Effects of educational mismatch on wages across industry and occupations: sectoral comparison

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Abstract

Purpose – This study conducts a comparative analysis of the impact of educational mismatch on Spanish wages. This paper aims to focus on the industrial, construction and service sectors at three levels of disaggregation: sector, occupation and gender.

Design/methodology/approach – The over-education, required education and under-education (ORU model), was applied to data from the 2018 Spanish Wages Structure Survey conducted by the Spanish National Statistics Institute.

Findings – The industrial sector is the one that best manages over-education by offering the highest returns to each year of over-education. It is also the sector that most values the education of women, particularly those in highly qualified positions.

Originality/value – This study compares the wage effects of educational mismatch in the service, industry and construction sectors. Previous literature has ignored the latter sectors in this field of study, but the results of the present study show that the industrial sectors significantly value and remunerates worker education. Therefore, it may be worthy to focus certain economic and social policies on this sector, to contribute to reducing gender wage gaps and gender employment discrimination in the economy.

Keywords Human capital, Wage differentials, Educational mismatch, Gender, Sectors

Paper type Research paper

1. Introduction

In developed countries, socioeconomic factors are affected by the quality and extent of education and education systems. If these educational aspects undergo improvements economic growth accelerates and the wellbeing of society improves (INEE, 2016).

In Spain, the high percentage of the population with tertiary education is an indication of the level of commitment to education. According to data on quality-of-life indicators from the Spanish National Statistics Institute (INE), between 2009 and 2018, the population aged between 25 and 35 years with tertiary education increased from 39.5% to 44.3%, and the population aged between 50 and 65 years with tertiary education increased from 18.8% to 27.6%.

Given this level of investment in education, it is relevant to investigate whether it is profitable. However, the Spanish labour market remains highly polarised (OECD, 2017), and

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thus, there is a demand for a significant percentage of unskilled workers with low productivity. Therefore, the level of education required by companies may differ from that offered by the education system. This could lead to an inefficient distribution of resources and educational mismatch in the labour market.

For example, the Spanish education system has been producing an increasingly qualified labour force, which does not match the actual demands of the Spanish labour market. For decades, the phenomenon of educational mismatch has attracted the attention of many authors in Spain and the rest of the world (Sun and Kim, 2021; Muñoz de Bustillo *et al.*, 2018; Nieto and Ramos, 2017). These authors have attempted to explain its origin, determinants and effects. The present study contributes to the literature by analysing the impact of educational mismatch on Spanish wages. To do so, we use an extension of the Mincer wage equation, known as the over-education, required education and under-education (ORU) [1] model, taking into account three levels of disaggregation: sector, job and gender.

(1) We analyse the impact of this phenomenon on the wages of the service and industrial sectors. We also distinguish the construction sub-sector. The analysis of these industrial sectors is of particular relevance because it has been barely addressed in the literature.

(2) The study included the actual occupation segments of the workers to take into account their potential impact on wages. To this end, three occupation segments were analysed (see the following sections).

(3) Finally, the analysis addressed the role of gender in the phenomenon. We examine whether the increase in the educational level of women and their greater weight in higher education levels is reflected in their labour demand.

2. Previous literature

The theory of human capital supports the concept of education as investment. It considers that higher levels of education and experience lead to increases in productivity and thus increases in wages (Becker, 1983).

The development of the Mincer earnings function (1974) gave rise to further research on wage differences caused by differences in returns to human capital (Casado-Díaz and Simón, 2016 Turner *et al.*, 2020). Other authors have used and adapted this methodology to analyse the wage effects of the phenomenon known as educational mismatch, the work of Duncan and Hoffman (1981) and Verdugo and Verdugo (1989) being seminal in this field. The phenomenon of educational mismatch can be defined as the discrepancy between the workers' level of education and the level required for their job. This difference can be used to define workers in terms of their level of education in relation to the job requirements: overeducation, required education, and undereducation, where the individual's level of education is higher, equal to or lower than that required by the job, respectively (Alba-Ramírez, 1993). Three methods have been developed to measure the appropriate educational level for jobs: worker surveys (subjective method), external assessment (objective method) and the application of various statistical formulae (statistical method).

The study of educational mismatch is based on a set of theories that contribute to its understanding [2]. Among these are the theory of human capital (Becker, 1964; Mincer, 1974), the job-competition model (Thurow, 1975), the assignment model (Sattinger, 1993) and the job-market signalling or filter models (Arrow, 1973; Spence, 1973; Stiglitz, 1975).

The theory of human capital suggests that individual returns to wages depend on human capital (i.e. experience and years of education). Thus, under this theory, a supply-side approach is followed according to the characteristics of the individual. In addition, because this theory assumes that each year of education yields an increase in returns, it does not recognise the existence of differences in wages caused by educational mismatch. Other authors have addressed over-education but have considered it to be a temporary effect caused by a transitory mismatch between supply and demand in the labour market (Sicherman, 1991).

Demand-side approaches are represented by the job-competition model (Thurow, 1975) and the job-market signalling or filter models (Arrow, 1973; Spence, 1973; Stiglitz, 1975). These models suggest that individuals compete for jobs in the labour market. Therefore, they use their level of education to signal employers that they are capable of being trained within the company. They also suggest that most of the labour and specific work skills are obtained within the company and that, once the job is acquired, the marginal returns to education are null (Muysken and Weel, 1999).

