Analyzing the Beginning of the Career Path of Young Professionals from a Gender Perspective

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Abstract. Young graduates are confronted with rough conditions when they want to enter the labor market. They face higher unemployment rates and are more often engaged in precarious employment, like part-time and/ or temporary positions. Young women, especially, suffer from relatively more severe labor market outcomes and perform worse than their male peers. We aim to analyze how gender and field specialization differentials among young professionals lead to different labor market outcomes in the following dimensions: (i) *probability of being employed*, (ii) *for employed graduates, the probability of being self-employed*, (iii) *for salaried workers, the probability of being a full-time worker* and (iv) *for salaried workers, the wage determinants and the association of wages and gender and field of study*. We use a data set that provides relevant information about 6,981 students that graduated in 2015 from the University of the Basque Country and their labor market situation in 2018. We find no evidence for gender gaps in both the probability of being employed and the probability of being self-employed. However, women have fewer chances to find full-time employment and earn significantly less than men. The different fields of specialization have a substantial predictive power to explain these results. But, even after controlling for several further job-characteristics and firm-specific attributes, gender gaps that are yet unexplained still prevail.

Key Words: young professionals, graduates, employability, gender gap in labor market outcomes

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1 Introduction and Motivation

The Spanish labor market suffered greatly owing to the recent financial and European sovereign debt crises. In particular, for young graduates, the situation worsened enormously. For example, in the peak of the crisis, the unemployment rate with respect to people aged between 15 and 24 years reached 55.5%. This was the second-highest rate in the European Union. This age group is characterized by young adults who recently graduated and aim to enter the labor market. Furthermore, extending the age group to 15-29 years shows that freshly integrated labor market participants have also been affected strongly. In 2013, 41.1% of them were unemployed. Additionally, young men faced rougher situations – their rise in unemployment was higher. This led to a narrowing of the gender gap in employment. The most alarming observation throughout the crisis is that these dismissals and the reduction in hiring often resulted in long-term (more than 12 months) unemployment, for 15-24-year-old youths, it reached 21.9% in 2013.

One of the upcoming questions is why young Spanish adults have been hit so hard, more so than their European counterparts, during the crises. Employment conditions play a crucial role. In Spain, precarious employment is common among labor market entrants. Spain has one of the highest shares of part-time employment as well as temporary employment in the European Union. The temporary positions in particular make young adults the most vulnerable profile: As soon as their contract expires, during crises, they will not be re-hired. It serves as a quick and easy instrument for businesses to reduce the workforce. In 2019, 71.4% of all employed 15-24-year-olds worked in temporary positions. Although a similar pattern can be observed in other countries, like Germany (51%) or the Netherlands (52.6%), it is important to evaluate the source of these positions. While in the latter two countries it is usually a voluntary decision, Spanish youths between 15 and 34 years stated in the ad-hoc module of the Labor Force Survey in 2016 that 81.7% of them worked involuntarily in temporary positions. The share of part-time employments increased also throughout the crisis and reached 40% for 15-24-year-olds in 2013 and has been almost constant since then. But this characteristic is again rather impressed on labor market entrants. During the crisis, almost 60% stated they worked involuntarily in this condition and the main reason remains that the youths could not find a full-time job.[1]

However, the labor market outcomes, as well as the employment conditions, vary highly between gender. Although the crisis led to a narrowing of gender gaps in unemployment, young

[1] All presented data of the first two paragraphs has been obtained by the European Union Labor Force Survey. Last access: 22.06.2020.

women faced higher unemployment rates before the crisis and again recently in 2019. Moreover, young women are more likely to find themselves in precarious jobs: they are more represented within temporary employment and indeed by far more present in part-time positions. In the last stage, often the hourly earnings of women are lower than those of men. But these labor market outcome gaps cannot (always) be explained by, for example, differences in education or occupations – there remain unexplained gender gaps. These observations lead to the question of whether they characterize an "entrance gap" or if they evolve later. In other words, do women, given that they have the same skills and knowledge as men, face different labor market entry chances?

Labor market conditions also vary widely by educational levels. Participants with tertiary education show the lowest unemployment rates in years. Moreover, they are most likely to find employment after graduation. These are only two of the reasons why engagement in higher education is increasing steadily. As more and more youths decide to attain tertiary education, it is interesting to analyze their labor market entrance chances. Does tertiary education "grant" employment? Does it provide better working conditions and stability? Do graduates from all fields have the same chances of obtaining employment or are there fields with better or worse chances?

Especially the last thought raises some further questions. As different fields might be differently acknowledged by the labor market, it is important to understand the distribution of students among them. Furthermore, even more essential is the gender perspective. In recent years, the engagement of women in tertiary education increased constantly and, in many countries, they even outnumber men. But women do not only outnumber men in enrollment numbers. Women also tend to have higher graduation rates and they perform better. Nevertheless, it is empirically shown that men and women choose different majors. Some fields are more gender-neutral than other ones. For example, men (still) dominate technical and math-intensive fields like Engineering, while women show higher engagement in Humanities and Education. The male-dominated fields are often more academically demanding and prestigious, which consequently leads to higher-paid occupations on the labor market. Therefore, the choice of field of study needs to be considered when analyzing labor market gender gaps. This leads to the question: Do men and women, graduating from the same field of tertiary education, experience the same opportunities in the beginning of their career?

To answer all these questions, we investigate data of graduates of the University of the Basque Country. Graduates of 2015 were asked three years after their graduation about their labor market situation and their employment characteristics. Since the data set used only contains information of graduates of the same university in one community of Spain, it is necessary to present briefly the differences between the "local" labor market of the Basque Country and the average Spanish labor market. The Basque Country is characterized by one of the lowest unemployment rates of all Spanish communities. In 2019, the overall unemployment rate was 9.15%. Still, the situation for young adults was and is tougher. They faced an unemployment rate of 27.4%. As mentioned before, unemployment rates vary strongly by educational levels. Half of the Basque population, aged between 25 and 64 years, completed a tertiary education (50.8%) by 2019, which is the highest rate among all autonomous communities in Spain. Moreover, among those receiving tertiary education, there are more women in comparison to men. This confirms the global trend of a higher share of women engaging in tertiary education also for the Basque Country: 48.9% of the male population and 52.6% of the female population (in 2019, 25-64 years) possess a tertiary education. The unemployment rate for this subgroup is remarkably low: recently it reached its lowest value since the 2008 crisis with 4.5%. However, the unemployment rate differs across genders. While Basque men are below the average (3.7%), Basque women show a higher value (5.3%).[2]

The available data set allows us to characterize the labor market entrance conditions of young Basque graduates. We want to find out how gender and field specialization differentials among them lead to the following different labor market outcomes:

1. The probability of being employed.
2. Conditional on being employed, the probability of being self-employed.
3. Conditional on being salaried workers, the probability of being a full-time worker.
4. Wage determinants, and the association of wages and gender and field of study.

As these questions show, we will start with an overall picture of the participants' situation in the labor market and we will refine the questions to describe them in more detail. We want to find profiles that could describe the optimum characteristics of students to find a job after graduation. Moreover, we will focus on analyzing if both men and women have the same entry chances or if there are observable differences among them. If there are differences, we aim to test if they are explained by different preferences between men and women – whether they

[2] All presented data of this paragraph have been obtained by the *Explotación de las variables educativas de la Encuesta de Población Activa (INE)* of the *Ministerio de Educación y Formación Profesional* of the Spanish Government. Last access: 22.07.2020.

"self-select" them into different study fields –, or by an entrance gap even when they decide on the same fields.

The rest of the thesis is structured as follows. Section 2 provides a brief review of the literature examining reasons for tertiary education and the choice of major and their implications on labor market outcomes. The data set will be presented in Section 3 and the descriptive analysis is done in Section 4. Section 5 describes the methodology used. The results will be presented in Section 6 and Section 7 concludes.

2 Literature

There are two main literature areas that we want to point out. The first part is the literature answering questions about why youths decide to engage in higher education and if they do so, why they choose a specific major. One important determinant for the decision to attend higher education are the expectations about lifetime earnings. This has been pointed out early by Willis and Rosen (1979). Further, greater career prosperities and a good job have been recently underlined by Gallup and Strada Educational Network (2018) who conducted a U.S. survey across 86,000 individuals that attained higher education. The individuals were asked to report their main reasons and motivation to pursue higher education. 58% stated that finding a job is their main motive. Byrne et al. (2012) highlight the same incentive for a sample of accounting students and additionally mention that they observe intellectual growth as further motivation.

Pursuing higher education opens the thought about the field of education. As pointed out in the introduction, men and women choose different majors. This observation is not only a momentum but historically true, see e.g. Barone (2011) or Bradley (2000). Altonji et al. (2012) provide an excellent overview of the literature on major choices. They point out trends in college majors and they discuss studies that try to investigate the impact of expected lifetime earnings on the major choice. Moreover, they also take into account newer insights on preferences as well as ability and preparation. According to Sloane et al. (2019), there has been a slight convergence in college majors but women still choose majors associated with lower potential wages. Quadlin (2020) recently pointed out that even if men and women declare the same preferences in the choice of a major, they choose different majors: Men still significantly choose those majors that are better paid. For example, if both men and women stated that their preference is a field that enables them to help other people, men would preferably choose biology or medicine paths, while women would choose nursery. This observation was also pointed out by Carnevale et al. (2018). They give an example for the male-dominated field of

Engineering: within Environmental Engineering – the lowest-paid Engineering degree – the share of women was almost double as high as in Petroleum Engineering – the highest-paid Engineering degree – (32% vs 17%). So not only do women choose different fields that themselves imply lower earnings, but they also choose the lower-paid majors within fields.

The second literature stream deals with the implications of attending higher education as well as with this "self-selection" and investigates the consequences on later labor market outcomes. Garrouste and Rodrigues (2012) examined the employability of young European graduates and found out that graduates of first-stage tertiary education (ISCED level 5 and 6[3]) have the highest chances to find a job within one to three years after their graduation. Moreover, they show that female graduates are less likely to have an indefinite contract as well as to work full-time. However, one of the most discussed labor market outcomes is the gender pay gap. To explain this observed gender gap, the choice of fields of study is one of the crucial determinants (see e.g. Corbett and Hill (2012); Arcidiacono (2004)). However, a great magnitude of the gender wage gap remains unexplained. Also, graduates from the same field can differ in their entry wages. For example, Bredtmann and Otten (2010) use a sample of economics graduates from a German university and show that entry wages for women are significantly lower.

The thesis aims to contribute to the second presented literature stream. Answering the stated questions will provide evidence on the employability as well as on employment conditions among recent graduates from a gender perspective. Moreover, we will investigate the explanatory power of the fields of study throughout the thesis but also intend to find further variables that could explain possible observed differences.

3 Data

This section will deal with the data set. First, there will be a brief overview of the data and their collection. Second, the variables of the data set will be divided into groups and the contained variables with their relevance to our questions will be explained.

The data set is obtained from the *Encuesta de Inserción laboral de alumnos y alumnas de la Universidad del País Vasco (UPV/EHU)* conducted by Lanbide, a service of the Basque government. The collection of the data is designed as follows. The university provided Lanbide data about 6,981 students that graduated in 2015 including detailed information about their university life and a few socio-demographics. Three years later (in November and December

[3] The educational attainment level is measured by the International Standard Classification of Education, short ISCED, of 2011. There exist 8 levels and starting with level 5, tertiary education is measured.

2018) Lanbide collected a random sample of these students and asked them about their current labor market situation. These insights were collected by a telephone interview that 5,040 alumni (72%) responded.

Table 1 gives a brief general overview of the data set. Of the 6,981 graduates, the share of women is 57.26%. The average graduate in 2015 was 25 years old, achieved a final grade of 7.11, and took 5 years to finish his studies. In 2018, 56.53% of the respondents were women. 86.75% of all respondents were employed in 2018 and earned on average a net monthly salary of 1,388 €. 37.10% of the alumni held an indefinite contract and 77.25% were employed full-time.

Table 1: General overview of the data set.

Part I 2015	
Number of graduates	6,981
% Women	57.26
Average age when graduating in years	25.31
Average final grade	7.11
Average duration of studies in years	4.70
Part II 2018	
Number of responses	5,040
% Responses	72.20
% Women	56.53
% Employment (5,013 observations)	86.75
Average salary in € (4,056 observations)	1,388
% Indefinite employment	37.10
% Full-time employment	77.25

The variables of the data set can be roughly divided into three main groups:

1. Demographic variables, such as gender and age.
2. Educational level variables, such as the field of study, the specific degree, the duration, and the final grade.

3. Labor market variables, such as time to find a job, current employment situation, employment condition characteristics, monthly net salary[4], details about the occupation, and the economic sector of employment.

The detailed information about the field of studies serves for several purposes. First, the distribution of fields of study among men and women can be compared to the empirical distribution and confirm or refuse the fact that men and women chose different majors. At the same time, if there are gender differences observed, the fields of study can be crucial to contribute an explanation for them. The third set of variables helps us to control for differences in the labor market outcomes. We want to test whether unconditional gender and field of specialization gaps remain the same when we condition young workers to share similar labor market characteristics, such as occupation and sector, as well as labor market outcomes, such as the salary.

4 Descriptive Statistics

This section will provide some descriptive statistics of the data set. This will be done by analyzing chosen variables out of the three groups. The focus will be on differentials by gender, fields of study, and a combination of both. This structure will help to understand the later proposed estimations and their results better.

4.1 Fields of Study

To begin this section, the distribution of the different fields of study in general and by gender is illustrated in Figure 1. On average, Engineering and Social Sciences are the two main groups. They represent 26.74% and 24.82% of all graduates, respectively. Nevertheless, the figure confirms the empirical evidence that men and women specialize in different fields. While men are mostly present in Engineering (43.03%), the highest proportion of women holds a degree in Social Sciences (31.45%). Furthermore, women are more engaged in Health and Arts. The fields of Experimental Sciences and Economics and Law are relative gender neutral. This is already an important finding and its importance, as well as its implications, will be pointed out throughout the rest of the thesis.

[4] From now on only referred to as salary or wage.

