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| **Title** | Gender wage gap among highly educated workers: Some evidence from Spain |
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| **Abstract** | **Purposes** - This research provides new evidence concerning the drivers of the gender pay gap for highly educated workers in Spain. **Design/Methodology/Approach -** The study estimates wage models controlled for sample selection bias and applies the traditional Blinder-Oaxaca decomposition to examine the gender wage gap. **Findings** - The results show the existence of empirical evidence about the presence of gender wage gap among tertiary-educated workers. An interesting conclusion is that holding a master's degree has a positive impact since it diminishes the unexplained component of the gender pay gap. **Research limitations/implications** - The survey used only analyses the labour insertion of tertiary-educated workers and its temporal scope does not allow us to examine the evolution of the gender wage gap throughout their careers. **Social implications –** The findings indicate that there is room for the implementation of policies aimed to diminish the gender inequality in the labour market even for highly educated workers, which could complement the current Spanish labour legislation regulating gender pay gap in firms. **Originality/value** – This article bridges two bodies of the economic literature: human capital returns and gender wage gap. The data used represent a contribution to the economic literature. |
| **Licence Statement** |  |
| **Declaration of interest statement** | This article has no conflict of interest. |

## 1. Introduction

The current knowledge-based economy is focused on digitalisation and scientific innovation. This fact reinforces the importance of human capital, and especially undergraduate or postgraduate studies, as a means to attain the competences required to transition to a digital-based society. As such, tertiary education is expected to increase the likelihood of obtaining a good job match, which positively will affect workers' careers. Focusing on the Spanish case, the implementation of the European Higher Education Area (EHEA) reduced the duration of the university degrees, which led to structural changes in individual educational trajectories. The EHEA promoted a common higher education system for the countries of the European Union in order to improve employment opportunities and increase geographical labour mobility of European graduates. For example, it gave rise to the rapid expansion of postgraduate studies. In particular, there has been a significant increase of 62% in the number of students enrolled on master's degree courses between the academic years 2015-2016 and 2022-2023. In addition, the predominance of female students is striking since the academic year 2015-2016. This positive gender bias in favour of women is observed at all levels of higher education. However, the effort made by the Spanish female collective to invest in higher education is not compensated for better labour market outcomes when compared to the male collective. Although individual choices could partially explain gender inequalities, it is well known that female workers face challenges when it comes to conciliating paid and unpaid work given the traditional gender role asymmetry in the distribution of household tasks. In spite of the initiatives undertaken and the efforts made by policymakers to reduce the gender wage gap, there is room to advance in this field, increase the productivity of the workforce, and improve the competitiveness of the Spanish economy. For example, in 2023, the activity (unemployment) rate was 54% (14%) for women and 64% (11%) for men, respectively.

These facts mean it would be interesting to undertake an analysis of the labour market from a gender perspective. As such, this research provides new empirical evidence concerning the drivers of the gender pay gap among tertiary-educated workers. In particular, it examines whether holding a master's degree has a positive impact on the careers of female workers by reducing gender wage discrimination in comparison to college-only graduates. This article contributes to ascertaining whether the educational effort made by women is rewarded by employers, which would help to eliminate the barriers in place for accessing high-paying occupations and economic sectors.

The gender pay gap has decreased in Spain since the beginning of the 21st century. This positive evolution has been boosted by policies implemented by the successive Governments of Spain. For example, the Spanish Royal Decree Law 902/2020 regulating gender pay gap in firms. According to the OECD (2022), the gender wage gap in Spain, stood at 6.7% in 2022, 5.4 pp below the mean of the OECD countries, but 2 pp above the value corresponding to Norway. These statistical facts suggest it would be interesting to explore this topic further, and observe whether the gender wage gap varies for college-only graduate workers compared to those with postgraduate studies.

The second Survey on the Labour Insertion of University Graduates (SLIU) is the data set used in this study. It was conducted by the National Statistics Institute (Spain) (INE, 2019) and its temporal scope allows us to select a homogenous sample of tertiary-educated workers who were interviewed during the same reference period (2019). The methodology applied formulates log-wage models by gender and uses the Blinder-Oaxaca decomposition [Blinder (1973) and Oaxaca (1973)]. Log-wage models are controlled for sample selection bias and the completion of a master's degree is addressed as an endogenous explanatory variable. Considering jointly both complications represents a contribution to the economic literature focused on the Spanish case. Furthermore, using the SLIU to analyse the gender pay gap of tertiary-educated workers also entails a methodological novelty in relation to previous studies.

The main findings reveal the existence of gender wage gap for highly educated workers. In particular, log-wage predictions show that the predicted mean wage for men is approximately 10% higher than for women. Second, the completion of a master's degree increases female wages by more than 20% and diminishes the unexplained gender pay gap in favour of men.

The rest of the article is organised as follows. Section 2 reviews some interesting contributions made by the economic literature. Sections 3 and 4 describe the data set and the econometric specification, respectively. Section 5 submits and discusses the main results. Finally, section 6 presents the conclusions together with some implications and recommendations.

## 2. Literature review

The international literature has produced a large body of research regarding the gender pay gap. Firstly, it is worth highlighting a branch of economic thought focusing on the analysis of taste-based discrimination (Becker, 1971). This theory posits that discrimination emerges within firms because decisions are taken mainly by men. Moreover, the statistical theory of discrimination (Phelps, 1972) assumes that there is a subjective presumption about the low productivity of women, which arises from a labour market with asymmetric information. Focusing on the supply side of the labour market, Polachek (1981) examines how temporary interruptions due to family responsibilities influence on potential female earnings. These interruptions affect female investments in skills and drive them to occupations which are less demanding in terms of qualifications. In sum, family responsibilities generate a gender bias towards certain jobs which leads to gender stereotypes and gender-bias socialisation, as feminist theories have highlighted (England, 1993). These gender stereotypes could be anticipated by women, which would influence on their choice of degree, wages and access to high-status occupations. In this way, Black et al. (2008) find that pre-labour market factors such as educational characteristics explain more than half of the gender wage gap. The female preferences to certain job attributes related to work flexibility could counteract their gain in human capital accumulation, and the effects of equal pay legislation implemented in most developed countries. For example, Petrongolo and Ronchi (2020) indicate that women could accept lower-paying jobs in return for shorter commuting distance.

