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Do labour market outcomes influence why women are underrepresented in engineering?

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Abstract

Despite women outnumbering men in higher education, significant gender segregation persists in the choice of field of study. In the 2020/2021 academic year, only 8% of Spanish female students were enrolled in Engineering, compared to 29.5% of male students. This paper investigates the determinants of the underrepresentation of women in Engineering in Spain by examining whether differences in future labour market outcomes influence this anomaly. Using data from the 2019 University Graduate Employment Outcomes Survey, we find significantly worse labour outcomes for female Engineering graduates than for those in Health. Within fields, we find a larger gender gap in labour outcomes in Engineering than in Health. Our results suggest that gender segregation in higher education can be partly driven by differences in labour market expectations by field of study and gender. Many women who could pursue Engineering based on their pre-university track and accomplishments may opt instead for other fields like Health due to better career prospects: higher probability of finding a job and higher earnings, and lower likelihood of experiencing vertical and horizontal mismatches.

Keywords Gender differences · Higher education · Labour market entry · Field of study · Gender segregation · Engineering

Introduction

The increasing participation of women in higher education over the past few decades has eliminated gender differences in college enrolment, and now women represent the majority of university students. However, the pattern of sorting into fields has not been uniform, and significant gender segregation remains in the choice of field of study.[1] Most notably,

[1] See Alon & DiPrete (2015); Barone & Assirelli (2020); Blau & Kahn (2017); Bradley (2000); Charles & Bradley (2009); England & Li (2006); Kugler et al. (2017); Vaarmets (2018); Zafar (2013).

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women are severely underrepresented in technology and maths-intensive science fields, such as Engineering. In 2021, 59.1% of graduates in OECD countries were women. However, while women accounted for 84% of graduates in Education and 78% in Health, they only represented 28% of graduates in Engineering and 21% in Information and Communication (ICT) studies (OECD, 2023).

The gender gap in science, technology, engineering, and mathematics (STEM) fields can have important and long-lasting economic and social implications. First, the overrepresentation of women in sectors such as health and their underrepresentation in STEM may contribute to the persistence of gender pay gaps, as most of the STEM occupations—especially engineering and computer science—typically pay higher salaries (Francesconi & Parey, 2018). Second, increasing women's participation in STEM fields can help alleviate the current STEM labour supply shortage, thus meeting the growing demand.[2] Third, gender segregation across fields may adversely impact productivity, as theoretical and empirical studies show that greater gender diversity can foster innovation (Yang et al., 2022), improve problem-solving (Hong & Page, 2004), provide better access to different resources and connections (Ferreira, 2010), and even enhance productivity directly (Campbell & Mínguez-Vera, 2008; Jones, 2009; Page, 2008). Finally, the underrepresentation of women in STEM occupations may lead to technological developments that ignore women's preferences (Jiang, 2021).

The determinants of the gender gap in STEM have been widely studied yet have not been fully explained, as multiple factors may influence the choice of field of study. The literature has explored the following[3]: personality traits such as competitiveness, self-confidence, underestimation of mathematical abilities, or risk attitudes (Buser et al., 2014; Reuben et al., 2017; Shi, 2018); pre-university preparedness such as courses taken, technology and maths skills, achievements in upper secondary education, or university admission test scores (Aucejo & James, 2021; Card & Payne, 2021); educational environmental factors such as teacher influence, role models, and peer gender composition (Carrell et al., 2010; Fischer, 2017); norms, cultural, and family stereotypes (Cheryan et al., 2017; Kahn & Ginther, 2018); and the role of subjective expectations about their future employment and earnings and preferences over pecuniary and non-pecuniary aspects of the future job—e.g., proximity to home, less competitive work environments, job roles oriented towards care or altruistic activities, and better job-family life balance (Ding et al., 2021; Ersoy & Speer, 2022; Herbaut & Barone, 2021; Reuben et al., 2017; Wiswall & Zafar, 2021; Zafar, 2013).

This paper explores the determinants of the underrepresentation of women in Engineering in Spain by analysing the link between the choice of university major and the ensuing labour market consequences of these choices. Similar to other OECD countries, only 8% of female university students in Spain were enrolled in Engineering in 2021, compared to 29.5% of male students (MU, 2023). Spain provides an interesting context for this analysis. First, Spain has one of the highest youth unemployment rates in the EU, with longstanding difficulties in entering the job market, even for bachelor graduates. Second, the admission process to Spanish universities is centralised. Applicants are admitted to specific degree programs based on the track chosen in high school, their high school scores, entry exam scores, and the availability of slots. Third, students are generally committed to their

[2] In 2021, 62.8% of European businesses faced challenges filling ICT vacancies and the EU's estimated demand for 20 million digital experts by 2030 may not be satisfied. However, the share of female digital experts stood at 18.9% in 2022, having risen by just 1.9 pp over the 2012–2022 decade (Eurostat, 2023).

[3] See Altonji et al. (2012), Kanny et al. (2014), and Patnaik et al. (2021) for reviews of this literature.

selected major once admitted, as changing degree programs can be administratively complex and may require additional coursework.

For our analysis, we use data from the 2019 University Graduate Employment Outcomes Survey (EILU), a rich dataset on graduates' transition to the labour market. We first study differences in labour market outcomes between fields (Engineering and Health) separately for men and women. For female graduates, we find that those in Engineering are less likely to be employed and to have worked more than 12 months after graduation, and more likely to earn lower wages and experience vertical and horizontal skill-job mismatches than those in Health. In contrast, we do not find significant differences across fields for male graduates.