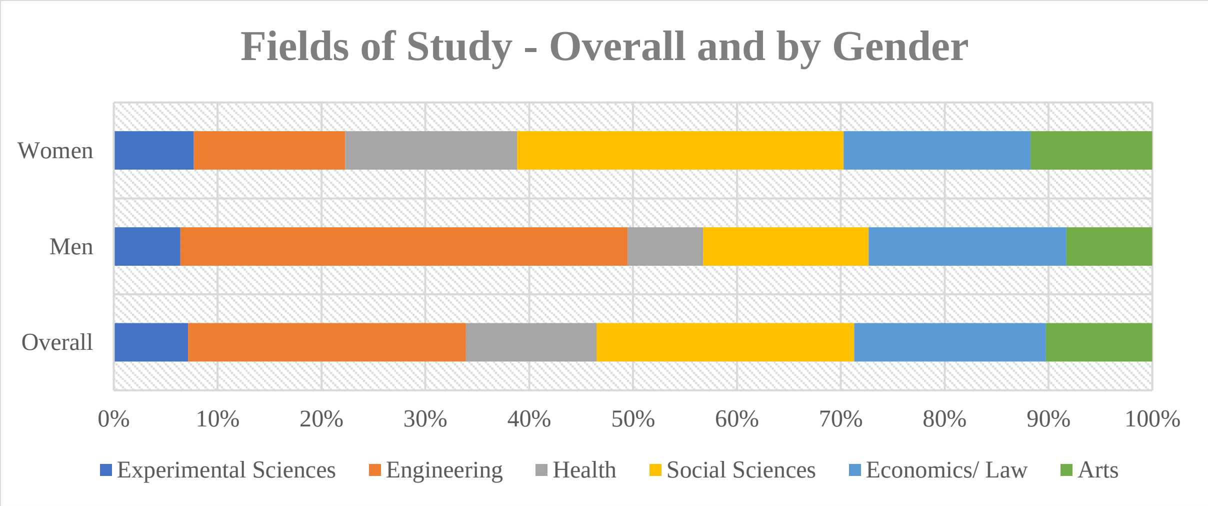

Figure 1: Distribution of the fields of study, overall and by gender.

4.2 Labor Market Situation

The first step to evaluate differences in labor market outcomes is to look at the current employment situation. This is depicted by the three following figures. Figure 2 provides a general overview and shows the differences by gender. On average, the unemployment rate is 9.24%. This is higher than the Basque average of tertiary educated people but remarkably lower than the overall unemployment rate of those under 25 years (27.4%). For both, employment and unemployment rates, there are no great differences by gender. While men are more engaged in self-employment or a fellowship, a higher share of women pursues further education.

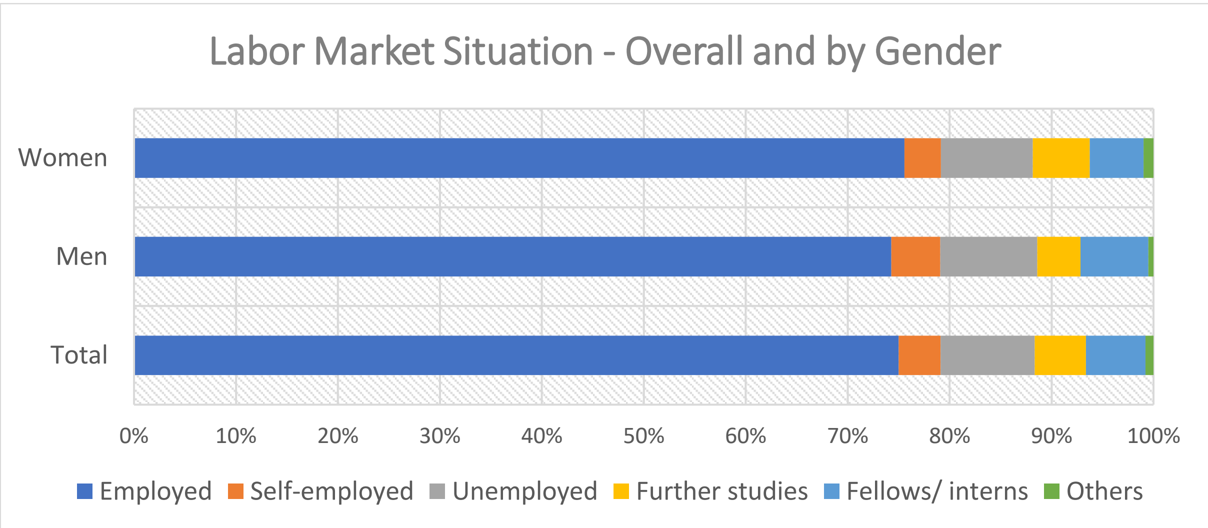

Figure 2: Labor market situation, overall and by gender.

The situation changes when the employment status is differentiated by the fields of specialization. Figure 3 reveals that graduates of Engineering and Health have the lowest unemployment rates (4.18% and 4.49%). On the contrary, Arts graduates face a rate above the average (17.23%). The majority of graduates that follow further education or a fellowship/ internship graduated in Experimental Sciences. This share is particularly low for Engineering and Health graduates.

To evaluate possible differences among men and women of the same specialization, Figure 4 splits the previous depiction by gender. In most fields, there exist a few imbalances. In Social Sciences, Economics and Law, Arts, and Engineering, the unemployment rate for women is lower than the one for men. It is also striking that the self-employment rate of female Engineering graduates is almost as double as high as for men.

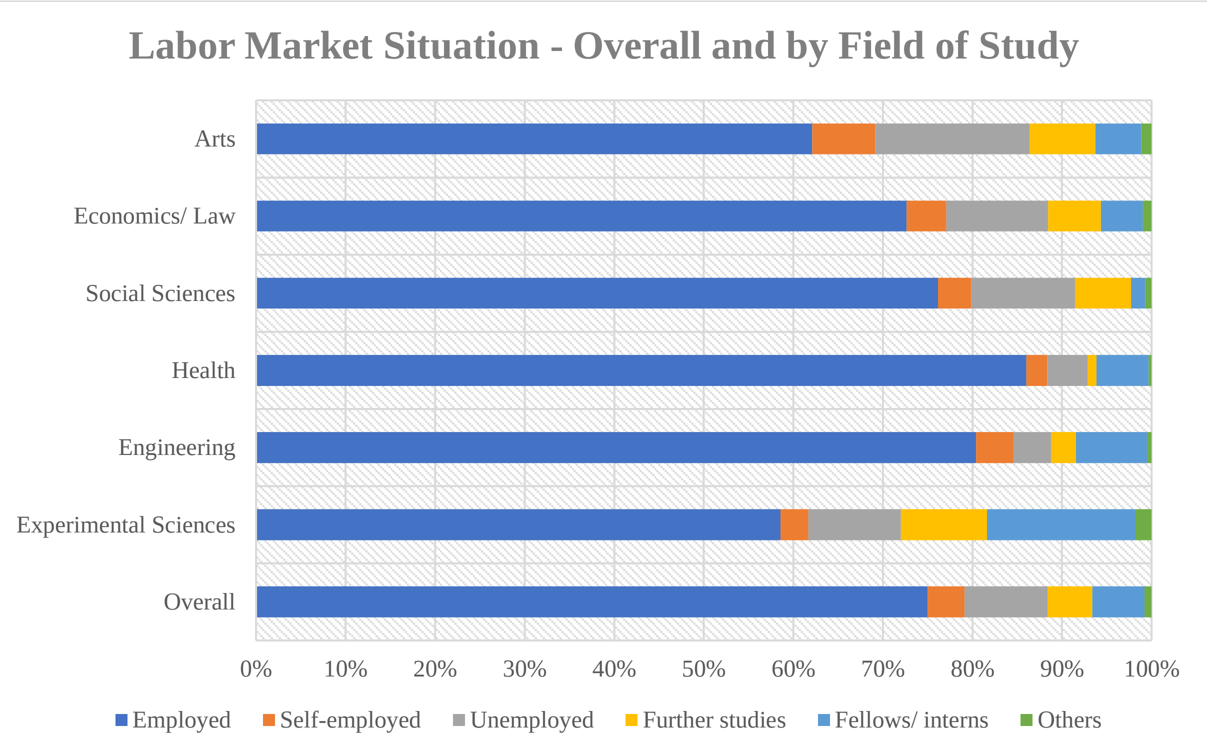

Figure 3: Labor market situation, overall and by field of study.

Comparing the labor market situation shows that on average there are no strong differences between men and women. However, presenting the situation differentiated by fields shows that Engineering and Health graduates have lower unemployment shares. This might be an indicator that those two fields provide the best chances to find employment after graduation. Men and women graduating from the same field do not differ strongly in their employment situation, although there are fields where women inhabit lower unemployment rates (Social Sciences, Economics and Law, Arts, and Engineering).

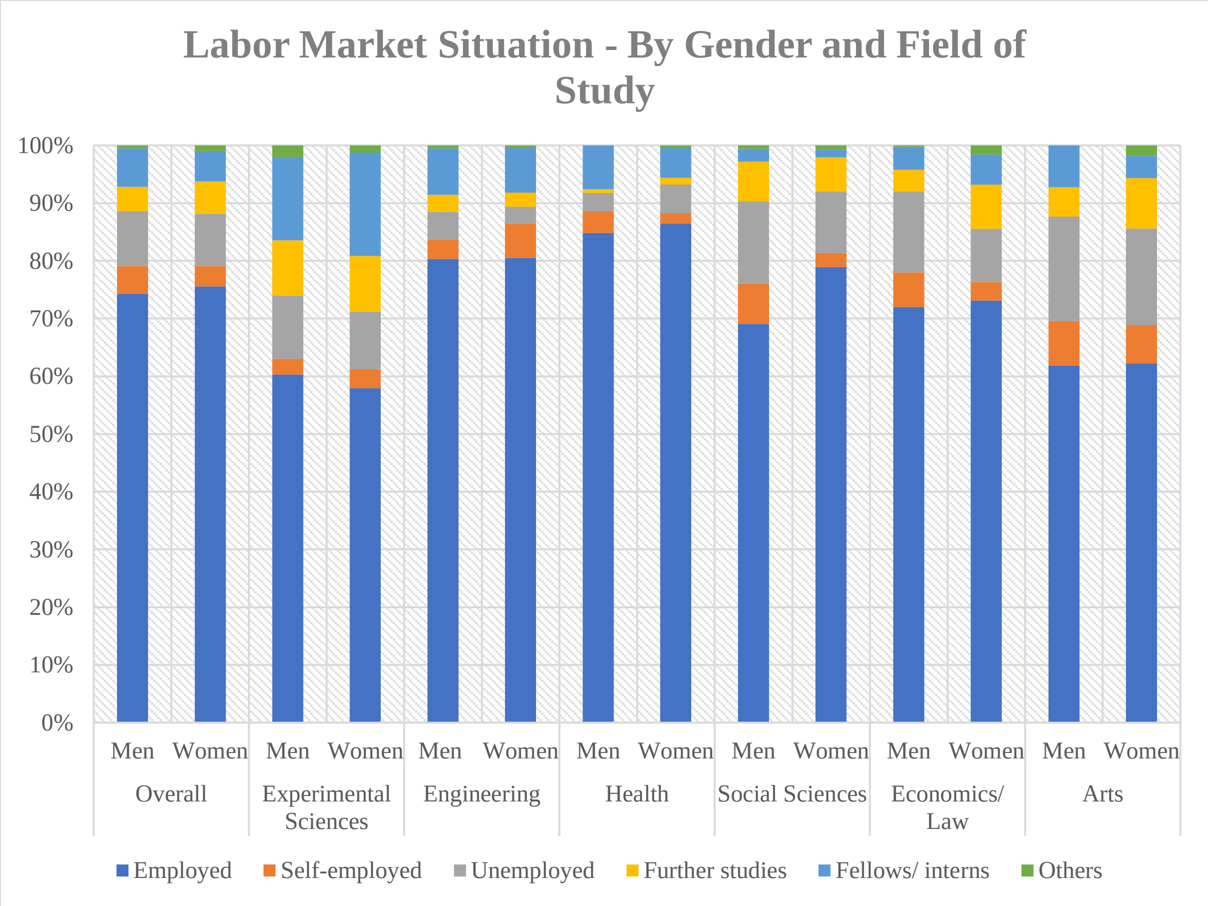

Figure 4: Labor market situation, by gender and field of study.

4.3 Employment Conditions: Full-time vs Part-time

As pointed out earlier, women are found more often in precarious employments, i.e. in part-time or temporary positions. In this thesis, we aim to estimate who has the highest chances to work full-time. Figure 5 helps to understand if those differences are also observed among the Basque graduates. To find out if graduates from different fields have different chances to find a full-time position, Figure 6 presents the differences across fields.

Notably, men were more often engaged in full-time positions (84.09%) than women (71.9%). Among fields, there are high variations. Graduates from Engineering, followed by Economics and Law, and Health show the highest shares of full-time employment. By far the lowest proportions of full-time positions are in Arts and Social Sciences. As shown in the beginning, women were more present in Social Sciences, whereas men dominated the field of Engineering. Combining this knowledge with these observations could serve as an initial explanation of why the gender difference is so strong within Figure 5. The next step is to compare men and women in the same field. This is done in Figure 7.

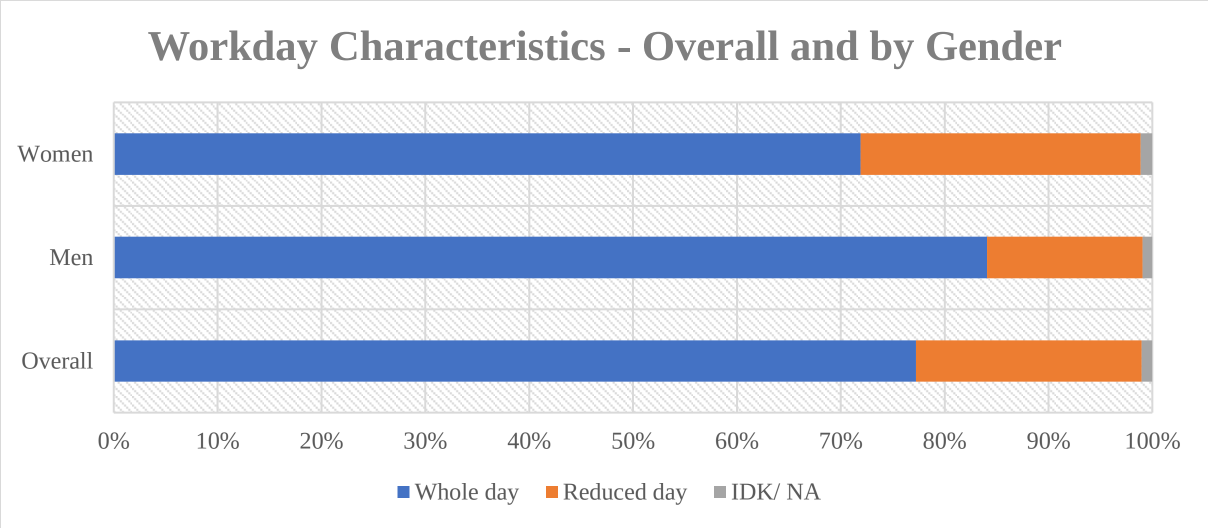

Figure 5: Workday characteristics, overall and by gender.