The assignment model (Sattinger, 1993) addresses the problem of assigning heterogeneous workers to jobs with different levels of demand. This model follows a supply- and demand-side approach by taking into account differences between the characteristics of workers, jobs and sectors, among other aspects (McGuinness, 2006). This model lies between the other two models in that it assumes that wages depend both on workers (human capital) and jobs (job competition). Educational mismatch can be included in this theoretical framework because it is defined as mismatch between the workers' level of education (supply side) and the job requirements (demand side). The demand side and job requirements can be included in this model by incorporating occupation segments, such as the study of Gabriel and Schmitz (2005).

From the time of the publication of *The Overeducated American* (Freeman, 1976) until the present, educational mismatch has continued to generate great interest among researchers who not only focus on the theoretical framework and measurement of the phenomenon, but also on its determinants, effects and consequences. Thus, there is a large empirical literature that, on the one hand, has tried to explain, its determinant factors (Caroleo and Pastore, 2018; Delaney *et al.*, 2020), These authors observed that education attained, family origins and labour market flexibility, among other aspects, are relevant factors in explaining the emergence of educational mismatch. On the other hand, we draw attention to empirical studies on the consequences of this phenomenon on wages, productivity and job satisfaction (Ordine and Rose, 2011; McGuiness and Poulikas, 2016; Grunau, 2016; Mateos-Romero and Salinas-Jiménez, 2018). These authors studied several European countries and found that educational mismatch leads to wage inequalities with clear penalties for overeducated and undereducated workers, as well as having negative effects on individuals' productivity and job satisfaction.

This paper contributes to this empirical literature by analysing educational mismatch from a labour supply and demand perspective. In relation to labour demand, we also take into account occupation segments, job characteristics and whether the job belongs to the service sector or to the industrial or construction sector. Furthermore, we also determined whether our model falls within the scope of assignment theory, the job-competition model, or the theory of human capital. The main contribution of this study is that it analyses the effect of educational mismatch on wages by disaggregating by sector and by occupation segment. The interest of the disaggregation by sector lies in the scarcity of literature on the industrial and construction sectors, while the analysis by occupational category [3] may shed light on some job characteristics that could have an impact on wages.

Finally, in relation to the supply side, we consider gender and worker characteristics using variables typically included in the Mincerian wage equation as well as additional variables. All analyses used the method described by Duncan and Hoffman (1981) (see next section).

3. Methods

For the study of the effect of educational mismatch on wages or returns to education, it is crucial to choose the correct form of measurement of educational mismatch among the three proposed. The importance of this choice lies in the fact that each of these methods can yield widely varying results on the incidence of educational mismatch. However, according to Hartog (2000) the results of wage returns to years of educational mismatch are generally consistent regardless of the measurement method used, so the choice of this method depends on the availability of data In this study, in the absence of worker self-assessments (subjective method) and external assessment (objective method), the third measure of mismatch, the statistical method, will be used. Specifically, we will use the formula used by Kiker *et al.* (1997) who, based on the statistical method developed by Verdugo and Verdugo (1989), replace the mean by the mode as a measure of central tendency. Regarding the choice of the years of education required, we calculate the mode of years of education for each specific occupation, following the National Classification of Occupations (CNO-11), disaggregated to two digits. Workers who are above or below this measure are considered to be over-educated or under-educated, respectively. Using the mode of years of education as a measure of the appropriate educational level for each occupation reduces sensitivity to outliers and provides a more accurate measure of required education.

Next, we address the issue of the most appropriate methodology or model to be used to analyse the returns produced by educational mismatch. The most widely used model is the Mincer wage equation (1974). However, wage equations can be estimated using a modification of the Mincer equation. This method is known as the ORU model (Duncan and Hoffman, 1981), which is the one used in this study. In this model, years of education (S_a) are replaced by years of required education (S_r), over-education (S_o), and under-education (S_u). The variables years of over- and under-education would be constructed as follows:

$$S_o = \begin{cases} S_a - S_r \; if \; S_a > S_r \\ 0 \; otherwise \end{cases} \quad S_u = \begin{cases} S_r - S_a \; if \; S_a < S_r \\ 0 \; in\ any\ other\ case \end{cases} \tag{1}$$

Having disaggregated the years of formal education, these expressions are included in the Mincer wage equation, and the estimated wage equation is obtained:

$$LnWbhour_i = \beta_0 + \beta_1 S_r + \beta_2 S_o + \beta_3 S_u + \beta_4 X_i + u_i \tag{2}$$

where the dependent variable is the gross real wage per hour (base = 2010) expressed as logarithms. β_0 is the constant, which refers to that part of the wage not explained by the independent variables, but by other factors. X_i refers to a set of control variables that also affect wages. Finally, u_i represents the error term.

On the other hand, β_1 is the return to each additional year of required education, which is expected to be positive ($\beta_1 > 0$). β_2 is the return to each year of overeducation, defined as the increase in an individual's wages for each year of overeducation compared to an individual who is in the same job and whose years of schooling match the job requirements (Iriondo and Pérez-Amaral, 2016). In this case, this coefficient is expected to be positive, but less than the return to required years, showing a decreasing marginal return to years of over-education ($\beta_2 > 0$). Finally, β_3 refers to the return to each year of under-education, defined as the decrease in an individual's wages for each year of under-education compared to an individual who is in the same job and whose years of schooling match the job requirements. In this case, this coefficient is expected to be negative ($\beta_3 < 0$).

It should be noted that Equation (2) allows the comparison of the three theoretical models previously referred to that could contribute to furthering our understanding of educational mismatch. The theory of human capital suggests that each year of education or educational mismatch generates the same returns ($\beta_2 = \beta_1 = -\beta_3$), the job-competition model suggests that, once the job is acquired, the marginal returns to every year of education, even if it is more than or less than that required for the job, are null ($\beta_2 = \beta_3 = 0$), and the assignment model suggests that wages are affected by the characteristics of the workers and the job: thus, the returns to under-, required and over-education would be different from zero ($\beta_2 \neq \beta_1 \neq \beta_3 \neq 0$).