Next, we study within-field gender differences in labour market outcomes. We find that gender gaps are generally larger in Engineering than in Health, suggesting that female graduates in Engineering face considerable discrimination—possibly both statistical and taste-based—relative to their male counterparts.

Under the assumption of no gender differences in productivity, our results are consistent with heterogeneous graduates sorting into fields where they have a comparative advantage, but with women facing comparatively worse labour market conditions than men—possibly stemming from discrimination. Comparatively worse outcomes for females in Engineering than in Health may explain their underrepresentation in this field. If women who are qualified to enter Engineering are less likely to find a first job in this field compared to other fields such as Health, or if the gender pay gap is wider for female Engineering graduates than the one in Health, they may opt for Health over Engineering. These results are in line with Kirkeboen et al. (2017), who find that different fields of study yield different labour market outcomes, and individuals tend to choose degrees where they hold a comparative advantage.

Although our results are consistent with sorting on comparative advantage, heterogeneous preferences for extrinsic incentives between male and female students, as well as within gender, may also shape field choices, as students—particularly women—can place different weights on extrinsic and intrinsic factors, such as work environment, job flexibility, and satisfaction. Existing research finds that preferences of students can explain part of the gender gap in major choice (Patnaik et al., 2021; Zafar, 2013), but different factors matter differently for male and female students (Ersoy & Speer, 2022), with female students placing more value on non-pecuniary factors (Ding et al., 2021; Ersoy & Speer, 2022). Moreover, Ding et al. (2021) find that, even among students who prefer high-paying majors, female students are less responsive to wage information than male students.

This study contributes to the limited but growing literature on how expected salaries influence the choice of field of study by examining indirectly the association between various labour market outcomes and the choice of field of study, and their potential impact on the gender gap in STEM in Spain. Existing research shows that expected earnings are indeed important determinants of educational choices (Arcidiacono et al., 2012; Conlon, 2021; Stinebrickner & Stinebrickner, 2014), particularly for men (Alon & DiPrete, 2015; Ding et al., 2021). However, there is no conclusive evidence that salary expectations matter for the gender gap in STEM: while men typically expect higher salaries than women, and such expectations affect their field choice, this does not fully account for differences in field choice (Mann & DiPrete, 2013; Osikominu & Pfeifer, 2018). Meanwhile, Ganley et al. (2018) find that perceived gender bias against women is a key driver of gender imbalance in college degrees, whereas Galos and Strauss (2023) argue that the decline of the "male breadwinner" model has strengthened women's motivation to earn high incomes, potentially influencing them to pursue "female-atypical" degrees.

Table 1 Distribution of students and graduates by gender and field of study in Spain, academic year 2020/2021

Gender distribution	Students		Graduates	
	Female	Male	Female	Male
Across fields (%)				
Engineering	8.0	29.5	6.7	26.9
Health	24.5	12.5	24.7	14.5
Science	5.8	7.1	5.7	7.1
Social Sciences	50.0	41.8	53.4	44.1
Arts-Humanities	11.7	9.1	9.5	7.4
Within field (%)				
Engineering	25.6	74.4	27.3	72.7
Health	71.5	28.5	72.0	28.0
Science	50.7	49.3	54.7	45.3
Social Sciences	60.5	39.5	64.5	35.5
Arts-Humanities	62.3	37.7	65.5	34.5
Total	*56.3*	*43.7*	*60.0*	*40.0*

Source: MU (2023)

Furthermore, little work to date has examined how labour outcomes affect gender disparities in college field choice of contexts with high youth unemployment and persistent difficulties in transition to the labour market such as Spain. Those studies have mainly focused on the impact of earnings, often overlooking other job-related aspects, such as employment prospects and educational mismatch.

The Spanish context

In Spain, women started to outnumber men in both enrolment and graduation in higher education since the late- 1980 s. While in 1971, women accounted for only 25.8% of university students, this figure rose to 44% in 1981 and reached 50.1% by 1987 (MEC, 1983). By 2021, 55.8% of enrolled university students (MU, 2023) were women. The share of female graduates was 59.2% in 2021, in line with the OECD average of 59.1% (OECD, 2023).

Yet, as in almost all OECD countries, we observe ongoing gender segregation in fields of study. Table 1 shows the gender distribution across and within the five main broad fields of study (Engineering, Health, Sciences, Social Sciences, and Arts-Humanities)[4] for new bachelor's entrants and graduates in the academic year 2020/2021.

There is significant variation between men and women in field choice: women are the majority in all fields except Engineering, where they are notably underrepresented—25.6% of Engineering students are women, compared to 56.3% across all fields; this percentage increases for graduates to 27.3% compared to 60% across all fields. Furthermore, among

[4] In Spain, university studies are categorised into these five broad fields of study (https://www.universidades.gob.es/wp-content/uploads/2023/06/Metodologia_EEU.pdf).

Traditionally, Engineering-Architecture, Health, and Sciences are grouped together under a broader category known as Science and Technology.