Other studies have specifically examined the effect of motherhood for certain collectives, confirming an increase in the gender pay gap after the birth of the first child. For example, Bertrand and Hallock (2001) analyse the gender wage gap for tertiary-educated workers in the US corporate and financial sectors controlling for job characteristics such as firm size and occupational category. They find that men and women have similar earnings at the outset of their careers, although this situation begins to diverge with age since corporate and financial sectors penalise the temporary interruptions associated with the birth of children and family responsibilities. On the other hand, Grund (2015) reveals that gender pay gap is more pronounced for experienced managers with children in the German chemical sector. In the same line, Arulampalam (2007) finds that the gender wage gap is higher among highly educated workers in professions such as managerial positions where the intrinsic characteristics of these types of job would generate costs if employers implemented flexible schedules compatible with childcare responsibilities. These results are coherent with the greedy jobs theory (Goldin, 2014), which posits that a significant portion of the unexplained gender wage gap is due to employers' incentives to reward employees willing to work longer hours.

Focusing on the most recent contributions, particularly noteworthy is the work of Blau and Kahn (2017), who overview the research on the gender wage gap and more specifically analyse how this has evolved in the US from 1980-2010. They find that it has decreased, although remains at around 20%, with the most important factors being segregation by occupation and industry. On the other hand, the importance of variables such as education or work experience was in decline, standing at only 8% in 2010. However, this pattern was not homogenous throughout the wage distribution; in particular, they found that the reduction of the gender wage gap was slower at the top of the distribution. Related to these findings, Gharehgozli and Atal (2020) find that the ratio of female to male wages increases moderately at all deciles of the distribution from 1986-2016. On the other hand, Quadlin et al. (2023) using data from Census and American Community Survey conclude that higher education has not had the expected impact to reduce the gender pay gap at the top-end of the wage distribution. An amount of this gender pay gap is explained by a compositional effect caused by gender segregation when selecting the field of study, but there is an unexplained portion caused by unobservable factors such as gender patterns of childcare and household labour.

For the Spanish case, we focus on some significant research contributions made over the last few decades. First, it is worth highlighting the work of Caparrós Ruiz et al. (2004), who examine the influence of job mobility on gender wage gap controlling for human capital variables and household characteristics. They observe that the unexplained gender wage gap is higher for involuntary movers than for stayers or voluntary movers, which suggests a higher wage discrimination for the former group of female workers. Second, De la Rica et al. (2008) report that highly educated women start their careers receiving similar wages to men until they reach the so-called glass ceiling which impedes their access to the highest-paid jobs. As noted in previous research, the gender pay gap could also be attributed to the interruptions to women's careers brought about by family responsibilities. This is verified by Cebrián and Moreno (2015), who demonstrate that the different gender patterns of employment interruptions generate more human capital depreciation for women influencing negatively on their wages. An interesting new research issue is the role of women in the emerging ICT sectors. In this context, Segovia-Pérez et al. (2020) examine the gender wage gap and discrimination in ICT professions, which have been traditionally male-dominated fields. They find the presence of vertical segregation, as women are practically absent from the top of the wage distribution in these jobs. Finally, Callado Muñoz and Utrero-González (2024) reveal for different university majors that gender wage gap increased after the 2008 economic crisis.

Spain offers an interesting case with which to complement the existing literature given the structural deficiencies of its labour market in comparison to other developed countries. In this regard, this study quantifies the gender pay gap among highly educated entrants to the labour market in order to detect the existence of gender wage discrimination. In fact, this paper bridges two bodies of the economic literature: human capital returns and gender wage gap.

## 3. Data

The data set used is the second SLIU (INE, 2019), which represents Spanish university graduates in the 2013-2014 academic year. The study focuses on employees with a maximum tenure of 5 years. This allows us to analyse individuals who obtained their jobs in the period between the completion of their undergraduate studies and the conducting of the survey.

The SLIU tabulates monthly labour earnings into seven intervals, and the distribution of wage earners by gender into these wage categories in 2019 is depicted in Table 1. The results reveal gender pay differences at the bottom and top of the wage distribution. More specifically, the percentage of women with a monthly wage below €999 reaches 20%, which is 9 pp higher than for men. On the other hand, only 6% of women register a monthly wage above €2,500, which is 5 pp lower than for men.

[Insert TABLE 1]

It would be interesting to delve deeper into the causes of these wage disparities. In this regard, we formulate a model in which wages are explained by a set of covariates traditionally used by the economic literature when analysing the gender pay gap. This group of explanatory variables comprises personal characteristics (household composition, knowledge area of the degree, participation or not in the Erasmus Programme, holding or not a master's degree), job type (firm size, type of working day, occupation, highly valued competences for the current job) and whether the individual is overeducated. Table 2 depicts the mean values for these regressors by gender. Regarding the degree subject, the results reflect an under-representation of women in STEM fields, since only 24% are undergraduates in these knowledge areas and are outnumbered by men with 48%. The literature has found that the preference of women to study non-STEM subjects is related to subjective factors such as personal interest, their lower preferences for competitive jobs, or gender stereotypes (Buser et al., 2017).

[Insert TABLE 2]

Secondly, as previously mentioned in section 1, women are relatively more widely represented than men in tertiary education. This is also observed for the collective with a master's degree, since female workers with this educational level account for 43% (3 pp higher than for men). In relation to job characteristics, it is noteworthy that occupational distribution is not homogenous by gender, since there is a higher percentage of women compared to men in the occupations "scientific and intellectual professionals and technicians" and "administrative-type employees" with an overall percentage of 72%, which is 7 pp higher than for men. On the other hand, as expected, a greater number of females are employed part-time (19% of women compared to 11% of men).