Finally, we note that, given the nature of the data and methodology employed, it is not possible to separate individual heterogeneity from job characteristics. Thus, we do not attempt to examine causal relationships; rather, we study heterogeneity by sector, occupation and gender between the correlations of wages with each year of under-, required and over-education. Nevertheless, in this study, our analysis follows the approach employed by the other authors mentioned.

4. Data and variables

The database used was obtained from the 2018 wages structure survey, which is conducted every 4 years by the Spanish National Statistics Institute. This survey obtained individualised information on wages as well as on their productive characteristics (e.g. experience, tenure, educational level, jobs) and the characteristics of the company (e.g. sector of activity, number of workers). This survey structures data by sector using the National Classification of Activities (CNAE-2009). The present study considers occupation segments as well as the job characteristics of the industrial sector (distinguishing manufacturing and construction) and the service sector. Thus, we obtained 174,027 observations, of which 118,779 correspond to the services sector, 44,623 to the industrial sector and 10,614 to the construction sector. However, we removed observations corresponding to wages below the 2018 inter-professional minimum gross wage of 3.66 EUR per hour given that rates lower than this are illegal.

Using these data, Equation (2) was estimated by gender and then estimated for each occupation segment in the service, industrial and construction sectors, also by gender.

In line with other authors such as García-Pozo *et al.* (2014), occupation segments were aggregated into an adapted version of the traditional classification of workers as "White-Collar" and "Blue-Collar". This study addresses three occupation segments following the Spanish National Classification of Occupations (CNO-2011): white-collar workers (codes 10–41), intermediate workers (codes 42–55) and manual workers (codes 56–96).

Regarding the variables used in the estimates, "The hourly gross wage" represents the dependent variable, and the mismatch variables "Years of required education"-which refers to the required years of education for each occupational level , "Years of over-education" and "Years of under-education" represent the independent variables. The remaining variables included in the model are control variables (see Table A1, Appendix).

4.1 Incidence of educational mismatch

Table 1 shows the incidence of educational mismatch in the sample, expressed as the percentage of overeducated workers, undereducated workers and appropriately educated workers in each occupation segment. The table also shows its incidence within the service, industrial and construction sectors by gender.

The results show significant levels of mismatch in the sample: under-education was higher in the White-Collar segment, whereas over-education was higher in the manual worker segment. These results are consistent with those Yeo and Maani (2017), who suggested that there is an increased probability of over-educated workers in jobs with lower educational requirements and vice versa.

Over-education in white-collar occupations was higher in the industrial sector, especially in the construction sector, whereas over-education in intermediate and manual occupations

Sectors	Occupations	Overeducated (%) Men	Overeducated (%) Women	Undereducated (%) Men	Undereducated (%) Women	Adequately educated (%) Men	Adequately educated (%) Women	Obs. Men	Obs. Women
Services	White-Collar	9.74	9.24	34.51	30.09	55.75	60.67	24,450	28,010
	Intermediate Worker	26.30	25.36	24.81	22.29	48.89	52.35	8,859	18,328
	Manual Worker	28.71	32.03	7.49	6.79	63.79	61.18	20,228	18,904
Industry	White-Collar	16.85	16.94	39.33	32.65	43.82	50.41	9,103	4,239
	Intermediate Workers	25.48	25.76	31.52	31.62	43.00	42.62	679	1,654
	Manual Workers	28.91	26.41	5.48	1.96	65.61	71.63	23,632	5,316
Construction	White-Collar	25.81	14.85	30.38	42.49	43.81	42.66	1,639	586
	Intermediate Workers	25.74	24.23	39.71	39.80	34.56	35.97	136	392
	Manual Workers	17.77	32.73	11.78	4.55	70.46	62.73	7,751	110

Source(s): Author's own work based on the EES-2018 data

Table 1.
Incidence of educational mismatch

was higher in the service sector. These results could be due to the fact that in the construction and industrial sector, the manual worker segment includes low-level jobs that require specific education: however, this is not the case in the service sector. This aspect could explain the greater probability of over-education in the service sector than in the rest of the sectors, even when no criterion of occupational segregation is applied (Ortiz and Kucel, 2008).

Under-education has a higher incidence in construction sector for the 3 occupational levels. This may derive from the stereotype of low educational requirements that exists in this sector (Strachan *et al.*, 2020) and which may cause the labour supply that is aimed at this sector to have a lower average level of qualification.

Regarding gender, the traditional view that the highest percentage of over-education is found among women (Frank, 1978; Groot and Van den Brink, 2000) was only the case for manual workers in the service and construction sector. In all other categories, over-education was higher among men. This result may seem counter-intuitive given that women have a higher average level of education than men and a higher percentage of tertiary education than men. However, other studies have obtained similar results in Spain and in other countries of the European Union (e.g. Cainarca and Sgobbi, 2012; Muñoz de Bustillo *et al.*, 2018).

Finally, there were higher percentages of under-educated women in the White-Collar segment in the construction sector. This inclusion of women in the higher occupational categories may be related to the fact that employers are placing more value on other non-quantifiable skills in women that differ from their educational qualifications. A similar suggestion was made by Mun and Jun (2018). They studied the effect of institutional pressure to incorporate women into leadership positions as a way of making diversity visible in companies. According to these authors, women may sometimes attain high positions before men without having the same quantifiable skills as their male colleagues.