Table 2 Average scores for public university entrance in Spain by gender and field of study, academic year 2020/2021

	Female	Male
Final entry score[a]		
Engineering	10.14	9,60
Health	11.27	11.06
Sciences	11.06	10.97
% of female/male with entry score ≥ 12[a]		
Engineering	25.67	16.31
Health	39.71	38.30
Sciences	39.14	29.39
Mathematics score in the entry exam[b]		
Engineering	7.29	7.14
Health	7.38	7.45
Sciences	7.51	7.86

Source: [a]MU (2023); [b]MU, Integrated University Information System. Own calculations

women, only 8% enroll in Engineering compared to 29.5% of the male population, and just 6.7% of women graduates come from Engineering compared to 26.9% of male graduates. In contrast, women were overrepresented in Health: 24.5% of all female students selected Health, and women accounted for 71.5% of enrollees and 72% of graduates.

What factors can explain this underrepresentation of women in Engineering? As students need prerequisites to enter this field, a substantial portion of the gender segregation in higher education results from differences in pre-university track and educational attainment. In Spain, upper-secondary education requires students to choose a track that ultimately determines the undergraduate programs they can later pursue. In the academic year 2020/2021, the percentage of women per track was 73.9% in Arts, 64.5% in Humanities, 54.5% in Social Sciences, and 47.7% in Science and Technology (MEFP, 2023). This is consistent with gender segregation in upper-secondary education that carries over to university studies and can largely explain why women prefer fields like Social Sciences and Arts-Humanities over Science and Technology, as noted in Table 1.

However, differences in early tracking cannot account for the large gender segregation in Engineering compared to Health and Science. Students pursuing these three fields typically have similar educational training at the start of their university career, as they come from the same Science and Technology track, and they have taken similar courses.[5] Moreover, any student from this track can pursue university studies in Engineering, Health, or Sciences.

Additionally, the underrepresentation of women in Engineering cannot be attributed to gender differences in skills and achievements at entry into college. In the academic year 2020/2021, Table 2 shows that, on average, female students entered university with higher scores, and the percentage of top students was consistently higher for women across the three fields considered. In fact, the average cut-off grades for Engineering were lower than

[5] Upper-secondary Science and Technology students study the same Mathematics curriculum, but they can study different combinations of subjects such as Physics and Chemistry and choose other subjects (Biology, Technical Drawing, …). While the combination of subjects may vary, however, the content within each subject is the same across all students.

for the other two fields. Additionally, gender disparities in field choice cannot be attributable to variation between men and women in mathematical skills, as male and female in all three fields achieved, on average, similar maths scores in the university entry exam. Our analysis suggests that the lack of women pursuing Engineering is not related to lower general or specific skills at university entry, but rather to lower expected outcomes.

If factors such as pre-university qualifications or university entry exam grades do not explain why fewer women pursue Engineering compared to men, what can account for this difference? One potential explanation is the disparities among different fields of study in employment opportunities, job quality, and the mismatch between training and the work performed. This aspect may be particularly relevant in labour markets with persistent frictions, such as Spain.

Data from Spain seem to support this hypothesis. According to data from 2019 EILU used in this paper and described in the next section, 75.1% of Spanish graduates reported that their degree choices were mainly driven by expected labour market outcomes after graduation. This percentage is higher among women than men (76.2% versus 73.6%), and even higher for individuals in Engineering fields (79.9%). In contrast, only 16.1% of undergraduates chose their studies for self-satisfaction, with this figure being 14.9% for female graduates and 17.7% for male graduates.

Data and methodology

Data

To empirically examine whether the gender gap in Engineering can be explained by differences in the labour market outcomes, we use microdata coming from the EILU conducted by the National Statistics Institute (INE). The EILU is a nationwide survey that provides detailed information about the transition from the university to the labour market (INE, 2020).[6] One of the main advantages of this survey is that it combines data from administrative records (Integrated University Information System, Social Security, State Public Employment Service, National Database for People with Disabilities, and the Spanish Census) with self-reported responses. This provides rich data on graduates' personal and demographic characteristics, education and learning, and labour market outcomes.

We use data from the 2019 wave of this survey. The dataset includes information on 31,651 college graduates from undergraduate studies from various fields in 2019, sampled from the graduation cohort 2013/2014. Our study focuses primarily—though not exclusively—on the comparison between graduates in Engineering and Health for two reasons. First, these fields exhibit large and opposite gender segregation: while Health is a female-dominated field, Engineering is heavily male-dominated. Second, individuals pursuing degrees in these two fields are assumed to have comparable prior skills, as they typically follow the same track in upper-secondary education, thus making them homogeneous given observables. Consequently, the decision to pursue a particular degree cannot be attributed to differences in pre-university education. Our sample therefore comprises 11,193 graduates (6705 from Engineering and 4488 from Health).

[6] Detailed information on EILU Methodology can be found in https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736176991&menu=metodologia&idp=1254735976597

To characterise labour market outcomes of graduates, we construct five variables related to the employment of individuals at the time of the survey (2019). Individuals are interviewed 5 years after graduation. This allows us to analyse outcomes in a more stable stage of their professional careers compared to their employment situation immediately after graduation. Labour market outcomes include both the employment status and the quality of working conditions. Thus, we consider whether the graduates are employed (*Employed*), and three measures of job quality: vertical mismatch (*Vertical-Mismatch*), horizontal mismatch (*Horizontal-Mismatch*), and net monthly salary. Vertical mismatch measures the subjective perception that the current job does not require a college degree, while horizontal mismatch is a subjective perception that the current job is unrelated to the field of study. As for salaries, since the survey does not provide information on individual salaries but only on categories, we construct a variable indicating whether graduates earn more than 1500€ net per month (*Salary + 1500*). Additionally, we consider a variable measuring job duration (*Employed + 12*), indicating whether individuals have been employed for more than 12 months since graduation.

