM (Univ)						
Distance to higher education program	-0.014***	-0.022***	-0.008***	-0.011**	-0.010***	-0.015***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)
Education						
Distance to higher education program	-0.014***	-0.002	-0.008***	0.002	-0.010***	-0.001
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Exogenous variables	No	No	Yes	Yes	Yes	Yes
Province FE	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57204	57204	57204	57204	57087	57087

NOTE.– Exogenous variables include gender, foreign background, number of siblings, parental background, day of birth. Province FE includes fixed effects at the province level. Relative distance to closest tertiary education is measured in kilometers. Each higher education program is either (Col), vocational college, or (Univ), academic university. Education is a single program.

Table A12: Balance test on high-school grades

	(1)	(2)	(3)	(4)	(5)
Distance to higher education program	0.000	0.002	0.002	0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Local labor market controls		✓	✓	✓	✓
Urbanization index			✓	✓	✓
Province quality				✓	✓
Student characteristics					✓
Observations	7780	7780	7780	7780	7780
R^2	0.000	0.006	0.010	0.010	0.099

NOTE.– Higher secondary education grades are self-reported grades, which gives us information about the position of individuals relative to their peers in higher secondary education, expressed in quarters. Column 2 controls for each of the 22 arrondissement in Flanders (2-digit NIS code) and the arrondissement-specific non-employment rate at the age of 18. Column 3 adds controls for degree of urbanization of 4-digit NIS codes, developed by the European Commission (Flexurba package), and the share of urban and rural population. Column 4 adds the level of taxable income at the 4-digit NIS code as provided by STATBEL. Column 5 adds categorical controls for gender, foreign background, number of siblings, parental background, day of birth. Moreover, it includes education characteristics: delay in primary and secondary education, track choices in the 3rd and 5th year of secondary education, final diploma in secondary education.

A.5 Instruments

Table A13: Relative distance and labor market outcomes

	(1) Skill mismatch (first job)	(2) Log-hourly wage (age 23)	(3) Log-hourly wage (age 26)	(4) Log-hourly wage (age 29)
Distance to higher education program	-0.001	-0.002	-0.004	-0.009
	(0.002)	(0.003)	(0.006)	(0.005)
Observations	4393	4393	3384	3123
R^2	0.002	0.002	0.004	0.005

NOTE.– Each column reports a separate OLS regression of the indicated outcome on relative distance to the closest tertiary education program. All regressions include province fixed effects and cluster standard errors at the province level. The wage columns are estimated on the age-specific wage samples, while the first column uses the first-job mismatch sample. Relative distance is measured in kilometers.

Table A14: Regression of relative distance on individual characteristics

	(1)
Female	0.000
	(0.045)
Number of siblings	0.068
	(0.112)
Foreign origin	1.304
	(1.224)
Father years of education	0.017
	(0.043)
Mother years of education	0.034
	(0.038)
Day of birth	0.001
	(0.001)
Cohort 1978	-0.328
	(0.700)
Cohort 1980	-0.781
	(0.860)
Province FE	Yes
Observations	8159
R^2	0.668

NOTE.– The table reports an OLS regression of relative distance to the closest tertiary education program on predetermined individual characteristics and province fixed effects. Standard errors are clustered at the province level. Female, foreign origin, and cohort indicators are binary variables; number of siblings, parental education, and day of birth enter linearly.

Table A15: Unobserved heterogeneity: distance to tertiary education program j

	(1) Type 1	(2) Type 2	(3) Type 3
Humanities and Arts (Col)			
Distance to tertiary education program j	-0.008	-0.020***	-0.021***
	(0.005)	(0.004)	(0.005)
Humanities and Arts (Univ)			
Distance to tertiary education program j	-0.036***	-0.017***	-0.020***
	(0.006)	(0.005)	(0.005)
Business and Law (Col)			
Distance to tertiary education program j	-0.008**	-0.015***	-0.011***
	(0.003)	(0.003)	(0.003)
Business and Law (Univ)			
Distance to tertiary education program j	-0.015***	-0.008**	-0.006
	(0.003)	(0.003)	(0.004)
Social sciences (Col)			
Distance to tertiary education program j	-0.007	0.001	-0.001
	(0.005)	(0.004)	(0.005)
Social sciences (Univ)			
Distance to tertiary education program j	-0.024***	-0.017***	-0.016***
	(0.004)	(0.004)	(0.004)
Health (Col)			
Distance to tertiary education program j	-0.003	-0.006	-0.007
	(0.004)	(0.003)	(0.004)
Health (Univ)			
Distance to tertiary education program j	-0.023***	-0.017***	-0.016***
	(0.004)	(0.004)	(0.005)
STEM (Col)			
Distance to tertiary education program j	-0.002	-0.003	0.001
	(0.003)	(0.003)	(0.003)
STEM (Univ)			
Distance to tertiary education program j	-0.016***	-0.012***	-0.011**
	(0.004)	(0.003)	(0.004)
Education			
Distance to tertiary education program j	-0.004	0.001	-0.002
	(0.003)	(0.003)	(0.004)
Exogenous variables	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unobserved types	Yes	Yes	Yes
Observations	55083	55433	55419

NOTE.– Exogenous variables include gender, foreign background, number of siblings, parental background, day of birth. Province FE includes provincial fixed effects. Relative distance to closest tertiary education is measured in kilometers. Each higher education program is either (Col), vocational college, or (Univ), academic university. Education is a single program.

Table A16: Distance and pre-tertiary educational outcomes, by latent type

	All	Type 1	Type 2	Type 3
Panel A: Delay (Primary)				
Distance to tertiary education program j	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Delay (Secondary)				
Distance to tertiary education program j	-0.001	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Panel C: HS Dropout				
Distance to tertiary education program j	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.000)	(0.001)	(0.002)
Panel D: HS Track (Vocational)				
Distance to tertiary education program j	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Panel E: HS Track (Technical)				
Distance to tertiary education program j	0.002	0.001	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Panel F: HS Track (Academic)				
Distance to tertiary education program j	-0.002*	-0.002*	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Panel G: HS Grade (1Q)				
Distance to tertiary education program j	-0.001*	-0.000	-0.001*	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Panel H: HS Grade (2Q)				
Distance to tertiary education program j	0.000	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Panel I: HS Grade (3Q)				
Distance to tertiary education program j	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Panel L: HS Grade (4Q)				
Distance to tertiary education program j	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)

NOTE.– All of these regressions include the exogenous variables in Table 1. Distance to tertiary education program j is the distance to each program an individual enrolled in the first year of tertiary education in kilometers.

Table A17: Unobserved heterogeneity: distance to tertiary education program j, late graduation, skill mismatch and wages

	All	Type 1	Type 2	Type 3
Panel A: Distance and log-hourly wages				
Distance to tertiary education program j	-0.000	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
p-value (Distance to tertiary education program j=0)	0.337	0.267	0.421	0.449
Panel B: Distance and skill mismatch in first occupation				
Distance to tertiary education program j	-0.001	-0.001	-0.001	-0.001*
	(0.000)	(0.001)	(0.000)	(0.001)
p-value (Distance to tertiary education program j=0)	0.175	0.357	0.232	0.081
Panel C: Late graduation and log-hourly wages				
Late graduation	-0.024*	0.007	-0.009	-0.028
	(0.012)	(0.015)	(0.016)	(0.024)
p-value (Late graduation=0)	0.059	0.667	0.591	0.272
Panel D: Late graduation and skill mismatch in the first occupation				
Late graduation	0.090***	0.064*	0.056**	0.069**
	(0.023)	(0.035)	(0.021)	(0.030)
p-value (Late graduation=0)	0.002	0.088	0.017	0.038

NOTE.– All of these regressions include the exogenous variables in Table 1. Distance to tertiary education program j is the distance to each program an individual enrolled in the first year of tertiary education in kilometers.

Table A18: First stage estimates: graduation timing and skill mismatch

	(1) Skill mismatch (first job)	(2) Skill mismatch (first job)	(3) Skill mismatch (first job)
Graduated in the second period	0.067**	0.079***	0.103***
	(0.022)	(0.022)	(0.023)
Exogenous variables	No	Yes	Yes
Educational attainment	No	No	Yes
Observations	8189	8189	8189
R^2	0.001	0.009	0.054

NOTE.– Exogenous variables include gender, foreign background, number of siblings, parental background, day of birth. Educational attainment includes fields of study program in BA and MA, grades in BA and MA, and secondary education variables. Each higher education program is either (Col), vocational college, or (Univ), academic university. Education is a single program.

Table A19: Late graduation and entry skill mismatch

	(1) K3: Linear experience	(2) K3: Flex months	(3) K2: Linear experience	(4) K2: Flex months
Late graduation	0.123***	0.116***	0.123***	0.116***
	(0.027)	(0.026)	(0.027)	(0.026)
p-value (Late graduation=0)	0.000	0.000	0.000	0.000
Observations	9662	9662	9662	9662
R^2	0.098	0.101	0.098	0.101

NOTE.– Dependent variable is skill mismatch in first occupation. Columns compare linear experience controls versus flexible months-since-graduation controls (linear and quadratic, with age interactions) under K=3 and K=2. All columns include demographic, family, schooling, unemployment, and province/cohort/age fixed effects. Observations count stacked person-age records in the analysis sample, not unique individuals. Standard errors are clustered at the program × cohort level and shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A20: Within-field mismatch wage penalty by enrollment propensity

	(1) Humanities and arts	(2) Business and law	(3) Social sciences	(4) Health	(5) STEM	(6) Education
Mismatch penalty (low propensity)	-0.044	-0.021	-0.033	-0.058*	0.004	-0.007
	(0.027)	(0.024)	(0.023)	(0.031)	(0.033)	(0.021)
Extra mismatch penalty (high vs low)	-0.027	-0.030	-0.015	0.055	-0.042*	-0.078
	(0.061)	(0.022)	(0.028)	(0.046)	(0.021)	(0.059)
Penalty (low propensity)	-0.044	-0.021	-0.033	-0.058	0.004	-0.007
Penalty (high propensity)	-0.071	-0.051	-0.048	-0.003	-0.039	-0.086
p-value (high-low difference=0)	0.660	0.189	0.595	0.245	0.058	0.199
Observations	511	1010	447	625	1077	654
R^2	0.182	0.291	0.307	0.199	0.249	0.136

NOTE.– Each column reports a field-specific regression of log hourly wage on skill mismatch and its interaction with a high-propensity indicator. The sample includes tertiary enrollees with observed wages at ages 23, 26, and 29. Low/high propensity = bottom/top tercile of predicted enrollment propensity. Low and high propensity are the bottom and top terciles of predicted tertiary-enrollment propensity (estimated from observables and latent-type probabilities p_2 and p_3). Mismatch penalty (low propensity) is the coefficient on mismatch; Extra mismatch penalty (high vs low) is the interaction coefficient; Penalty (high propensity) is their sum. Regressions include demographic and schooling controls, potential experience, unemployment, cohort and age fixed effects, and province fixed effects. Standard errors (in parentheses) are clustered at the program × cohort level. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Table A21: Late graduation and wages within occupation cells

	(1) First job	(2) + Types	(3) + Occ. FE	(4) Panel Occ. FE
Late graduation	-0.023*	-0.022	-0.018	-0.007
	(0.013)	(0.016)	(0.015)	(0.009)
Skill mismatch	-0.058***	-0.057***	-0.033***	-0.017*
	(0.009)	(0.011)	(0.011)	(0.009)
Latent type controls	No	Yes	Yes	Yes
Occupation fixed effects	No	No	Yes	Yes
Age fixed effects	No	No	No	Yes

NOTE.– The dependent variable is log hourly wage. Columns (1)–(3) use the first-job wage; column (4) uses the age 23/26/29 wage panel. All columns include observed background, education, province, and field-by-cohort controls. Columns with latent type controls include the posterior probabilities of latent types 2 and 3. Occupation fixed effects use ISCO-08 first-job occupation. Column (4) also controls for potential experience, unemployment, and age. Standard errors clustered by program-by-cohort are in parentheses.

B Results

Table A22: Model selection by number of types

K	Start	Neg. Log Likelihood	AIC	BIC	Max SE	SE filter	Preferred
1	1	105797.353	212770.705	216892.907	–	No	No
2	1	105458.633	212157.266	216503.805	1.094	Yes	No
2	2	105797.012	212834.024	217180.563	1.086	Yes	No
2	3	105795.817	212831.634	217178.174	1.086	Yes	No
2	4	105438.295	212116.589	216463.129	1.083	Yes	No
2	5	105433.794	212107.588	216454.127	1.080	Yes	No
3	1	105018.920	211341.840	215912.717	2.642	No	No
3	2	105214.139	211732.279	216303.155	1.091	Yes	No
3	3	105182.923	211669.846	216240.722	1.089	Yes	Yes
3	4	104953.635	211211.269	215782.146	2.794	No	No
3	5	105151.802	211607.604	216178.481	1.970	No	No

NOTE.– Each row reports a separate estimation of the model. Rows with the same number of latent types K use different starting values. The negative log likelihood column reports the minimized value of the objective function. AIC and BIC are computed as $2p+2\text{NLL}$ and $p\log(N)+2\text{NLL}$, respectively, where p is the number of estimated parameters and N is the estimation sample size. Lower values indicate a better penalized fit. The preferred specification is selected among estimates that pass the standard-error filter.

Table A23: Unobserved types and higher secondary education

	Type 1	Type 2	Type 3
Delay in primary education	-0.003	0.002	0.000
Delay in secondary education	-0.051	0.037	0.005
HS Dropout	0.135	-0.152	0.056
Vocational HS	-0.208	0.323	-0.198
Technical HS	-0.299	-0.075	0.396
Academic HS	0.346	-0.077	-0.252
HS grades - 1st Q	-0.069	0.073	-0.023
HS grades - 2nd Q	-0.006	-0.009	0.017
HS grades - 3rd Q	0.061	-0.047	-0.002
HS grades - 4th Q	0.078	-0.077	0.018

NOTE.- Entries are Pearson correlations between observed pre-tertiary characteristics and indicators for the modal posterior unobserved type. Each individual is assigned to the type with the highest posterior probability. Repetition, high-school track, and high-school grade-quarter variables are measured before tertiary enrollment; the correlations are descriptive and are not structural parameters.

B.1 Difference between and within fields of study

Table A24: Returns to field of study completion (baseline mismatch measure)

	(1) BA degree	(2) MA degree
Humanities and Arts	0.045***	0.100***
	(0.003)	(0.002)
Business and Law	0.078***	0.138***
	(0.002)	(0.002)
Social Sciences	0.019***	0.075***
	(0.002)	(0.002)
Health	0.110***	0.169***
	(0.002)	(0.002)
STEM	0.087***	0.147***
	(0.002)	(0.002)
Education	0.013***	
	(0.002)	

NOTE.– Log-hourly wage at age 23, 26, 29, with age and cohort fixed effects. We control for potential experience, non-employment rates and dynamic selection. Returns are weighted averages across vocational (Col) and academic (Univ) higher education institutions, using simulated enrollment probabilities as weights. BA degree are defined when attaining 3 years of higher tertiary education, while MA degree are defined over attaining more than 3 years of higher tertiary education. In the Belgian system, there is not a MA degree for Education degrees. To construct the counterfactual outcome Y_{ijd}, we assign each individual to completion of program j at degree level d. We aggregate programs into fields of study and later investigate the role of higher education type. This outcome is compared to the non-enrollment potential outcome Y_{i0}. In this counterfactual, high school graduates observed at ages 23 (26, 29) are assigned 5 (8, 11) years of potential labor market experience, and outcomes are adjusted for age and cohort fixed effects. DSA = Direct Self-Assessment; JA = Job Analysis.