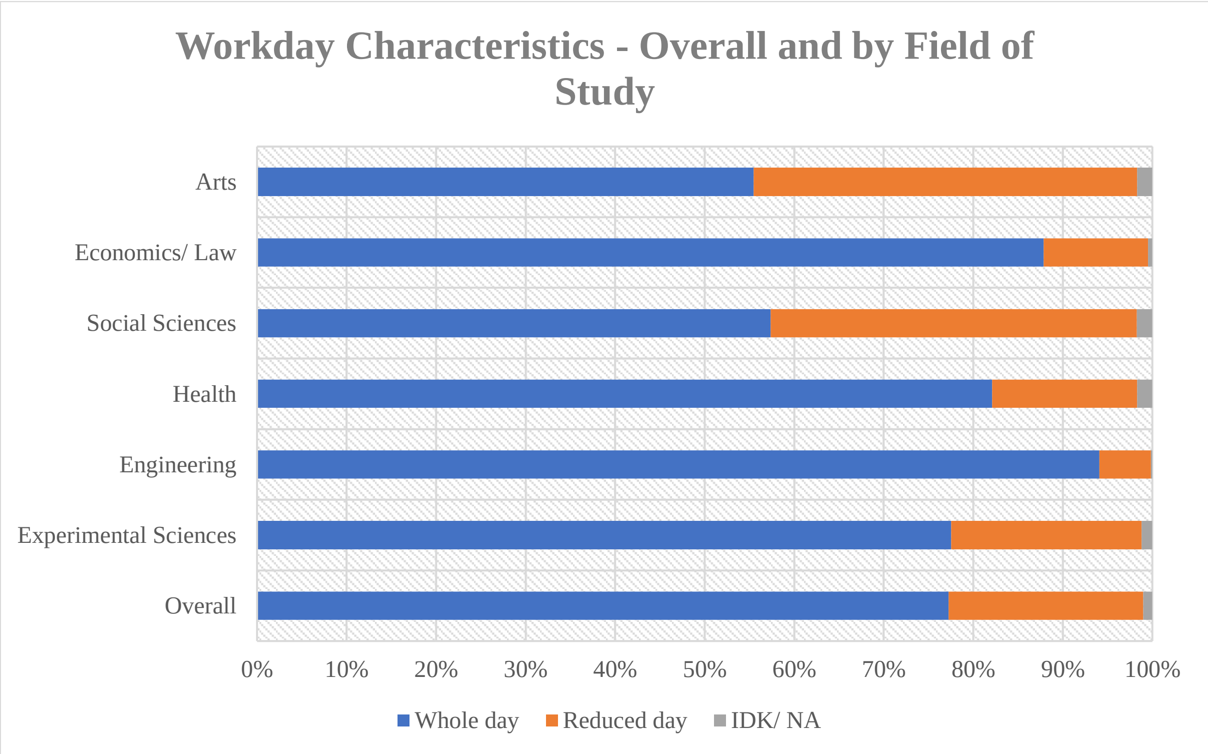

Figure 6: Workday characteristics, overall and by field of study.

The figure uncovers that for all fields it is true that a lower proportion of women than men is employed in a full-time position. This trend is most pronounced in Economics and Law (91.86% vs 84.42%) and in Arts (62.57% vs 51.03%). The lowest gender gap is observed in Engineering (1.14 percentage points (pp)).

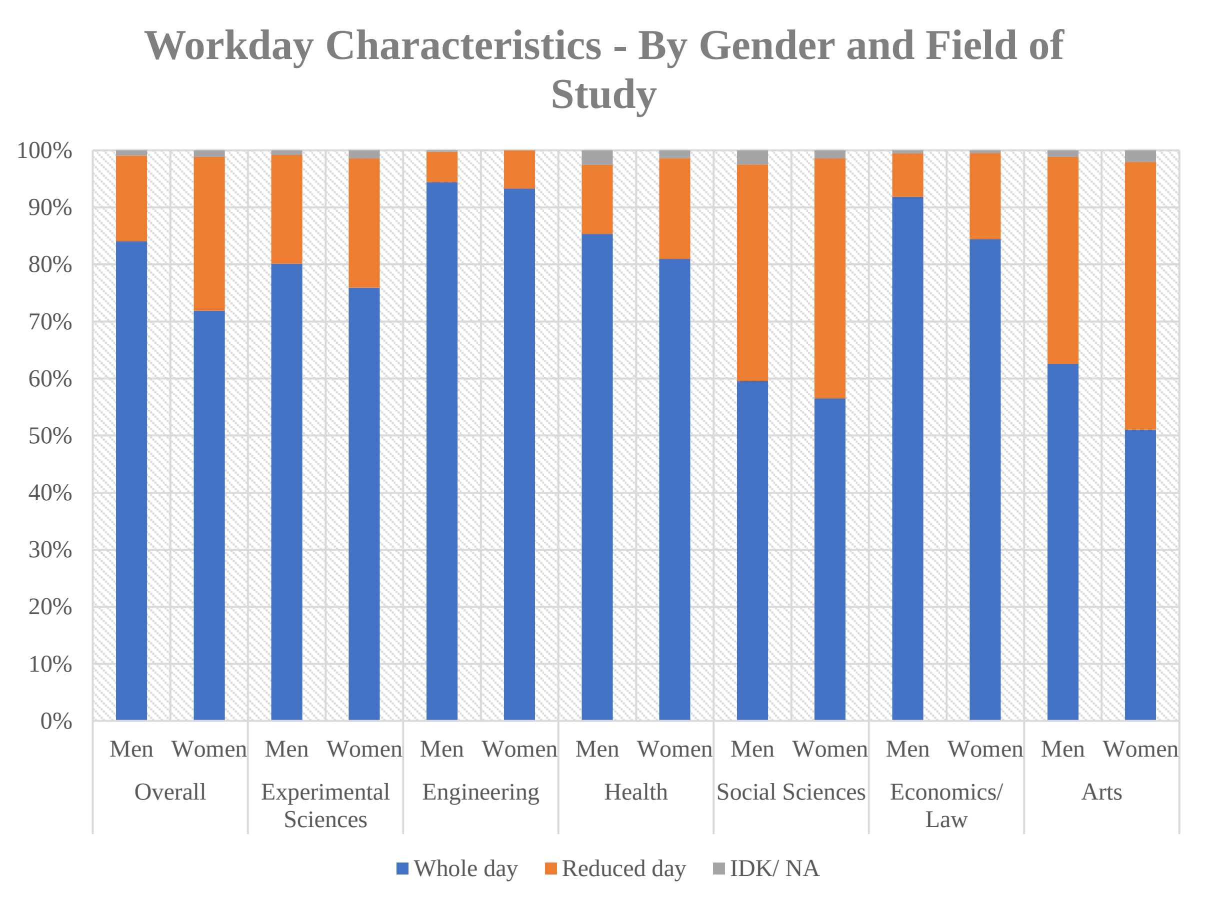

Figure 7: Workday characteristics, by gender and field of study.

4.4 Salary

The gender wage gap is one of the hottest topics comparing labor market outcomes. Figure 8 and Figure 9 will present how the Basque graduates are distributed over defined salary groups. The average income was 1,388€. Male graduates earned on average more than their female peers (1,487€ vs 1,310€). Figure 8 confirms this. The highest share of women (18.27%) earned a salary between 901€ and 1,200€, while the highest share of men was found in an upper group: 22.71% earned between 1,201€ and 1,500€ a month. Overall, female graduates are more present in the first three salary groups, while men dominate all other ones. More than one quarter of men are found in the highest three income groups. In comparison, only 17% of all women are present in those groups.

To find possible explanations for those observations, the different fields of specializations provide important insights. As depicted in Figure 9, the distribution of the salary varies strongly by the field. Arts reports the highest share of low-income earners: 20.9% of all graduates earned less than 600€ and 18.41% between 601€ and 900€. On the other side, graduates in Engineering are almost not present in these two groups (cumulated 5.58%). Most Engineers (54.01%) earned more than 1,500€ and more than three quarters (80.65%) earned more than 1,200€. The field of Health shows a similar picture. Less than 10% of Health graduates are employed within the lowest two groups of payment. The relative majority (26.02%) of them earns between 1,801€ and 2,100€. 60.59% earn more than 1,500€. For Economics and Law, the most frequent salary groups are 901€ to 1,200€ and 1,201€ to 1,500€. Additionally, Economics and Law also reports a low share of low-income earners (less than 600€) of 3.88%. In the field of Social Sciences, the first five salary groups (up to 1,800€) almost show an equal density and cover 91.37% of all graduates. In Experimental Science, more than three quarters (81.61%) of the graduates earn a salary within the four first salary groups. Overall, Figure 9 shows that there are higher and lower-paid fields. Men are more present in higher-paid fields as Engineering (average income 1,629€), while women are more present in lower-paid fields as Social Sciences (average income 1,154€). This partially explains the different frequencies of men and women in the salary groups.

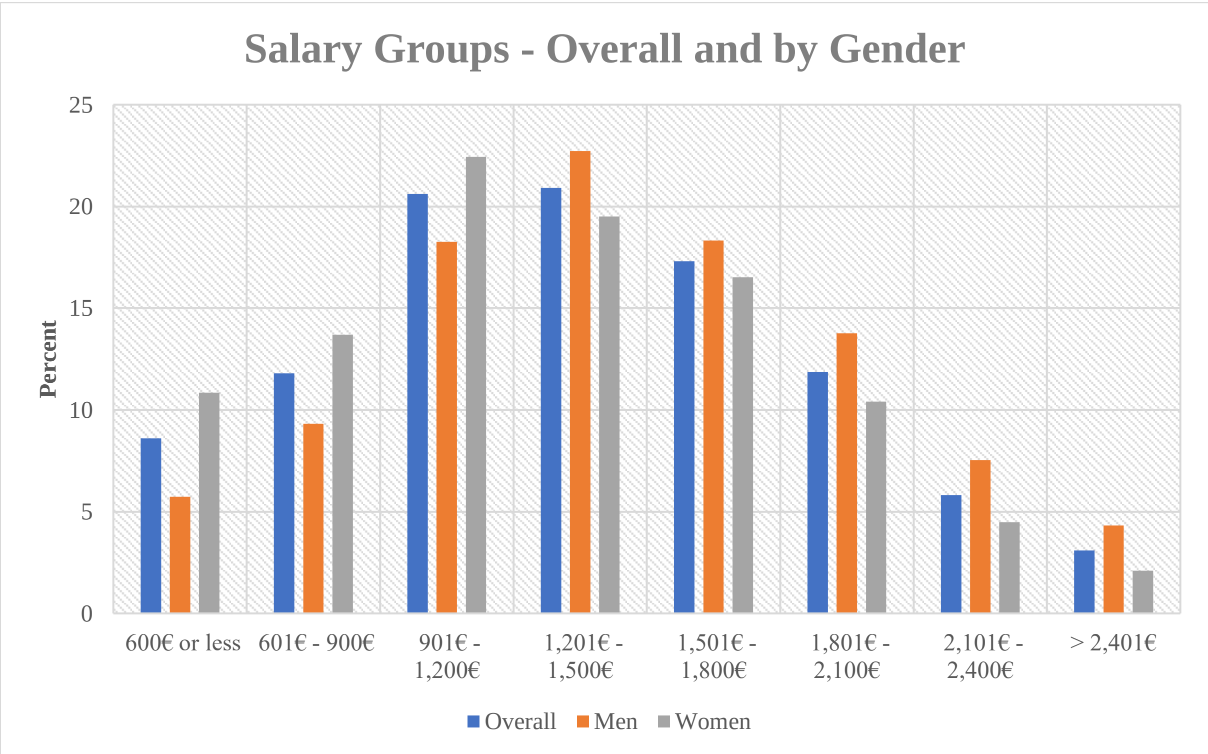

Figure 8: Salary groups, overall and by gender.

But there are also differences between men and women graduating in the same field. Figure 10 reveals that in all fields, except for Experimental Sciences, women earned on average less than their male peers. The highest difference is found in the field of Economics and Law: Women earned on average only 88% of what men did, followed by Arts (91%) and Engineering (91%). In Social Sciences they earned 95% of the male mean salary; within Health, 97%. In the latter, women obtained their highest mean salary. In Experimental Sciences, women earned 103% of those what men did.

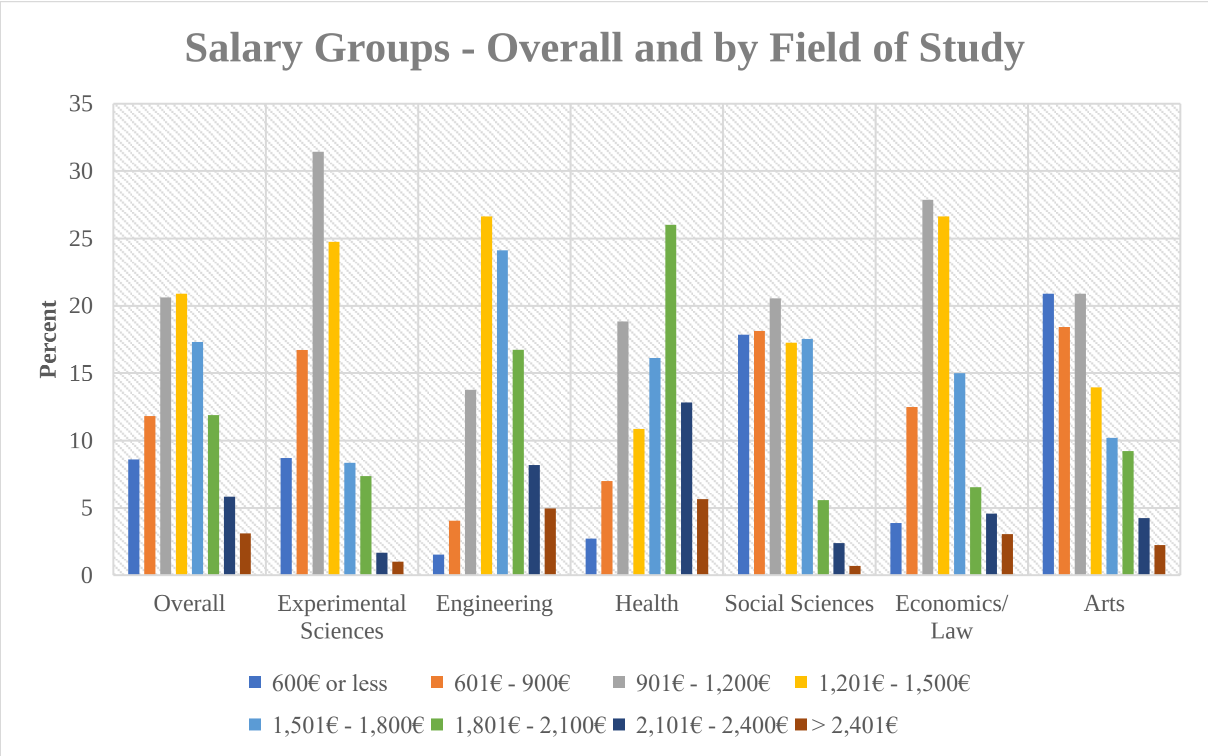

Figure 9: Salary groups, overall and by field of study.