The methodology applied takes into account the sample selection bias caused by estimating log-wage models only for the group of employees. Accordingly, this requires the formulation of a model to explain the probability of being a wage earner versus being unemployed, which includes characteristics of the degree and household composition as explanatory variables. Table 3 illustrates the mean values for these covariates. It is noteworthy that undergraduates in arts and humanities register the highest positive difference when comparing unemployed with wage earners. For example, male and female undergraduates in arts and humanities account for 23% and 19% of unemployed. These percentages are 14 pp and 8 pp higher than those observed for wage earners, respectively.

[Insert TABLE 3]

The methodology proposed also considers the completion of a master's degree as an endogenous regressor depending on a set of explanatory variables including age, knowledge area of the degree and parents' maximum education level. This empirical strategy is also used by Caparrós Ruiz (2023), who examines the impact of holding a master's degree on earnings and on upward wage mobility. Table 4 reports the mean values for these explanatory variables.

[Insert TABLE 4]

With reference to the knowledge area of the degree, the highest divergence is registered in natural sciences where 16% of men and 13% of women completed a master's degree. This is 9 pp and 6 pp higher than the gender percentages observed for college-only graduates. Finally, the percentage of individuals whose father and/or mother have higher education is larger in the group with a master's degree (48% for men and 39% for women).

**4. Econometric specification**

The methodology used follows the traditional method proposed by the literature to address the gender pay gap; that is, the estimation of log-wage models. In addition, we consider the possibility of sample selection bias, and the existence of an endogenous regressor (holding or not a master's degree). As such, it is first necessary to formulate a model for the propensity of being a wager earner, which is expressed by equation 1:

$$y_{1ij}^{*} = X_{1ij}'\beta_{1j} + u_{1ij} \quad (1)$$

$y_{1ij}^{*}$ is the unobserved propensity of being a wage earner for an individual i and gender j, that is male (m) or female (f), and $X_{1ij}$ includes factors influencing this propensity such as characteristics of the degree (knowledge area and whether the university is public or private) and household composition. From this equation, it is possible to define a binary variable $y_{1ij}$ (equation 2) that takes value 1 if the individual is a wage earner ($y_{1ij}^{*} > 0$), and 0 otherwise:

$$y_{1ij} = \begin{cases} 0 & if\ \ y_{1ij}^{*} \leq 0 \\ 1 & otherwise \end{cases} \quad (2)$$

On the other hand, the log-wage model includes explanatory variables based on the human capital theory (Becker, 1994). The regressors have been enumerated in the previous section and are related to workers' productivity, job characteristics, and household composition as a proxy of aspects related to social gender role stereotypes.

The SLIU tabulates wages into intervals, then the log-wage interval model controlling for the endogeneity of the sample selection is jointly specified by equations 3 and 4:

$$y_{2ij}^{*} = X_{2ij}'\beta_{2j} + u_{2ij} \quad (3)$$

$$y_{2i} = \begin{cases} unknown \quad if\ \ y_{1ij}^{*} \leq 0 \\ 1 \quad if\ \alpha_1 \leq y_{2ij}^{*} \leq \alpha_2\ and\ y_{1ij}^{*} > 0 \\ 2 \quad if\ \alpha_2 < y_{2ij}^{*} \leq \alpha_3\ and\ y_{1ij}^{*} > 0 \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ 7 \quad if\ \alpha_7 < y_{2ij}^{*} \leq \alpha_8\ and\ y_{1ij}^{*} > 0 \end{cases} \quad (4)$$

$y_{2i}^{*}$ is the latent wage (outcome variable) expressed in logarithms, $y_{2ij}$ indicates in which interval $y_{2i}^{*}$ lies, and $X_{2i}$ is a vector containing the covariates. This econometric specification accounts for the possible correlation between the error term of the model for the unobserved propensity of being a wage earner ($u_{1ij}$) and the error term of the log-wage econometric model ($u_{2ij}$). Ignoring this potential correlation between the error terms could lead to inconsistent estimators for $\beta_{2j}$. On the other hand, we have included the type of university as regressor in equation (1) but not in equation (3). According to Canal Domínguez and Rodríguez Gutiérrez (2020), studying at a private university does not affect wages but increases the probability of being employed at the Spanish labour market.

An additional complication added to this model is to consider that completing or not a master's degree is an endogenous regressor. In this way, we take into account that master's degree holders may are not random. The unobserved propensity of holding a master's degree is expressed in equation (5):

$$y_{3ij}^{*} = X_{3ij}'\beta_{3j} + u_{3ij} \tag{5}$$

This model allows us to control for the possible correlation between the error terms $u_{2ij}$ and $u_{3ij}$. In this case, the set of regressors collected in the vector $X_{3ij}$ includes age, knowledge area of the degree and parents' maximum education level. This last explanatory variable aims to capture the influence of the intergenerational transmission of education (e.g. Fleury and Gilles, 2018). From equation 5, it is possible to generate the endogenous regressor $y_{3ij}$, which is included in the log-wage models and is defined by equation (6):

$$y_{3ij} = \begin{cases} 0 & if\ \ y_{3ij}^{*} \leq 0 \\ 1 & otherwise \end{cases} \tag{6}$$

$\beta_{1j}$, $\beta_{2j}$ and $\beta_{3j}$ are jointly estimated by maximum likelihood using the Stata's module dedicated to performing extended interval regression models (Statacorp, 2019). Furthermore, we assume probit models to account for the endogenous selection process and for the endogenous regressor. Once the coefficients of the wage models are estimated separately for men and women, they will be used to verify the existence of gender wage gap. The methodology applied for this analysis is the traditional Blinder-Oaxaca decomposition [Blinder (1973) and Oaxaca (1973)], which splits the gender wage gap into two portions: one due to differences in the characteristics between female and male wage earners (explained component) and another attributed to differences in the characteristics' returns (unexplained component).