Table A25: Difference in returns across college majors

	(1) BA degree (Col)	(2) MA degree (Col)	(3) BA degree (Univ)	(4) MA degree (Univ)
Business and Law	-0.007	-0.002	0.110***	0.110***
	(0.014)	(0.014)	(0.022)	(0.022)
Social Sciences	-0.028	-0.022	-0.002	-0.009
	(0.017)	(0.017)	(0.024)	(0.024)
Health	0.058***	0.063***	0.087***	0.089***
	(0.018)	(0.017)	(0.026)	(0.026)
STEM	0.034**	0.038***	0.064**	0.064**
	(0.014)	(0.014)	(0.025)	(0.025)
Education	-0.030*			
	(0.016)			

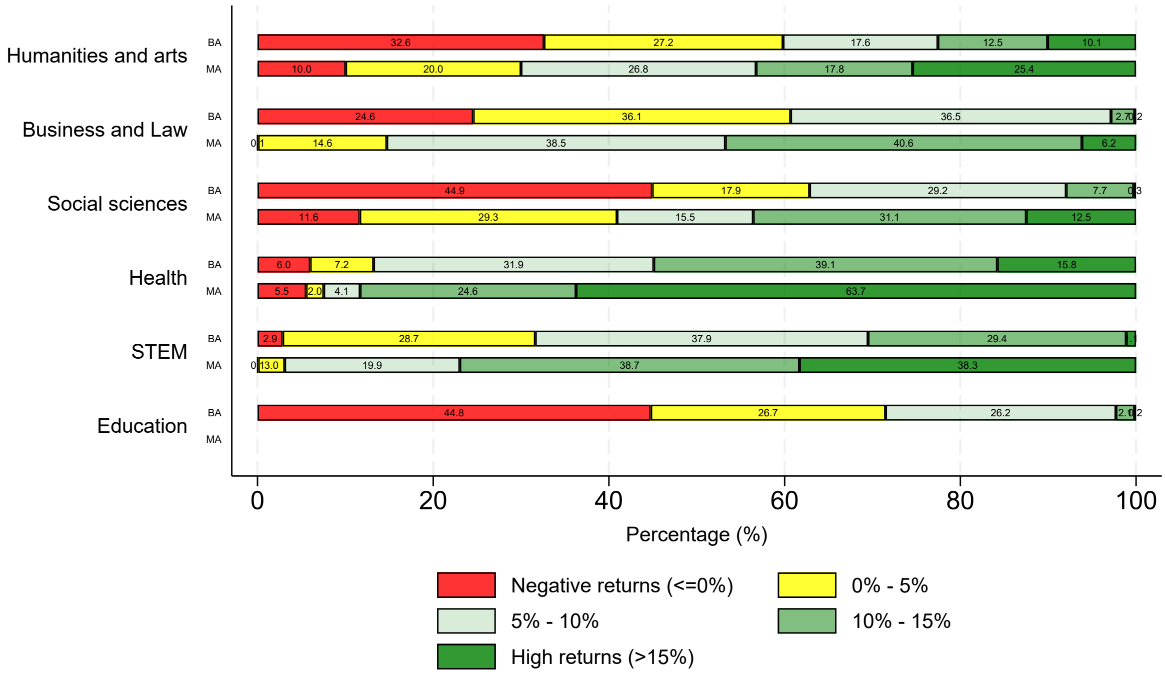
NOTE.– Log-hourly wage at age 23, 26, 29, with year and cohort fixed effects. We control for potential experience, unemployment rates and dynamic selection. BA degree are defined when attaining 3 years of higher tertiary education, while MA degree are defined over attaining more than 3 years of higher tertiary education. Col includes vocational higher tertiary education institutions, while Univ includes accademic higher tertiary education institutions. In the Belgian system, there is not a MA degree for Education degrees.

Table A26: Negative returns by field of study (in %, baseline mismatch measure)

	Field of Study	(1) Average Mismatch (in %)	(2) Without Mismatch (in %)	(3) Full Mismatch (in %)
BA Degree	Humanities and Arts	25.8	15.0	32.7
	Business and Law	1.6	1.1	2.9
	Social Sciences	37.4	28.0	51.4
	Health	8.9	0.9	48.1
	STEM	0.6	0.1	2.8
	Education	44.8	43.7	53.3
MA Degree	Humanities and Arts	5.8	0.1	9.2
	Business and Law	0.0	0.0	0.0
	Social Sciences	13.5	1.1	28.3
	Health	3.3	0.0	16.3
	STEM	0.0	0.0	0.0

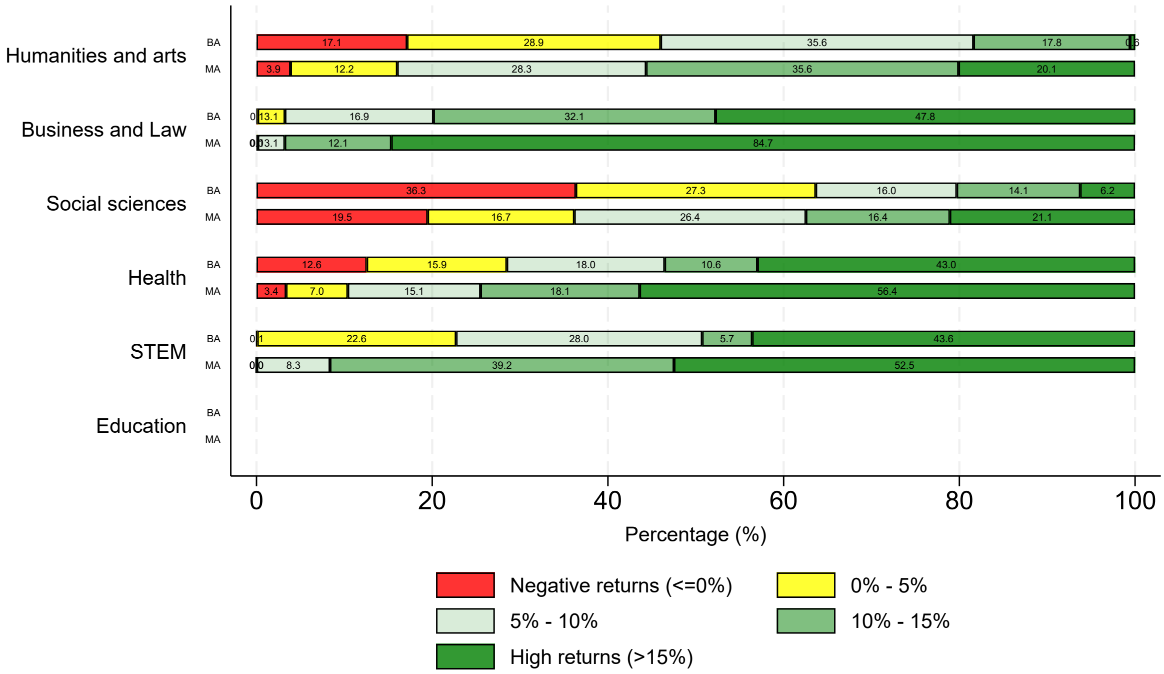
NOTE.– For each field of study, we report the fraction (percentage) of individuals with negative returns, defined as returns <= 0. Point estimates only (no standard errors) because they are computed from the mean distribution. Results are weighted averages across vocational (Col) and academic (Univ) higher education institutions, using simulated enrollment probabilities as weights. Column (1) Average Mismatch is computed as a weighted average of Without and Full Mismatch using the field-degree-specific absolute mismatch probability. These probabilities are mixture weights and are not the relative mismatch-sorting differences. Column (2) Without Mismatch shows results obtained by removing mismatch in the counterfactual. Column (3) Full Mismatch shows results obtained by imposing mismatch in the counterfactual. DSA = Direct Self-Assessment; JA = Job Analysis.

Figure A1: Fraction of negative returns to higher education programs (Vocational College only)



NOTE.– BA and MA denote Bachelor's and Master's degrees. In Belgium, an MA Degree in Education does not exist. The figure includes the individual return to enrolling and obtaining a BA or an MA in higher education program j.

Figure A2: Fraction of negative returns to higher education programs (University only)



NOTE.– BA and MA denote Bachelor's and Master's degrees. In Belgium, an MA Degree in Education does not exist. The figure includes the individual return to enrolling and obtaining a BA or an MA in higher education program j.

B.2 Skill mismatch and penalty

Table A27: Skill mismatch sorting (relative to humanities and arts, baseline mismatch measure)

	(1) BA degree	(2) MA degree
Business and Law	-0.371***	-0.345***
	(0.003)	(0.003)
Social Sciences	-0.207***	-0.173***
	(0.004)	(0.005)
Health	-0.437***	-0.423***
	(0.003)	(0.003)
STEM	-0.400***	-0.381***
	(0.003)	(0.003)
Education	-0.495***	
	(0.003)	

NOTE.– Model-implied counterfactual mismatch-rate differences relative to Humanities and Arts under assignment to field j. For fields offered in both vocational (Col) and academic (Univ) institutions, rates are weighted averages using simulated enrollment probabilities. BA degree are defined when attaining 3 years of higher tertiary education, while MA degree are defined over attaining more than 3 years of higher tertiary education. In the Belgian system, there is not a MA degree for Education degrees. DSA = Direct Self-Assessment; JA = Job Analysis.

Table A28: Returns to field of study and skill mismatch (full results, baseline mismatch measure)

	Field of Study	(1) Without Mismatch	(2) Full Mismatch	(3) Mismatch Penalty
BA Degree	Humanities and Arts	0.057***	0.017***	-0.040***
		(0.002)	(0.003)	(0.002)
	Business and Law	0.083***	0.067***	-0.016***
		(0.001)	(0.002)	(0.001)
	Social Sciences	0.046***	-0.004	-0.049***
		(0.002)	(0.003)	(0.001)
	Health	0.118***	0.028***	-0.090***
		(0.002)	(0.004)	(0.002)
	STEM	0.095***	0.052***	-0.043***
		(0.002)	(0.003)	(0.001)
	Education	0.014***	-0.009**	-0.022***
		(0.002)	(0.004)	(0.003)
MA Degree	Humanities and Arts	0.121***	0.069***	-0.053***
		(0.002)	(0.002)	(0.001)
	Business and Law	0.147***	0.118***	-0.029***
		(0.001)	(0.002)	(0.001)
	Social Sciences	0.110***	0.048***	-0.062***
		(0.002)	(0.003)	(0.001)
	Health	0.182***	0.080***	-0.103***
		(0.002)	(0.004)	(0.002)
	STEM	0.159***	0.104***	-0.055***
		(0.002)	(0.003)	(0.001)

NOTE.– Returns are weighted averages across vocational (Col) and academic (Univ) higher education institutions, using simulated enrollment probabilities as weights. Column (1) shows returns without mismatch (counterfactual removing mismatch). Column (2) shows returns with full mismatch (counterfactual with only mismatch). Column (3) shows the mismatch penalty (difference between columns 2 and 1). Log-hourly wage at age 23, 26, 29, with time and cohort fixed effects. We control for potential experience, non-employment rates and dynamic selection. Standard errors in parentheses. DSA = Direct Self-Assessment; JA = Job Analysis.

Table A29: Returns to field of study and skill mismatch (Vocational College only, baseline mismatch measure)

	Field of Study	(1) Without Mismatch	(2) Full Mismatch	(3) Mismatch Penalty
BA Degree	Humanities and Arts	0.068***	-0.010***	-0.078***
		(0.002)	(0.004)	(0.002)
	Business and Law	0.033***	0.033***	0.000
		(0.001)	(0.002)	(0.001)
	Social Sciences	0.018***	0.011***	-0.007***
		(0.002)	(0.003)	(0.002)
	Health	0.112***	-0.033***	-0.145***
		(0.002)	(0.005)	(0.003)
	STEM	0.084***	0.046***	-0.038***
		(0.001)	(0.002)	(0.001)
	Education	0.014***	-0.009**	-0.022***
		(0.002)	(0.004)	(0.003)
MA Degree	Humanities and Arts	0.132***	0.042***	-0.090***
		(0.002)	(0.003)	(0.002)
	Business and Law	0.098***	0.085***	-0.013***
		(0.002)	(0.002)	(0.001)
	Social Sciences	0.082***	0.063***	-0.020***
		(0.002)	(0.003)	(0.002)
	Health	0.177***	0.019***	-0.158***
		(0.002)	(0.005)	(0.003)
	STEM	0.148***	0.098***	-0.051***
		(0.002)	(0.002)	(0.001)

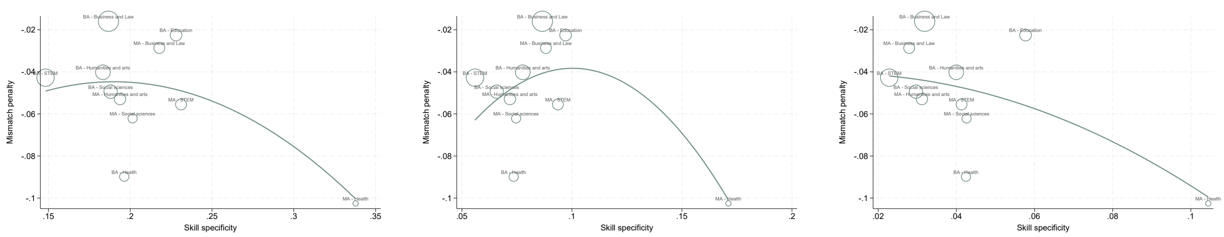
NOTE.– Results are for vocational college (Col) programs only. Column (1) shows returns without mismatch (counterfactual removing mismatch). Column (2) shows returns with full mismatch (counterfactual with only mismatch). Column (3) shows the mismatch penalty (difference between columns 2 and 1). Log-hourly wage at age 23, 26, 29, with time and cohort fixed effects. We control for potential experience, non-employment rates and dynamic selection. Standard errors in parentheses. DSA = Direct Self-Assessment; JA = Job Analysis.