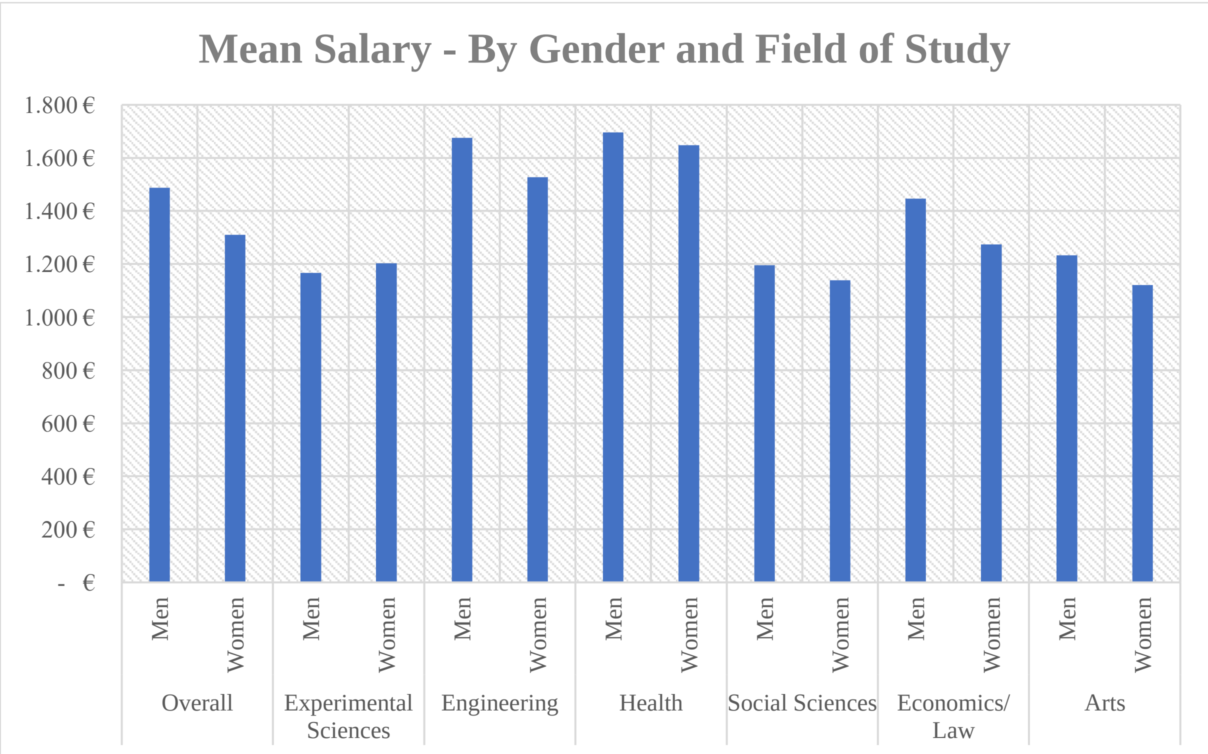

Figure 10: Mean salary, by gender and field of study.

Overall, these last observations underline the observations of Figure 7. Even within female-dominated fields, which on average already have a lower income, male graduates still showed a higher mean salary. But the same logic does not hold for the opposite case: Women did not earn more in fields where they are underrepresented in. Therefore, there remains potential to explain the observed differences between male and female graduates from the same fields.

These descriptive statistics show that there are observable differences by gender and by field of study in all aspects. The essential observation is that not all fields are gender neutral. Because of this fact differences between fields help to understand average differences by gender. While some of the differences are minor, e.g. within employment, some are more pronounced as within full-time and for the salary. In the latter two ones there remains an explanation gap because men and women perform differently even though considering they are from the same field. Mostly male graduates performed better.

5 Empirical Assessment – Methodology

Once descriptive evidence has been presented, this section aims to estimate the factors which underlie differences in labor market outcomes of young graduates in the Basque country. To do so, the descriptive evidence presented above must be accompanied by estimations of each of the different labor market outcomes. We must check the extent to which gender and/or field specialization differences remain when we control for factors, such as differences in the degree performance, work experience, or business-specific variables.

To do so, each of the estimations of the potential labor market outcomes is presented in a four steps procedure (summarized in Table 2). The first step is to see if there exists an unconditional gender gap in the outcome under study. This is followed by an estimation of raw differences in the different fields of specialization. The second step is important because, as already explained in the literature section and confirmed by the descriptive statistics, men and women choose historically different fields of study. Therefore, this second step allows us to answer whether there exist gender differences within fields in step 3. The last step is to estimate and extend the conditional model, where we add further covariates. With this 4-step procedure, we aim to compare unconditional gender and field of specialization differentials for each of the labor market outcomes under study with conditional ones, i.e. when we look at gender and field differentials for workers who share very similar labor market characteristics.

Table 2: 4-step-testing procedure for all estimations.

Step	**Test**
1	Unconditional gender gap
2	Raw differences by field
3	Gender gap conditional on fields of study
4	Gender gap conditional on fields of study and further covariates

5.1 Estimation Models

The chosen estimation models are presented in the following. To start with, it helps to look at a non-technical overview of our sample and the partitioning for every estimation. This is depicted in Figure 11. The figure shows at every stage what we will assess as well as which graduates are included. Every number refers to one of the stages explained below.

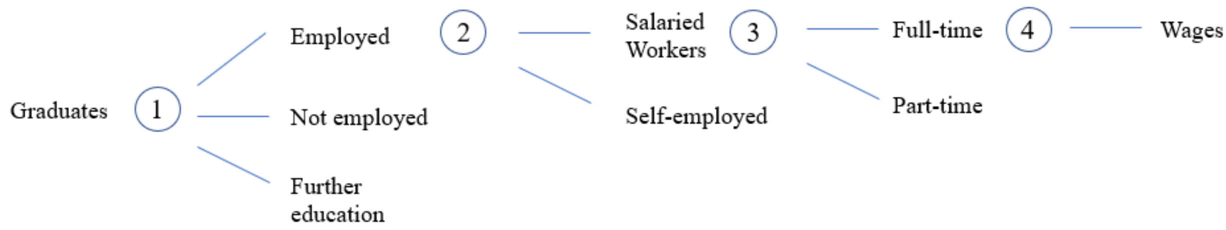

Figure 11: Non-technical overview of the estimations.

Stage 1: Probability of Being Employed – Which characteristics affect the chances to be employed?

Contrary to the empirical facts, the descriptive statistics did not show a clear difference between (un)employment rates by gender. What it did report are high variations between fields and within fields, there are small imbalances. Furthermore, we have learned so far that women tend to pursue further education and especially graduates in Experimental Sciences and Arts. These graduates cannot be dealt with as being unemployed. Therefore, this estimation will not only predict the probability of being employed, but also the probability of pursuing further education. It avoids a distorted picture. In this estimation graduates count as being employed when their labor market situation was *employed*, *self-employed*, *fellow/ intern*, *working in a family business (paid)* or *cooperative member*. Consequently, the used model is a multinomial logit model with a categorical dependent variable with three different outcomes: (1) Being employed, (2) Pursuing further education, and (3) Neither (1) nor (2), referred to as unemployed. The covariates that will be added are the following: relative grade, age, duration of studies, and a dummy on work experience, as a priori they affect the probability of being employed.

Setting outcome (3) as the base, i.e. $\beta_3 = 0$, the economic model can be described as:

Employed:
$$\Pr(y = employed|X) = \frac{exp(X'\beta_1)}{exp(X'\beta_1) + exp(X'\beta_2) + 1} \quad (1)$$

Pursuing further studies:
$$\Pr(y = pursue\ further\ education|X) = \frac{exp(X'\beta_2)}{exp(X'\beta_1) + exp(X'\beta_2) + 1} \quad (2)$$

Not employed (base outcome):
$$\Pr(y = not\ employed|X) = \frac{1}{exp(X'\beta_1) + exp(X'\beta_2) + 1} \quad (3)$$

where X is the vector of covariates and β_1 and β_2 are vectors including the intercept and coefficients for the effect of the covariates on outcome *employed* and *pursue further education*, respectively. The vector of covariates will be adjusted with every step of the procedure as described by the 4-steps procedure.

Stage 2: For employed workers, which characteristics are more associated with self-employment?

Self-employees form a “special” group among employed people. Their employment is different in several characteristics and it is hard to compare them with salaried workers. To avoid distortions in the results of later questions, self-employed graduates will be excluded. Nevertheless, before doing so, they are still an interesting sub-group. Empirically, self-employees are more likely to be men than women. The descriptive section confirmed this, although there exist differences among fields. To test if there are significant differences among the Basque graduates, a probit model is designed with the binary dependent variable and its outcomes (1) Self-employed and (0) Not self-employed. Given that this estimation only makes use of employed workers, it is necessary to control for the probability of being employed. We do so by estimating a 2-step approach: In the first step, we obtain the predictive probability of being employed from the first estimation. In the second step, we include such prediction as an additional explanatory variable. By doing so, we estimate the probability of self-employment versus salaried employment controlling for the probability of being employed. Hence, we take into account that employed workers might not be representative of all individuals included in the sample. The economic model can then be described as:

Pre-step
$$Pr(employed = 1|\omega) = \Phi(\omega\gamma) \tag{4}$$

Main model
$$Pr(self - employed = 1|\, X, Z) = \Phi\left((X \quad Z)\begin{pmatrix}\beta \\ \delta\end{pmatrix}\right) \tag{5}$$

where ω and X represent the vectors of covariates and γ and β the vector of coefficients. ω includes the same covariates as defined in the previous model, i.e. being female, fields of study, relative grade, age, duration of studies, and the work experience. The predicted probability of the pre-step is represented by Z. Its magnitude is measured by δ.

The vector X will include the already seen covariates gender, fields of study, relative grade, age, the work experience, and the probability of being employed predicted by the pre-step. It will be further augmented by covariates that describe the occupational field and the economic sector. For example, the ad-hoc module of the 2017 Labor Force Survey shows that dependent self-employment is most common in the construction sector and independent self-employment is most common in the agriculture, forestry and fishing sector. Therefore, these covariates help to characterize the determinants of self-employment.

Stage 3: For salaried workers, which characteristics promote full-time employment?

The next three estimations concentrate on salaried workers and two of their labor market outcomes. The first estimation addresses the workday – if graduates found a full-time position or not. As seen in the empirical facts as well as in the descriptive analysis of the data set, a lower share of women works in a full-time position. Some of the differences to men might be explained by the different field choices, as the share of full-time positions is higher for male-dominated fields as for female-dominated fields. But the previous analysis also revealed that within all fields, women were less often employed full-time. To investigate the magnitude, to evaluate the significance, and to provide possible explanations, this estimation aims to pin down determinants of the probability of working full-time. This will be done by a probit model with the binary dependent variable and its outcomes (1) Working full-time and (0) Not working full-time. Again, self-employees are excluded from now on. For all other graduates, the pre-step is the estimation of the probability of being a salaried worker. Like the previous model, this estimation can be divided into a pre-step and the main model:

Pre-step
$$\Pr(salaried\, worker = 1|\omega) = \Phi(\omega\gamma) \tag{6}$$

Main model
$$Pr(full - time\, worker = 1|X, Z) = \Phi\left((X\, Z)\, \binom{\beta}{\delta}\ \right) \tag{7}$$

where ω and X represent the vectors of covariates and γ and β the vector of coefficients. ω includes the same covariates as defined in equation (4). The predicted probability of the pre-step is represented by Z. Its magnitude is measured by δ.

In addition to the covariates of the previous main model in equation (5), the vector X will be expanded by job characteristics (requirement of the degree and contract type) as well as firm characteristics (ownership of the firm, operating area) as they might influence the chances of full-time employment.

Stage 4: Wage determinants – How are gender and field of study associated with salary?

Comparing the mean salaries showed differences by gender and by fields of specialization. Moreover, even for men and women from the same field, salaries vary widely. In all fields, except for Experimental Sciences, women earned on average less than their male peers. This finding needs an explanation because, intuitively, the gender pay gap should not exist or should be relatively small as we consider a relatively homogenous group of graduates from the same university. There indeed exist higher and lower-paid fields, but we control for this. Especially after graduation, the young labor market entrants show similar characteristics and have the (dis)advantage of being more comparable than after a few years into the labor market. We use two estimations to address the question of how gender and the fields of study are associated with the salary. First, the logarithm of the salary will be tested with a two-stage Heckman model. The data set does not provide information about the exact working hours. Therefore, we are not able to compute hourly wages. To still provide a clear and not distorted picture of workers with similar labor market attachment, we will focus on workers with a clear high labor market attachment, i.e. full-time workers. This filtering describes the selection model. The main model will estimate the influence of the same covariates introduced before. Thus, the estimation model can be characterized as follows.

Selection model	$Pr(full-time\,worker=1\vert\omega)\ =\Phi(\omega\gamma)$	(8)
Main model	$E(wage\vert full-timeworker=1)=X\beta+\rho\sigma\hat{\lambda}(\omega\gamma)$	(9)

where ω and X represent the vectors of covariates and γ and β the vector of coefficients. ρ is the correlation between the bivariate distribution of the discrete model (full-time worker yes or no) of the first step and the continuous variable (wage) of the second step, σ is the standard deviation of the error term of the regression equation and $\hat{\lambda}(\omega\gamma)$ describes the inverse Mills ratio. To predict the probability of a full-time worker, ω includes the covariates gender, fields of study, relative grade, age, and work experience.

The vector X includes the covariates used before: gender, fields of study, relative grade, age, work experience, occupation field, economic sector, job characteristics, and firm characteristics, all introduced as explained in the 4-step procedure. In the last step, we include a variable that states the proportion of women per degree to control for high female proportions within fields to check if women from a female-dominated field do better than men of the same field.