According to the standard Blinder-Oaxaca decomposition, the gender wage gap is the difference of the predicted means of the dependent variables: $\overline{\hat{y}_{2,m}} - \overline{\hat{y}_{2,f}}$. It is formulated in equation 7 and assumes that the log-wage structure for men is non-discriminatory, that is, male wage structure would be applied to both male and female in the absence of discrimination:

$$\left(\overline{\hat{y}_{2,m}} - \overline{\hat{y}_{2,f}}\right) = (\overline{X_{2,m}} - \overline{X_{2,f}})'\hat{\beta}_{2,m} + \overline{X_{2,f}}'(\hat{\beta}_{2,m} - \hat{\beta}_{2,f}) \tag{7}$$

$\overline{X_{2,m}}$ and $\overline{X_{2,f}}$ are vectors which include the means of the regressors for men and women, respectively, while $\hat{\beta}_{2,m}$ and $\hat{\beta}_{2,f}$ are the estimates of the coefficient vectors expressed in equation. The first component on the right side of equation 7 measures the portion of the wage differential explained by group differences in the covariates (endowment effect). The second term refers to the portion attributable to differences in the coefficients (coefficient effect). This last term is known as the unexplained component of the gender pay gap and represents the wage gain that female workers would receive whether they were remunerated as male workers given their mean characteristics. Thus, discrimination is defined as the wage gap non-attributable to differences in productivity or voluntary decisions related to labour supply.

All the covariates included in equation 7 are dummy regressors, which implies that the coefficient effect depends on the base category. This is known as the identification problem in detailed decomposition of wage differentials. To solve this issue, we will use normalised regression following Yun (2008). This procedure imposes the constraint that the coefficients of all categories of each dummy explanatory variable must add up to zero.

**5. Results**

This section is dedicated to discussing the estimates obtained for the econometric specification proposed. It is worth highlighting that we have verified the existence of correlation between the error terms included in the models for the log-wage, the propensity of being a wage earner and the propensity of holding a master's degree. This supports the suitability of the econometric procedure.

First, Table 5 reports the marginal effects for the probit model formulated to explain the probability of being a wager-earner. Focusing on the knowledge area of the degree, the fields with the highest probability of being a wage earner are computing and medical sciences for men, and engineering and medical sciences for women. The opposite is true for undergraduates in arts and humanities for both genders, which reflects their difficulties in finding work and suggests the need to enhance their employability. In fact, the educational system should highlight the competences acquired in these fields and their links with soft skills valued by employers such as creativity, communication or adaptability that have a positive effect on the productivity of workers. On the other hand, it is noteworthy that the type of university exerts a significant influence on the probability of being wage earner for women. In particular, the effect is negative for female undergraduates from a public university. This result is coherent with Canal Domínguez and Rodríguez Gutiérrez (2020) and reveals that the higher costs of the private university are offset by a higher probability of finding a job. From this result arises the need to increase the professional orientation of the public university to increase equal opportunities in access to employment. Finally, most dummy variables reflecting the type of household are significant, and show similar patterns for men and women. For example, the category with the highest likelihood of being employee is one-person household.

[Insert TABLE 5]

Second, Table 6 shows the marginal effects for the probit model explaining the probability of holding a master's degree. Regarding knowledge areas, graduates in natural sciences or arts and humanities have the highest probability of pursuing a master's degree, being the difference in relation to the reference category ("services") higher for women than for men. For example, a female graduate in natural sciences has a 23 pp higher likelihood of holding a master's degree than a female graduate in "services". In addition, a positive influence was observed in relation to the parents' maximum educational level. Men (women) with parents (father and/or mother) with tertiary education have a 6 pp (5 pp) higher likelihood of holding a master's degree than other individuals. This result reveals that parents' educational preferences for acquiring higher education are transmitted to their children.

[Insert TABLE 6]

Focusing on the log-wage models for men and women, Table 7 shows the estimates of the coefficients corresponding to the main equation. To interpret the estimates, it is necessary to consider that the model is semilogarithmic and all regressors are dummy variables. In particular, the covariates effects are calculated subtracting 1 to the exponential of each coefficient (Halvorsen and Palmquist, 1980).

[Insert TABLE 7]

Regarding the household composition, the results suggest the existence of conflicts between unpaid and paid work. In particular, living as a one-person household increases wages to around 13% for men and 9% for women, which represents a positive difference of 5 pp in relation to women living as a couple and with children. This result suggests the importance of continuing to advance in reducing the traditional gender roles, and increasing incentives to hire care services. Concerning the knowledge area of the degree, computing, engineering and technology, and medical sciences register the highest wages; however, it differs according to gender. For example, male workers with a degree in computing, experience a rise in wages of 23% in relation to the reference category ("services"), while for women this percentage is only 8%. This wage pattern in STEM fields has also been observed by other studies such as Michelmore and Sassler (2016). On the other hand, the knowledge areas of arts and humanities, and natural sciences exert the highest negative effects on wages. Furthermore, participating in the Erasmus Programme generates a wage premium for men which almost doubles that for women. This educational activity could help to increase employers' information about various workers' characteristics such as their willingness to be geographically mobile or their ability to adapt to a different work environment. This result is complemented with the effect of the variable indicating whether the individual has a knowledge of other languages, which exerts a positive effect of 10% both for men and women. Concerning the effect of holding a master's degree, it is observed a significant positive influence. In particular, female wage earners holding a master's degree see their wages increase by more than 20% compared to college-only degree holders. This outcome highlights that the competences and skills acquired by taking a master's degree are recognised and rewarded with higher wages.