Table A30: Returns to field of study and skill mismatch (University only, baseline mismatch measure)

	Field of Study	(1) Without Mismatch	(2) Full Mismatch	(3) Mismatch Penalty
BA Degree	Humanities and Arts	0.043***	0.052***	0.008***
		(0.004)	(0.004)	(0.001)
	Business and Law	0.157***	0.118***	-0.040***
		(0.002)	(0.003)	(0.002)
	Social Sciences	0.072***	-0.017***	-0.089***
		(0.003)	(0.004)	(0.002)
	Health	0.125***	0.113***	-0.013***
		(0.003)	(0.005)	(0.003)
	STEM	0.115***	0.063***	-0.052***
		(0.003)	(0.005)	(0.003)
MA Degree	Humanities and Arts	0.108***	0.104***	-0.004***
		(0.003)	(0.004)	(0.001)
	Business and Law	0.222***	0.169***	-0.053***
		(0.002)	(0.003)	(0.001)
	Social Sciences	0.136***	0.034***	-0.102***
		(0.003)	(0.004)	(0.001)
	Health	0.190***	0.164***	-0.026***
		(0.003)	(0.005)	(0.003)
	STEM	0.180***	0.115***	-0.064***
		(0.003)	(0.005)	(0.003)

NOTE.– Results are for university (Univ) programs only. Education is not available at University level in the Belgian system. Column (1) shows returns without mismatch (counterfactual removing mismatch). Column (2) shows returns with full mismatch (counterfactual with only mismatch). Column (3) shows the mismatch penalty (difference between columns 2 and 1). Log-hourly wage at age 23, 26, 29, with time and cohort fixed effects. We control for potential experience, non-employment rates and dynamic selection. Standard errors in parentheses. DSA = Direct Self-Assessment; JA = Job Analysis.

Figure A3: Mismatch penalty and skill specificity (ISCO-08 aggregation level)



(a) 1-digit ISCO **(b)** 2-digit ISCO **(c)** 4-digit ISCO

NOTE.– Each point is a field of study × degree (BA/MA), aggregating over college/university programs. The horizontal axis measures *skill specificity* as a Herfindahl–Hirschman Index (HHI) computed over the distribution of ISCO-08 occupations *among matched graduates only*: $\text{HHI}_{gd} = \sum_o s_{ogd}^2$, where s_{ogd} is the share of matched individuals in occupation o within group g and degree d. The vertical axis reports the estimated mismatch penalty for the same group. Marker size is proportional to the number of matched graduates in the group. Solid lines are linear fits.

B.3 Further analysis

Table A31: Educational returns to tertiary enrollment by enrollment-propensity bin

	(1) [0.0, 0.2)	(2) [0.2, 0.4)	(3) [0.4, 0.6)	(4) [0.6, 0.8)	(5) [0.8, 1.0]
Year-1 completion (grades)	0.313***	0.376***	0.430***	0.464***	0.637***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Dropout within 3 years	0.687***	0.619***	0.547***	0.469***	0.107***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.002)
BA completion within 3 years, same program	0.123***	0.164***	0.200***	0.211***	0.254***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)

NOTE.– Columns report model-implied educational returns to tertiary enrollment within bins of the model-implied tertiary enrollment propensity score, defined as one minus the simulated first-period non-enrollment probability. For each individual, enrollment outcomes are aggregated across the 11 simulated programs using the program probabilities conditional on tertiary enrollment. Year-1 completion is defined as a simulated first-year grade outcome above the lowest category. Dropout within 3 years is defined as being out of tertiary education by year 3. BA completion within 3 years requires three completed years while remaining in the initial program. Because the untreated state is non-enrollment, the reported values can be read as treatment effects in probability points.

Table A32: Potential experience, unemployment, and mismatch by enrollment-propensity bin

	(1) [0.0, 0.2)	(2) [0.2, 0.4)	(3) [0.4, 0.6)	(4) [0.6, 0.8)	(5) [0.8, 1.0]
Enrollment: Potential experience	-2.539***	-2.251***	-2.429***	-2.824***	-4.161***
	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)
Enrollment: Non-employment	0.160***	0.123***	0.116***	0.125***	0.143***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Enrollment: Skill mismatch	-0.007*	-0.015***	-0.025***	-0.032***	-0.186***
	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
BA completion: Potential experience	-4.059***	-3.660***	-3.663***	-3.856***	-4.471***
	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
BA completion: Non-employment	0.149***	0.118***	0.112***	0.120***	0.126***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BA completion: Skill mismatch	-0.242***	-0.189***	-0.134***	-0.087***	-0.232***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)

NOTE.– Columns report treatment effects within bins of the model-implied tertiary enrollment propensity score, defined as one minus the simulated first-period non-enrollment probability. Enrollment effects compare the simulated tertiary-enrollment path with the high-school counterfactual. BA-completion effects compare a weighted average of program-specific BA-completion counterfactuals with the high-school counterfactual, where the weights are the program probabilities conditional on tertiary enrollment. Potential experience is measured in years, unemployment is a simulated unemployment indicator, and skill mismatch is the simulated mismatch indicator from the mismatch equation. Potential experience and unemployment are averaged across ages 23, 26, and 29, consistent with the main post-estimation tables.

Table A33: Observed characteristics, secondary outcomes, and unobserved types by enrollment-propensity bin

	(1) [0.0, 0.2)	(2) [0.2, 0.4)	(3) [0.4, 0.6)	(4) [0.6, 0.8)	(5) [0.8, 1.0]
Observations	374	1594	1684	951	3586
(A) Observed characteristics					
Female	0.350	0.403	0.462	0.516	0.556
Foreign origin	0.241	0.120	0.039	0.024	0.027
Number of siblings	2.556	1.976	1.547	1.575	1.529
Father years of education	2.126	3.105	5.204	8.557	7.876
Mother years of education	1.936	2.944	5.059	7.633	7.185
Day of birth	176.468	167.208	174.546	184.540	168.585
Cohort 1978	0.366	0.317	0.315	0.355	0.350
Cohort 1980	0.342	0.340	0.363	0.382	0.327
(B) Higher secondary education					
Delay in primary education	0.035	0.020	0.011	0.024	0.011
Delay in secondary education	0.896	0.203	0.051	0.027	0.020
Vocational HS	0.468	0.365	0.268	0.162	0.003
Technical HS	0.134	0.391	0.573	0.709	0.026
Academic HS	0.000	0.000	0.000	0.000	0.967
HS grades - 1st Q	0.241	0.327	0.435	0.544	0.487
HS grades - 2nd Q	0.430	0.437	0.390	0.308	0.388
HS grades - 3rd Q	0.251	0.168	0.107	0.078	0.095
HS grades - 4th Q	0.078	0.068	0.068	0.070	0.031
(C) Unobserved types					
Type 1	0.246	0.374	0.451	0.533	0.031
Type 2	0.701	0.553	0.480	0.384	0.781
Type 3	0.053	0.073	0.069	0.083	0.188

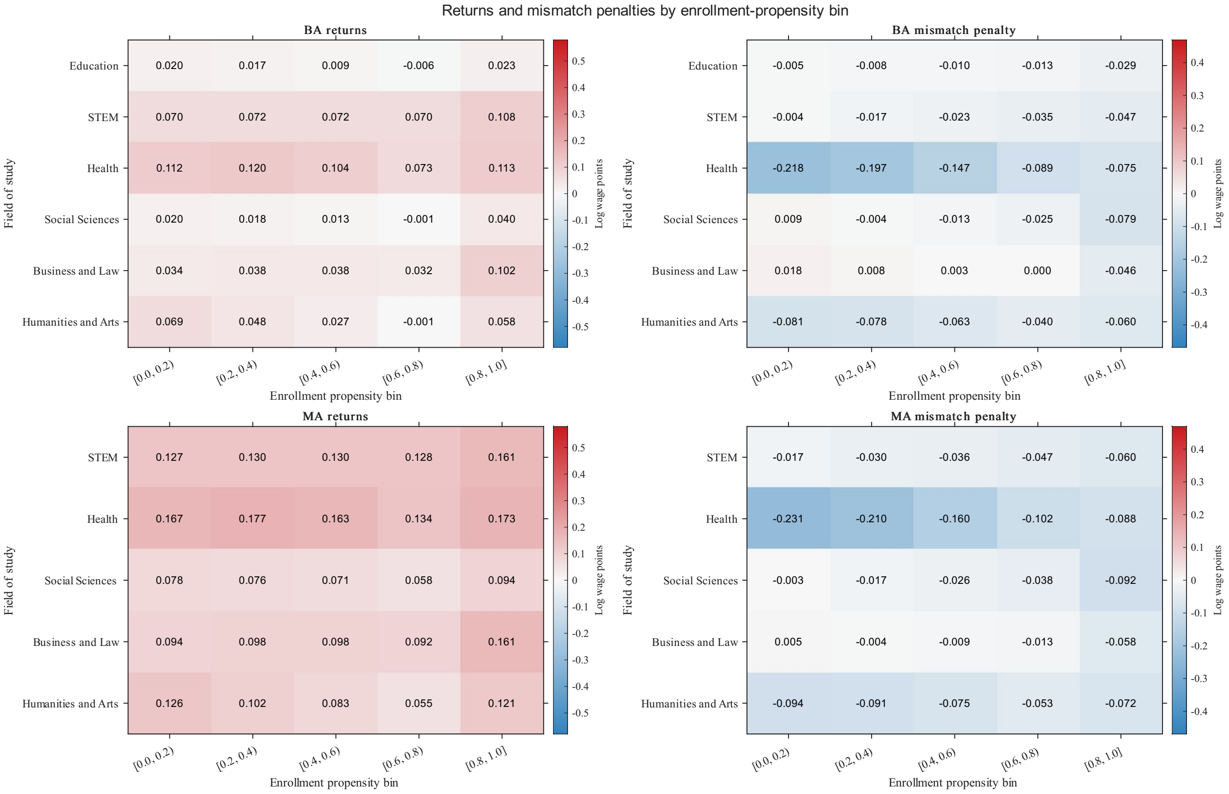
NOTE.– Columns report within-bin sample counts and means using the point-estimate tertiary enrollment propensity score from the final unperturbed simulation draw, defined as one minus the simulated first-period non-enrollment probability. Observed characteristics are taken directly from the model sample. Higher secondary education rows report delays, track shares, and grade-quartile shares. Unobserved-type rows report the share of individuals assigned to each modal latent type using the maximum posterior probability. Indicator rows can be read as shares.

C Heterogeneity analysis

We extend the analysis by allowing the returns to tertiary education enrollment to vary with skill mismatch status.

First, Appendix Figures A5 and A6 plot the treatment effect (TE) curve of tertiary education completion on log hourly wages along two margins: the tertiary education enrollment margin

Figure A4: Probability to enrollment, field of study, returns and mismatch penalty



NOTE.– Columns report bins of the model-implied probability of tertiary enrollment, defined as one minus the simulated first-period non-enrollment probability: $[0, 0.2)$, $[0.2, 0.4)$, $[0.4, 0.6)$, $[0.6, 0.8)$, and $[0.8, 1]$. Rows correspond to fields of study. The four panels report average BA returns, BA mismatch penalties, MA returns, and MA mismatch penalties, respectively, in log wage points. Within each propensity bin and field, estimates are weighted averages of vocational-college and university programs using the simulated enrollment shares of each institution type. The mismatch penalty is defined as expected returns under full mismatch minus expected returns without mismatch, so more negative values indicate larger wage losses from mismatch. BA outcomes refer to completion after three years of tertiary education, while MA outcomes refer to completion after more than three years. Education has no MA counterpart in the Belgian system.

and the field-of-study choice margin. Along the enrollment margin, the horizontal axis is the predicted probability of tertiary enrollment, so higher values correspond to individuals who are more likely to enroll. Returns are positive and statistically significant for all individuals in Business and Law, Health, and STEM. In contrast, returns in Humanities and Arts, Social Sciences, and Education are smaller and often statistically insignificant, indicating that the gains from higher education are concentrated in specific fields. Along the field-of-study margin, the horizontal axis is a normalized field-choice propensity index, so higher values correspond to individuals who are more likely to choose the field conditional on entering higher education. Returns are positive for individuals with a high field-choice propensity in Social Sciences and Education, but are not statistically significant for those with a low propensity to choose these fields. For Humanities and Arts, returns are not statistically different from zero across the distribution. For Business and Law and STEM, the returns are positive along the entire distribution, while for Health the returns increase substantially with field-choice propensity.

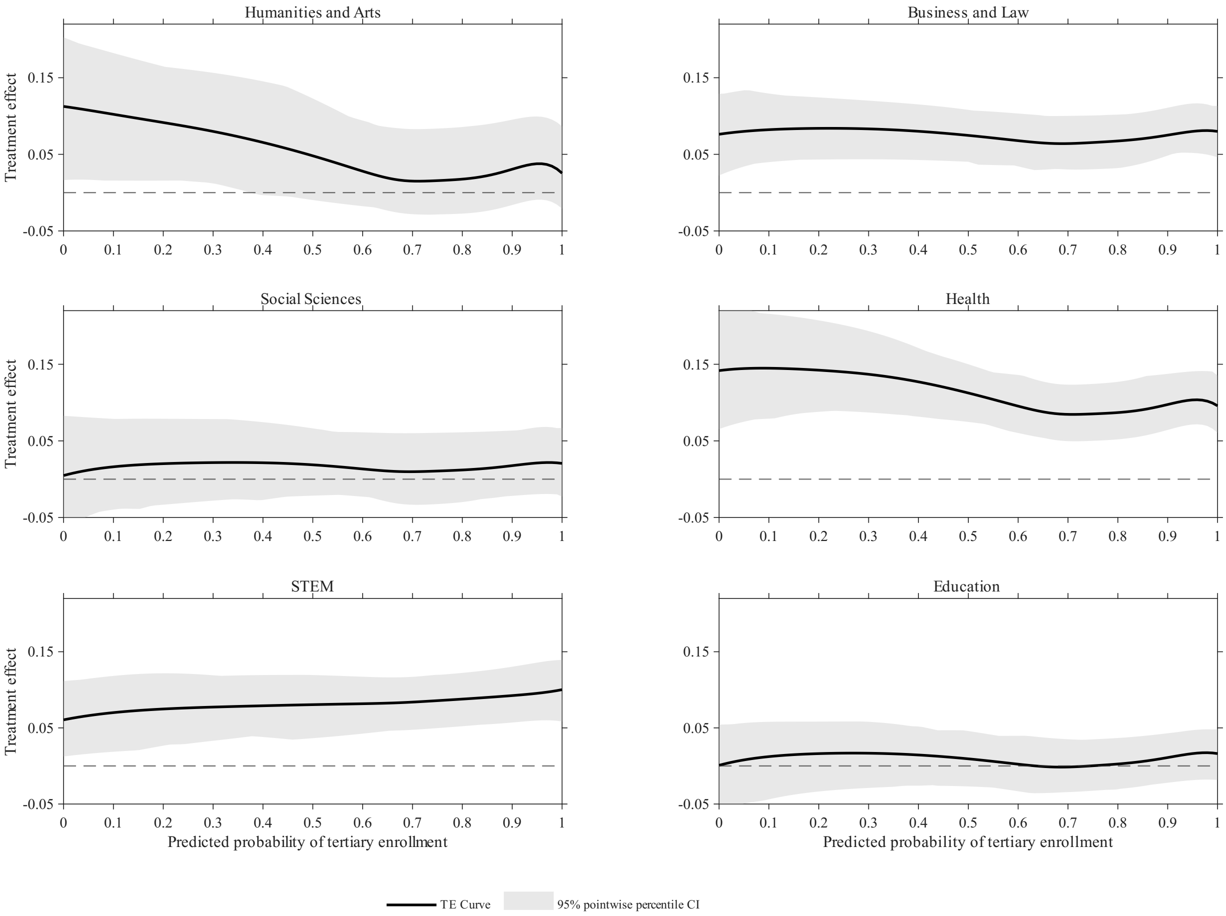
Second, in Figure A7, degree completion reduces mismatch risk in Humanities and Arts and Social Sciences mainly among individuals with high predicted enrollment probabilities. For the other fields, the reduction is present across a broader part of the enrollment-propensity distribution.

