Overeducation or overskilling: Do working environments matter?

Sobreeducación o sobrecualificación: ¿Importan los entornos laborales?

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Abstract

Overeducation concern in recent years has been stimulated by evidence challenging the productive value of education. A group of empirical studies suggest that returns to education can be limited, namely by (the required) job characteristics. This paper analyses how working environments affect the relationship between overeducation and worker's earnings in Spain. To do so, the Spanish sample of the PIAAC data has been used, relying on wage type-equations (ORU specification) at the individual level, estimated using PIAACREG and Heckman two steps econometrics techniques. Results achieved suggest that job limits to marginal productivity (and in turn, wages) of those overeducated can be smaller when the working environments entail dealing with uncertain economic contexts and engage more in innovation activities. Higher education policy should rethink education oriented towards challenging and changing jobs (working environments).

Keywords: Overeducation, working environment, innovation, PIAAC, Spain.

Resumen

El creciente interés en los últimos años por la sobreeducación ha venido de la mano de cierta evidencia que cuestiona el valor productivo de la educación.

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Un grupo de investigaciones ha venido a sugerir que el rendimiento educativo puede verse limitado por las características (requeridas) de los puestos de trabajo. La sobreeducación se ha convertido en un fenómeno generalizado que conlleva importantes costes a lo largo de la vida laboral de los individuos, de especial relevancia sobre los jóvenes, pero también sobre las organizaciones y la sociedad en su conjunto. Este artículo analiza cómo los entornos laborales afectan la relación entre la sobreeducación y los ingresos de los trabajadores en España. Para ello, empleando la muestra española de los datos PIAAC se estiman ecuaciones salariales (especificación ORU) a nivel individual, empleando técnicas econométricas (Heckman en dos etapas y PIAACREG). Los resultados alcanzados sugieren que, los límites a la productividad marginal (y, a su vez, sobre los salarios) de aquellos sobreeducados impuestos por los puestos de trabajo pueden ser menores cuando los entornos laborales enfrentan contextos económicos inciertos y participan más en actividades de innovación. La política de educación debería repensarse en una educación orientada hacia empleos (desafiantes) y en permanente cambio (entornos laborales). Las actuaciones entre los diferentes ciclos del sistema educativo y el mercado laboral deberían alinearse como forma de responder a los rápidos cambios de los requerimientos educativos y competenciales de los entornos laborales, unido a la formación continua, cabrían considerarse medidas dirigidas a mejorar la orientación de los alumnos desde etapas educativas tempranas respecto a los tipos de formación existentes y con mejores salidas profesionales, pero también, promoviendo estrategias de formación dual, experiencias de movilidad nacional e internacional por motivos de estudios o laborales, e incluso más contenidos formativos prácticos.

Palabras Clave: Sobreeducación, entornos laborales, innovación, PIAAC, España.

Introduction

In the last decades, many countries have experienced a sustained growth in their level of human capital (CEDEFOP, 2015). However, despite increasing the level of education and skills of individuals, the demand for qualified labour has been unable to absorb it (Hartog, 2000), thus, these individuals have ended up in jobs of lower quality or with different educational requirements (CEDEFOP, 2015; Mavromaras et al, 2015). The fact is that educational mismatch (Freeman, 1976), the inadequacy of individual qualification with that required in their jobs, have come to be labelled as a growing, pervasive and persistent phenomenon (Flisi et al, 2017; McGuiness, 2006; Buchel, 2002) in developed economies, but more

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important, having high costs on individual, organisations and society as whole (McGuinness, 2006).

Mainstream economic literature has tried to explain this phenomenon relying on educational arguments within the labour market theories. From a supply side, the human capital theory suggests that investment in education contributes to raising the marginal product and hence, its returns (Schultz, 1961; Becker, 1964), as for labour demand theories, the competition and signalling models regardless improving recruitment opportunities sets that marginal product is determined by the job requirements (Thurow, 1979; Spence, 1973), or the assignment theory, integrating both demand and supply side arguments, explain that the degree to which individuals can use their skills will depend, at least in part, on the job characteristics, which can limit the productivity of individual, and the returns to education (Sattinger, 1993). The latter theory has been questioned in recent years, as education and skills are not straightforward related, and thus, can lead to apparent rather than real overeducation (DiPietro and Urwin, 2006).