5. Results and discussion

Firstly, Equation (2) is estimated in a baseline model in which no distinction is made between gender, sector or occupation using the ORU model in which a semi-logarithmic function is used for greater comparability and clarity of results. Thus, we expected to observe the overall effect of educational mismatch on workers' wages, as well as the relevance of the explanatory variables in the model. Table 2 presents the results of this estimation. Subsequently, Tables 3–5 show the estimations made separately for the services, industrial and construction sectors, respectively, by which we aim to capture the heterogeneity generated by the sector, occupation and gender of the worker in the sample.

The F statistic and the adjusted R^2 values confirm the significance of the models and the goodness-of-fit of the estimates. The adjusted R^2 values also show that in all cases the proposed models explain around 30% of the variation in wages.

Regarding the hypotheses on the theory of human capital ($\beta_o = \beta_r = -\beta_u$), the job-competition model ($\beta_o = \beta_u = 0$), and the assignment model ($\beta_o \neq \beta_r \neq \beta_u \neq 0$), Table A2 (Appendix) shows that the first two hypotheses were rejected. Regarding the assignment model, the null hypothesis that all variables are equal to 0 was rejected, thus confirming the alternative hypothesis ($\beta_o \neq \beta_r \neq \beta_u \neq 0$) and showing that educational mismatch influences wages. Thus, we based this study on the assignment model.

5.1 Results of the baseline model (general estimation)

In the estimation of the baseline model, we observe that the results of the mismatch variables years of over-, required and over-education were significant and as expected according to previous literature (e.g. Duncan and Hoffman, 1981; McGuinness, 2006; Iriondo and Pérez-Amaral, 2016). They show a positive return for each year of required education, a lower but

Variables	Coefficient
Required years of ed	0.055*** (0.000)
Years of over-education	0.024*** (0.000)
Years of under-education	−0.029*** (0.000)
Experience	0.005*** (0.000)
Experience square	−0.000*** (0.000)
Tenure	0.020*** (0.000)
Tenure square	−0.000*** (0.000)
Gender	0.132*** (0.002)
Sector	
Services	−0.100*** (0.002)
Construction	0.007 (0.004)
Occupation	
Intermediate workers	−0.160*** (0.003)
Manual workers	−0.056*** (0.004)
Working day	0.054*** (0.002)
Duration of contract	0.023*** (0.003)
Responsibility	0.204*** (0.003)
Company agreement	0.091*** (0.002)
Small-size firm	−0.145*** (0.002)
EU non Spanish	0.067*** (0.006)
Rest of the world	0.026 (0.018)
Constant	1.703*** (0.009)
R^2	0.4368
RECM	0.39243
F-statistic	7103.56***
F-Prob	0.000
Observations	174,016

Note(s): Significance: * 10%. ** 5%. *** 1%. Standard errors are in parentheses; General estimation
Source(s): Author's own work based on the EES-2018 data

Table 2. Estimates of the ORU model

Table 3.
Estimates of the ORUmodel

	Service sector					
	WC		IW		MW	
Variables	Men	Women	Men	Women	Men	Women
Required years of ed.	0.070*** (0.001)	0.074*** (0.001)	0.028*** (0.002)	0.031*** (0.001)	0.041*** (0.002)	0.029*** (0.002)
Years of overeducation	0.041*** (0.002)	0.036*** (0.002)	0.028*** (0.002)	0.018*** (0.001)	0.027*** (0.002)	0.013*** (0.001)
Years of undereducation	−0.044*** (0.001)	−0.042*** (0.001)	0.002 (0.002)	−0.006*** (0.002)	−0.015*** (0.002)	−0.023*** (0.002)
Experience	0.012*** (0.001)	0.007*** (0.001)	0.004*** (0.002)	0.002** (0.001)	0.005*** (0.001)	−0.001 (0.001)
Experience square	0.000** (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000* (0.000)
Tenure	0.029*** (0.001)	0.030*** (0.001)	0.016*** (0.001)	0.010*** (0.001)	0.021*** (0.001)	0.018*** (0.001)
Tenure square	0.000*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Working day	0.106*** (0.011)	0.090*** (0.007)	0.039*** (0.010)	0.029*** (0.006)	0.069*** (0.008)	0.040*** (0.006)
Duration of contract	0.087*** (0.009)	0.004 (0.007)	0.042*** (0.012)	0.024*** (0.007)	0.005 (0.007)	−0.042*** (0.007)
Responsability	0.241*** (0.007)	0.158*** (0.007)	0.206*** (0.013)	0.155*** (0.011)	0.165*** (0.012)	0.171*** (0.016)
Company agreement	0.019*** (0.007)	0.009 (0.006)	0.025*** (0.009)	0.065*** (0.006)	0.121*** (0.006)	0.086*** (0.007)
Small-size firm	−0.159*** (0.007)	−0.196*** (0.006)	−0.127*** (0.010)	−0.099*** (0.006)	−0.076*** (0.006)	−0.104*** (0.007)
EU non Spanish	0.128*** (0.023)	0.068*** (0.020)	0.073*** (0.026)	0.096*** (0.017)	0.027 (0.016)	0.013 (0.016)
Rest of the world	0.284 (0.176)	−0.012 (0.067)	0.223* (0.131)	0.053 (0.051)	0.056 (0.050)	−0.011 (0.035)
Constant	1,298,509*** (0.025)	1,294,507*** (0.022)	1,803,767*** (0.027)	1,796,666*** (0.017)	1,762,375*** (0.021)	189,414*** (0.020)
R^2	0.3750	0.3598	0.2595	0.1905	0.2557	0.1604
RECM	0.45197	0.41307	0.36932	0.34579	0.3759	0.36653
F-statistic	1094.70	1181.08	214.00	297.70	514.79	247.37
F-Prob	0.000	0.000	0.000	0.000	0.000	0.000
Observations	24,450	28,010	8,859	18,328	20,228	18,904