Methodology

Our working hypothesis is that the underrepresentation of Spanish women in Engineering can be partly attributed to comparatively lower labour outcomes for women in this field. We aim to find indirect empirical evidence to support this hypothesis. Our approach is to find evidence that male and female graduates obtain different labour market outcomes depending on their field of study (Engineering versus Health), with studying Health being more favourable on average for women than Engineering. To test this, we estimate for each gender the Average Treatment Effect (ATE) on the probability of achieving a specific labour market outcome (*Employed*, *Vertical-Mismatch*, *Horizontal-Mismatch*, *Salary + 1500*, *Employed + 12*) by studying a degree in a particular field (treatment group) versus studying a degree in another field (control group).

To estimate the ATE, we need to overcome the problem that the degree choice is not randomly assigned. It can potentially suffer from an endogeneity bias, as factors that affect the self-selection into university studies can also affect the labour market outcomes. To address this problem and control for these confounders, we use an inverse probability weighting regression adjustment (IPWRA) approach.

The IPWRA relies on three assumptions to obtain reliable estimates of ATE (Hernan & Robins, 2020): (1) The conditional-independence assumption (CIA), which requires that, after conditioning on covariates, the unobservable factors that affect the treatment are conditionally independent of potential outcomes—that is, we have selection on observables. (2) The overlap assumption (OA), which requires that each individual has a positive probability of receiving the treatment. (3) The Stable Unit Treatment Value Assumption (SUTVA), which implies that the treatment status of one individual does not affect the outcomes of other individuals.

To assess whether these assumptions hold in our setting, we first test the OA by constructing overlap plots. They would allow us to determine whether comparisons between individuals studying in different fields of study are valid, given the different characteristics of individuals. Second, as the CIA cannot be tested empirically (Wooldridge, 2010), we have carefully selected the variables included in the treatment and outcome equations. Finally, the SUTVA is likely to hold, as the individual outcomes of studying each field do not depend on the outcomes of other individuals.

The implementation of the IPWRA requires three steps. First, we estimate a treatment equation to assess the probability of studying Engineering versus Health for each gender using a probit model. The treatment variable (*Engineering*) equals 1 if an individual has a bachelor's degree in Engineering and zero otherwise. We control for socioeconomic characteristics (age, nationality, disability status, and region of residence) and parental educational level. Second, the estimated inverse probabilities of treatment are used to reweight the observations in the probit estimations of labour market outcomes for each gender. We control for socioeconomic characteristics (age, nationality, and disability status), university characteristics (region of the university where graduation took place and whether the university is public or private), graduate's skills (ICT proficiency, foreign language skills, and excellence scholarship awarded during their university studies), mobility variables (mobility to another Spanish university, domestic moves for employment, and international mobility), post-graduate studies (variables indicating whether additional university studies were pursued), and additional variables (internship during studies, and, a variable indicating part-time employment is also used for the salary analysis).[7] Third, the means of the treatment-specific predicted outcomes are used to estimate the ATE.

An important advantage of IPWRA compared to alternative approaches is that estimators are doubly robust. ATE estimates remain consistent even under misspecification of either of the two equations (treatment or outcome) on which they are based (Sloczynski & Wooldridge, 2018).

Results

Gender differences in labour market outcomes across fields

Table 3 reports the ATE estimates for male and female graduates of studying Engineering versus Health for each of the outcome variables. The overidentification test for covariate balance by Imai and Ratkovic (2014) confirms that the propensity score is correctly specified in all cases. The overlap plots presented in the Appendix show that there is no evidence that the OA is violated.

For women, studying Engineering compared to Health has a negative and significant effect on all labour market outcome variables, with at least a 10%. Female graduates in Engineering have a 2.5 pp lower probability of being employed than females in Health. Additionally, they are less likely to earn over 1500€ (6.9 pp) and to have worked more than 12 months since graduation (1.2 pp) and are more likely to experience vertical (7.8 pp) and horizontal mismatch (12.6 pp). In contrast, for men, we only observe significant differences in the mismatch outcomes, with higher vertical (6.3 pp) and horizontal mismatch (5.9 pp) in Engineering.

[7] These variables are commonly used in studies on graduates' outcomes in the Spanish labour market (Albert & Davia, 2018; Arrazola et al., 2024; Canal-Domínguez & Rodríguez-Gutiérrez, 2019). The inclusion of post-treatment variables in the outcome equation does not seem to pose any problem since these variables are not directly affected by the treatment (Hernan & Robins, 2020). In the Spanish university context, factors like university type or region where the university is located are not expected to be determined by the field of study as all degrees are available nationwide in public and private universities. Similarly, the skill measures and individual's mobility are not expected to be conditioned by the chosen field of study. Selection and outcome estimations results are available upon request.