The last estimation serves as an additional source to increase the robustness of the estimation. There will be a dummy for the interaction of being female with different fields. This helps to identify if women do especially good within a particular field. This estimation will be conducted similarly as the last model of the previous one, i.e. with all covariates included. The selection model and the main regression model are described by the same structure as in equation (8) and (9). The covariate vector will be adjusted in two points. The age variable will be removed as it is not overall significant, and the economic sector will be reduced to a dummy on the industry sector since this is the sector with the highest salaries. In the next step, the estimation will also be combined with the control variable of the proportion of women per degree. Furthermore, the same estimation will be conducted with a change of the reference group of the fields of study. Until now the reference group was set to Engineering. Now it will be changed to Experimental

Sciences because here women perform better than men do. This is done on the one hand to see how female graduates of Engineering perform and on the other hand to evaluate if the other coefficients change.

6 Empirical Results

Stage 1: Probability of Being Employed – Which characteristics affect the chances to be employed? Are there gender and field of study gaps?

As explained in the previous section, this estimation has three different outcomes. All results on the probability of being employed and on the probability of pursuing further education are in relation to the probability of being unemployed. Table 3 reports the results for Outcome 1 and Table 4 reports the results for Outcome 2. The coefficients are reported as marginal effects.

Both columns (1) show the unconditional gender gap. For Outcome 1, there are no significant raw differences by gender. **Thus, on average, both male and female graduates are equally likely to be employed comparably to being unemployed.** Regarding the probability of pursuing further education, there are raw gender differences. **On average female graduates are more likely to continue their education relatively to being unemployed.**

The descriptive analysis pointed out that the employability across fields varies. This observation is confirmed by column (2) of Outcome 1. In comparison to Engineering, the probability of being employed relative to the probability of being unemployed decreases within the fields of Experimental Sciences, Social Sciences, Economics and Law, and Arts. The strongest decrease is estimated for graduates of Arts (-18.3 pp). Health graduates face the same probability as Engineers because the coefficient is not significant. Consequently, **depending on the field of specialization, the probability of being employed vs being unemployed varies strongly. The probability is highest for the fields of Engineering and Health.**

The descriptive analysis showed that graduates of Experimental Sciences were the ones that most often pursued further studies, whereas graduates of Engineering and Health reported the lowest share of continue studying. Column (2) verifies that these observed differences are significant. In all fields, except for Health, the probability of engaging in further education vs being unemployed increases comparably to the probability for Engineers. The highest increase can be observed for Experimental Sciences (+6.82 pp). **Hence, there are raw field differences in the probability of pursuing further education. Graduates from Experimental Sciences are most likely to continue their studies.**

Combining the first two models, columns (3) show the gender gap of men and women within the same fields for both outcomes. For both outcomes, the coefficient of being female is not significant. This means that **even conditioning on the fields of studies, men and women have the same chances to be employed or to continue their studies relatively to be unemployed.**

Inspecting the coefficient on the relative grade within columns (4) and (5) shows that a higher relative grade increases the probability of being employed but has no effect on the probability of engaging in further studies. The age group as well as the duration of studies both do not change the probability of the outcomes. In contrast, previous work experience is highly significant in both cases. While on the one hand, it increases the probability of finding employment (+6.5 pp), on the other hand, it decreases the probability of continuing studies (-2.59 pp), both in relation to being unemployed. It can be concluded that **work experience is a strong determinant of both probabilities.**

Overall, estimation A does not show (un)conditional gender differences in either of the two outcomes relative to the third outcome. Consequently, **men and women inhabit the same opportunities for finding employment or to continue with their studies.** Important variations are found among fields: Engineering and Health graduates have the highest chances to be employed and the lowest chances to engage in further education comparably to being unemployed. Moreover, the work experience is an important variable to consider.

Table 3: Results of the estimation of the probability of being employed and the probability of pursuing further education. Outcome 1: Being employed.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Being female	-0.0140		0.00951	0.00727	0.0116
	(0.0103)		(0.0105)	(0.0105)	(0.0102)
Fields of Study **Reference Group: Engineering**					
Experimental Sciences		-0.140***	-0.142***	-0.141***	-0.114***
		(0.0221)	(0.0222)	(0.0222)	(0.0212)
Health		0.0166	0.0143	0.0146	0.00573
		(0.0120)	(0.0123)	(0.0123)	(0.0116)
Social Sciences		-0.111***	-0.114***	-0.113***	-0.114***
		(0.0131)	(0.0136)	(0.0135)	(0.0135)
Economics/Law		-0.108***	-0.108***	-0.108***	-0.110***
		(0.0148)	(0.0148)	(0.0148)	(0.0144)
Arts		-0.183***	-0.185***	-0.184***	-0.181***
		(0.0203)	(0.0205)	(0.0205)	(0.0205)
Relative Grade				0.0104**	0.0100*
				(0.00504)	(0.00541)
Age Group **Reference Group: up to 22 years**					
23-24 years					-0.00782
					(0.0120)
25-29 years					-0.0173
					(0.0145)
Over 29 years					-0.0397*
					(0.0204)
Duration of Studies					-0.000255
					(0.00235)
Work Experience					0.0650***
					(0.0139)
Observations	5,017	5,017	5,017	5,017	4,905

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

Table 4: Results of the estimation of the probability of being employed and the probability of pursuing further education. Outcome 2: Pursuing further education.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Being female	0.0141**		0.00849	0.00812	0.00455
	(0.00641)		(0.00660)	(0.00663)	(0.00571)
Field of studies **Reference Group: Engineering**					
Experimental Sciences		0.0682***	0.0661***	0.0662***	0.0384***
		(0.0156)	(0.0157)	(0.0157)	(0.0125)
Health		-0.0177***	-0.0192***	-0.0191***	-0.00988*
		(0.00605)	(0.00624)	(0.00624)	(0.00540)
Social Sciences		0.0347***	0.0319***	0.0320***	0.0259***
		(0.00814)	(0.00840)	(0.00841)	(0.00744)
Economics/Law		0.0313***	0.0302***	0.0302***	0.0292***
		(0.00905)	(0.00920)	(0.00920)	(0.00835)
Arts		0.0462***	0.0441***	0.0443***	0.0344***
		(0.0122)	(0.0123)	(0.0123)	(0.0108)
Relative Grade				0.00172	-0.00102
				(0.00305)	(0.00299)
Age Group **Reference Group: up to 22 years**					
23-24 years					0.000205
					(0.00696)
25-29 years					-0.00751
					(0.00766)
Over 29 years					-0.00645
					(0.0104)
Duration of Studies					-8.82e-06
					(0.00152)
Work Experience					-0.0259***
					(0.00881)
Observations	5,017	5,017	5,017	5,017	4,905

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

Stage 2: For employed workers, which characteristics are more associated with self-employment? Are there gender and field of study gaps?

The results of the probit model are shown in Table 5. The results of the pre-step model, the probability of being employed, are shown in the Appendix. The coefficients are reported as marginal effects.

As column (1) shows, the coefficient of being female is significantly negative. That means, **on average there is an unconditional gender gap,** stating that women are less likely (-1.46 pp) to be self-employed. Regarding the raw differences by fields, we can derive from column (2) that **only for Health graduates the probability of being self-employed is significantly decreased relative to Engineers.** For all other fields, there is no difference in the probability comparably to Engineering.

Combining the two models, column (3) reports a decrease in the significance level for the coefficient of being female. In other words, **comparing men and women from the same fields, the gender gap seems to disappear.**

Columns (4) to (8) show a step by step introduction of further covariates that makes the graduates more equal or comparable to each other. The relative grade is significant in the first place (column (4)) but its importance vanishes when controlling for the age group. Concerning the age structure, it holds throughout the different models that for 25-29-years-old graduates the probability of being self-employed increases significantly (approximately +3 pp) in relation to graduates up to 22 years. The gender gap vanishes completely as soon as the dummy on work experience is included, although it is not significant. In comparison to the occupational field of Management, Engineering and Professionals, the probability of being self-employed is reduced within the occupation field of Administration as well as in Services (-4.75 pp and -2.94 pp, respectively)[5]. Furthermore, working in the economic sector of Industry or Construction also diminishes the probability relative to the sector of Services. The probability of being employed is only significant for the first model. Its significance vanishes once controlling for the fields.

Overall, although there **exists an unconditional gender gap**, **accounting for the gender differences in the fields of specialization almost eliminates the gap.** In the end, when we include the relative grade, the age, and the work experience, the gender gap vanishes. The

[5] The occupation fields are defined as follows: (i) Management, Engineering and Professionals, including *Business Management and Public Administration, and Engineers and University Professionals*. (ii) Engineering and Support, including *Engineers and support professionals*. (iii) Administration. (iv) Services. (v) Other, including *manual workers, agriculture, machinery and non-qualified workers.*

occupation field and the economic sector help to characterize self-employment characteristics. Therefore, it can be concluded that **both men and women are equally likely to be self-employed,** i.e. there is no conditional gender gap.

Table 5: Results of the estimation of the probability of being self-employed.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8
Being female	-0.0146**		-0.0136*	-0.0137*	-0.0136*	-0.0105	-0.00817	-0.00922
	(0.00658)		(0.00715)	(0.00713)	(0.00708)	(0.00823)	(0.00824)	(0.00821)
Fields of Study **Reference Group: Engineering**								
Experimental Sciences		-0.0166	-0.00581	0.00473	0.0162	-0.00807	-0.00733	-0.0252
		(0.0175)	(0.0179)	(0.0185)	(0.0193)	(0.0406)	(0.0387)	(0.0441)
Health		-0.0223**	-0.0165*	-0.0154*	-0.00899	-0.0104	-0.0122	-0.0287*
		(0.0106)	(0.00996)	(0.00873)	(0.00855)	(0.0120)	(0.0112)	(0.0162)
Social Sciences		-0.0111	0.000361	0.0101	0.0187	-0.00580	-0.00327	-0.0226
		(0.0152)	(0.0155)	(0.0154)	(0.0151)	(0.0395)	(0.0382)	(0.0435)
Economics/Law		-0.00203	0.00770	0.0180	0.0221	-0.00225	0.0107	-0.00595
		(0.0166)	(0.0164)	(0.0165)	(0.0155)	(0.0395)	(0.0407)	(0.0461)
Arts		0.0244	0.0436	0.0680*	0.0832**	0.0259	0.0273	0.00162
		(0.0296)	(0.0325)	(0.0367)	(0.0375)	(0.0786)	(0.0770)	(0.0761)
Relative Grade				-0.00823**	-0.00487	-0.00246	-0.00368	-0.00403
				(0.00361)	(0.00371)	(0.00500)	(0.00497)	(0.00495)
Age Group **Reference Group: up to 22 years**								
23-24 years					-0.000227	-0.00182	-0.000872	-0.000455
					(0.00750)	(0.00804)	(0.00798)	(0.00798)
25-29 years					0.0295***	0.0258**	0.0277**	0.0301**
					(0.0104)	(0.0116)	(0.0116)	(0.0118)
Over 29 years					0.0336**	0.0216	0.0222	0.0186
					(0.0131)	(0.0201)	(0.0198)	(0.0190)

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8
Work Experience						0.0164	0.0170	0.0189
						(0.0229)	(0.0228)	(0.0227)
Occupation Field **Reference Group: Management, Engineering and Professionals**								
Engineering and Support							-0.0149	-0.0122
							(0.00931)	(0.00957)
Administration							-0.0486***	-0.0475***
							(0.00637)	(0.00655)
Services							-0.0287***	-0.0294***
							(0.0104)	(0.00978)
Other							0.00834	0.0205
							(0.0245)	(0.0287)
Economic Sector **Reference Group: Services**								
Agriculture/ Farming/ Fishing								0.145
								(0.109)
Industry								-0.0406***
								(0.00635)
Construction								-0.0300**
								(0.0146)
Probability of Being Employed	-0.179***	-0.110	-0.0461	0.0534	0.0743	-0.152	-0.161	-0.192
	(0.0481)	(0.114)	(0.118)	(0.123)	(0.120)	(0.338)	(0.337)	(0.335)
Observations	4,245	4,245	4,245	4,245	4,245	4,245	4,245	4,231

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

Stage 3: For salaried workers, which characteristics promote full-time employment? – Are there gender and field of study gaps?

Table 6 reports the results for this question. The coefficients are reported as marginal coefficients. The raw gender difference seen in the descriptive analysis is confirmed to be highly significant (column (1)). The probability for female graduates to find full-time employment decreases by 11.8 pp. Hence, **on average women are less likely to be employed in a full-time position.** Furthermore, there are strong raw differences across the fields. For all fields, the probability of being a full-time worker decreases comparably to Engineering (column (2)). Arts and Social Sciences graduates face the strongest decrease: In relation to Engineers, their probabilities reduce by 45.8 pp and 39.8 pp, respectively. In conclusion, **the raw differences by fields are high**.

These high differences within fields can account for almost two thirds of the unconditional gender gap. Column (3) reports a conditional gender gap of 3.69 pp. **Taking into account the strong gender differences by fields, the gender gap reduces substantially, but it is still present.**

The next models in columns (4) to (11) show the introduction of further covariates step by step to explore further sources causing the gender difference. Among more comparable graduates the gender difference increases first to 5.6 pp (column (9)). The increase is caused by adding the work experience, although the variable itself is not significant. Moreover, the requirement of a degree significantly increases the probability of working full-time. The contract type increases the gender gap by almost 1 pp. Relative to an indefinite contract, a temporary contract reduces the probability of working full-time by more than 8 pp. This means that a temporary contract is highly associated with part-time employment and together they result in a double precariousness. A scholarship or internship increases the probability of working full-time (comparably to an indefinite contract) by approximately 6 pp. Attributes of the firm, as being in public ownership or operating multinational-widely, both increase the chances of being a full-time worker significantly (+4.3 pp and + 13.1 pp, respectively). Controlling for the occupational field as well as the economic sector lowers the gender gap to 4.77 pp (column (11)). Working in a service occupation (comparably to a position in Management, Engineering and Professionals) diminishes the probability (-12.8 pp) and working in the industry sector (comparably to the Services sector) significantly improves the probability (+9.72 pp).