Note(s): Significance: * 10%. ** 5%. *** 1%. Standard errors are in parentheses; service sector
Source(s): Author's own work based on the EES-2018 data

Table 4.
Estimates of the ORU model

	Industry sector					
	WC		IW		MW	
Variables	Men	Women	Men	Women	Men	Women
Required years of ed.	0.065*** (0.002)	0.077*** (0.003)	0.031*** (0.008)	0.052*** (0.005)	0.053*** (0.002)	0.051*** (0.004)
Years of overeducation	0.038*** (0.003)	0.048*** (0.003)	0.031*** (0.011)	0.034*** (0.005)	0.021*** (0.001)	0.022*** (0.003)
Years of under education	−0.039*** (0.002)	−0.037*** (0.004)	−0.029*** (0.008)	−0.015*** (0.004)	−0.011*** (0.002)	−0.014*** (0.004)
Experience	0.015*** (0.002)	0.019*** (0.002)	0.014** (0.007)	0.006* (0.003)	0.004*** (0.001)	0.002 (0.002)
Experience square	0.000*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000* (0.000)	0.000 (0.000)
Tenure	0.028*** (0.001)	0.022*** (0.002)	0.017*** (0.005)	0.011*** (0.003)	0.017*** (0.001)	0.009*** (0.002)
Tenure square	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000*** (0.000)	0.000 (0.000)
Working day	0.054* (0.029)	0.143*** (0.020)	0.036 (0.053)	0.017 (0.018)	0.020* (0.012)	0.016 (0.012)
Duration of contract	0.088*** (0.020)	0.161*** (0.023)	0.130** (0.052)	0.089*** (0.023)	0.051*** (0.007)	0.093*** (0.014)
Responsibility	0.192*** (0.009)	0.154*** (0.015)	0.219*** (0.066)	0.091** (0.044)	0.172*** (0.009)	0.172*** (0.028)
Company agreement	0.181*** (0.010)	0.131*** (0.014)	0.172*** (0.045)	0.152*** (0.028)	0.223*** (0.006)	0.162*** (0.014)
Small-size firm	−0.140*** (0.011)	−0.136*** (0.014)	−0.201*** (0.034)	−0.128*** (0.019)	−0.161*** (0.005)	−0.176*** (0.010)
EU non- Spanish	0.137*** (0.043)	0.119** (0.048)	−0.104 (0.078)	0.116** (0.047)	−0.011 (0.015)	0.051* (0.027)
Rest of the world	0.116 (0.102)	−0.069 (0.159)	−0.171*** (0.048)	−0.075 (0.092)	−0.078** (0.034)	0.015 (0.048)
Constant	1,436,244*** (0.044)	1,014,357*** (0.058)	1,711,408*** (0.130)	1,493,432*** (0.068)	183,209*** (0.022)	1,740,177*** (0.043)
R^2	0.4032	0.3651	0.3674	0.3319	0.3340	0.2542
RECM	0.41259	0.40397	0.38673	0.32599	0.35304	0.34765
F-statistic	494.05	201.50		55.07	901.91	133.70
F-Prob	0.000	0.000		0.000	0.000	0.000
Observations	9,103	4,239	679	1,654	23,632	5,316

Note(s): Significance: * 10%. ** 5%. *** 1%. Standard errors are in parentheses; Industry sector
Source(s): Author's own work based on the EES-2018 data

Table 5.
Estimates of the ORUmodel

	Construction sector					
	WC		IW		MW	
Variables	Men	Women	Men	Women	Men	Women
Required years of ed.	0.049*** (0.004)	0.055*** (0.007)	−0.013 (0.045)	0.041*** (0.014)	0.014*** (0.002)	0.008 (0.017)
Years of over-education	0.047*** (0.004)	0.037*** (0.009)	0.012 (0.017)	0.020** (0.020)	0.006*** (0.002)	0.003 (0.017)
Years of under-education	−0.029*** (0.007)	−0.018* (0.010)	0.004 (0.011)	−0.006 (0.007)	−0.003 (0.003)	0.008 (0.055)
Experience	0.008** (0.003)	0.013** (0.006)	0.006 (0.010)	0.014** (0.006)	0.007*** (0.001)	0.021** (0.010)
Experience square	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000* (0.000)
Tenure	0.018*** (0.003)	0.023*** (0.005)	0.011 (0.009)	0.016*** (0.005)	0.014*** (0.002)	0.011 (0.014)
Tenure square	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)
Working day	0.077 (0.058)	0.106*** (0.038)	0.039 (0.090)	−0.012 (0.035)	0.017 (0.026)	0.133* (0.078)
Duration of contract	0.158*** (0.026)	0.169*** (0.041)	0.072 (0.063)	0.072 (0.047)	0.014 (0.009)	0.086 (0.074)
Responsibility	0.250*** (0.020)	0.237*** (0.037)	0.189 (0.105)	0.095* (0.057)	0.124*** (0.016)	0.250* (0.130)
Company agreement	0.016 (0.052)	0.082 (0.074)	0.095 (0.147)	0.163* (0.095)	−0.021 (0.028)	−0.077 (0.135)
Small-size firm	−0.145*** (0.019)	−0.106*** (0.032)	−0.088 (0.058)	−0.064 (0.039)	−0.094*** (0.008)	−0.025 (0.084)
EU non- Spanish	0.034 (0.084)	0.074 (0.128)	–	0.164 (0.167)	−0.001 (0.014)	0.071 (0.085)
Rest of the world	−0.007 (0.149)	0.472*** (0.133)	–	–	0.004 (0.029)	–
Constant	1,586,679*** (0.093)	1,344,515*** (0.138)	2,251,005*** (0.552)	1,535,459*** (0.190)	2,134,741*** (0.035)	1,795,103*** (0.227)
R^2	0.3213	0.3312	0.3882	0.1581	0.1123	0.1529
RECM	0.39086	0.36082	0.27965	0.29356	0.30465	0.32748
F-statistic	52.96	19.47	7.82	7.84	59.82	1.81
F-Prob	0.000	0.000	0.000	0.000	0.000	0.0524
Observations	1,639	586	136	392	7,751	110

Note(s): Significance: * 10%. ** 5%. *** 1%. Standard errors are in parentheses; Construction sector
Source(s): Author's own work based on the EES-2018 data

positive return for each year of over-education, and a negative return for each year of under education.