Table 3 ATE of studying a degree in Engineering versus in Health. IPWRA estimations

	Employed	Mismatch		Salary + 1500	Employed + 12
		Vertical	Horizontal		
Female					
ATE	– 0.025** (0.010)	0.078*** (0.011)	0.126*** (0.015)	– 0.069*** (0.017)	– 0.012* (0.007)
Test-covariate balance [*p*-value]	15.435 [0.751]	19.342 [0.500]	19.085 [0.516]	20.300 [0.439]	15.374 [0.755]
Observations	*4734*	*4285*	*4280*	*4211*	*4732*
Male					
ATE	– 0.006 (0.011)	0.063*** (0.014)	0.059*** (0.017)	0.032 (0.023)	– 0.003 (0.006)
Test-covariate balance [*p*-value]	13.290 [0.774]	12.021 [0.856]	12.6629 [0.811]	14.974 [0.663]	13.380 [0.769]
Observations	*5272*	*4859*	*4853*	*4760*	*5271*

Standard errors (SE) in parentheses

**p*-value <0.1; ***p*-value <0.05; ****p*-value <0.01

The results show that, after controlling for individual characteristics and potential selection biases, female Health graduates have better employment conditions than their Engineering counterparts, but there are no significant differences for men. This shows that differences in labour outcomes can explain why a higher proportion of women choose Health degrees over Engineering.[8]

To confirm if individuals tend to choose degrees with better labour market outcomes, we perform two further analyses. First, we examine differences in employability for each field of study between the most popular degrees among men and women and the rest.[9] Given the high employment rates among graduates in these fields, we only examine mismatch and salary outcomes by gender and field.

The ATE estimates (see Table S1 in the supplementary information) show that women studying popular degrees are less likely to experience vertical and horizontal mismatch, and in Health, they are more likely to earn over 1500€. For men, studying these degrees increases the likelihood of having a salary above 1500€, and in Engineering, reduces the probability of vertical and horizontal mismatch. These findings suggest that both women and men tend to choose degrees with better labour market prospects, confirming our

[8] The results obtained when excluding post-treatment variables provide supportive evidence that female graduates in Health obtain better outcomes than female graduates in Engineering. Additionally, we estimated the ATE on the Treated and the ATE on the Untreated. The results are aligned with those of the ATE, which further supports the hypothesis that female graduates in Engineering face worse outcomes than those in Health. Estimations are available upon request.

[9] In Engineering, the most popular degrees among women are Computer Science, Civil Engineering, and Architecture, representing 26.4% of female graduates in this field. For men, the most popular degrees are Computer Science, Civil Engineering, and Industrial Technology Engineering, accounting for 36.23% of male graduates in the field. In Health, the most popular degrees are Nursing, Medicine, and Psychology for both men and women, representing 48.5% and 62.9% of male and female graduates in Health, respectively.

hypothesis that gender segregation can be partly due to gender differences in expected career outcomes.

In the second analysis, we extend the sample with 2777 Science graduates and estimate the ATE by gender for studying Engineering or Health versus Sciences for all employment outcomes. As previously mentioned, students in Engineering, Health, and Sciences have similar pre-university skills—in fact, Engineering or Health students could have also pursued a Science degree. We therefore expect that our findings from the Engineering/Health comparison hold when comparing Engineering/Sciences and Health/Sciences.

The results show that, for both men and women, studying a degree in Engineering or Health instead of a Science degree improves employability in all measures of labour market outcomes (see Table S2 in the supplementary information). For women, the differential in terms of labour market outcomes with respect to Science is greater if they study Health rather than Engineering, while for men the difference is more balanced. These results are consistent with women predominantly opting for Health degrees over Engineering or Science degrees, and men choosing Engineering over Science.

Gender differences in labour market outcomes within fields

Another factor influencing the quality of graduate employability is that gender gaps in terms of labour market outcomes might differ in magnitude across fields. Table 4 presents, by field and gender, the proportion of graduates in the sample for each of the labour market outcomes considered and the gender difference in these outcomes for each field.

Overall, gender differences in labour market outcomes are larger in Engineering than in Health. The proportion of female Engineering graduates who are employed and earn over 1500€ is significantly lower (3 pp versus 12.3 pp) than that of men. In Health, however, there are no gender differences in terms of employment status, and the proportion of women with salaries above 1500€ is lower than that of men, but less than in Engineering

Table 4 Proportion of graduates and differences by gender

	Employed	Mismatch		Salary + 1500	Employed + 12
		Vertical	Horizontal		
Engineering					
Female	0.898	0.161	0.251	0.617	0.957
Male	0.929	0.159	0.196	0.740	0.971
Difference female/male	– 0.031*** (0.007)	0.002 (0.010)	0.055*** (0.011)	– 0.123*** (0.013)	– 0.014*** (0.005)
Observations	*6705*	*6135*	*6124*	*6000*	*6703*
Health					
Female	0.913	0.065	0.098	0.554	0.966
Male	0.915	0.094	0.128	0.605	0.966
Difference female/male	– 0.002 (0.009)	– 0.028*** (0.009)	– 0.030*** (0.011)	– 0.050*** (0.017)	– 0.0002 (0.006)
Observations	*4488*	*4078*	*4075*	*3981*	*4487*

SE in parentheses

***p-value < 0.01

Source: 2019 EILU. Own calculations

(5 pp). For mismatch and duration of employment, there are no gender differences, or it is favourable for female graduates in Health. However, in Engineering, a higher proportion of women have higher horizontal mismatch and lower rates of being employed more than 12 months compared to men.

The results in Table 4 suggest that Spanish female Engineering graduates might face greater gender discrimination than those in Health. However, it should be noted that two potential issues may be driving these results: a compositional effect that arises from the fact that factors different from field of study and gender (such as age, language skills, ICT skills, or whether the university is public of private) may affect employability, and a selection effect previously discussed due to the non-random nature of degree choice, which could bias estimations.