Third, when looking at mismatch penalties by field of study, individuals with higher predicted enrollment probabilities experience the largest wage losses from mismatch, especially for MA degrees in Humanities and Arts and Social Sciences (see Figures A9 and A10). Overall, we do not document substantial heterogeneity in the mismatch penalty along this margin, and most estimates are not statistically different from zero. The significant wage losses from mismatch are concentrated among individuals who are most likely to enroll in higher education, especially in Humanities and Arts, Social Sciences, and Education programs. This pattern mirrors the baseline TE results in Figure 2: individuals with the highest potential returns to tertiary education are also those who face the largest losses when they sort into mismatched occupations in these programs.

The heterogeneity analysis highlights two important factors: first, returns to tertiary education are shaped not only by field of study but also by differential exposure to and consequences of skill mismatch; second, selection on gains operates through occupational sorting mechanisms. Individuals who are more likely to enroll are both more exposed to mismatch penalties and more able to reduce mismatch risk through completion, especially in less vocationally structured fields.

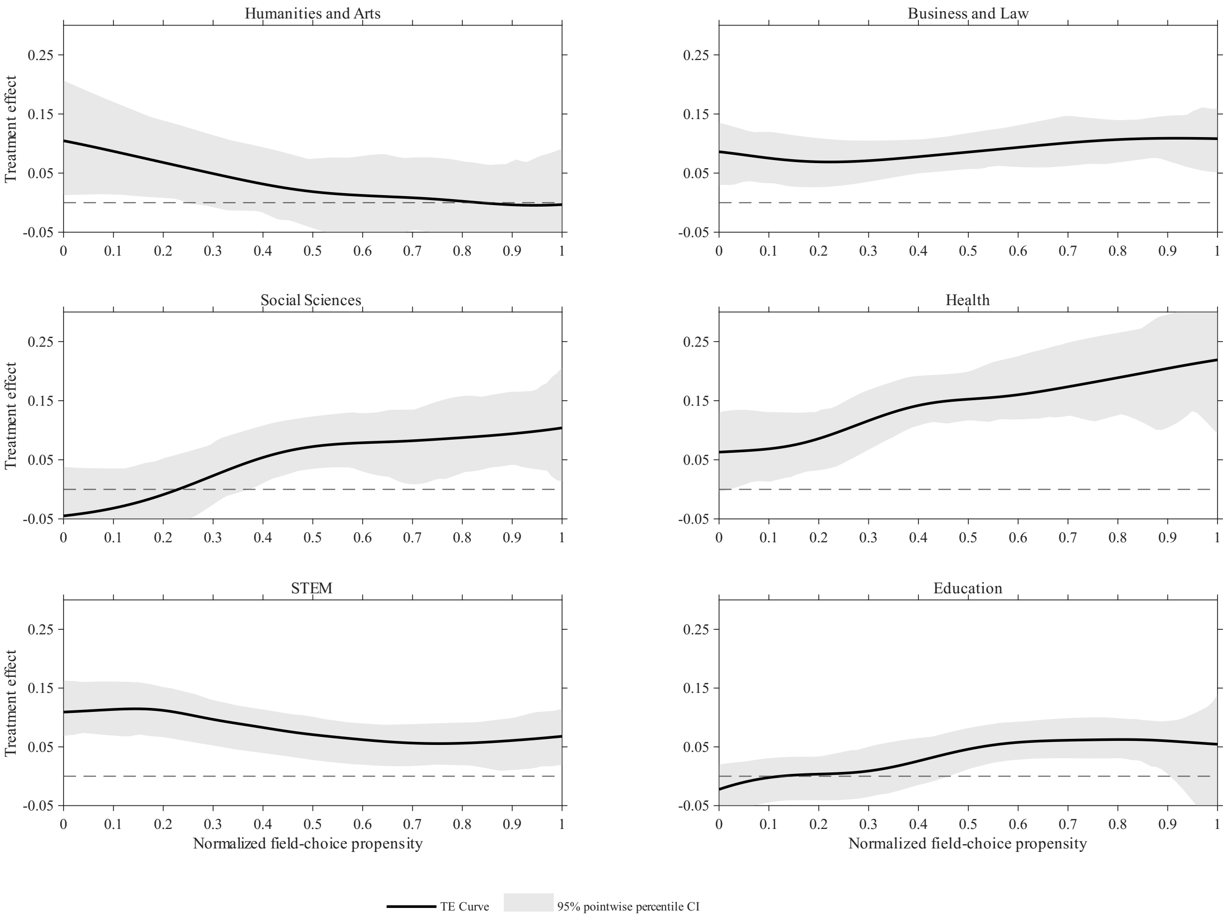
Taken together, these results highlight that the skill mismatch penalty is highly heterogeneous and depends on the relevant margin of choice. At the enrollment margin, mismatch disproportionately harms individuals with high potential returns to tertiary education.

Figure A5: Log-hourly wages: TE curve of tertiary education completion along the enrollment margin



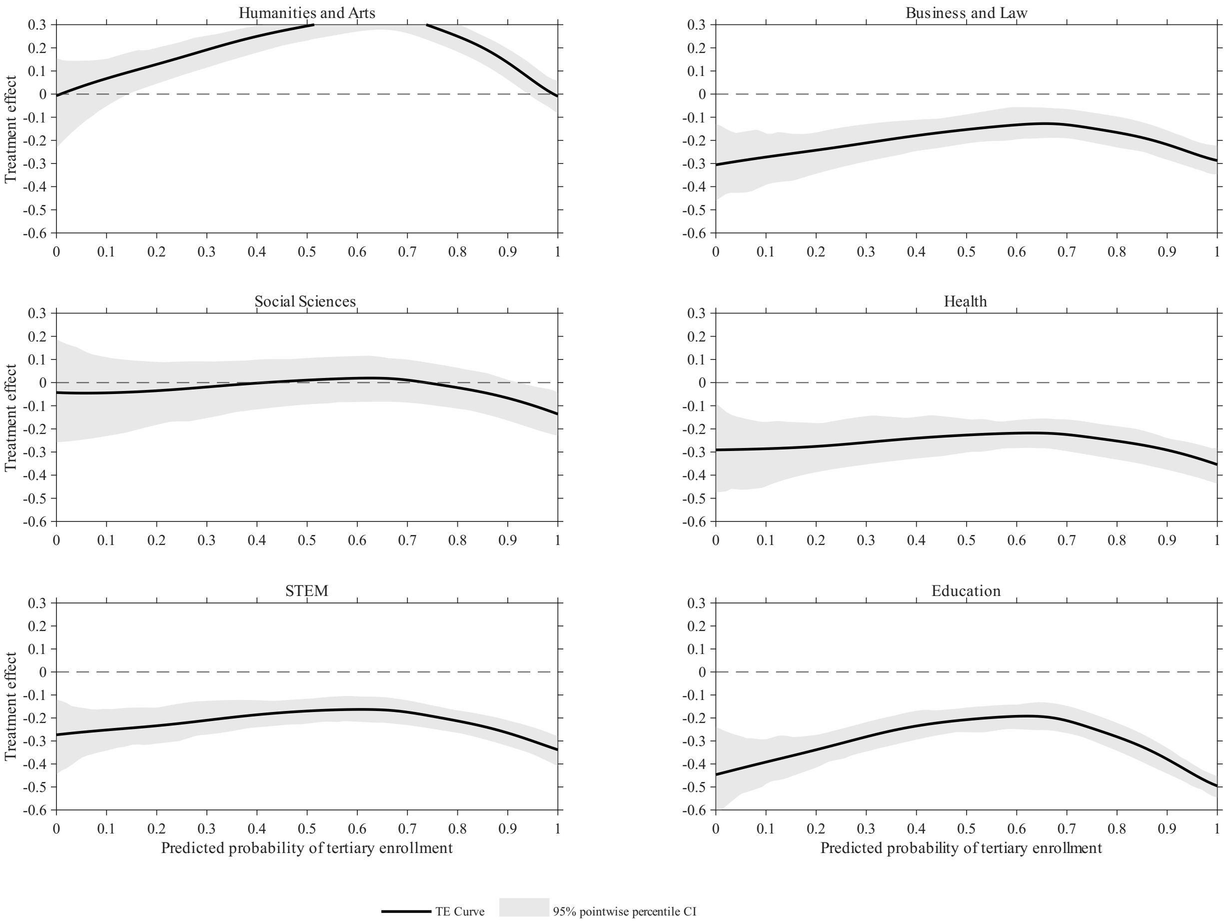
NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *enrollment margin*. The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$, computed from the higher-education choice model. Higher values indicate greater enrollment likelihood, so the curves run from individuals least likely to enroll on the left to individuals most likely to enroll on the right. The vertical axis reports the treatment effect of degree completion on log hourly wages relative to high-school completion. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A6: Log-hourly wages: TE curve of tertiary education completion along the field of study margin



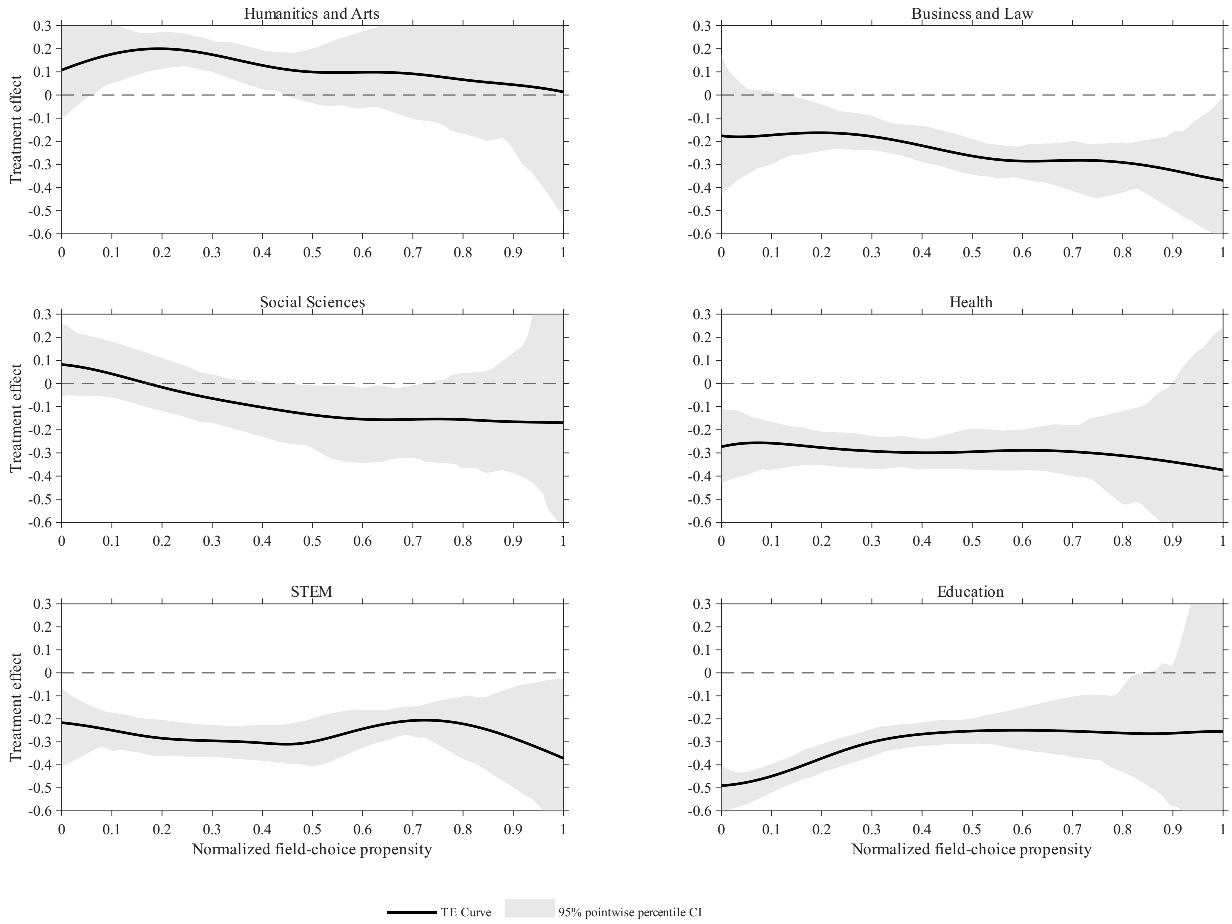
NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *field-of-study margin*. The horizontal axis is a normalized field-choice propensity index. For field j, the index is constructed from the model-implied probability of choosing that field conditional on tertiary enrollment, $q_{ij} = P(C_{i1} \in j \mid C_{i1} \neq 0, S_{i1}^{c}, \theta_i)$, and rescaled to the unit interval within each simulation draw and field. The index is therefore not an absolute probability. Higher values indicate greater propensity to choose the field, so the curves run from individuals least likely to choose the field on the left to individuals most likely to choose it on the right. The normalization is used because the raw field-specific probabilities do not provide sufficient common support across fields. The vertical axis reports the treatment effect of degree completion on log hourly wages relative to high-school completion. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A7: Mismatch probability: TE curve of tertiary education completion along the enrollment margin