On the other hand, the value obtained for the gender variable is also noteworthy. This coefficient is significant and positive, showing that the male workers in the sample are paid more than the female workers. With regard to the occupational categories, the coefficients are significant and negative, such that the reference category (White collar) stands out as the one with the highest wage premium in relation to other categories. Finally, with regard to sectors, where the reference variable is the industrial sector, a significant and negative coefficient is observed for services and a non-significant coefficient for construction. Thus, it seems that, in general terms, there are no significant differences in the wage determination of industry and construction. However, we performed Chow's test of structural change and Pearson's test, which show, on the one hand, that there are significant differences in the wages of men and women in the three sectors of interest [4], and on the other hand, that there are correlations between educational mismatch and the productive sectors analysed [5]. These tests justify conducting separate estimations with this triple perspective (gender, occupation and sector) for the service, industry and construction sectors.

5.2 Overeducation, required education and under-education results of the separate estimates

Tables 3–5 show the effects of educational mismatch, and other control factors, for men and women in each occupational category in the services, industry and construction sectors, respectively.

The results of the ORU model on mismatch were those expected according to the previous general estimation and previous literature mentioned above. The only exceptions were male Intermediate Workers in the service and the industrial sector. In both cases, the returns to over-education were about the same as the returns to required education. A possible explanation for this result is that workers classified as having the required years of education were those whose educational level corresponds to the mode of that occupation. However, it may be difficult to obtain the mode for certain occupations. This would mean that workers classified as overeducated in these occupations may actually have the required level of education. This margin of error in the definition of the required level of education for each position might also lead to this unexpected result. Kler (2005) obtained similar results in a study of Australian workers. The author suggested that advances in technology could alter workplace requirements faster than changes in occupation titles. In technology-dependent sectors, such advances could establish workers as being over-educated when they may in fact have the required level of education.

Next, we highlight various educational mismatch results from these separate estimates. We begin by summarising the effect of educational mismatch in the productive sectors of interest. Subsequently, we highlight for each occupational category (white collar, intermediate worker and manual worker) some results regarding the wage effect of educational mismatch. We also compare certain wage effects of this phenomenon for men and women, in these occupational categories, according to the productive sector.

On average, workers with the required education and over-education are paid more in the industrial sector. At the same time, years of under-education are more heavily penalised in the services sector. However, there are relevant differences by gender and occupational category that require further elaboration of these results.

The white-collar segment had the greatest returns to years of over-education, as well as the greatest penalties for each year of under-education. Yeo and Maani (2017) obtained similar results. They suggested that white-collar segment can manage over-education in a way that is productive for the company. In this way, under-education is penalised in this segment because it involves a loss of productivity.

It was also found that in this occupation segment women are paid more for each year of required education. At the same time, men are penalised more for years of under-education. In the industrial sector, women are paid more for each year of over-education. It is also in this sector that we find the highest returns to training for women, compared to those of women workers in this category in services and construction sectors.

Although intermediate workers had positive and significant returns to required education, these returns are relatively low. In fact, these returns were the lowest of all three occupation segments in some of the sectors analysed. This result could be due to the type of work performed in the intermediate worker segment, which typically entails clerical work or work related to customer services. The skills involved in performing these tasks such as those obtained from tenure are valued more than formal education (García-Pozo *et al.*, 2011).

We highlight three results on differences in returns to educational mismatch by gender in the intermediate worker segment. Firstly, there are higher returns to each year of required education and over-education for women in the industrial and construction sector than for women in the service sector. Secondly, there is a higher wage penalty for each year of under-education for women in the industrial and construction sector than for women in the service sector. These results may be due to the specialised education often required by these sectors. However, this type of education is not required in the poorly paid positions typically occupied by female workers in the service sector, and thus under-education in this sector has a lower wage penalty. Thirdly, there is a common result for Intermediate and manual workers: women are paid more for each year of over-education in the industry sector, whereas men are paid more for this reason in the service sector. In line with the latter result, García-Pozo *et al.* (2011) found that in the service sector returns to education were higher among men than among women in these segments. This result may suggest that trained men are preferred to trained women, even if the male workers are over-educated.

In terms of manual worker, it is relevant to note, on the one hand, that the penalty for each year of under-education is higher for female in all sectors, although the highest penalisation is in the service sector. On the other hand, the construction sector is the lowest paid sector for each year of over-education. In addition, the returns to each year of over-education for female manual workers in the industrial sector are more than double those for female manual workers in the service sector. However, the latter result could be explained by the way in which this segment has been designed, given that it is made up of just 5 groups.

5.3 Results for control variables of the separate estimations

The results for the control variables are in line with those of other studies (Lillo-Bañuls and Casado-Díaz, 2010). However, some of the results are of particular relevance.

(1) In the construction sector, women are paid more for their years of experience than their male counterparts (Ons-Cappa *et al.*, 2017).