Concerning the labour characteristics, firm size has a positive effect on wages. For example, working in firms with more than 249 employees leads to a wage increase by more than 21% compared to employees in companies with less than 10 employees. This outcome reflects the traditional duality of the labour market in Spain, which is explained by the labour market segmentation theory (Doeringer and Piore, 1971). Related to this duality, it is also observed that full-time jobs are more highly paid than part-time jobs, especially for male workers. Concerning occupations, it is notable that male managers see an increase in their wages of 25% compared to unskilled workers, 7 pp higher than for women. This result is linked with the positive wage effect observed for the competences related to management, planning and entrepreneurship skills. Finally, it is remarkable that overeducation has a negative impact on wages which is similar for male and female workers, decreasing wages around 16% compared to non-overeducated workers. This is coherent with the results obtained by recent studies, such as that of Sun and Kim (2022), and shows the negative effect of job mismatches. However, the theory of career mobility formulated by Sicherman and Galor (1990) posits that overeducated individuals compensate their initial wage penalties with better promotion prospects that generate higher wages, and this could also be applicable for highly educated workers.

Once the wage model by gender has been estimated, interest is focused on analysing the gender wage gap. The first step is to obtain point linear predictions from the log-wage models taking into account its complications. The results show the existence of a log-wage means difference in favour of men, where the mean wage for males is around 10% higher than for females.

The next step is to decompose the gender log-wage gap between differences due to characteristics (explained component) and differences due to characteristics' returns (unexplained component) using Yun's methodology (Yun, 2008). Table 8 shows the wage gap decomposition by groups of variables. Differences in the regressors' means, i.e., the endowment effect, represent the main contribution with 75.47%. A positive entry shows a salary advantage in favour of men. In this regard, the main gender differences influencing positively on the wage gap are observed for the variables "knowledge area of the degree" and "type of working day" (31.96% and 63.38%, respectively). The first variable reflects the gender segregation related to the choice of degree in the Spanish educational system, since men are more represented in STEM degrees, which is related to social gender stereotypes and their links with the professions (Verdugo-Castro et al., 2022). In this setting, building links between companies and schools could shed light about STEM occupations, improving women's knowledge about their options for having a successful career in these types of jobs. On the other hand, the effect observed for the variable "type of working day" is also an indicator of the difficulty faced by women to obtain full-time jobs that allow them to conciliate paid and unpaid work. This leads to a situation where involuntary part-time employment is predominant for female workers, even for highly educated individuals. With regards the negative entries, it is significant that holding a master's degree has a contribution of -7.52%, which shows that the female effort to take postgraduate courses in a higher proportion compared to men, has a positive influence on wages.

[Insert TABLE 8]

The coefficient effect (unexplained component) accounts for 24.53% of the gender log-wage gap, which shows possible discriminatory patterns. The main positive entry corresponds to the constant term of the log-wage model, which would indicate that a male worker receives a wage premium over a female employee for equal productivity and equal job. Pay transparency could help identifying those jobs with unjustified wage differences between women and men. As such, it is worth highlighting the Spanish Royal Decree Law 902/2020 establishing a mechanism to detect gender wage discrimination, and the 2023/970/EU Directive regulating that applicants for employment can know their initial wage prior to the conclusion of the contract.

In relation to the rest of contributions, firstly, the main positive input corresponds to the variable showing whether the individual has or not a full-time contract (90.91%). In relation to the knowledge area of the degree, the highest positive and negative entries are for medical sciences (19.44%), and arts and humanities (-27.74%), respectively. As regards the variable indicating the completion of a master's degree, there is a positive entry on the unexplained wage gap for those individuals without postgraduate studies (30.17%), but negative for those with a master's degree (-22.48%). This result shows that the acquisition of highly specialised skills and competences provided by the master's degree diminishes the discriminatory component of the gender pay gap. This result is supported by the negative entry registered for scientific and intellectual professionals and technicians, which is the occupation where 58% of female wage-earners with tertiary education are found. On the other hand, there is a slight positive impact of the variable that shows if the individual is a manager, which is consistent with the findings of Arulampalam (2007) and Goldin (2014) mentioned in section 2. In relation to the variables showing household composition, the decomposition indicates that there is a discriminatory component for women living as a couple with and without children.

## 6. Conclusion

This study has focused on the labour trajectories of highly educated workers from a gender perspective. More specifically, it has provided empirical evidence about the presence of gender pay gap for tertiary-educated workers, controlling for the sample selection bias and considering the completion or not of a master's degree as an endogenous regressor. One interesting conclusion is that holding a master's degree has a negative impact on the unexplained component of the gender pay gap. Thus, postgraduate studies could be narrowing the discriminatory component against women, which could help to break the glass ceiling and facilitate access to high-paying occupations and economic sectors. This result may have been anticipated by the female collective, and would explain why they reach a higher percentage within the group of individuals with a master's degree. Women with master's degrees could be accessing segments of the labour market with higher rates of unionisation and with less discretionary pay (Waite, 2017). Furthermore, it is expected that the recent Spanish labour legislation (Royal Decree Law 902/2020) regulating gender pay gap in firms or EU legislation such as the 2023/970/EU Directive would be reinforcing this trend for highly educated workers. These active policies against discrimination would be fostering pay transparency since they would be contributing to identify unjustified gender pay differences. In addition, gender differences in the choice of the knowledge area of the degree leads to a gender wag gap mainly in the explained component. This result shows that decreasing the segregation by gender in choosing the knowledge area would diminish the gender wage gap. In this regard, it would be useful to have information campaigns in schools aimed at the female collective which explain the advantages of STEM subjects from a career perspective, and which could help change gender stereotypes.

In relation to other variables, the type of working day represents 63.38% of the overall impact of the endowment effect. This reveals the difficulties faced by highly educated female workers to conciliate paid and unpaid work, and suggests the need to continue implementing measures which favour the balance between family and work. For example, it would be necessary to advance in family policies that extend the workers' possibility to access to flexible work schedule such as the Spanish Royal Decree Law 6/2019.