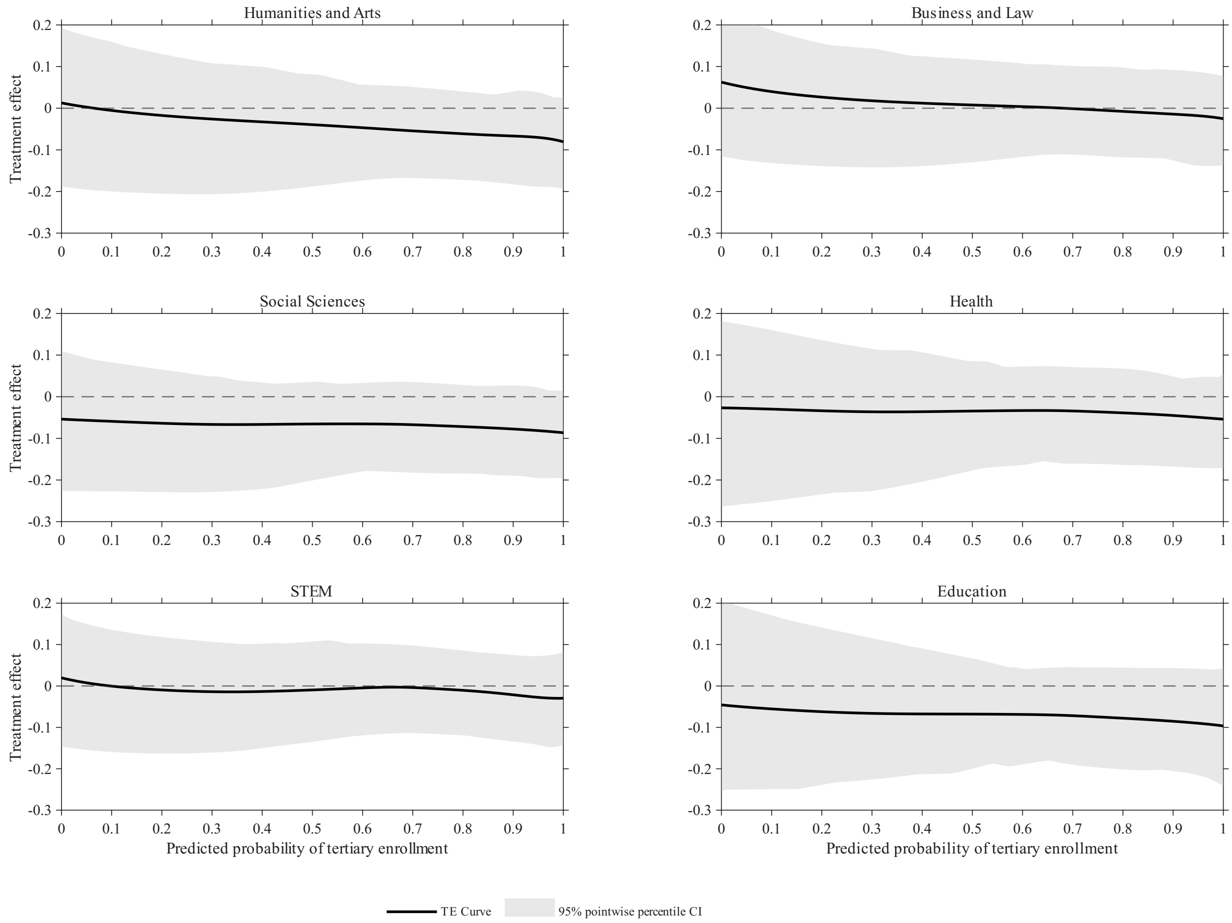
NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *enrollment margin*. The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$, computed from the higher-education choice model. Higher values indicate greater enrollment likelihood, so the curves run from individuals least likely to enroll on the left to individuals most likely to enroll on the right. The vertical axis reports the treatment effect of degree completion on the probability of first-job mismatch relative to high-school completion; negative values indicate a lower mismatch risk under completion. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A8: Mismatch probability: TE curve of tertiary education completion along the field of study margin



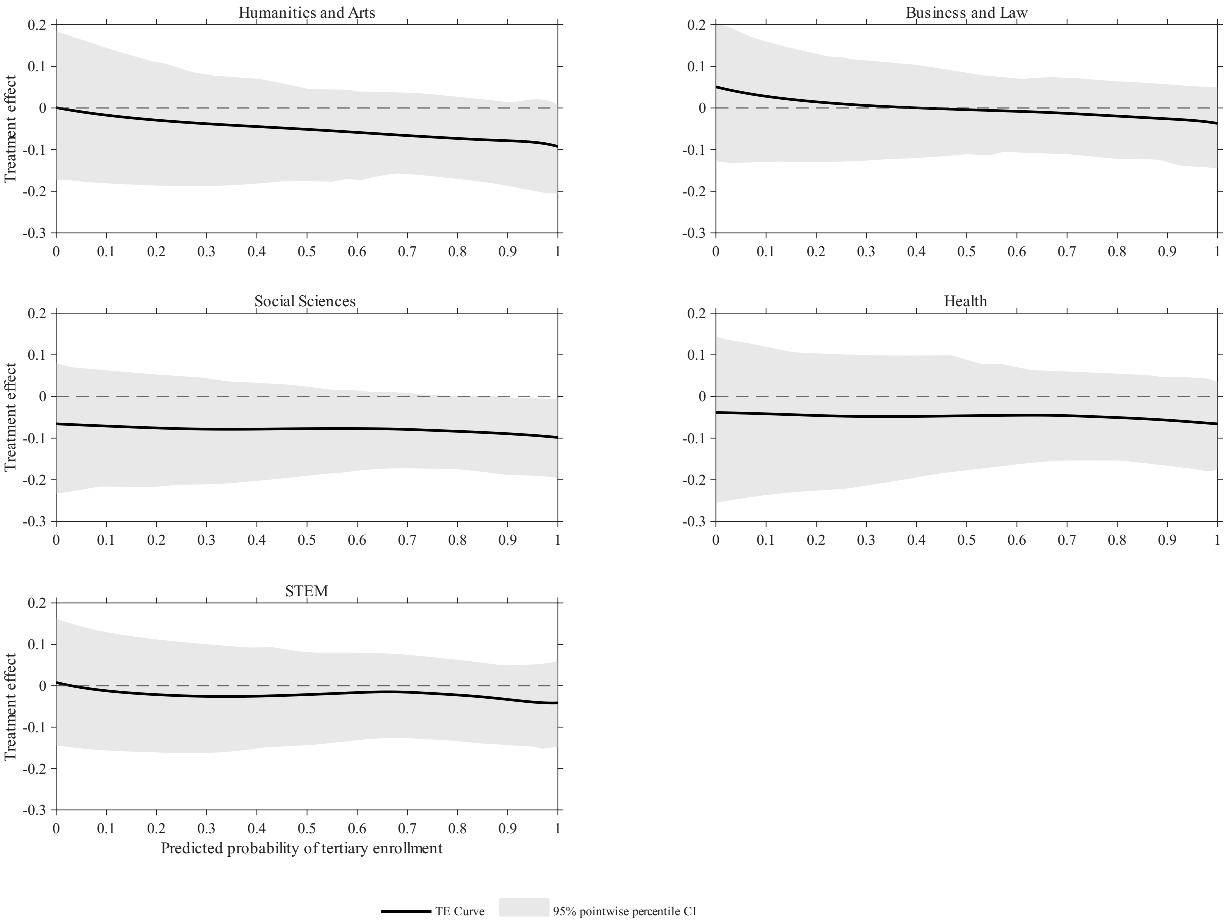
NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *field-of-study margin*. The horizontal axis is a normalized field-choice propensity index. For field j, the index is constructed from the model-implied probability of choosing that field conditional on tertiary enrollment, $q_{ij} = P(C_{i1} \in j \mid C_{i1} \neq 0, S^c_{i1}, \theta_i)$, and rescaled to the unit interval within each simulation draw and field. The index is therefore not an absolute probability. Higher values indicate greater propensity to choose the field, so the curves run from individuals least likely to choose the field on the left to individuals most likely to choose it on the right. The normalization is used because the raw field-specific probabilities do not provide sufficient common support across fields. The vertical axis reports the treatment effect of degree completion on the probability of first-job mismatch relative to high-school completion; negative values indicate a lower mismatch risk under completion. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A9: Mismatch penalty: TE curve of BA degree completion along the enrollment margin



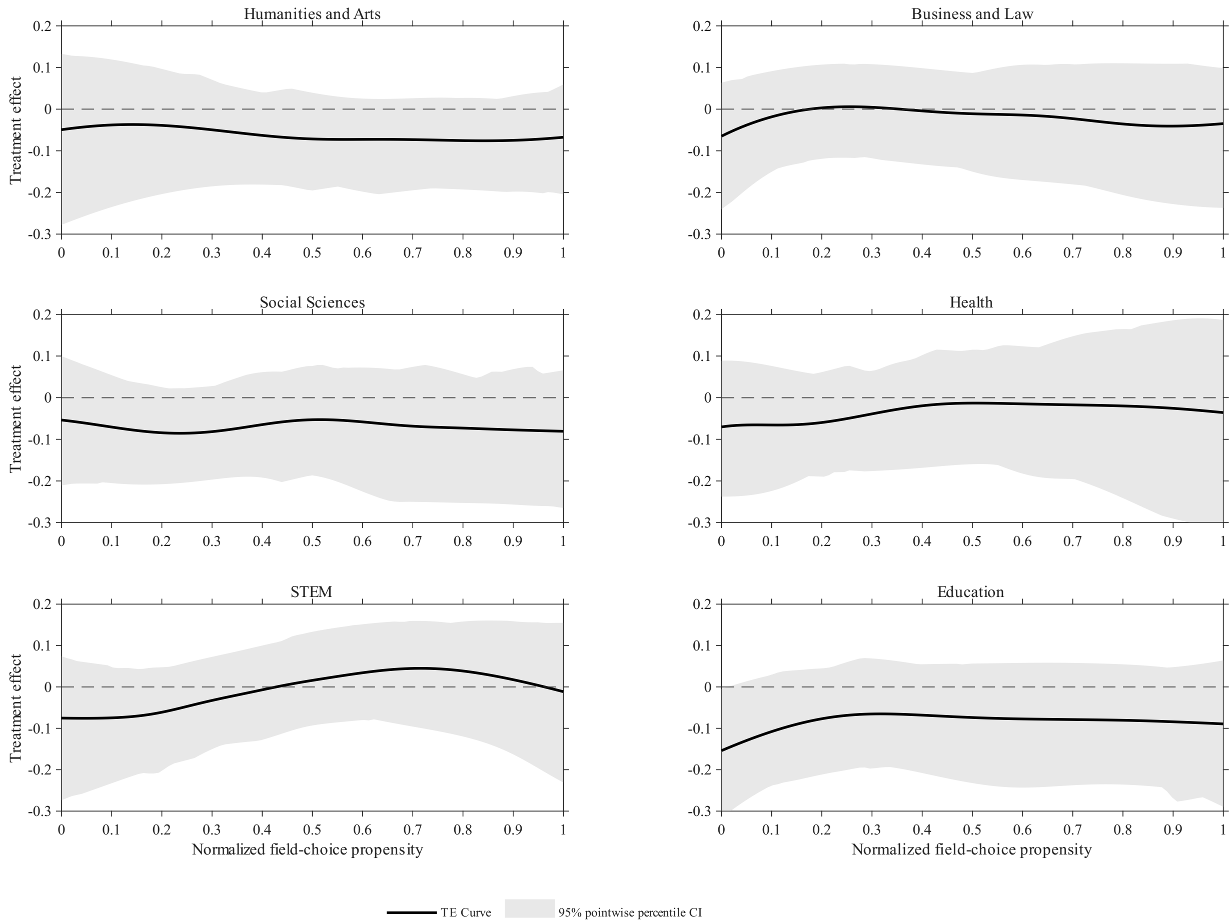
NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *enrollment margin*. The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$, computed from the higher-education choice model. Higher values indicate greater enrollment likelihood, so the curves run from individuals least likely to enroll on the left to individuals most likely to enroll on the right. The vertical axis reports the BA mismatch penalty in log wage points, defined as the return under first-job mismatch minus the return without first-job mismatch; negative values indicate wage losses from mismatch. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A10: Mismatch penalty: TE curve of MA degree completion along the enrollment margin



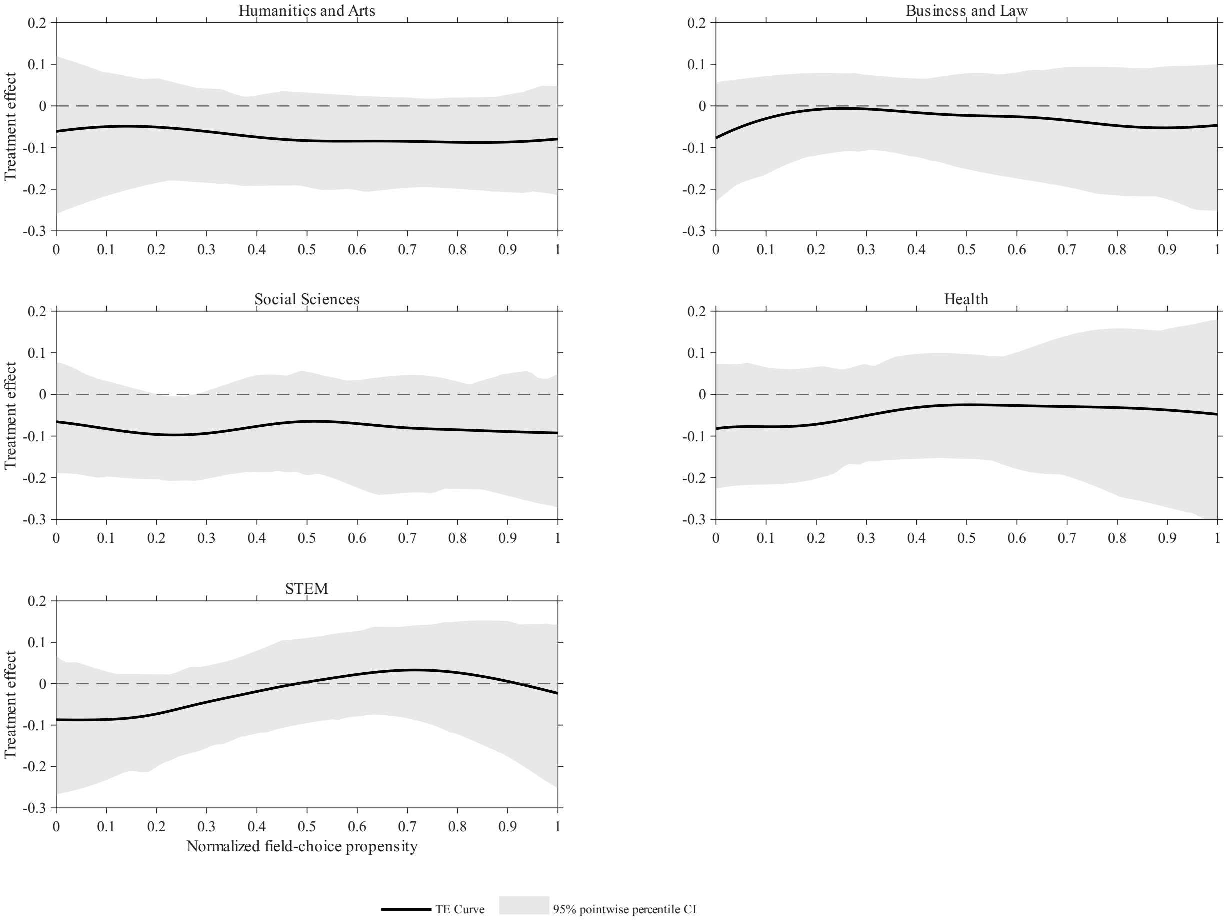
NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *enrollment margin*. The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$, computed from the higher-education choice model. Higher values indicate greater enrollment likelihood, so the curves run from individuals least likely to enroll on the left to individuals most likely to enroll on the right. The vertical axis reports the MA mismatch penalty in log wage points, defined as the return under first-job mismatch minus the return without first-job mismatch; negative values indicate wage losses from mismatch. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A11: Mismatch penalty: TE curve of BA degree completion along the field of study margin



NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *field-of-study margin*. The horizontal axis is a normalized field-choice propensity index. For field j, the index is constructed from the model-implied probability of choosing that field conditional on tertiary enrollment, $q_{ij} = P(C_{i1} \in j \mid C_{i1} \neq 0, S^c_{i1}, \theta_i)$, and rescaled to the unit interval within each simulation draw and field. The index is therefore not an absolute probability. Higher values indicate greater propensity to choose the field, so the curves run from individuals least likely to choose the field on the left to individuals most likely to choose it on the right. The normalization is used because the raw field-specific probabilities do not provide sufficient common support across fields. The vertical axis reports the BA mismatch penalty in log wage points, defined as the return under first-job mismatch minus the return without first-job mismatch; negative values indicate wage losses from mismatch. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

Figure A12: Mismatch penalty: TE curve of MA degree completion along the field of study margin



NOTE.– Each panel reports the TE curve for a specific field of study estimated on the *field-of-study margin*. The horizontal axis is a normalized field-choice propensity index. For field j, the index is constructed from the model-implied probability of choosing that field conditional on tertiary enrollment, $q_{ij} = P(C_{i1} \in j \mid C_{i1} \neq 0, S^c_{i1}, \theta_i)$, and rescaled to the unit interval within each simulation draw and field. The index is therefore not an absolute probability. Higher values indicate greater propensity to choose the field, so the curves run from individuals least likely to choose the field on the left to individuals most likely to choose it on the right. The normalization is used because the raw field-specific probabilities do not provide sufficient common support across fields. The vertical axis reports the MA mismatch penalty in log wage points, defined as the return under first-job mismatch minus the return without first-job mismatch; negative values indicate wage losses from mismatch. The solid black line shows the estimated TE, and the shaded region displays the 95% pointwise percentile confidence interval, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution.