(2) Compared to temporary contracts, wages are higher for women with permanent contracts than those of men in the industrial and construction sector (De la Rica, 2007). This situation is the opposite of that of women with permanent contracts in the service sector.

(3) Wages are also higher for female manual workers in positions of responsibility in the construction and service sector than those of men in their segment. This result is relevant because it is in contrast to the results of the literature, which suggest that positions of responsibility are rewarded more in men. This result may be due to two main reasons: on the one hand that workers from 5 occupational groups are included within the manual workers segment and, on the other hand, that in the case of the

construction sector, women tend to have positions of intermediate responsibility (Infante *et al.*, 2012).

(4) The returns to firm size support the results of previous studies such as that of García-Pozo *et al.* (2014). These authors found negative returns to workers in small-size firms. This penalty is higher for women in the service sector. This result could be a reflection of the over-representation of women in these lower-paid positions in small businesses, which account for a high weight in the services sector (Dirección General de Industria y de la PyME, 2020).

6. Conclusions

In line with the economic literature reviewed, the conventional wisdom is that as developed economies increase their investment in education, there is a concomitant increase in educational mismatch in their workforce. Our results support this view in the case of Spain, where 23% of workers in highly qualified positions in the construction sector are overeducated, close to 30% of workers in intermediate and low-skilled positions in the service sector are over-educated and 20% of both male and female workers in all sectors are under-educated.

The ORU model (Duncan and Hoffman, 1981) was applied to data from the 2018 wage structure survey to estimate wage equations. The equations were estimated for each gender in each occupation segment in each sector. The following conclusions were obtained:

Firstly, by occupation segment, positions with the highest educational requirements have the highest returns to each year of required education and over-education, whereas in such positions each year of under-education is penalised. This result suggests that the loss of productivity is potentially greater when workers are employed in positions with higher educational requirements.

Secondly, we also found that intermediate workers in the service sector, rather than manual workers, were the ones least valued for each year of required education and the least penalised for each year of under-education. This counterintuitive result could have its origin in the type of work conducted in this segment in this sector, in which skills relative to the individual's work see tenure are valued to the detriment of the value given to formal education.

Thirdly, we suggest that greater returns to each year of over-education are offered by the industrial sector than by the rest of the sectors. This finding may be related to the need for workers with certain types of technical or specific training in the industrial sector. This need could lead to employers preferring workers with a certain level of over-education and technical skills, thus they would anticipate a future technical obsolescence in the workforce.

Fourthly, by sector and gender, the results show that female worker education is more valued by the industrial sector. Therefore, we highlight the following:

(1) In positions requiring high or medium qualifications, each year of required or over-education yields considerably higher returns to women in the industrial sector than their male counterparts except for the required education of manual workers . In addition, it is worth noting women in industry have higher returns for these variables than those for women in the service sector.

(2) In high-skilled jobs in the construction sector, we observed higher returns to human capital factors related to informal education experience and seniority – for women than for men. This may reflect the greater importance given to on-the-job training in this sector.

(3) Overall, the service sector places more value on over-education in male workers. This sector offers lower returns to education of female workers, which may be due in part to their concentration in low-paid positions. In these jobs, moreover, they are required to have a certain level of training which, if not attained, leads to higher penalties.

Fifthly, the results on the control variables suggest that much remains to be done to break the so-called "glass ceiling" and to achieve equal wages for women in positions of responsibility in higher categories.

As research implications, we highlight the relevance of considering other productive sectors that have been less analysed in the literature, such as industry given the sectoral heterogeneity observed in this paper, and the different and interesting results obtained in terms of gender , and investigate the effect of educational mismatch on wages by gender in this sector. In this way, future work could study educational mismatch by sector as a possible amplifying factor (e.g. in the case of services) or reducing factor (e.g. in the case of industry) of the gender wage gap.

On the other hand, the results of this study also have practical and political implications. We have observed the unfavourable effects and inefficiencies generated by educational mismatch and, in a country like Spain, where public investment in education is very strong, and these consequences can only be aggravated. Thus, structural reform is needed to adapt the educational level of workers to the requirements demanded by companies. Part of such structural reform could be implemented by promoting intermediate vocational training to bring Spain closer to European levels in these terms. Higher-skilled jobs could be promoted in sectors such as industry, which has been shown to better absorb excess training, especially that of female workers. Matching labour supply and demand could lead to better job satisfaction and higher levels of productivity that would allow the country's investment in education to provide a far better return.

Regarding the limitations of this study, only cross-sectional data were available and thus it was impossible to incorporate bias related to the observational error. Had panel data been available, fixed effects could be included in the model to incorporate such bias. This issue could be addressed in future lines of research providing the required data are available.

Notes

1. ORU is the abbreviation of Overeducation, Required education, Undereducation.
2. Regarding theoretical frameworks of educational mismatch, a good literature review can be found in Leuven and Oosterbeek (2011).
3. In this paper, we follow Salinas-Jiménez *et al.* (2013), although in this case we use occupational levels to control for individual heterogeneity, understanding it as a proxy that captures different skill levels, given that each occupational category requires different skill content.
4. Chow or structural change tests were conducted to determine any structural changes between men and women's wages, and between industry, construction and service sector wages. Significant differences were found between wages in both cases and the null hypothesis was rejected. The results of this test highlight the relevance of studying the impact of educational mismatch on Spanish wages by gender and sector.
5. Several Pearson tests were conducted, showing correlations between educational mismatch and occupations, and between educational mismatch and the three sectors of interest. These results justify conducting estimations with this triple perspective.