We address the compositional effect issue with Oaxaca-Blinder decomposition, applying Bauer and Sinning's (2008) approach for non-linear models. We decompose the gender difference for each outcome variable into two components. The first component is the explained part that relates to differences in characteristics other than gender. The second component is the unexplained part that captures gender differences in the effect of those characteristics on labour market outcomes and is related to institutional factors in the labour market or social factors. The unexplained part, not affected by compositional effect issues, is typically interpreted as a measure of discrimination (Blau & Kahn, 2017). This decomposition requires a control group, which is typically the group assumed to face potential discrimination against. We consider female graduates as the control group.

To account for the selection bias in degree choice, we use propensity score matching (PSM) techniques. First, we estimate, separately for male and female, the probability of studying each field (Engineering versus Health) controlling for observable characteristics using a probit model, and calculate the propensity scores. These propensity scores are then used as (inverse) weights to balance covariates in probit models of labour market outcomes needed to implement the Bauer-Sinning decomposition. For each stage, we include the same covariates as those chosen in IPWRA estimations[10] in Table 3.

Table 5 shows the weighted gender gap using PSM as well as its explained and unexplained decomposition. After eliminating compositional effects and controlling for potential endogeneity in field choice (unexplained part), female Engineering graduates generally have worse labour market outcomes than males. While the unexplained part of the gender gap in employment status (*Employed*) is −0.017, significant at 1%, for Engineering, it is 0.006 and not significant at 5% for Health. Similar patterns are observed in employment duration and horizontal and vertical mismatch, favouring women in Health. Regarding the salary variable, the unexplained part significantly contributes to the salary gap against women both in Health and Engineering, but it is larger in Engineering (− 0.100 vs −0.041).

In Engineering, the unexplained part, which consistently disadvantages female graduates, accounts for over 65% of the gender gap in all labour market outcomes except for vertical mismatch. This finding suggests that a large portion of the gender gap can be attributed to institutional factors against female graduates in this field, leading to worse outcomes in the transition from university to the labour market compared to their male counterparts with identical characteristics.

Our results suggest that Spanish female Engineering graduates face considerable discrimination (possibly both statistical and taste-based) in the integration from university to the labour market compared to their male counterparts. This may be linked to the fact that Engineering occupations are heavily male-dominated, creating a "glass barrier" that female

[10] Estimation results are available upon request.

Table 5 Bauer-Sinning decomposition of gender differences in labour outcomes for graduates in Engineering/Health

	Employed		Mismatch				Salary + 1500		Employed + 12	
			Vertical		Horizontal					
	Coeff	%	Coeff	%	Coeff	%	Coeff	%	Coeff	%
Engineering										
Diff. female/male	− 0.026*** (0.006)		− 0.009 (0.011)		0.037*** (0.013)		− 0.128*** (0.015)		− 0.010** (0.005)	
Explained-part	− 0.009*** (0.003)	34.6	− 0.010*** (0.004)	111.1	− 0.001 (0.004)	− 2.7	− 0.028*** (0.008)	21.9	− 0.003* (0.002)	30
Unexplained-part	− 0.017*** (0.006)	65.4	0.001 (0.010)	11.1	0.038*** (0.013)	102.7	− 0.100*** (0.014)	78.1	− 0.007 (0.006)	70
Observations	*6035*		*5532*		*5525*		*5433*		*6033*	
Health										
Diff. Female/Male	0.002 (0.011)		− 0.030** (0.015)		− 0.033** (0.014)		− 0.072*** (0.018)		0.001 (0.004)	
Explained-part	− 0.004 (0.005)	− 200	− 0.004 (0.005)	13.3	− 0.022*** (0.007)	66.7	− 0.031*** (0.011)	43.1	− 0.002 (0.006)	− 200
Unexplained-part	0.006 (0.011)	300	− 0.026* (0.011)	86.7	− 0.011 (0.012)	33.7	− 0.041*** (0.015)	56.9	0.003 (0.010)	300
Observations	*3971*		*3612*		*3601*		*3538*		*3970*	

SE in parentheses

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

Estimations obtained with PSM

graduates find difficult to crack since the start of their professional careers. In contrast, for Health, the unexplained part is only significant and against women for the salary variable, suggesting less discrimination in the labour market.

In summary, when analysing gender differences in labour market outcomes, female Engineering graduates experience worse conditions compared to female graduates in Health. These findings provide supportive evidence that Spanish women tend to concentrate in fields with better labour market outcomes compared to men (particularly in Health) and avoid those with worse conditions (such as Engineering).

To confirm whether the proportion of women is higher in fields with a smaller gender gap in labour market outcomes, we compare heavily female-dominated degrees[11] and the rest for both Engineering and Health fields. For each category, we compute the weighted gender gap and its decomposition for different labour outcomes (see Table S3 in the supplementary information). The results show that, in both categories, only the unexplained part of the gender salary gap is significant, and its magnitude is larger in non-heavily female-dominated degrees.

Finally, to confirm our within-field results, we extend the sample to include Sciences graduates in the analysis (see Table S4 in the supplementary information). As in Health, the unexplained part favours women in horizontal mismatch and duration of employment, though not significant at 1%. For the remaining labour market outcomes, consistent with Engineering findings, the unexplained differences are unfavourable for women but not significant. Female Science graduates face an intermediate situation between those in Engineering and Health regarding gender differentials. This finding is consistent with Science being a more gender-balanced field compared to Engineering and Health.