C.1 Unobserved types heterogeneity

Table A34: Returns to fields of study (Unobserved types, aggregated)

Field of study	Unobserved types	(1) BA degree	(2) MA degree
Humanities and Arts	(Type 1)	0.041***	0.095***
		(0.003)	(0.002)
Business and Law		0.074***	0.134***
		(0.002)	(0.002)
Social Sciences		0.018***	0.074***
		(0.002)	(0.002)
Health		0.111***	0.171***
		(0.002)	(0.002)
STEM		0.082***	0.142***
		(0.002)	(0.002)
Education		0.009***	
		(0.002)	
Humanities and Arts	(Type 2)	0.049***	0.105***
		(0.003)	(0.002)
Business and Law		0.078***	0.139***
		(0.002)	(0.002)
Social Sciences		0.019***	0.075***
		(0.002)	(0.002)
Health		0.110***	0.169***
		(0.002)	(0.002)
STEM		0.088***	0.148***
		(0.002)	(0.002)
Education		0.013***	
		(0.002)	
Humanities and Arts	(Type 3)	0.042***	0.097***
		(0.003)	(0.002)
Business and Law		0.081***	0.140***
		(0.002)	(0.002)
Social Sciences		0.022***	0.077***
		(0.002)	(0.002)
Health		0.109***	0.169***
		(0.002)	(0.002)
STEM		0.094***	0.154***
		(0.002)	(0.002)
Education		0.018***	
		(0.002)	

NOTE.– Log-hourly wage at age 23, 26, 29, with year and cohort fixed effects. We control for potential experience, unemployment rates and dynamic selection. Type-specific rows are posterior-probability weighted means from the same benchmark simulation used in the pooled tables. Returns are weighted averages across vocational (Col) and academic (Univ) higher tertiary education institutions using the common pooled simulated enrollment shares, so the pooled estimates are posterior-share weighted averages of the type-specific rows. BA degree are defined when attaining 3 years of higher tertiary education, while MA degree are defined over attaining more than 3 years of higher tertiary education. In the Belgian system, there is not a MA degree for Education degrees.

Table A35: Returns to fields of study and skill mismatch (Unobserved types, aggregated)

Field of study	Unobserved types	(1) BA degree (mismatch)	(2) BA degree (match)	(3) BA degree (penalty)	(4) MA degree (mismatch)	(5) MA degree (match)	(6) MA degree (penalty)
Humanities and Arts	(Type 1)	0.021***	0.055***	-0.034***	0.073***	0.120***	-0.047***
		(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Business and Law		0.068***	0.078***	-0.010***	0.120***	0.142***	-0.022***
		(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Social Sciences		-0.003	0.042***	-0.045***	0.049***	0.106***	-0.057***
		(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Health		0.029***	0.117***	-0.088***	0.081***	0.182***	-0.101***
		(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
STEM		0.053***	0.090***	-0.037***	0.104***	0.154***	-0.050***
		(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Education		-0.005	0.011***	-0.016***			
		(0.004)	(0.002)	(0.002)			
Humanities and Arts	(Type 2)	0.017***	0.057***	-0.040***	0.069***	0.121***	-0.053***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Business and Law		0.068***	0.083***	-0.015***	0.119***	0.147***	-0.028***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Social Sciences		-0.004	0.045***	-0.049***	0.048***	0.110***	-0.062***
		(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Health		0.027***	0.118***	-0.090***	0.079***	0.182***	-0.103***
		(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
STEM		0.051***	0.095***	-0.043***	0.103***	0.159***	-0.056***
		(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Education		-0.009**	0.013***	-0.022***			
		(0.005)	(0.002)	(0.003)			
Humanities and Arts	(Type 3)	0.011***	0.060***	-0.049***	0.063***	0.125***	-0.062***
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Business and Law		0.063***	0.089***	-0.026***	0.114***	0.153***	-0.039***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Social Sciences		-0.005*	0.051***	-0.056***	0.047***	0.115***	-0.069***
		(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Health		0.028***	0.119***	-0.091***	0.079***	0.183***	-0.104***
		(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
STEM		0.053***	0.102***	-0.049***	0.105***	0.166***	-0.062***
		(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Education		-0.012***	0.019***	-0.031***			
		(0.004)	(0.002)	(0.003)			

NOTE.– Log-hourly wage at age 23, 26, 29, with time and cohort fixed effects. We control for potential experience, unemployment rates and dynamic selection. Type-specific rows are posterior-probability weighted means from the same benchmark simulation used in the pooled tables. Returns are weighted averages across vocational (Col) and academic (Univ) higher tertiary education institutions using the common pooled simulated enrollment shares, so the pooled estimates are posterior-share weighted averages of the type-specific rows. Mismatch denotes the full-mismatch counterfactual and match denotes the counterfactual that removes mismatch; the penalty is mismatch minus match.

Table A36: Returns to fields of study (Unobserved types)

Field of study	Unobserved types	(1) BA degree (Col)	(2) MA degree (Col)	(3) BA degree (Univ)	(4) MA degree (Univ)
Humanities and Arts	(Type 1)	0.030***	0.086***	0.055***	0.108***
		(0.003)	(0.003)	(0.004)	(0.004)
Business and Law		0.028***	0.089***	0.143***	0.202***
		(0.002)	(0.002)	(0.003)	(0.002)
Social Sciences		0.011***	0.071***	0.025***	0.076***
		(0.002)	(0.003)	(0.003)	(0.003)
Health		0.099***	0.159***	0.127***	0.187***
		(0.002)	(0.002)	(0.004)	(0.004)
STEM		0.072***	0.130***	0.102***	0.163***
		(0.002)	(0.002)	(0.003)	(0.003)
Education		0.009***			
		(0.002)			
Humanities and Arts	(Type 2)	0.047***	0.105***	0.053***	0.105***
		(0.003)	(0.002)	(0.004)	(0.004)
Business and Law		0.033***	0.094***	0.147***	0.206***
		(0.002)	(0.002)	(0.002)	(0.002)
Social Sciences		0.013***	0.074***	0.025***	0.076***
		(0.002)	(0.002)	(0.004)	(0.003)
Health		0.099***	0.158***	0.125***	0.185***
		(0.002)	(0.002)	(0.004)	(0.004)
STEM		0.074***	0.132***	0.112***	0.176***
		(0.002)	(0.002)	(0.003)	(0.003)
Education		0.013***			
		(0.002)			
Humanities and Arts	(Type 3)	0.039***	0.096***	0.046***	0.098***
		(0.002)	(0.002)	(0.004)	(0.004)
Business and Law		0.037***	0.097***	0.147***	0.205***
		(0.002)	(0.002)	(0.002)	(0.002)
Social Sciences		0.015***	0.074***	0.029***	0.080***
		(0.002)	(0.003)	(0.004)	(0.003)
Health		0.099***	0.158***	0.123***	0.183***
		(0.002)	(0.002)	(0.004)	(0.003)
STEM		0.079***	0.137***	0.122***	0.186***
		(0.002)	(0.002)	(0.003)	(0.003)
Education		0.018***			
		(0.002)			

NOTE.– Log-hourly wage at age 23, 26, 29, with year and cohort fixed effects. We control for potential experience, unemployment rates and dynamic selection. BA degree are defined when attaining 3 years of higher tertiary education, while MA degree are defined over attaining more than 3 years of higher tertiary education. Col includes vocational higher tertiary education institutions, while Univ includes accademic higher tertiary education institutions. In the Belgian system, there is not a MA degree for Education degrees.

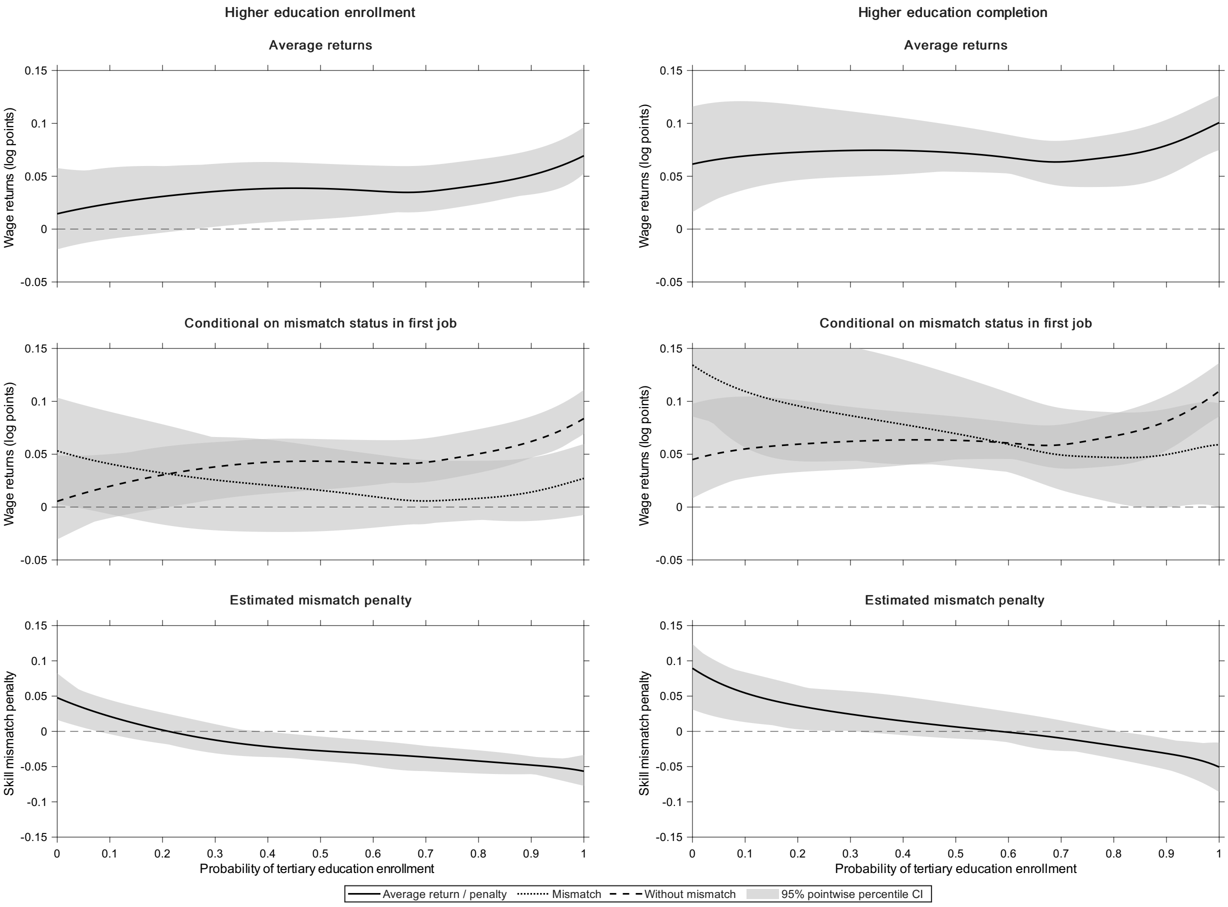
Table A37: Returns to fields of study and skill mismatch (Unobserved types)

Field of study	Unobserved types	(1) BA degree (mismatch)	(2) BA degree (match)	(3) BA degree (penalty)	(4) MA degree (mismatch)	(5) MA degree (match)	(6) MA degree (penalty)
Humanities and Arts (Col)	(Type 1)	-0.006*	0.071***	-0.077***	0.046***	0.135***	-0.089***
		(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Humanities and Arts (Univ)		0.056***	0.036***	0.020***	0.108***	0.100***	0.008***
		(0.004)	(0.004)	(0.001)	(0.004)	(0.003)	(0.001)
Business and Law (Col)		0.033***	0.027***	0.005***	0.084***	0.092***	-0.007***
		(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
Business and Law (Univ)		0.122***	0.154***	-0.032***	0.174***	0.219***	-0.044***
		(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Social Sciences (Col)		0.013***	0.013***	-0.000	0.065***	0.077***	-0.013***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Social Sciences (Univ)		-0.017***	0.069***	-0.086***	0.035***	0.133***	-0.099***
		(0.004)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Health (Col)		-0.037***	0.112***	-0.149***	0.015***	0.176***	-0.161***
		(0.005)	(0.002)	(0.003)	(0.005)	(0.002)	(0.004)
Health (Univ)		0.121***	0.125***	-0.003	0.173***	0.189***	-0.016***
		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
STEM (Col)		0.047***	0.079***	-0.032***	0.098***	0.144***	-0.045***
		(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
STEM (Univ)		0.064***	0.109***	-0.045***	0.115***	0.174***	-0.058***
		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)
Education		-0.005	0.011***	-0.016***			
		(0.004)	(0.002)	(0.002)			
Humanities and Arts (Col)	(Type 2)	-0.011***	0.067***	-0.078***	0.041***	0.131***	-0.090***
		(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Humanities and Arts (Univ)		0.052***	0.043***	0.009***	0.104***	0.108***	-0.004***
		(0.004)	(0.004)	(0.001)	(0.004)	(0.003)	(0.001)
Business and Law (Col)		0.034***	0.033***	0.001	0.086***	0.098***	-0.012***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Business and Law (Univ)		0.118***	0.158***	-0.039***	0.170***	0.222***	-0.052***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Social Sciences (Col)		0.012***	0.018***	-0.006***	0.063***	0.082***	-0.019***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Social Sciences (Univ)		-0.018***	0.072***	-0.090***	0.033***	0.136***	-0.103***
		(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Health (Col)		-0.034***	0.112***	-0.146***	0.018***	0.176***	-0.159***
		(0.005)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)
Health (Univ)		0.112***	0.125***	-0.013***	0.164***	0.190***	-0.026***
		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
STEM (Col)		0.045***	0.084***	-0.039***	0.097***	0.148***	-0.051***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
STEM (Univ)		0.063***	0.115***	-0.052***	0.115***	0.179***	-0.064***
		(0.006)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)
Education		-0.009**	0.013***	-0.022***			
		(0.005)	(0.002)	(0.003)			
Humanities and Arts (Col)	(Type 3)	-0.015***	0.065***	-0.079***	0.037***	0.129***	-0.092***
		(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Humanities and Arts (Univ)		0.045***	0.054***	-0.010***	0.096***	0.119***	-0.022***
		(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.001)
Business and Law (Col)		0.032***	0.041***	-0.009***	0.083***	0.105***	-0.022***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Business and Law (Univ)		0.109***	0.162***	-0.052***	0.161***	0.226***	-0.065***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Social Sciences (Col)		0.006**	0.024***	-0.018***	0.058***	0.088***	-0.030***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Social Sciences (Univ)		-0.015***	0.077***	-0.092***	0.037***	0.141***	-0.104***
		(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Health (Col)		-0.026***	0.113***	-0.138***	0.026***	0.177***	-0.151***
		(0.005)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)
Health (Univ)		0.102***	0.127***	-0.025***	0.154***	0.191***	-0.037***
		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)
STEM (Col)		0.047***	0.089***	-0.043***	0.098***	0.154***	-0.056***
		(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
STEM (Univ)		0.064***	0.124***	-0.060***	0.116***	0.189***	-0.073***
		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
Education		-0.012***	0.019***	-0.031***			
		(0.004)	(0.002)	(0.003)			

NOTE.– Log-hourly wage at age 23, 26, 29, with time and cohort fixed effects. We control for potential experience, unemployment rates and dynamic selection. Type-specific rows are posterior-probability weighted means from the same benchmark simulation used in the pooled tables, so the pooled estimates are weighted averages of the type-specific estimates. Mismatch denotes the full-mismatch counterfactual and match denotes the counterfactual that removes mismatch; the penalty is mismatch minus match.