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(The Appendix follows overleaf)

Appendix

Variables	Description	Services	Industry	Construction
The gross hourly wage	The gross real wage per hour (base = 2010) expressed as logarithms	15,191 (11,103)	16,033 (10,564)	12,501 (6,730)
Age	Age of the individual in years	43,819 (10,641)	44,449 (10,044)	43,764 (9,731)
Years of required education	Years of formal education typically required for an occupation (mode method)	11,220 (3,969)	9,497 (3,219)	8,309 (3,531)
Years of over-education	Years of formal education more than those typically required for a given occupation (mode method)	0.964 (1,917)	1,120 (1,960)	1,109 (2,008)
Years of under-education	Years of formal education less than those typically required for a given occupation (mode method)	1,058 (1,840)	1,005 (1,701)	0.979 (1,658)
Experience	Years of work experience of the individual [theoretical experience [1] -tenure]	14,889 (10,288)	15,231 (10,043)	21,584 (11,052)
Tenure	Total years of tenure [years plus months of tenure]	10,100 (10,000)	12,422 (10,823)	5,932 (7,610)
Part-/full-time	Dummy variable that takes value 1 if the individual has a full-time contract and 0 if it is a part-time contract	0.762 (0.426)	0.911 (0.285)	0.941 (0.236)
Contract type	Dummy variable that takes value 1 if the individual has a fixed contract and 0 if it is a temporary contract	0.776 (0.417)	0.865 (0.341)	0.577 (0.494)
Position of responsibility	Dummy variable that takes value 1 if the individual has a position of responsibility and 0 otherwise	0.138 (0.345)	0.154 (0.361)	0.156 (0.363)
Labour agreement	Dummy variable that takes value 1 if the individual has a labour agreement with the company and 0 if it is another type of labour agreement	0.360 (0.480)	0.292 (0.455)	0.030 (0.172)
Small business	Dummy variable that takes value 1 if the enterprise is small [2] as defined by the European Union (EU) criteria (i.e. less than 50 employees) and 0 when it is a medium or large enterprise with more than 50 employees	0.256 (0.437)	0.362 (0.481)	0.655 (0.475)
EU non-Spanish	Dummy variable that takes the value 1 if the individual is a non-Spanish individual from the European Union and 0 otherwise	0.024 (0.154)	0.022 (0.145)	0.053 (0.223)
Rest of the world	Dummy variable that takes the value 1 if the individual is a non-Spanish individual from a non-EU country and 0 otherwise	0.002 (0.045)	0.003 (0.054)	0.007 (0.085)
Observations	Sample observations	118.788	44.624	10.615

Note(s): The parentheses show the standard deviations of the variables. Source: Adapted by the authors based on the Spanish Wage Structure Survey (WSS-18); descriptive statistics

[1]Theoretical experience is defined as the difference between the age of the individual and their years of education minus 6 years, because is it assumed that schooling began at 6 years (i.e. theoretical experience = age – years of study – 6) (Mincer, 1974)

[2]To define this variable, we followed Annex I of the commission regulation (EU) 651/2014, which defines the differences between micro-, small- and medium-sized enterprises. This regulation defines a “micro-enterprise” as one with less than 10 workers, a “small enterprise” as one with 10–49 workers and a “medium-sized enterprise” as a company with 50–249 workers

Source(s): Author’s own work based on the EES-2018 data

Table A1.
Description of the variables used in the model

Hypothesis	White-collar	Intermediate worker	Manual worker
Services			
Theory of human capital ($\beta_o = \beta_r = -\beta_u$)	211.58***	82.29***	63.70***
Job-competition model ($\beta_o = \beta_u = 0$)	822.74***	85.93***	220.53***
Assignment model ($\beta_o \neq \beta_r \neq \beta_u \neq 0$)	1383.74***	108.80***	201.80***
$\beta_r = 0$	3191.41***	199.26***	406.98***
$\beta_o = 0$	360.47***	169.26***	301.55***
$\beta_u = 0$	1019.60***	0.83	57.97***
$\beta_r = \beta_o = \beta_u$	1853.30***	45.46***	199.02***
Industry			
Theory of human capital ($\beta_o = \beta_r = -\beta_u$)	124.70***	0.02	223.27***
Job-competition model ($\beta_o = \beta_u = 0$)	301.87***	16.50***	153.78***
Assignment model ($\beta_o \neq \beta_r \neq \beta_u \neq 0$)	563.94***	13.20***	301.84***
$\beta_r = 0$	1476.84***	14.08***	840.66***
$\beta_o = 0$	202.24***	7.70***	203.61***
$\beta_u = 0$	272.85***	12.53***	36.18***
$\beta_r = \beta_o = \beta_u$	609.43***	19.49***	268.56***
Construction			
Theory of human capital ($\beta_o = \beta_r = -\beta_u$)	3.64**	0.25	17.34***
Job-competition model ($\beta_o = \beta_u = 0$)	83.96***	0.25	5.03***
Assignment model ($\beta_o \neq \beta_r \neq \beta_u \neq 0$)	77.36***	0.18	19.71***
$\beta_r = 0$	189.55***	0.08	48.21***
$\beta_o = 0$	113.42***	0.50	7.93***
$\beta_u = 0$	16.06***	0.14	1.24
$\beta_r = \beta_o = \beta_u$	54.29***	0.21	8.44***

Note(s): *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Within the assignment model, rejection of the null hypothesis could occur even if some or all coefficients are zero but measured with error. Therefore, we test whether the mismatch coefficients, one by one, are equal to zero, and whether they are jointly equal to zero, using an F-statistic, such that there is no error in the interpretation of this theoretical model
Source(s): Author's own work based on the EES-2018 data

Table A2. Estimation of the hypotheses of the economic theories about educational mismatch

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