These findings highlight the importance of future research based on longitudinal surveys in order to analyse the careers of highly educated workers from a gender perspective. In this way, it would be convenient to identify the opportunity costs and the difficulties that female graduates face in completing a master's degrees or the effects of their lifelong learning on wages. Furthermore, these surveys should contain matched employee-employer data in order to provide detailed information on the tasks and the pay structures associated with each job. This would help classify and value the work according to objective criteria such as educational requirements, skills, responsibility or working conditions. This knowledge would be useful to identify and penalise gender-pay differences based on subjective criteria, which would help advance towards achieving the principle of equal pay for equal work regardless of the gender of workers.

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**Table 1. Distribution of individuals among wage intervals by gender (%)**

| Wage interval (€) | Men | Women |
|---|---|---|
| Less than 700 | 3.95 | 7.54 |
| 700-999 | 6.59 | 12.02 |
| 1,000-1,499 | 31.68 | 38.40 |
| 1,500-1,999 | 31.95 | 27.69 |
| 2,000-2,499 | 15.10 | 8.89 |
| 2,500-2,999 | 5.55 | 3.00 |
| More than 2,999 | 5.18 | 2.46 |
| All | 100 | 100 |

**Source**: Own elaboration using the SLIU (INE, 2019).

**Table 2. Regressors' means included in the log-wage models**

| Regressors | Men | Women |
|---|---|---|
| **Type of household** | | |
| One-person household | 0.19 | 0.14 |
| Couple without children | 0.33 | 0.39 |
| Couple with children | 0.08 | 0.08 |
| Other type of household | 0.40 | 0.39 |
| **Knowledge area of the degree** | | |
| Agricultural sciences | 0.05 | 0.03 |
| Arts and humanities | 0.09 | 0.11 |
| Business administration and law | 0.14 | 0.15 |
| Computing | 0.08 | 0.01 |
| Education | 0.05 | 0.15 |
| Engineering and technology | 0.24 | 0.10 |
| Medical sciences | 0.09 | 0.21 |
| Natural sciences | 0.11 | 0.10 |
| Services | 0.06 | 0.03 |
| Social sciences, journalism and documentation | 0.09 | 0.11 |
| **Erasmus Programme** | | |
| Yes | 0.13 | 0.13 |
| No | 0.87 | 0.87 |
| **Holding a master's degree** | | |
| Yes | 0.40 | 0.43 |
| No | 0.60 | 0.57 |
| **Firm size (number of workers)** | | |
| Less than 10 | 0.13 | 0.17 |
| Between 10 and 19 | 0.08 | 0.09 |
| Between 20 and 49 | 0.15 | 0.13 |
| Between 50 and 249 | 0.23 | 0.21 |
| More than 249 | 0.41 | 0.40 |
| **Type of working day** | | |
| Full-time | 0.89 | 0.81 |
| Part-time | 0.11 | 0.19 |
| **Occupation** | | |
| Management of companies or public administration | 0.04 | 0.03 |
| Scientific and intellectual professionals and technicians | 0.54 | 0.58 |
| Support technicians and professionals | 0.19 | 0.13 |
| Administrative-type employees | 0.11 | 0.14 |
| Catering, personal services, security, and retail workers | 0.06 | 0.10 |
| Workers in agriculture and fishing | 0.01 | 0.01 |
| Craftsmen and skilled manufacturing | 0.01 | 0.01 |
| Installation and machinery operators | 0.01 | 0.01 |
| Unskilled workers | 0.02 | 0.02 |
| **Competences highly valued to find the current job** | | |
| Theoretical knowledge | 0.53 | 0.54 |
| Practical skills | 0.68 | 0.71 |
| Knowledge of languages | 0.44 | 0.40 |
| ICT skills | 0.54 | 0.48 |
| Personal and social competences | 0.79 | 0.85 |
| Management, planning and entrepreneurship skills | 0.34 | 0.42 |
| **Overeducated** | | |
| Yes | 0.22 | 0.24 |
| No | 0.78 | 0.76 |
| **Observations** | 6159 | 8688 |

**Source**: Own elaboration using the SLIU (INE, 2019).

**Table 3. Regressors' means explaining the probability of being wage earner versus being unemployed**

| Regressors | Men | | Women | |
|---|---|---|---|---|
| | Wage earner | Unemployed | Wage earner | Unemployed |
| **Type of household** | | | | |
| One-person household | 0.19 | 0.10 | 0.14 | 0.06 |
| Couple without children | 0.33 | 0.17 | 0.39 | 0.25 |
| Couple with children | 0.08 | 0.06 | 0.08 | 0.10 |
| Other type of household | 0.40 | 0.59 | 0.39 | 0.59 |
| **Knowledge area of the degree** | | | | |
| Agricultural sciences | 0.05 | 0.04 | 0.03 | 0.03 |
| Arts and humanities | 0.09 | 0.23 | 0.11 | 0.19 |
| Business administration and law | 0.14 | 0.13 | 0.15 | 0.14 |
| Computing | 0.08 | 0.03 | 0.01 | 0.01 |
| Education | 0.05 | 0.08 | 0.15 | 0.22 |
| Engineering and technology | 0.24 | 0.13 | 0.10 | 0.05 |
| Medical sciences | 0.09 | 0.04 | 0.20 | 0.10 |
| Natural sciences | 0.11 | 0.13 | 0.10 | 0.11 |
| Services | 0.06 | 0.06 | 0.03 | 0.04 |
| Social sciences, journalism and documentation | 0.09 | 0.13 | 0.11 | 0.12 |
| **Type of university** | | | | |
| Private | 0.12 | 0.13 | 0.12 | 0.08 |
| Public | 0.88 | 0.87 | 0.88 | 0.92 |
| **Observations** | 6159 | 740 | 8688 | 1198 |