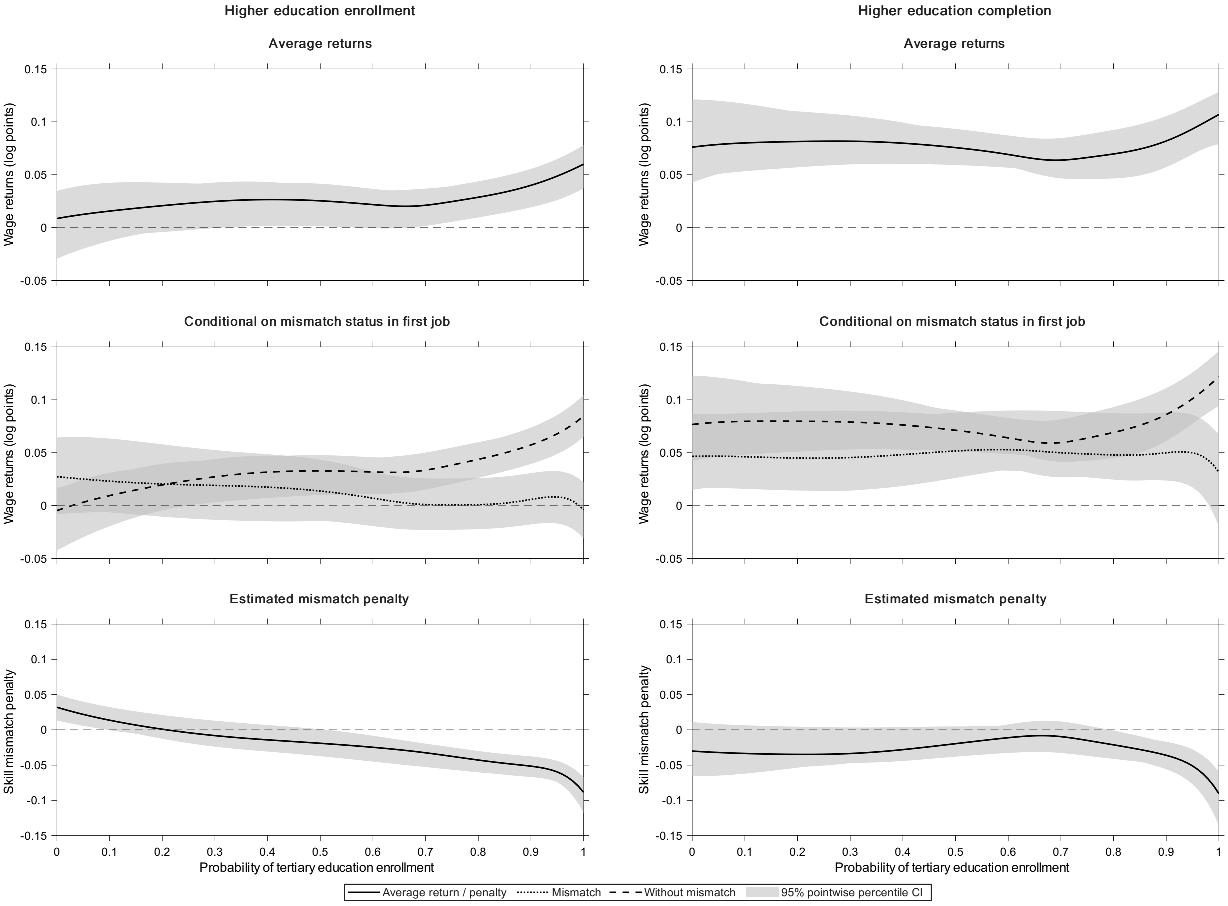
D Robustness checks

Figure A13: Treatment Effect (TE) curves and mismatch penalties under the DSA mismatch definition



NOTE.– The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, computed from the higher education choice model as $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$. Higher values therefore indicate higher enrollment likelihood. The figure follows the same structure as Figure 2: columns distinguish higher education enrollment and higher education completion, while rows report average wage returns, returns conditional on mismatch status in the first job, and the estimated mismatch penalty. Results use the DSA mismatch measure. To construct the enrolled counterfactual outcome, if the simulated first-period choice is non-enrollment we assign the second-highest alternative and simulate the full subsequent education path, yielding Y_1; this is compared with the non-enrollment counterfactual Y_0. The mismatch penalty compares counterfactual earnings under mismatched and matched states conditional on education $(Y_1(d=1 \mid E_i) - Y_1(d=0 \mid E_i))$. Shaded bands are 95% pointwise percentile confidence intervals, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution. DSA = Direct Self-Assessment.

Figure A14: Treatment Effect (TE) curves and mismatch penalties under the JA mismatch definition



NOTE.– The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, computed from the higher education choice model as $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$. Higher values therefore indicate higher enrollment likelihood. The figure follows the same structure as Figure 2: columns distinguish higher education enrollment and higher education completion, while rows report average wage returns, returns conditional on mismatch status in the first job, and the estimated mismatch penalty. Results use the JA mismatch measure. To construct the enrolled counterfactual outcome, if the simulated first-period choice is non-enrollment we assign the second-highest alternative and simulate the full subsequent education path, yielding Y_1; this is compared with the non-enrollment counterfactual Y_0. The mismatch penalty compares counterfactual earnings under mismatched and matched states conditional on education $(Y_1(d = 1 \mid E_i) - Y_1(d = 0 \mid E_i))$. Shaded bands are 95% pointwise percentile confidence intervals, computed at each grid point from the 2.5th and 97.5th percentiles of the simulated TE distribution. JA = Job Analysis.

Table A38: Returns to completed field of study: plain OLS vs full model

	(1) Plain OLS	(2) + Observables	(3) Full Model
BA degree			
Humanities and Arts	0.111***	0.106***	0.045***
	(0.016)	(0.017)	(0.003)
Business and Law	0.090***	0.091***	0.078***
	(0.009)	(0.010)	(0.002)
Social Sciences	0.055***	0.069***	0.019***
	(0.009)	(0.010)	(0.002)
Health	0.117***	0.134***	0.110***
	(0.010)	(0.010)	(0.002)
STEM	0.150***	0.125***	0.087***
	(0.009)	(0.010)	(0.002)
Education	0.020***	0.034***	0.013***
	(0.007)	(0.008)	(0.002)
MA degree			
Humanities and Arts	0.121***	0.124***	0.100***
	(0.017)	(0.018)	(0.002)
Business and Law	0.214***	0.211***	0.138***
	(0.015)	(0.017)	(0.002)
Social Sciences	0.133***	0.151***	0.075***
	(0.018)	(0.019)	(0.002)
Health	0.161***	0.183***	0.169***
	(0.019)	(0.020)	(0.002)
STEM	0.201***	0.180***	0.147***
	(0.011)	(0.013)	(0.002)
Education			

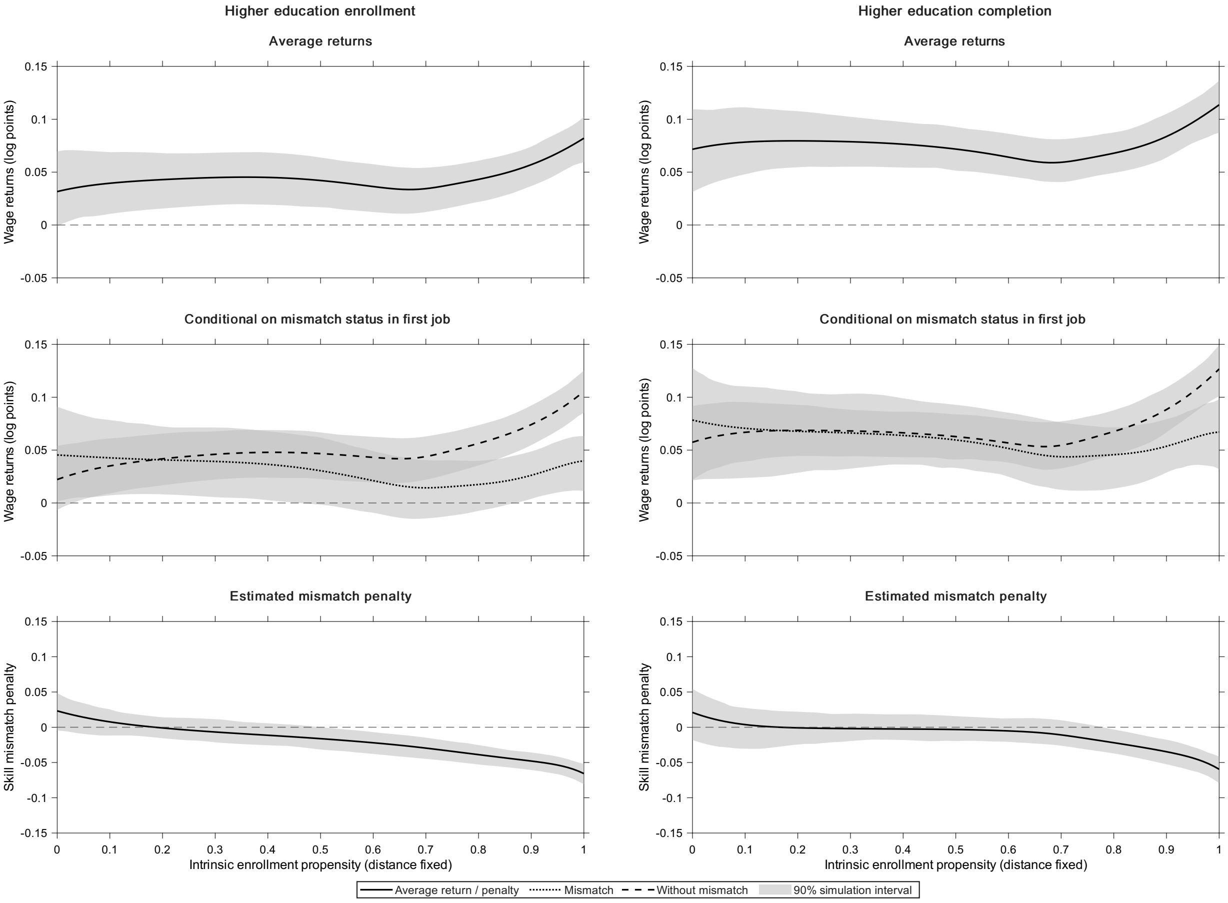
NOTE.– Column (1) reports OLS estimates from a pooled wage regression with completed field-of-study indicators, mismatch, field-specific mismatch interactions, and age fixed effects only. Column (2) adds sex, foreign origin, siblings, parental education, cohort, birth timing, secondary-school delay, potential experience, and local unemployment rates. Column (3) reports the average structural return from the selected full model. BA rows use individuals attaining at least a BA in the field; MA rows use individuals attaining an MA in the field. Standard errors are clustered at the individual level for OLS and based on simulation dispersion for the full model. MA Education is not separately reported.