In conclusion, the estimation reveals that **there is an unconditional gender gap in the probability of working full-time.** The main driver to reduce this gender gap is to control for differences among the different fields of specialization. Graduates of Health and Social Sciences face significantly lower chances to find full-time employment than Engineers. Although we take this into account as well as gender differences in occupations, contract types, or the economic sector, **there remains an unexplained gender gap in the probability, i.e. women are less likely to be engaged full-time.**

Table 6: Results of the estimation of the probability of being a full-time worker.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11
Being female	-0.118***		-0.0369***	-0.0361***	-0.0356***	-0.0455***	-0.0461***	-0.0554***	-0.0560***	-0.0515***	-0.0477***
	(0.0122)		(0.0132)	(0.0132)	(0.0132)	(0.0171)	(0.0169)	(0.0172)	(0.0171)	(0.0171)	(0.0170)
***Fields of Study* Reference Group: Engineering**											
Experimental Sciences		-0.187***	-0.165***	-0.176***	-0.164***	-0.114*	-0.113*	-0.113	-0.0915	-0.0801	-0.0660
		(0.0291)	(0.0300)	(0.0308)	(0.0311)	(0.0634)	(0.0634)	(0.0693)	(0.0701)	(0.0707)	(0.0735)
Health		-0.0996***	-0.0970***	-0.0928***	-0.0939***	-0.118***	-0.126***	-0.102***	-0.105***	-0.105***	-0.0669**
		(0.0172)	(0.0178)	(0.0173)	(0.0178)	(0.0349)	(0.0358)	(0.0323)	(0.0330)	(0.0325)	(0.0277)
Social Sciences		-0.398***	-0.370***	-0.382***	-0.369***	-0.309***	-0.300***	-0.270***	-0.231***	-0.215***	-0.183**
		(0.0218)	(0.0250)	(0.0255)	(0.0265)	(0.0747)	(0.0746)	(0.0796)	(0.0804)	(0.0813)	(0.0818)
Economics/Law		-0.0785***	-0.0632***	-0.0713***	-0.0679***	-0.0277	-0.0296	-0.0250	-0.0131	-0.00866	0.00493
		(0.0176)	(0.0187)	(0.0193)	(0.0197)	(0.0502)	(0.0505)	(0.0545)	(0.0571)	(0.0586)	(0.0621)
Arts		-0.458***	-0.413***	-0.440***	-0.425***	-0.298**	-0.291**	-0.260*	-0.221	-0.191	-0.178
		(0.0448)	(0.0489)	(0.0509)	(0.0520)	(0.148)	(0.147)	(0.154)	(0.151)	(0.148)	(0.148)
Relative Grade				0.0104	0.0156**	0.00904	0.00622	0.00475	0.00168	0.000288	0.00302
				(0.00638)	(0.00670)	(0.00978)	(0.00971)	(0.00995)	(0.00991)	(0.00984)	(0.00982)
***Age Group* Reference Group: up to 22 years**											
23-24 years					0.0408***	0.0460***	0.0492***	0.0454***	0.0440***	0.0433***	0.0426***
					(0.0148)	(0.0160)	(0.0159)	(0.0161)	(0.0161)	(0.0160)	(0.0158)
25-29 years					0.0304*	0.0416*	0.0485**	0.0440**	0.0457**	0.0443**	0.0353*
					(0.0175)	(0.0214)	(0.0211)	(0.0214)	(0.0212)	(0.0211)	(0.0213)
Over 29 years					0.0268	0.0549	0.0576	0.0349	0.0376	0.0348	0.0317
					(0.0208)	(0.0361)	(0.0359)	(0.0378)	(0.0375)	(0.0373)	(0.0371)

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11
Work Experience						-0.0432	-0.0302	-0.0390	-0.0459	-0.0467	-0.0403
						(0.0469)	(0.0467)	(0.0472)	(0.0468)	(0.0465)	(0.0464)
Degree Needed?							0.100***	0.0945***	0.0951***	0.0644***	0.0603***
							(0.0133)	(0.0138)	(0.0138)	(0.0161)	(0.0162)
***Contract Type* Reference Group: Indefinite**											
Temporary								-0.0857***	-0.0826***	-0.0844***	-0.0819***
								(0.0132)	(0.0134)	(0.0133)	(0.0133)
Scholarship/ Internship								0.0670***	0.0621***	0.0567**	0.0572**
								(0.0218)	(0.0227)	(0.0227)	(0.0231)
Public									0.0430***	0.0421***	0.0528***
									(0.0152)	(0.0150)	(0.0149)
Multinational									0.131***	0.136***	0.110***
									(0.0207)	(0.0209)	(0.0215)
***Occupation Field* Reference Group: Management, Engineering and Professionals**											
Engineering and Support										-0.00194	-0.0126
										(0.0195)	(0.0198)
Administration										0.0117	-4.00e-05
										(0.0256)	(0.0261)
Services										-0.147***	-0.128***
										(0.0310)	(0.0298)
Other										0.0432	0.0125
										(0.0360)	(0.0412)

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11
***Economic Sector* Reference Group: Services**											
Agriculture/ Farming/ Fishing											0.0977
											(0.0958)
Industry											0.145***
											(0.0168)
Construction											0.0972***
											(0.0365)
Probability of Being a Salaried Worker	1.318***	-0.337*	-0.156	-0.288	-0.245	0.314	0.212	0.165	0.255	0.315	0.190
	(0.0792)	(0.183)	(0.195)	(0.210)	(0.212)	(0.644)	(0.640)	(0.657)	(0.652)	(0.647)	(0.646)
Observations	4,446	4,446	4,446	4,446	4,446	4,446	4,446	4,044	4,044	4,044	4,030

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

Stage 4: Wage determinants – How are gender and field of study associated with salary?

The last question is answered by two estimations. The results of the first estimation are reported in Table 7. The coefficients are reported as marginal effects.

As column (1) shows, the coefficient of being female is not significant. Thus, **on average men and women do not differ in their earnings.** However, **there are namely differences across the fields** (column (2)). In comparison to Engineering, Experimental Sciences is the worst paid field as the salary decreases by 26.8 pp. On the contrary, Health graduates report an increase in salary (+5.53 pp) comparably to Engineers. Once we consider the gender differences in the distribution of fields of specialization, there appears a gender pay gap of 4.92 pp (column (3)). Consequently, **female and male graduates from the same field differ in their payments – women earn significantly less.**

Columns (4) to (12) show the introduction of further covariates that help to explain and reduce the observed conditional difference step by step. Although the relative grade is not significant in the first place (column (4)), once controlling also for the age group, it significantly increases the salary by 1.6 pp (column (5)). Regarding the age group, graduates aged over 29 years earn a 20.7 pp higher salary than young graduates up to 22 years. Additionally, previous work experience and the requirement of a degree both positively influence the salary (column (6) and (7)). Regarding the contract type, in comparison to an indefinite contract, both temporary contracts as well as scholarships/ internships decrease the wage.

From column (8) to (9) and from (9) to (10) the gender gap declines the most. In both public owned and multinational businesses, the salary increases. Introducing these two covariates also affects the relative coefficient of the field of Health: Health graduates do not show higher salaries relative to Engineers anymore as most of them work within a public business. Also, controlling for the occupation has a high effect since all other occupational fields show significantly lower earnings than graduates within the occupation field of Management, Engineering and Professionals. Adding the economic sector shows that the Industry sector is the best-paid sector. It increases the salary by 7.7 pp in relation to the Service sector (column (11)). Including a control variable for the proportion of women per degree diminishes the gap further, though the coefficient is not significant.

To sum up, **there is no raw gender difference in earnings.** However, controlling for the gender differences within fields, **there appears a conditional gender gap.** This gender wage gap can be partially explained by further variables. The most important ones are previous work experience, the requirement of a degree, the contract type, the ownership, and the operating area of the business as well as the occupation field and the economic sector. Nevertheless, in the end, **there remains a gap** that cannot be explained by our dataset.

As explained in the methodology section, the previous estimation will be conducted again with the interactions of the female dummy and the different fields. The results for this estimation are presented in Table 8. The coefficients are reported as marginal effects.

The interactions reveal that within both Experimental Sciences (column (1)) and Social Sciences (column (3)) women perform better than their male peers. The contrary is true for women holding a degree in Economics and Law. The coefficient is significantly negative (column (4)). Within the other fields, the coefficients of the interactions are not significant, indicating that men and women perform the same. **Still, there is a conditional gender gap as observed before.** Nevertheless, it is interesting that the gender pay gap in model (4) seems to disappear as it is only significant at the 10% level. Table 13 in the Appendix shows that once adding the proportion of women it is not significant anymore. Consequently, considering the worse performance of women in Economics and Law explains the gap seen before.

To be sure that the coefficients and results are not distorted because the reference group of the fields of study is Engineering – a field dominated by men –, the same estimation is done with a change of the reference group to Experimental Sciences – the field where women perform the best. But this is not the only motivation. Additionally, we want to examine if women in Engineering are better off. However, the results do not differ from the previous ones. Also, women in Engineering do not show better performance than men in Engineering. The results are shown in the Appendix in Table 14 and 15.

Overall, answering the last question we can conclude that **on average there does not exist a gender difference.** However, the differences across fields are high. Engineering and Health are better-paid fields, while Experimental Sciences is associated with a lower salary. Accounting for the gender differences in the fields of specialization shows a gender pay gap. That means, **men and women graduating in the same field do not earn the same – female graduates earn less.** Nevertheless, women within Experimental Sciences or Social Sciences do perform better than men in those fields. In the end, after controlling for gender differences in various job-related variables, **there remains a gender wage gap that cannot be explained.**

Table 7: Results of the estimation of salary.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11	(12) Model 12
Being female	-0.0117		-0.0492***	-0.0501***	-0.0429***	-0.0424***	-0.0437***	-0.0469***	-0.0410***	-0.0362***	-0.0320***	-0.0288**
	(0.0131)		(0.0122)	(0.0123)	(0.0120)	(0.0121)	(0.0120)	(0.0116)	(0.0114)	(0.0113)	(0.0113)	(0.0118)
Fields of Study **Reference Group: Engineering**												
Experimental Sciences		-0.268***	-0.264***	-0.264***	-0.242***	-0.237***	-0.233***	-0.183***	-0.214***	-0.212***	-0.197***	-0.187***
		(0.0270)	(0.0240)	(0.0240)	(0.0238)	(0.0240)	(0.0239)	(0.0234)	(0.0234)	(0.0233)	(0.0235)	(0.0258)
Health		0.0553***	0.0675***	0.0677***	0.0919***	0.0991***	0.0927***	0.0974***	0.00177	-0.00122	0.0188	0.0343
		(0.0213)	(0.0191)	(0.0191)	(0.0190)	(0.0193)	(0.0192)	(0.0191)	(0.0210)	(0.0209)	(0.0213)	(0.0266)
Social Sciences		-0.154***	-0.160***	-0.160***	-0.141***	-0.138***	-0.126***	-0.131***	-0.143***	-0.139***	-0.113***	-0.0984***
		(0.0391)	(0.0254)	(0.0253)	(0.0252)	(0.0262)	(0.0268)	(0.0270)	(0.0280)	(0.0282)	(0.0291)	(0.0326)
Economics/Law		-0.171***	-0.164***	-0.164***	-0.161***	-0.164***	-0.156***	-0.167***	-0.169***	-0.135***	-0.115***	-0.106***
		(0.0166)	(0.0162)	(0.0162)	(0.0159)	(0.0159)	(0.0159)	(0.0153)	(0.0149)	(0.0156)	(0.0161)	(0.0186)
Arts		-0.154***	-0.166***	-0.166***	-0.152***	-0.149***	-0.127***	-0.115***	-0.150***	-0.142***	-0.119***	-0.107***
		(0.0425)	(0.0309)	(0.0308)	(0.0305)	(0.0313)	(0.0318)	(0.0316)	(0.0323)	(0.0326)	(0.0331)	(0.0351)
Relative Grade				0.00441	0.0160***	0.0164***	0.0145**	0.0228***	0.0114**	0.00877	0.0104*	0.0109*
				(0.00562)	(0.00596)	(0.00595)	(0.00591)	(0.00570)	(0.00564)	(0.00561)	(0.00557)	(0.00560)
Age Group **Reference Group: up to 22 years**												
23-24 years					0.000904	-0.00268	0.00148	-0.00341	-0.0138	-0.0106	-0.0112	-0.0115
					(0.0143)	(0.0143)	(0.0142)	(0.0137)	(0.0134)	(0.0133)	(0.0132)	(0.0132)
25-29 years					0.0235	0.0143	0.0225	0.00534	-0.00248	0.000160	0.000873	0.00196
					(0.0162)	(0.0164)	(0.0163)	(0.0158)	(0.0154)	(0.0153)	(0.0152)	(0.0152)
Over 29 years					0.207***	0.179***	0.192***	0.172***	0.129***	0.126***	0.123***	0.124***
					(0.0203)	(0.0221)	(0.0221)	(0.0213)	(0.0210)	(0.0209)	(0.0207)	(0.0207)
Work Experience						0.0501***	0.0527***	0.0453***	0.0410***	0.0418***	0.0459***	0.0458***
						(0.0154)	(0.0153)	(0.0147)	(0.0144)	(0.0142)	(0.0142)	(0.0142)
Degree Needed?							0.103***	0.120***	0.114***	0.0754***	0.0734***	0.0734***
							(0.0157)	(0.0151)	(0.0147)	(0.0161)	(0.0161)	(0.0161)

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11	(12) Model 12
Contract Type **Reference Group: Indefinite**												
Temporary								-0.0325***	-0.0620***	-0.0583***	-0.0597***	-0.0594***
								(0.0118)	(0.0118)	(0.0117)	(0.0116)	(0.0116)
Scholarship/ Internship								-0.308***	-0.348***	-0.347***	-0.350***	-0.351***
								(0.0202)	(0.0200)	(0.0198)	(0.0196)	(0.0196)
Public									0.180***	0.177***	0.188***	0.188***
									(0.0146)	(0.0145)	(0.0146)	(0.0146)
Multinational									0.0545***	0.0596***	0.0448***	0.0446***
									(0.0133)	(0.0132)	(0.0134)	(0.0134)
Occupation Field **Reference Group: Management, Engineering and Professionals**												
Engineering and Support										-0.0296*	-0.0323**	-0.0325**
										(0.0153)	(0.0152)	(0.0152)
Administration										-0.148***	-0.156***	-0.157***
										(0.0217)	(0.0215)	(0.0216)
Services										-0.0730**	-0.0670**	-0.0669**
										(0.0299)	(0.0298)	(0.0297)
Other										-0.0998***	-0.125***	-0.126***
										(0.0362)	(0.0362)	(0.0362)

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11	(12) Model 12
***Economic Sector* Reference Group: Services**												
Agriculture/ Farming/ Fishing											-0.0769	-0.0756
											(0.108)	(0.108)
Industry											0.0770***	0.0758***
											(0.0142)	(0.0143)
Construction											0.0183	0.0197
											(0.0282)	(0.0282)
Proportion of Women per Degree												-0.0377
												(0.0387)
Constant	7.413***	7.396***	7.405***	7.405***	7.373***	7.371***	7.274***	7.311***	7.303***	7.342***	7.312***	7.322***
	(0.0102)	(0.0124)	(0.0108)	(0.0108)	(0.0149)	(0.0150)	(0.0210)	(0.0210)	(0.0212)	(0.0225)	(0.0232)	(0.0255)
Lambda	-0.259	0.00696	0.0500	0.0512	0.0237	0.0131	0.0144	0.0111	0.0150	0.0132	0.0156	0.0153
Observations	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,652	3,652

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

Table 8: Results of the estimation of salary with the interactions of being female and the different fields of study. Version A: Without the proportion of women per degree.