**Source**: Own elaboration using the SLIU (INE, 2019).

**Table 4. Regressors' means explaining the probability of completing a master's degree**

| Regressors | Men | | Women | |
|---|---|---|---|---|
| | College-only degree | Master's degree | College-only degree | Master's degree |
| **Age (years)** | | | | |
| Under 30 | 0.47 | 0.66 | 0.60 | 0.75 |
| Between 30 and 34 | 0.38 | 0.26 | 0.30 | 0.19 |
| Over 34 | 0.15 | 0.08 | 0.10 | 0.06 |
| **Knowledge area of the degree** | | | | |
| Agricultural sciences | 0.06 | 0.04 | 0.04 | 0.03 |
| Arts and humanities | 0.08 | 0.11 | 0.08 | 0.16 |
| Business administration and law | 0.15 | 0.14 | 0.16 | 0.14 |
| Computing | 0.10 | 0.05 | 0.01 | 0.01 |
| Education | 0.06 | 0.03 | 0.19 | 0.10 |
| Engineering and technology | 0.24 | 0.22 | 0.10 | 0.10 |
| Medical sciences | 0.10 | 0.07 | 0.22 | 0.17 |
| Natural sciences | 0.07 | 0.16 | 0.07 | 0.13 |
| Services | 0.06 | 0.07 | 0.04 | 0.03 |
| Social sciences, journalism and documentation | 0.08 | 0.11 | 0.09 | 0.13 |
| **Parents' maximum educational level** | | | | |
| Less than higher education | 0.59 | 0.52 | 0.67 | 0.61 |
| Higher education | 0.41 | 0.48 | 0.33 | 0.39 |
| **Observations** | 3703 | 2456 | 4979 | 3709 |

**Source:** Own elaboration using the SLIU (INE, 2019).

**Table 5. Probability of being a wage earner: Marginal effects[a,b]**

| Regressors | Men | | Women | |
|---|---|---|---|---|
| **Type of household** | | | | |
| One-person household | 0.092 | *** | 0.120 | *** |
| Couple without children | 0.087 | *** | 0.076 | *** |
| Couple with children | 0.059 | *** | 0.009 | |
| **Knowledge area of the degree** | | | | |
| Agricultural sciences | -0.014 | | 0.013 | |
| Arts and humanities | -0.093 | *** | -0.043 | ** |
| Business administration and law | -0.003 | | 0.011 | |
| Computing | 0.067 | ** | 0.041 | |
| Education | -0.057 | ** | -0.024 | |
| Engineering and technology | 0.019 | | 0.063 | ** |
| Medical sciences | 0.055 | ** | 0.073 | *** |
| Natural sciences | -0.029 | * | -0.001 | |
| Social sciences, journalism and documentation | -0.035 | ** | 0.002 | |
| **Type of university** | | | | |
| Public | 0.023 | ** | -0.046 | *** |
| **Observations** | 6889 | | 9932 | |

**Note:**
(a) The reference is an individual not living with a partner, or as one-person household, and who is a college-only graduate from a private university in the knowledge area of services.
(b) (***) Significant at 1%, (**) at 5%, (*) at 10%.
**Source**: Own elaboration using the SLIU (INE, 2019).

**Table 6. Probability of completing a master's degree: Marginal effects[a,b]**

| Regressors | Men | | Women | |
|---|---|---|---|---|
| **Age (years)** | | | | |
| Between 30 and 34 | -0.145 | *** | -0.132 | *** |
| Over 34 | -0.181 | *** | -0.176 | *** |
| **Knowledge area of the degree** | | | | |
| Agricultural sciences | -0.066 | ** | 0.046 | |
| Arts and humanities | 0.064 | ** | 0.223 | *** |
| Business administration and law | -0.022 | | 0.027 | |
| Computing | -0.104 | ** | -0.026 | |
| Education | -0.131 | *** | -0.068 | ** |
| Engineering and technology | -0.031 | | 0.072 | ** |
| Medical sciences | -0.081 | ** | 0.005 | |
| Natural sciences | 0.176 | *** | 0.233 | *** |
| Social sciences, journalism and documentation | 0.045 | | 0.152 | *** |
| **Parents' maximum educational level** | | | | |
| Higher education | 0.061 | *** | 0.050 | *** |
| **Observations** | 6159 | | 8734 | |

**Note**:
(a) The reference is an individual under 30 years old, with a degree in the knowledge area of 'services' and a father and/or mother without higher education.
(b) (***) Significant at 1%, (**) at 5%.
**Source**: Own elaboration using the SLIU (INE, 2019).