Table A39: Skill mismatch penalty: plain OLS vs full model

	(1) Plain OLS	(2) + Observables	(3) Full Model
BA degree			
Humanities and Arts	-0.065***	-0.056**	-0.040***
	(0.023)	(0.023)	(0.002)
Business and Law	-0.030**	-0.025**	-0.016***
	(0.013)	(0.012)	(0.001)
Social Sciences	-0.028*	-0.033**	-0.049***
	(0.017)	(0.017)	(0.001)
Health	-0.061**	-0.065**	-0.090***
	(0.030)	(0.030)	(0.002)
STEM	-0.038***	-0.034**	-0.043***
	(0.015)	(0.015)	(0.001)
Education	-0.027	-0.023	-0.022***
	(0.021)	(0.022)	(0.003)
MA degree			
Humanities and Arts	-0.061**	-0.049**	-0.053***
	(0.025)	(0.025)	(0.001)
Business and Law	-0.087***	-0.073***	-0.029***
	(0.022)	(0.022)	(0.001)
Social Sciences	-0.085***	-0.082***	-0.062***
	(0.028)	(0.027)	(0.001)
Health	-0.064	-0.073	-0.103***
	(0.058)	(0.059)	(0.002)
STEM	-0.061***	-0.050***	-0.055***
	(0.018)	(0.018)	(0.001)
Education			

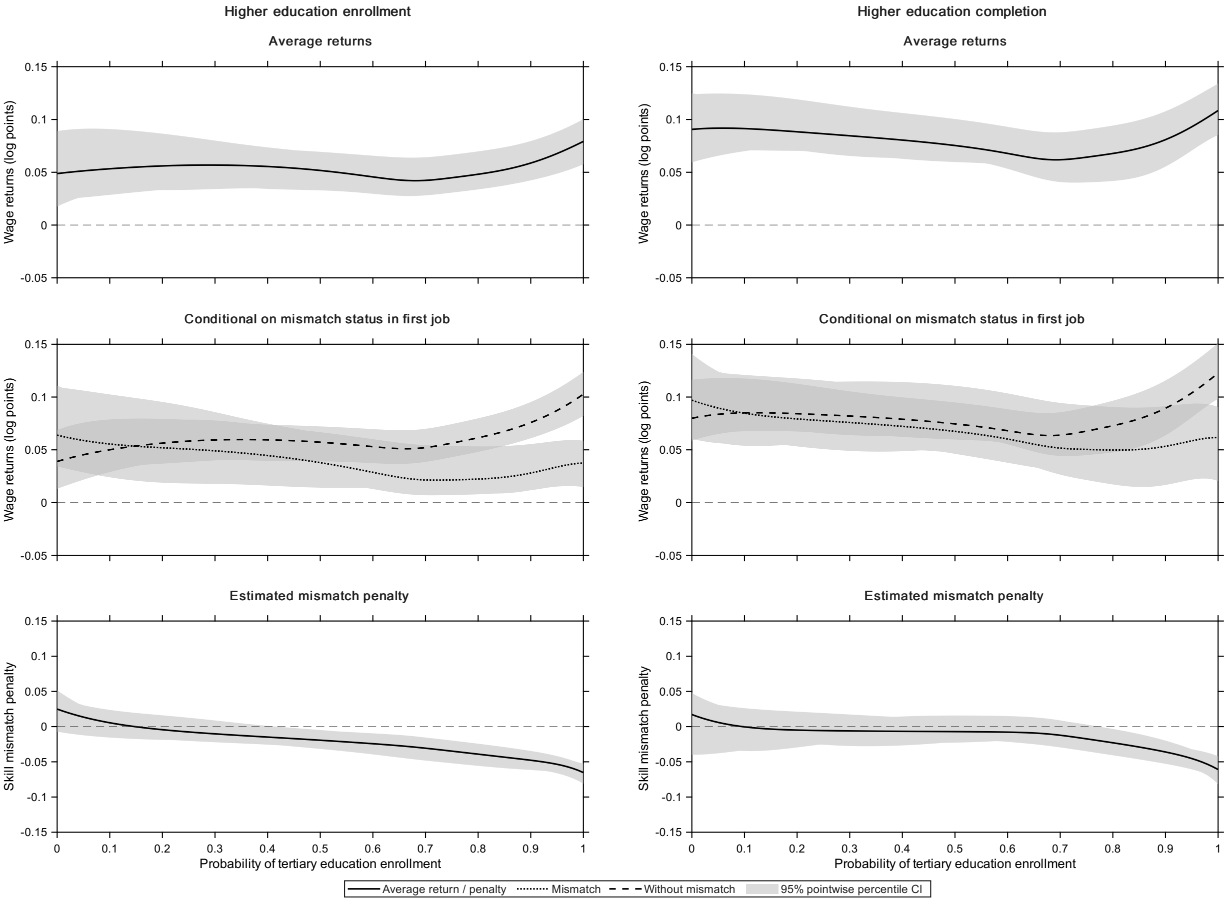
NOTE.– Column (1) reports OLS mismatch penalties from the same pooled wage regression, where the penalty for each field-degree cell equals the baseline mismatch effect plus the corresponding field-specific mismatch interaction. Column (2) adds the full set of observables described in the returns table. Column (3) reports the structural mismatch penalty from the selected full model. Standard errors are clustered at the individual level for OLS and based on simulation dispersion for the full model. MA Education is not separately reported.

Figure A15: Treatment Effect (TE) curves and mismatch penalties for tertiary education enrollment and completion (distance fixed)



NOTE.– The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, computed from the higher education choice model after holding geography fixed: $p_i^\circ = P(C_{i1} \neq 0 \mid S_{i1}^c(Z^\circ), \theta_i)$, where Z° is the sample-mean vector of program-specific distance variables. Higher values therefore indicate higher enrollment likelihood net of geographic proximity. Columns distinguish higher education enrollment and higher education completion. Rows report, respectively, average wage returns, wage returns by first-job mismatch status, and the estimated mismatch penalty. In the second row, "mismatch" and "without mismatch" refer to counterfactual first-job mismatch regimes. In the third row, the mismatch penalty is defined as the return under mismatch minus the return without mismatch, so negative values indicate wage losses from entering a mismatched job. Potential outcomes are simulated as in the baseline figure; only the sorting index on the horizontal axis is recomputed at Z°. To construct the enrolled counterfactual outcome, if the simulated first-period choice is non-enrollment we assign the second-highest alternative and simulate the full subsequent education path, including field, progression, grades, and completion, yielding Y_1; this is compared with the non-enrollment counterfactual Y_0. The completion column conditions on degree completion, removing uncertainty about dropout and subsequent educational progression. TE curves are estimated by local-linear smoothing over a grid of $u \in [0,1]$, following `mtefe` (Andresen, 2018). Shaded bands are 90% pointwise percentile intervals, computed at each grid point from the 5th and 95th percentiles of the simulated TE distribution; this robustness figure uses the narrower interval to keep the distance-fixed curves readable.

Figure A16: Treatment Effect (TE) curves and mismatch penalties for tertiary education enrollment and completion, with experience path corrected



NOTE.– The horizontal axis is the predicted probability of enrolling in tertiary education in period 1, $p_i = P(C_{i1} \neq 0 \mid S^c_{i1}, \theta_i)$, computed from the higher education choice model. Higher values therefore indicate higher predicted enrollment likelihood. Columns distinguish higher education enrollment and higher education completion. Rows report, respectively, average wage returns, wage returns by first-job mismatch status, and the estimated mismatch penalty. In the second row, "mismatch" and "without mismatch" refer to counterfactual first-job mismatch regimes. In the third row, the mismatch penalty is defined as the return under mismatch minus the return without mismatch, so negative values indicate wage losses from entering a mismatched job. The figure differs from the baseline specification by replacing the fixed higher-education potential-experience profile with experience implied by the simulated education path. For each individual and parameter draw, the simulated first-period program is set to the highest-ranked higher-education alternative, and the subsequent path determines educational exit. Potential labor-market experience is then recomputed from that exit date. Early dropouts therefore enter the labor market earlier, while delayed BA/MA paths enter later. The resulting enrolled potential outcome Y_1 is compared with the non-enrollment counterfactual Y_0. The completion column conditions on degree completion, removing uncertainty about dropout while retaining path-specific timing of labor-market entry. TE curves are estimated by local-linear smoothing over a grid of $u \in [0,1]$, following `mtefe` (Andresen, 2018). Shaded bands are 95% pointwise percentile intervals based on parameter draws from the asymptotic distribution.

Table A40: Returns to field of study completion: comparison across Baseline, DSA (Col only), JA, K=2 specifications

	(1) Baseline BA	(2) Baseline MA	(3) DSA (Col only) BA	(4) DSA (Col only) MA	(5) JA BA	(6) JA MA	(7) K=2 BA	(8) K=2 MA
Humanities and Arts	0.045***	0.100***	0.027***	0.085***	0.031***	0.095***	0.037***	0.093***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Business and Law	0.078***	0.138***	0.027***	0.086***	0.072***	0.129***	0.072***	0.130***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Social Sciences	0.019***	0.075***	0.010**	0.069***	0.006*	0.068***	0.023***	0.077***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
Health	0.110***	0.169***	0.095***	0.158***	0.127***	0.181***	0.119***	0.177***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
STEM	0.087***	0.147***	0.077***	0.136***	0.094***	0.149***	0.086***	0.142***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Education	0.013***		0.008***		0.011***		0.011***	
	(0.002)		(0.003)		(0.003)		(0.003)	

NOTE.– Measures: Returns are mean log-hourly wage differences between each program and high-school at ages 23, 26, 29. Controls include year and cohort fixed effects, potential experience, non-employment rates, and dynamic selection. For Baseline, JA, and K=2, aggregate results are weighted averages across vocational (Col) and academic (Univ) institutions using simulated enrollment probabilities. For DSA, university-level estimates are omitted because the DSA specification is not well identified at the university margin, especially for university STEM returns; DSA entries report vocational-college results only. Baseline = latent-factor mismatch measure with K=3 unobserved types. DSA = Direct Self-Assessment mismatch measure; because the university margin is not well identified, DSA entries report vocational-college results only. JA = Job Analysis mismatch measure. K=2 = baseline mismatch measure with two unobserved types.

Table A41: Skill mismatch penalty by field of study: comparison across Baseline, DSA (Col only), JA, K=2 specifications

	(1) Baseline BA	(2) Baseline MA	(3) DSA (Col only) BA	(4) DSA (Col only) MA	(5) JA BA	(6) JA MA	(7) K=2 BA	(8) K=2 MA
Humanities and Arts	-0.040***	-0.053***	-0.037***	-0.058***	-0.028***	-0.005	-0.054***	-0.065***
	(0.002)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Business and Law	-0.016***	-0.029***	-0.006*	-0.027***	-0.006***	0.017***	-0.024***	-0.035***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Social Sciences	-0.049***	-0.062***	0.002	-0.018***	-0.063***	-0.040***	-0.058***	-0.069***
	(0.001)	(0.001)	(0.005)	(0.006)	(0.003)	(0.003)	(0.002)	(0.003)
Health	-0.090***	-0.103***	-0.163***	-0.184***	-0.040***	-0.017	-0.089***	-0.101***
	(0.002)	(0.002)	(0.010)	(0.009)	(0.010)	(0.011)	(0.005)	(0.005)
STEM	-0.043***	-0.055***	-0.010***	-0.031***	-0.050***	-0.027***	-0.038***	-0.050***
	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Education	-0.022***		-0.010*		-0.014**		-0.023***	
	(0.003)		(0.005)		(0.006)		(0.003)	

NOTE.– Measures: Mismatch penalty equals returns under full mismatch minus returns under no mismatch. Returns are mean log-hourly wage differences between each program and high-school at ages 23, 26, 29 with the same controls as the main table. For Baseline, JA, and K=2, aggregate results are weighted averages across vocational (Col) and academic (Univ) institutions using simulated enrollment probabilities. For DSA, university-level estimates are omitted because the DSA specification is not well identified at the university margin, especially for university STEM returns; DSA entries report vocational-college results only. Baseline = latent-factor mismatch measure with K=3 unobserved types. DSA = Direct Self-Assessment mismatch measure; because the university margin is not well identified, DSA entries report vocational-college results only. JA = Job Analysis mismatch measure. K=2 = baseline mismatch measure with two unobserved types.

Table A42: Negative returns by field of study: comparison across Baseline, DSA (Col only), JA, K=2 specifications (in %)

	Field of Study	Baseline Avg. Mismatch (in %)	Baseline Without Mismatch (in %)	Baseline Full Mismatch (in %)	DSA (Col only) Avg. Mismatch (in %)	DSA (Col only) Without Mismatch (in %)	DSA (Col only) Full Mismatch (in %)	JA Avg. Mismatch (in %)	JA Without Mismatch (in %)	JA Full Mismatch (in %)	K=2 Avg. Mismatch (in %)	K=2 Without Mismatch (in %)	K=2 Full Mismatch (in %)
BA Degree	Humanities and Arts	25.8	15.0	32.7	36.8	32.0	46.8	27.3	26.4	28.1	24.1	15.0	42.9
	Business and Law	1.6	1.1	2.9	29.4	28.6	33.1	2.8	1.3	7.6	2.4	2.1	3.2
	Social Sciences	37.4	28.0	51.4	44.0	44.4	42.4	38.3	24.3	53.8	34.2	23.8	52.6
	Health	8.9	0.9	48.1	5.8	1.5	65.2	3.9	1.3	33.0	6.1	0.2	35.0
	STEM	0.6	0.1	2.8	3.1	1.3	12.5	0.1	0.0	0.7	0.2	0.0	0.6
	Education	44.8	43.7	53.3	44.6	44.5	46.2	47.1	46.9	50.5	45.2	44.2	52.0
MA Degree	Humanities and Arts	5.8	0.1	9.2	14.4	11.4	21.5	3.7	5.8	2.2	5.6	0.5	14.3
	Business and Law	0.0	0.0	0.0	3.9	1.6	15.2	0.0	0.0	0.0	0.0	0.0	0.0
	Social Sciences	13.5	1.1	28.3	16.5	13.3	31.0	14.9	5.2	25.6	14.2	1.1	32.3
	Health	3.3	0.0	16.3	3.0	0.0	52.0	2.2	0.0	26.1	1.7	0.0	8.6
	STEM	0.0	0.0	0.0	0.5	0.0	3.2	0.0	0.0	0.0	0.0	0.0	0.0

NOTE.– Measures: Negative returns are the fraction (percentage) of individuals with returns <= 0, computed from the mean distribution of individual returns. Average Mismatch is computed as a weighted average of Without and Full Mismatch using the field-degree-specific absolute mismatch probability; these probabilities are mixture weights and are not the relative mismatch-sorting differences. For Baseline, JA, and K=2, aggregate results are weighted averages across vocational (Col) and academic (Univ) institutions using simulated enrollment probabilities. For DSA, university-level estimates are omitted because the DSA specification is not well identified at the university margin, especially for university STEM returns; DSA entries report vocational-college results only. Baseline = latent-factor mismatch measure with K=3 unobserved types. DSA = Direct Self-Assessment mismatch measure; because the university margin is not well identified, DSA entries report vocational-college results only. JA = Job Analysis mismatch measure. K=2 = baseline mismatch measure with two unobserved types.

Table A43: Skill mismatch sorting: comparison across Baseline, DSA (Col only), JA, K=2 specifications

	(1) Baseline BA	(2) Baseline MA	(3) DSA (Col only) BA	(4) DSA (Col only) MA	(5) JA BA	(6) JA MA	(7) K=2 BA	(8) K=2 MA
Business and Law	-0.371***	-0.345***	-0.135***	-0.128***	-0.329***	-0.328***	-0.078***	-0.073***
	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
Social Sciences	-0.207***	-0.173***	-0.121***	-0.114***	-0.103***	-0.101***	0.038***	0.053***
	(0.004)	(0.005)	(0.011)	(0.010)	(0.011)	(0.009)	(0.008)	(0.009)
Health	-0.437***	-0.423***	-0.260***	-0.237***	-0.494***	-0.495***	-0.155***	-0.164***
	(0.003)	(0.003)	(0.010)	(0.009)	(0.006)	(0.006)	(0.007)	(0.008)
STEM	-0.400***	-0.381***	-0.165***	-0.153***	-0.438***	-0.438***	0.065***	0.070***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.008)
Education	-0.495***		-0.242***		-0.528***		-0.193***	
	(0.003)		(0.009)		(0.004)		(0.007)	

NOTE.– Measures: Mismatch sorting is the difference in model-implied counterfactual mismatch rates under assignment to field j, relative to Humanities and Arts. Rates are computed from the simulated mismatch indicator. For Baseline, JA, and K=2, aggregate results are weighted averages across vocational (Col) and academic (Univ) institutions using simulated enrollment probabilities. For DSA, university-level estimates are omitted because the DSA specification is not well identified at the university margin, especially for university STEM returns; DSA entries report vocational-college results only. Baseline = latent-factor mismatch measure with K=3 unobserved types. DSA = Direct Self-Assessment mismatch measure; because the university margin is not well identified, DSA entries report vocational-college results only. JA = Job Analysis mismatch measure. K=2 = baseline mismatch measure with two unobserved types.