VARIABLES	(1) Model 1-A	(2) Model 2-A	(3) Model 3-A	(4) Model 4-A	(5) Model 5-A
Being female	-0.0424***	-0.0371***	-0.0446***	-0.0236*	-0.0330***
	(0.0117)	(0.0120)	(0.0122)	(0.0127)	(0.0116)
Fields of Study					
Reference Group: Engineering					
Experimental Sciences	-0.260***	-0.207***	-0.203***	-0.211***	-0.208***
	(0.0326)	(0.0231)	(0.0235)	(0.0232)	(0.0231)
Health	0.00416	-0.00847	0.00665	-0.00290	0.000139
	(0.0209)	(0.0301)	(0.0212)	(0.0210)	(0.0209)
Social Sciences	-0.122***	-0.125***	-0.162***	-0.129***	-0.127***
	(0.0278)	(0.0276)	(0.0338)	(0.0280)	(0.0273)
Economics/Law	-0.117***	-0.118***	-0.117***	-0.0943***	-0.119***
	(0.0159)	(0.0159)	(0.0160)	(0.0199)	(0.0159)
Arts	-0.129***	-0.131***	-0.126***	-0.135***	-0.114***
	(0.0319)	(0.0318)	(0.0334)	(0.0321)	(0.0389)
Relative Grade	0.00669	0.00658	0.00605	0.00700	0.00649
	(0.00523)	(0.00524)	(0.00524)	(0.00524)	(0.00524)
Work Experience	0.0804***	0.0796***	0.0800***	0.0809***	0.0796***
	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Degree needed?	0.0660***	0.0657***	0.0651***	0.0655***	0.0661***
	(0.0161)	(0.0162)	(0.0162)	(0.0162)	(0.0162)
Contract Type					
Reference Group: Indefinite					
Temporary	-0.0673***	-0.0674***	-0.0673***	-0.0671***	-0.0677***
	(0.0116)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Scholarship/ Internship	-0.361***	-0.360***	-0.359***	-0.360***	-0.361***
	(0.0196)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
Public	0.204***	0.204***	0.204***	0.204***	0.204***
	(0.0144)	(0.0145)	(0.0144)	(0.0144)	(0.0145)
Multinational	0.0420***	0.0426***	0.0424***	0.0417***	0.0425***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
Occupation Field					
Reference Group: Management, Engineering and Professionals					
Engineering and Support	-0.0319**	-0.0314**	-0.0306**	-0.0318**	-0.0311**
	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)
Administration	-0.160***	-0.160***	-0.158***	-0.155***	-0.161***
	(0.0217)	(0.0217)	(0.0217)	(0.0219)	(0.0217)
Services	-0.0754**	-0.0740**	-0.0739**	-0.0722**	-0.0736**
	(0.0299)	(0.0300)	(0.0299)	(0.0299)	(0.0300)
Other	-0.129***	-0.131***	-0.128***	-0.130***	-0.131***
	(0.0363)	(0.0364)	(0.0364)	(0.0364)	(0.0364)
Sector Industry	0.0749***	0.0754***	0.0752***	0.0764***	0.0755***
	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0140)

VARIABLES	(1) Model 1-A	(2) Model 2-A	(3) Model 3-A	(4) Model 4-A	(5) Model 5-A
Female and Experimental Sciences	0.0901**				
	(0.0392)				
Female and Health		0.0144			
		(0.0320)			
Female and Social Sciences			0.0619**		
			(0.0292)		
Female and Economics/ Law				-0.0527**	
				(0.0260)	
Female and Arts					-0.0328
					(0.0422)
Constant	7.329***	7.327***	7.331***	7.323***	7.326***
	(0.0204)	(0.0204)	(0.0205)	(0.0204)	(0.0204)
Lambda	0.0305	0.0318	0.0253	0.0301	0.0340
Observations	3,652	3,652	3,652	3,652	3,652

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

7 Conclusion

It is historically shown that women face different labor market outcomes than men. Women have higher unemployment rates, work more often in part-time or temporary employment, and have lower salaries. The literature shows that, to some extent, differences in labor market outcomes for those with a tertiary education might be caused by self-selection: Men and women choose significantly different majors. While men are more represented in higher-paid fields such as Engineering, women are more engaged in lower-paid fields as Social Sciences, Humanities, and Arts. Therefore, the field of study can account for a substantial magnitude of differences in labor market outcomes between men and women.

We examined a data set of young professionals that graduated from the University of the Basque Country in 2015 and their labor market situation in 2018. Our main goal was to point out differences by gender and by field of study with respect to different labor market outcomes. Furthermore, we wanted to elaborate on which characteristics are related to those different outcomes.

Firstly, we presented descriptive statistics that confirmed empirically proven facts. Also, within our data set, male and female graduates chose different fields of specialization. Men were most present in Engineering and women were most present in Social Sciences. We further observed that there are high gender and differences in full-time positions, and within every field, fewer women were engaged full-time. Moreover, salaries varied strongly by gender and fields and, apart from Experimental Sciences, female graduates earned, on average, less in every field than their male peers.

We have conducted different estimation models for testing these labor market outcomes. Starting from a general perspective on the labor market situation, we moved on to a more restricted perspective of employment conditions. The results show no evidence of a gender gap in the employability and in the pursuit of further education. Moreover, conditioning on those graduates that work, there is no gender gap in the probability of being self-employed.

However, among salaried workers, we did find gender differences for both, the probability of working full-time and earnings. The results of the estimation of the probability of being a full-time worker revealed that a substantial magnitude (approximately two thirds) of the raw gender gap can be explained by gender differences within fields. Nevertheless, even after controlling for occupations, the economic sector, and further work-related variables, there remains a gap, indicating that female graduates have a lower probability of working full-time than male graduates.

In the last step, our target was to figure out how gender and field of study are associated with salary. We found that, on average, there is no difference in the earnings for men and women; but, once controlling for gender differences within fields there appears to exist a gender pay gap. This means that men and women graduating from the same field have a significantly different salary at the beginning of their careers. Moreover, controlling for occupation, the economic sector, and further employment-related variables does not help to explain the observed gender gap completely, in other words, there remains an unexplained gender wage gap. We saw that women perform better within Experimental Sciences and Social Sciences, worse within Economics and Law and similar in the other fields compared to their male peers.

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Appendix

Model Results

Table 9: Results of the estimation of the probability of being employed. Pre-step model for the probability of being self-employed.

VARIABLES	Being employed
Being female	0.0126
	(0.0102)
Fields of Study	
Reference Group: Engineering	
Experimental Sciences	-0.115***
	(0.0213)
Health	0.00566
	(0.0116)
Social Sciences	-0.114***
	(0.0135)
Economics/Law	-0.110***
	(0.0143)
Arts	-0.182***
	(0.0204)
Relative Grade	0.0101*
	(0.00533)
Age Group	
Reference Group: up to 22 years	
23-24 years	-0.00601
	(0.0121)
25-29 years	-0.0132
	(0.0144)
Over 29 years	-0.0387*
	(0.0201)
Duration of Studies	-0.000271
	(0.00228)
Work Experience	0.0628***
	(0.0133)
Observations	4,905

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

Table 10: Results of the estimation of the probability of being a salaried worker. Pre-step model for the probability of being a full-time worker.

VARIABLES	Salaried Worker
Being female	0.0158
	(0.0106)
Fields of Study	
Reference Group: Engineering	
Experimental Sciences	-0.119***
	(0.0219)
Health	0.00566
	(0.0120)
Social Sciences	-0.119***
	(0.0140)
Economics/Law	-0.116***
	(0.0149)
Arts	-0.199***
	(0.0216)
Relative Grade	0.0107*
	(0.00554)
Age Group	
Reference Group: up to 22 years	
23-24 years	-0.00632
	(0.0125)
25-29 years	-0.0160
	(0.0150)
Over 29 years	-0.0434**
	(0.0211)
Duration of Studies	-0.000275
	(0.00238)
Work Experience	0.0642***
	(0.0138)
Observations	4,701

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

Table 11: Results of the selection model of the estimation of salary.

VARIABLES	**(1) Model 1**	**(2) Model 2**	**(3) Model 3**	**(4) Model 4**	**(5) Model 5**	**(6) Model 6**	**(7) Model 7**	**(8) Model 8**	**(9) Model 9**	**(10) Model 10**	**(11) Model 11**	**(12) Model 12**
Being female	-0.215***	-0.218***	-0.226***	-0.227***	-0.222***	-0.221***	-0.221***	-0.220***	-0.221***	-0.221***	-0.222***	-0.222***
	(0.0519)	(0.0553)	(0.0539)	(0.0539)	(0.0538)	(0.0538)	(0.0538)	(0.0538)	(0.0539)	(0.0538)	(0.0539)	(0.0539)
Fields of Study **Reference Group: Engineering**												
Experimental Sciences	-0.846***	-0.664***	-0.666***	-0.666***	-0.661***	-0.661***	-0.661***	-0.662***	-0.662***	-0.662***	-0.665***	-0.665***
	(0.100)	(0.108)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Health	-0.279***	-0.572***	-0.574***	-0.574***	-0.569***	-0.569***	-0.569***	-0.569***	-0.569***	-0.569***	-0.569***	-0.569***
	(0.0839)	(0.0939)	(0.0924)	(0.0924)	(0.0924)	(0.0925)	(0.0925)	(0.0925)	(0.0925)	(0.0925)	(0.0926)	(0.0926)
Social Sciences	-1.167***	-1.291***	-1.288***	-1.288***	-1.288***	-1.289***	-1.289***	-1.289***	-1.289***	-1.290***	-1.294***	-1.294***
	(0.0769)	(0.0782)	(0.0777)	(0.0777)	(0.0778)	(0.0778)	(0.0778)	(0.0778)	(0.0778)	(0.0777)	(0.0779)	(0.0779)
Economics/Law	-0.442***	-0.248***	-0.242***	-0.242***	-0.246***	-0.247***	-0.247***	-0.248***	-0.247***	-0.248***	-0.246***	-0.246***
	(0.0829)	(0.0909)	(0.0911)	(0.0911)	(0.0910)	(0.0909)	(0.0909)	(0.0909)	(0.0909)	(0.0909)	(0.0909)	(0.0910)
Arts	-1.130***	-1.305***	-1.300***	-1.300***	-1.302***	-1.304***	-1.304***	-1.304***	-1.304***	-1.304***	-1.304***	-1.304***
	(0.0959)	(0.0955)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)
Relative Grade	0.0586**	0.0352	0.0295	0.0310	0.0355	0.0358	0.0359	0.0359	0.0360	0.0361	0.0341	0.0341
	(0.0237)	(0.0281)	(0.0273)	(0.0272)	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)
Age Group **Reference Group: up to 22 years**												
23-24 years	0.116**	0.166***	0.169***	0.169***	0.168***	0.167***	0.167***	0.166***	0.166***	0.166***	0.165***	0.165***
	(0.0558)	(0.0630)	(0.0625)	(0.0625)	(0.0629)	(0.0628)	(0.0629)	(0.0628)	(0.0628)	(0.0628)	(0.0629)	(0.0629)
25-29 years	0.0956	0.143*	0.142*	0.142*	0.147*	0.144*	0.144*	0.144*	0.144*	0.144*	0.135*	0.135*
	(0.0666)	(0.0753)	(0.0750)	(0.0749)	(0.0754)	(0.0753)	(0.0753)	(0.0753)	(0.0753)	(0.0753)	(0.0755)	(0.0755)
Over 29 years	0.358***	0.0693	0.0115	0.00983	0.0823	0.0781	0.0781	0.0779	0.0781	0.0781	0.0796	0.0796
	(0.0825)	(0.123)	(0.104)	(0.104)	(0.0946)	(0.0946)	(0.0946)	(0.0946)	(0.0946)	(0.0946)	(0.0946)	(0.0946)

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11	(12) Model 12
Work Experience	-0.0400	-0.103	-0.115*	-0.115*	-0.107	-0.0994	-0.0994	-0.0997	-0.0993	-0.0996	-0.104	-0.104
	(0.0590)	(0.0684)	(0.0667)	(0.0667)	(0.0669)	(0.0664)	(0.0663)	(0.0663)	(0.0664)	(0.0664)	(0.0664)	(0.0664)
Constant	1.402***	1.496***	1.507***	1.508***	1.495***	1.495***	1.495***	1.495***	1.495***	1.495***	1.498***	1.498***
	(0.0731)	(0.0774)	(0.0769)	(0.0769)	(0.0768)	(0.0768)	(0.0768)	(0.0768)	(0.0768)	(0.0768)	(0.0770)	(0.0770)
Observations	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,660	3,652	3,652

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12: Results of the selection model of the estimation of salary with the interactions of being female and the different fields of study. Both, version A: without the proportion of women per degree, and version B: with the proportion of women per degree.

VARIABLES	(1) Model 1-A	(2) Model 2-A	(3) Model 3-A	(4) Model 4-A	(5) Model 5-A
Being female	-0.224***	-0.225***	-0.222***	-0.224***	-0.225***
	(0.0539)	(0.0540)	(0.0538)	(0.0539)	(0.0540)
Fields of Study					
Reference Group: Engineering					
Experimental Sciences	-0.665***	-0.665***	-0.666***	-0.666***	-0.665***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Health	-0.569***	-0.568***	-0.570***	-0.569***	-0.568***
	(0.0925)	(0.0926)	(0.0925)	(0.0925)	(0.0926)
Social Sciences	-1.294***	-1.294***	-1.294***	-1.294***	-1.293***
	(0.0779)	(0.0779)	(0.0779)	(0.0778)	(0.0779)
Economics/Law	-0.246***	-0.246***	-0.246***	-0.247***	-0.245***
	(0.0910)	(0.0910)	(0.0910)	(0.0909)	(0.0910)
Arts	-1.303***	-1.303***	-1.304***	-1.303***	-1.303***
	(0.0954)	(0.0954)	(0.0954)	(0.0954)	(0.0954)
Relative Grade	0.0337	0.0337	0.0337	0.0337	0.0337
	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)
Age Group					
Reference Group: up to 22 years					
23-24 years	0.169***	0.169***	0.169***	0.169***	0.170***
	(0.0630)	(0.0630)	(0.0631)	(0.0630)	(0.0630)
25-29 years	0.136*	0.136*	0.135*	0.136*	0.136*
	(0.0753)	(0.0753)	(0.0753)	(0.0753)	(0.0753)
Over 29 years	0.0482	0.0462	0.0531	0.0482	0.0441
	(0.103)	(0.103)	(0.105)	(0.103)	(0.103)
Work Experience	-0.0953	-0.0947	-0.0967	-0.0952	-0.0940
	(0.0674)	(0.0674)	(0.0677)	(0.0675)	(0.0673)
Constant	1.499***	1.499***	1.499***	1.499***	1.500***
	(0.0769)	(0.0769)	(0.0769)	(0.0769)	(0.0769)
Observations	3,652	3,652	3,652	3,652	3,652

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

Table 13: Results of the estimation of salary with the interactions of being female and the different fields of study. Version B: With the proportion of women per degree.