Indirect test of the link between field choice and labour market outcomes

The EILU allows us to perform an indirect test of whether labour market outcomes may influence the choice of university studies. The survey includes a question on whether graduates would choose the same degree again. Based on our working hypothesis, we expect that the response to this question would be shaped by the labour market outcomes that graduates have experienced after graduation: successful transition into the labour market is likely to result in a positive response; otherwise, it would be negative.

To test this hypothesis, we analyse the effect of labour market outcomes on university satisfaction using probit models. Our outcome variable is "*Study the same degree again*" that equals 1 if the graduates would pursue the same degree again, and 0 otherwise. The sample includes Engineering and Health graduates, and models are estimated separately for women and men. To avoid biases, we use PSM techniques.[12]

We perform two analyses: first, we estimate a model for all individuals (employed or not), including *Employed*, *Salary + 1500*, and *Employed + 12* as regressors. In the second analysis, we estimate the model only for employed individuals, including *Salary + 1500*, *Employed + 12*, *Vertical-Mismatch*, and *Horizontal-Mismatch* as regressors.

The first two columns of Table 6 show the marginal effects for the full sample. The third and fourth columns report the marginal effects for the employed subsample. We

[11] We define a degree as heavily female-dominated if their female share exceeds the field average. In Engineering, heavily female-dominated degrees are those with a proportion of women exceeding 40%, and in Health, if they have more than 68% women.

[12] The weightings have been obtained in the same way as those used in Bauer-Sinning's decomposition analysis. Detailed results are available upon request.

see that favourable labour market outcomes increase the probability of choosing the same degree again. Employed individuals (men or women) are 20 pp more likely to respond positively than unemployed. Similarly, having a salary higher than 1500€ or having been employed for more than 12 months increases the likelihood of a positive response. Additionally, for the employed subsample, vertical and/or horizontal mismatch reduces this probability.

Finally, we consider separately graduates who reported choosing their degree for employment-related reasons and those who choose it for self-satisfaction. For each of these subsamples, we estimate a model equivalent to the one in the first two columns in Table 6 and display the results in the last four columns of Table 6. We find that even for graduates who chose their degree for personal satisfaction, their labour experience matters for their satisfaction with the chosen degree.

In summary, the results show that enjoying favourable labour conditions reaffirms individuals in their degree choice. This finding highlights the importance of individuals' expectations of their future labour outcomes on how they select their college degree.

Discussion and conclusion

Our results revealed the existence of differences in terms of labour market outcomes by gender and field of study: female graduates in Engineering do not experience better labour market outcomes compared to female graduates in Health, although they do when compared to those in Science. Among the three fields considered, female graduates in Health enjoy better labour outcomes, both compared to female graduates of Engineering and Sciences, and to male graduates within their field. However, this pattern does not hold for men.

Table 6 Probit models for "Study the same degree again." Marginal effects

	Full-sample		*Employed-subsample*		*Full-sample*			
					Employment-reason		Self-satisfaction	
	Female	Male	Female	Male	Female	Male	Female	Male
Employed	0.197*** (0.026)	0.201*** (0.027)			0.194*** (0.029)	0.213*** (0.030)	0.179*** (0.064)	0.129* (0.068)
Salary + 1500	0.148*** (0.016)	0.125*** (0.014)	0.098** (0.015)	0.066*** (0.015)	0.154*** (0.018)	0.120*** (0.016)	0.143*** (0.039)	0.112** (0.041)
Employed + 12	0.113*** (0.040)	0.077* (0.041)	– 0.012 (0.059)	0.209*** (0.061)	0.110** (0.045)	0.111** (0.048)	0.094 (0.102)	0.006 (0.1031)
Vertical-Mismatch			– 0.170*** (0.028)	– 0.148*** (0.020)				
Horizontal-Mismatch			– 0.187*** (0.023)	– 0.205*** (0.020)				
Observations	*4578*	*5088*	*4219*	*4685*	*3518*	*3966*	*575*	*646*

SE in parentheses

**p*-value < 0.1; ***p*-value < 0.05; ****p*-value < 0.01

Estimations obtained with PSM

Covariates: whether the individual is a Spanish citizen, has a disability, studied in a public university, and age

Our findings are consistent with the hypothesis that, in Spain, both men and women tend to opt for studies with better employment prospects for their gender—Health for women and Engineering for men—and suggest that the gender segregation observed in Engineering, Health, and Sciences could be partly explained by differences in labour market outcomes. When deciding whether to pursue Engineering, Health, or Science, women may prefer Health-related degrees over Engineering or Sciences, anticipating better employment conditions. The sorting of women into fields will follow an order consistent with their expected labour outcomes: first in Health, then in Engineering, and lastly in Science. Similarly, men's choices—Engineering, followed by Health, and then Sciences—reflect their labour market outcomes. These two sorting patterns determine that women are underrepresented in Engineering and heavily dominate in Health.

These results have implications for understanding gender segregation in higher education. In the context of the Spanish economy, characterised by extremely high youth unemployment and job insecurity (Bentolila et al., 2021), it seems rational that university students prioritise their future labour outcomes when choosing their degree. Other things being equal, they will be more likely to choose those with better career prospects. Therefore, if a degree exhibits gender employment gap, we expect that students of the gender with better employment expectations will predominantly choose that field, contributing to gender segregation in that field of study.