**Table 7. Estimates of the log-wage model by gender[a,b]**

| Regressors | Men | | Women | |
|---|---|---|---|---|
| **Type of household** | | | | |
| One-person household | 0.126 | *** | 0.084 | *** |
| Couple without children | 0.118 | *** | 0.054 | *** |
| Couple with children | 0.112 | *** | 0.038 | *** |
| **Knowledge area of the degree** | | | | |
| Agricultural sciences | 0.061 | ** | -0.026 | |
| Arts and humanities | -0.109 | *** | -0.102 | *** |
| Business administration and law | 0.041 | ** | -0.001 | |
| Computing | 0.205 | *** | 0.082 | ** |
| Education | -0.058 | ** | -0.071 | ** |
| Engineering and technology | 0.117 | *** | 0.060 | *** |
| Medical sciences | 0.144 | *** | 0.072 | *** |
| Natural sciences | -0.081 | *** | -0.116 | *** |
| Social sciences, journalism and documentation | -0.009 | | -0.081 | *** |
| **Erasmus Programme** | | | | |
| Yes | 0.045 | *** | 0.029 | *** |
| **Holding a master's degree** | | | | |
| Yes | 0.189 | *** | 0.213 | *** |
| **Firm size (number of workers)** | | | | |
| 10-19 | 0.061 | *** | 0.076 | *** |
| 20-49 | 0.100 | *** | 0.117 | *** |
| 50-249 | 0.117 | *** | 0.128 | *** |
| More than 249 | 0.193 | *** | 0.215 | *** |
| **Type of working day** | | | | |
| Full-time | 0.561 | *** | 0.495 | *** |
| **Occupation** | | | | |
| Management of companies or public administration | 0.220 | *** | 0.168 | *** |
| Scientific and intellectual professionals and technicians | 0.082 | *** | 0.113 | *** |
| Support technicians and professionals | 0.044 | * | 0.051 | * |
| Administrative-type employees | -0.001 | | -0.009 | |
| Catering, personal services, security, and retail workers | 0.011 | | -0.011 | |
| Workers in agriculture and fishing | 0.111 | | 0.071 | |
| Craftsmen and skilled manufacturing | 0.069 | * | 0.013 | |
| Installation and machinery operators | 0.099 | ** | -0.026 | |
| **Competences highly valued to find the current job** | | | | |
| Theoretical knowledge | 0.013 | * | 0.038 | *** |
| Practical skills | 0.031 | *** | -0.010 | |
| Knowledge of languages | 0.100 | *** | 0.095 | *** |
| ICT skills | -0.003 | | 0.004 | |
| Personal and social competences | 0.033 | *** | -0.027 | *** |
| Management, planning and entrepreneurship skills | 0.036 | *** | 0.033 | *** |
| **Overeducated** | | | | |
| Yes | -0.145 | *** | -0.153 | *** |
| **Constant** | 6.913 | *** | 6.990 | *** |
| **Wald test** | 5030.62 | *** | 7510.38 | *** |
| **Log-wage predictions' mean** | 7.32 | | 7.22 | |
| **Observations** | 6159 | | 8688 | |

**Note:**
(a) The reference is an individual not living with a partner, or as one-person household, a college-only graduate in the knowledge area of services and who has not participated in the Erasmus Programme. Moreover, he/she is working part-time in a firm with less than 10 employees as an unskilled worker and is not overeducated.
(b) (***) Significant at 1%, (**) at 5%, (*) at 10%.
**Source:** Own elaboration using the SLIU (INE, 2019).

**Table 8. Detailed decomposition of the gender wage gap (% contribution of each variable)**

| | Endowment effect | Coefficient effect |
|---|---|---|
| **Total log-wage gap** | 75.47 | 24.53 |
| **Type of household** | -1.31 | -35.39 |
| One-person household | 2.58 | -1.47 |
| Couple without children | -2.38 | 31.24 |
| Couple with children | -0.06 | 10.27 |
| Other type of household | -1.45 | -75.44 |
| **Knowledge area of the degree** | 31.96 | -26.46 |
| Agricultural sciences | 0.57 | 5.92 |
| Arts and humanities | 5.12 | -27.74 |
| Business administration and law | -0.06 | -5.10 |
| Computing | 17.25 | 3.33 |
| Education | 12.43 | -23.72 |
| Engineering and technology | 17.01 | 3.12 |
| Medical sciences | -18.37 | 19.44 |
| Natural sciences | -1.88 | -6.02 |
| Services | -1.26 | -7.39 |
| Social sciences, journalism and documentation | 1.15 | 11.69 |
| **Erasmus Programme** | 0.33 | -25.81 |
| Yes | 0.17 | 4.38 |
| No | 0.17 | -30.18 |
| **Holding a master's degree** | -7.52 | 7.70 |
| Yes | -3.76 | -22.48 |
| Not | -3.76 | 30.17 |
| **Firm size (number of workers)** | 8.79 | -6.98 |
| Less than 10 | 5.78 | 9.84 |
| 10-19 | 0.30 | -0.86 |
| 20-49 | 0.08 | -1.82 |
| 50-249 | 0.93 | 1.15 |
| More than 249 | 1.71 | -15.29 |
| **Type of working day** | 63.38 | 90.91 |
| Full-time | 31.63 | 117.83 |
| Part-time | 31.74 | -26.92 |
| **Occupation** | 4.26 | -188.63 |
| Management of companies or public administration | 2.23 | 2.85 |
| Scientific and intellectual professionals and technicians | -0.65 | -154.08 |
| Support technicians and professionals | -2.15 | -21.50 |
| Administrative-type employees | 2.50 | -12.88 |
| Catering, personal services, security, and retail workers | 2.75 | -2.58 |
| Workers in agriculture and fishing | 0.05 | 0.07 |
| Craftsmen and skilled manufacturing | -0.02 | 0.43 |
| Installation and machinery operators | 0.42 | 1.25 |
| Unskilled workers | -0.88 | -2.20 |
| **Competences highly valued to find the current job** | | |
| **Theoretical knowledge** | -0.27 | -4.71 |
| Yes | -0.14 | -29.30 |
| Not | -0.14 | 24.59 |
| **Practical skills** | -0.90 | 37.60 |
| Yes | -0.45 | 64.52 |
| Not | -0.45 | -26.93 |
| **Knowledge of languages** | 4.56 | -2.00 |
| Yes | 2.28 | 4.09 |
| Not | 2.28 | -6.09 |
| **ICT skills** | -0.26 | 0.50 |
| Yes | -0.13 | -8.29 |
| Not | -0.13 | 8.80 |
| **Personal and social competences** | -2.62 | 91.43 |
| Yes | -1.31 | 111.78 |
| Not | -1.31 | -20.35 |
| **Management, planning and entrepreneurship skills** | -3.81 | -0.76 |
| Yes | -1.90 | 1.98 |
| Not | -1.90 | -2.75 |
| **Overeducated** | 3.42 | -8.74 |
| Yes | 1.71 | 4.02 |
| No | 1.71 | -12.76 |
| **Constant** | | 171.36 |

**Source**: Own elaboration using SLIU (INE, 2019).