VARIABLES	(1) Model 1-B	(2) Model 2-B	(3) Model 3-B	(4) Model 4-B	(5) Model 5-B
Being female	-0.0400***	-0.0346***	-0.0422***	-0.0195	-0.0311***
	(0.0122)	(0.0126)	(0.0126)	(0.0133)	(0.0120)
Fields of Study **Reference Group: Engineering**					
Experimental Sciences	-0.253***	-0.200***	-0.195***	-0.200***	-0.202***
	(0.0342)	(0.0254)	(0.0257)	(0.0254)	(0.0254)
Health	0.0156	0.00319	0.0179	0.0123	0.0102
	(0.0261)	(0.0344)	(0.0263)	(0.0260)	(0.0262)
Social Sciences	-0.111***	-0.115***	-0.152***	-0.115***	-0.118***
	(0.0314)	(0.0312)	(0.0367)	(0.0315)	(0.0312)
Economics/Law	-0.111***	-0.112***	-0.110***	-0.0838***	-0.113***
	(0.0183)	(0.0183)	(0.0183)	(0.0226)	(0.0184)
Arts	-0.121***	-0.123***	-0.117***	-0.123***	-0.108***
	(0.0340)	(0.0339)	(0.0353)	(0.0342)	(0.0400)
Relative Grade	0.00705	0.00692	0.00640	0.00752	0.00680
	(0.00526)	(0.00526)	(0.00526)	(0.00526)	(0.00526)
Work Experience	0.0806***	0.0798***	0.0802***	0.0812***	0.0797***
	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Degree Needed?	0.0659***	0.0656***	0.0650***	0.0654***	0.0659***
	(0.0161)	(0.0162)	(0.0162)	(0.0161)	(0.0162)
Contract Type **Reference Group: Indefinite**					
Temporary	-0.0672***	-0.0673***	-0.0671***	-0.0669***	-0.0676***
	(0.0116)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Scholarship/ Internship	-0.361***	-0.361***	-0.360***	-0.360***	-0.361***
	(0.0196)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
Public	0.204***	0.204***	0.204***	0.203***	0.204***
	(0.0144)	(0.0145)	(0.0144)	(0.0144)	(0.0145)
Multinational	0.0418***	0.0424***	0.0422***	0.0413***	0.0424***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
Occupation Field **Reference Group: Management, Engineering and Professionals**					
Engineering and Support	-0.0320**	-0.0315**	-0.0307**	-0.0319**	-0.0312**
	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)
Administration	-0.160***	-0.161***	-0.158***	-0.155***	-0.161***
	(0.0217)	(0.0217)	(0.0217)	(0.0219)	(0.0217)
Services	-0.0753**	-0.0739**	-0.0738**	-0.0720**	-0.0736**
	(0.0299)	(0.0300)	(0.0299)	(0.0299)	(0.0299)
Other	-0.129***	-0.131***	-0.129***	-0.130***	-0.131***
	(0.0363)	(0.0364)	(0.0364)	(0.0363)	(0.0364)
Sector Industry	0.0739***	0.0745***	0.0742***	0.0752***	0.0746***
	(0.0141)	(0.0141)	(0.0141)	(0.0141)	(0.0141)

VARIABLES	(1) Model 1-B	(2) Model 2-B	(3) Model 3-B	(4) Model 4-B	(5) Model 5-B
Female and Experimental Sciences	0.0902**				
	(0.0392)				
Female and Health		0.0131			
		(0.0321)			
Female and Social Sciences			0.0619**		
			(0.0292)		
Female and Economics/ Law				-0.0560**	
				(0.0262)	
Female and Arts					-0.0299
					(0.0424)
Proportion of Women per Degree	-0.0283	-0.0269	-0.0280	-0.0385	-0.0248
	(0.0387)	(0.0388)	(0.0387)	(0.0391)	(0.0390)
Constant	7.338***	7.335***	7.339***	7.334***	7.333***
	(0.0233)	(0.0233)	(0.0234)	(0.0233)	(0.0234)
Observations	3,652	3,652	3,652	3,652	3,652

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

Table 14: Results of the estimation of salary with the interactions of being female and the different fields of study with a different reference group. Version A: Without the proportion of women per degree.

VARIABLES	(1) Model 1-A	(2) Model 2-A	(3) Model 3-A	(4) Model 4-A	(5) Model 5-A
Being female	-0.0263*	-0.0371***	-0.0446***	-0.0236*	-0.0330***
	(0.0138)	(0.0120)	(0.0122)	(0.0127)	(0.0116)
Fields of Study **Reference Group: Experimental Sciences**					
Engineering	0.217***	0.207***	0.203***	0.211***	0.208***
	(0.0249)	(0.0231)	(0.0235)	(0.0232)	(0.0231)
Health	0.207***	0.198***	0.210***	0.208***	0.209***
	(0.0240)	(0.0331)	(0.0240)	(0.0240)	(0.0240)
Social Sciences	0.0823***	0.0821***	0.0409	0.0811***	0.0810***
	(0.0264)	(0.0261)	(0.0328)	(0.0262)	(0.0260)
Economics/Law	0.0890***	0.0884***	0.0863***	0.116***	0.0892***
	(0.0238)	(0.0238)	(0.0239)	(0.0274)	(0.0237)
Arts	0.0768**	0.0753**	0.0771**	0.0759**	0.0941**
	(0.0308)	(0.0305)	(0.0310)	(0.0306)	(0.0388)
Relative Grade	0.00627	0.00658	0.00605	0.00700	0.00649
	(0.00524)	(0.00524)	(0.00524)	(0.00524)	(0.00524)
Work experience	0.0795***	0.0796***	0.0800***	0.0809***	0.0796***
	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Degree needed?	0.0653***	0.0657***	0.0651***	0.0655***	0.0661***
	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)
Contract Type **Reference Group: Indefinite**					
Temporary	-0.0672***	-0.0674***	-0.0673***	-0.0671***	-0.0677***
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Scholarship/ Internship	-0.360***	-0.360***	-0.359***	-0.360***	-0.361***
	(0.0197)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
Public	0.204***	0.204***	0.204***	0.204***	0.204***
	(0.0145)	(0.0145)	(0.0144)	(0.0144)	(0.0145)
Multinational	0.0428***	0.0426***	0.0424***	0.0417***	0.0425***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
Occupation Field **Reference Group: Management, Engineering and Professionals**					
Engineering and Support	-0.0313**	-0.0314**	-0.0306**	-0.0318**	-0.0311**
	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)
Administration	-0.161***	-0.160***	-0.158***	-0.155***	-0.161***
	(0.0217)	(0.0217)	(0.0217)	(0.0219)	(0.0217)
Services	-0.0754**	-0.0740**	-0.0739**	-0.0722**	-0.0736**
	(0.0300)	(0.0300)	(0.0299)	(0.0299)	(0.0300)
Other	-0.130***	-0.131***	-0.128***	-0.130***	-0.131***
	(0.0364)	(0.0364)	(0.0364)	(0.0364)	(0.0364)

VARIABLES	(1) Model 1-A	(2) Model 2-A	(3) Model 3-A	(4) Model 4-A	(5) Model 5-A
Sector Industry	0.0746***	0.0754***	0.0752***	0.0764***	0.0755***
	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0140)
Female and Engineering	-0.0255				
	(0.0228)				
Female and Health		0.0144			
		(0.0320)			
Female and Social Sciences			0.0619**		
			(0.0292)		
Female and Economics/ Law				-0.0527**	
				(0.0260)	
Female and Arts					-0.0328
					(0.0422)
Proportion of Women per Degree					
Constant	7.116***	7.121***	7.128***	7.112***	7.117***
	(0.0300)	(0.0297)	(0.0304)	(0.0299)	(0.0296)
Lambda	0.0283	0.0318	0.0253	0.0301	0.0340
Observations	3,652	3,652	3,652	3,652	3,652

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

Table 15: Results of the estimation of salary with the interactions of being female and the different fields of study with a different reference group. Version B: With the proportion of women per degree.

VARIABLES	(1) Model 1-B	(2) Model 2-B	(3) Model 3-B	(4) Model 4-B	(5) Model 5-B
Being female	-0.0246*	-0.0346***	-0.0422***	-0.0195	-0.0311***
	(0.0141)	(0.0126)	(0.0126)	(0.0133)	(0.0120)
***Fields of Study* Reference Group: Experimental Sciences**					
Engineering	0.210***	0.200***	0.195***	0.200***	0.202***
	(0.0273)	(0.0254)	(0.0257)	(0.0254)	(0.0254)
Health	0.210***	0.203***	0.213***	0.213***	0.212***
	(0.0246)	(0.0337)	(0.0245)	(0.0245)	(0.0245)
Social Sciences	0.0848***	0.0850***	0.0439	0.0852***	0.0838***
	(0.0267)	(0.0264)	(0.0331)	(0.0265)	(0.0263)
Economics/Law	0.0881***	0.0875***	0.0852***	0.117***	0.0883***
	(0.0239)	(0.0238)	(0.0240)	(0.0274)	(0.0238)
Arts	0.0776**	0.0764**	0.0781**	0.0774**	0.0933**
	(0.0308)	(0.0305)	(0.0310)	(0.0306)	(0.0388)
Relative Grade	0.00659	0.00692	0.00640	0.00752	0.00680
	(0.00527)	(0.00526)	(0.00526)	(0.00526)	(0.00526)
Work Experience	0.0796***	0.0798***	0.0802***	0.0812***	0.0797***
	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Degree Needed?	0.0652***	0.0656***	0.0650***	0.0654***	0.0659***
	(0.0162)	(0.0162)	(0.0162)	(0.0161)	(0.0162)
***Contract Type* Reference Group: Indefinite**					
Temporary	-0.0672***	-0.0673***	-0.0671***	-0.0669***	-0.0676***
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Scholarship/ Internship	-0.361***	-0.361***	-0.360***	-0.360***	-0.361***
	(0.0197)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
Public	0.204***	0.204***	0.204***	0.203***	0.204***
	(0.0145)	(0.0145)	(0.0144)	(0.0144)	(0.0145)
Multinational	0.0426***	0.0424***	0.0422***	0.0413***	0.0424***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
***Occupation Field* Reference Group: Management, Engineering and Professionals**					
Engineering and Support	-0.0314**	-0.0315**	-0.0307**	-0.0319**	-0.0312**
	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)
Administration	-0.161***	-0.161***	-0.158***	-0.155***	-0.161***
	(0.0217)	(0.0217)	(0.0217)	(0.0219)	(0.0217)
Services	-0.0753**	-0.0739**	-0.0738**	-0.0720**	-0.0736**
	(0.0300)	(0.0300)	(0.0299)	(0.0299)	(0.0299)
Other	-0.130***	-0.131***	-0.129***	-0.130***	-0.131***
	(0.0364)	(0.0364)	(0.0364)	(0.0363)	(0.0364)

VARIABLES	(1) Model 1-B	(2) Model 2-B	(3) Model 3-B	(4) Model 4-B	(5) Model 5-B
Sector Industry	0.0738***	0.0745***	0.0742***	0.0752***	0.0746***
	(0.0141)	(0.0141)	(0.0141)	(0.0141)	(0.0141)
Female and Engineering	-0.0242				
	(0.0229)				
Female and Health		0.0131			
		(0.0321)			
Female and Social Sciences			0.0619**		
			(0.0292)		
Female and Economics/ Law				-0.0560**	
				(0.0262)	
Female and Arts					-0.0299
					(0.0424)
Proportion of Women per Degree	-0.0240	-0.0269	-0.0280	-0.0385	-0.0248
	(0.0389)	(0.0388)	(0.0387)	(0.0391)	(0.0390)
Constant	7.129***	7.136***	7.144***	7.134***	7.131***
	(0.0373)	(0.0368)	(0.0374)	(0.0368)	(0.0371)
Lambda	0.0281	0.0315	0.0249	0.0294	0.0334
Observations	3,652	3,652	3,652	3,652	3,652

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

Table 16: Results of the selection model of the estimation of salary with the interactions of being female and the different fields of study with a different reference group. Both, version A: without the proportion of women per degree, and version B: with the proportion of women per degree.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Being female	-0.223***	-0.225***	-0.222***	-0.224***	-0.225***
	(0.0539)	(0.0540)	(0.0538)	(0.0539)	(0.0540)
Fields of Study **Reference Group: Experimental Sciences**					
Engineering	0.665***	0.665***	0.666***	0.666***	0.665***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Health	0.0965	0.0968	0.0963	0.0965	0.0968
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Social Sciences	-0.629***	-0.628***	-0.628***	-0.629***	-0.628***
	(0.0949)	(0.0949)	(0.0949)	(0.0949)	(0.0949)
Economics/Law	0.420***	0.420***	0.419***	0.419***	0.420***
	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)
Arts	-0.638***	-0.638***	-0.638***	-0.638***	-0.638***
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Relative Grade	0.0337	0.0337	0.0337	0.0337	0.0337
	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0270)
Age Group **Reference Group: up to 22 years**					
23-24 years	0.169***	0.169***	0.169***	0.169***	0.170***
	(0.0630)	(0.0630)	(0.0631)	(0.0630)	(0.0630)
25-29 years	0.135*	0.136*	0.135*	0.136*	0.136*
	(0.0753)	(0.0753)	(0.0753)	(0.0753)	(0.0753)
Over 29 years	0.0500	0.0462	0.0531	0.0482	0.0441
	(0.104)	(0.103)	(0.105)	(0.103)	(0.103)
Work Experience	-0.0958	-0.0947	-0.0967	-0.0952	-0.0940
	(0.0676)	(0.0674)	(0.0677)	(0.0675)	(0.0673)
Constant	0.834***	0.834***	0.833***	0.834***	0.835***
	(0.0944)	(0.0944)	(0.0944)	(0.0944)	(0.0944)
Observations	3,652	3,652	3,652	3,652	3,652

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