Do these findings imply that women base their educational choices only on future labour market outcomes? Gender segregation in higher education is multifaceted. In addition to gender differences in the labour market, cultural and social factors related to gender roles or discrimination in the workplace play an important role in these decisions. If on top of cultural and social pressures that dissuade women from pursuing Engineering studies, women who do pursue Engineering might face worse working conditions compared to in fields like Health, it is not surprising that women prefer the latter (Barone, 2011; Barone & Assirelli, 2020).

The existence of gender-based employment differences may imply an unequal treatment based on gender, and that these differences depend on the chosen degree. This discriminatory element highlights the professional barriers that individuals, typically women, encounter in the labour market, and how these barriers can shape their degree choices. Reducing this discrimination could lessen segregation in higher education. Public policies aimed at promoting STEM careers often focus on showcasing female role models in Engineering, addressing the lack of these role models as a barrier for women entering these fields. Our findings suggest that the current labour market conditions in Engineering do not support the emergence of female role models. To effectively encourage women to pursue Engineering, it is key not only to promote these studies at pre-university educational levels but also to improve employment conditions for female Engineering graduates as a tool to fostering greater gender balance in this field.

This study is not without its limitations. We only observe labour market outcomes 5 years after graduation, so it is unclear whether the observed differences by field and gender early in the graduate's working career would persist over their entire career. Furthermore, ex-post beliefs 5 years after graduation may differ from prior beliefs at the time of choosing their majors, as students can update their beliefs about wages and other labour market outcomes with new information, highlighting the dynamic nature of decision-making. Future studies should analyse whether labour market outcomes can shape pre-university track choice, consider other broad fields, and explore specific degrees to better understand women's underrepresentation in Engineering. Finally, more research is needed to understand the underlying mechanisms.

Appendix. Overlap plots

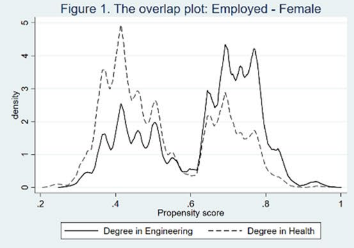

Figure 1. The overlap plot: Employed - Female

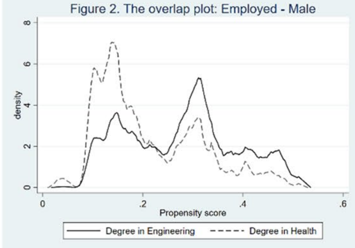

Figure 2. The overlap plot: Employed - Male

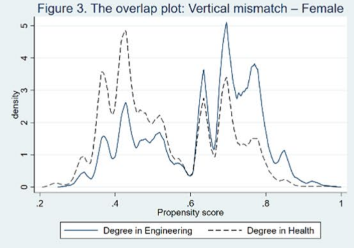

Figure 3. The overlap plot: Vertical mismatch – Female

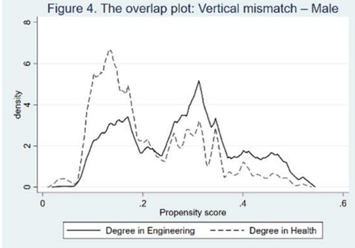

Figure 4. The overlap plot: Vertical mismatch – Male

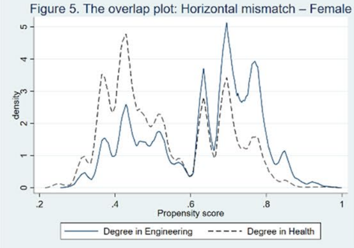

Figure 5. The overlap plot: Horizontal mismatch – Female

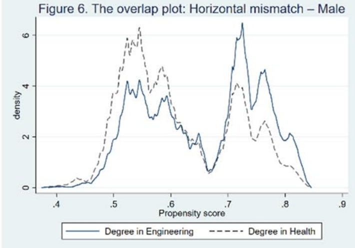

Figure 6. The overlap plot: Horizontal mismatch – Male

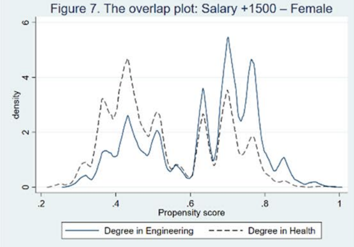

Figure 7. The overlap plot: Salary +1500 – Female

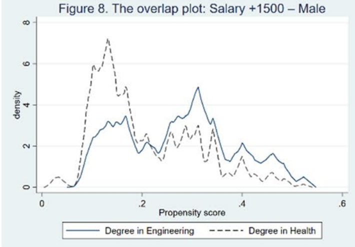

Figure 8. The overlap plot: Salary +1500 – Male

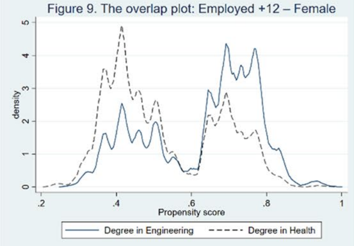

Figure 9. The overlap plot: Employed +12 – Female

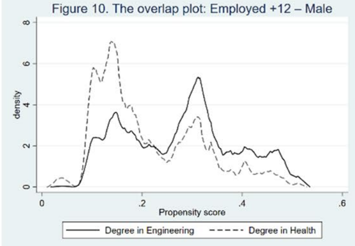

Figure 10. The overlap plot: Employed +12 – Male

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Data Availability The dataset analysed during the current study is available at the Spanish National Statistics Institute web page: https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736176991&menu=resultados&idp=1254735976597#!tabs-1254736195339.

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