Regarding the costs, at the individual level, over-educated workers have been found to earn less than similarly educated workers whose jobs match their qualifications, presumably because a proportion of their investment in education is underutilized and unproductive (McGuinness and Sloane, 2011; Mavromaras et al., 2009; Barcena-Martín et al., 2012). Findings also mention that these group of workers may also experience lower levels of job satisfaction (Tsang and Levin, 1985; Tsang et al., 1991; Battu et al., 1999) or even displace less-skilled workers toward unemployment, particularly in discouraged labour markets (Battu and Sloane, 2002). Of especial relevance are young people (in school-to-job transitions), where over-education levels reach the highest within the working life cycle of individuals. For this group overeducation can reduce their employability, hamper their employment-careers prospects, or leave them unemployed (Albert et al, 2018; Ramos, 2017). At higher levels, in organizations, several studies suggest that over-education may be associated with lower productivity (Tsang and Levin, 1985; Tsang, 1987) and higher job turnover, which in turn leads to a loss of investments in candidate selection/recruitment and training (Tsang et al., 1991; Alba-Ramírez, 1993). At the macroeconomic level, over-education can lead to a waste of investment in education and national production is potentially less than it could be if the skills of over-educated jobs were used optimally (Hanushek and Woessmann, 2008).

Findings about the wage effects of educational mismatch are quite consistent, however, as jobs characteristics affects individual productivity and returns to education, we argue that it is possible to assume that the wage impact of overeducation can be influence by specific working environments. Tarvid's (2015) study for 27 EU countries and Mahy et el (2015) investigation in Belgium, provide evidence that overeducation prevalence is different between industries and that workers productivity increases when higher skills are required in jobs.

Our investigation aims to delve over these issues for the Spanish economy, analysing the relationship between educational (and skill) mismatch and its returns across working environments. Specifically, the interest of this research is to measures the wage effects of overeducation (and overskilling) across different working environments, characterised by (i) the degree of innovation and (ii) the uncertainty of the economic context.

To address this issue our research strategy relies upon the ORU type specification (over, required, and under-education and skills) at the individual level (Duncan and Hoffman, 1981; Verdugo and Verdugo, 1989). Data used refers to the Spanish sample of the OECD's PIACC DB. The dependent variable will be workers' hourly wage. The independent variables will be overeducation and overskilling as defined by the mainstream literature (Flisi et al, 2017). The rest of covariates, namely control ones, include individual and household, human capital level and their job characteristics.

The rest of the document is structured as follows. Section 2 presents the framework underpinning the research objective. Section 3 describes the methodological framework (and research strategy). The following section (4) presents the results achieved and provides a brief discussion. Last (Section 5) conclusion and some final remarks are depicted with respect to policy implications, namely, in terms of education policy.

Mismatch wage effects in working environments

Mismatch and wage effects

Economic literature has traditionally analysed educational mismatch in relation to its wage effects. Research (Hartog, 2000; McGuinness, 2006; Mavromaras, 2015), disaggregates the educational attainment of workers

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in the years of education required by the jobs and in the years above or below this threshold (Duncan and Hoffman, 1981; Verdugo and Verdugo, 1989). Results show that over-educated workers suffer a wage penalty if compared to other individuals who, with the same educational level, are well matched to their jobs (Verdugo and Verdugo, 1989).

This group of results relies on the framework of the assignment theory (Sattinger, 1993), assuming that productivity and, consequently, wages, are determined both by the educational level of individuals and the (educational) requirements associated with the job. More recently, another group of studies have pointed out that not only the education achieved, but also the use of skills (acquired or not in the workplace) determine workers' wages (Allen and Van der Velden, 2001), suggesting that the assignment theory could be determined by the relation between over-education and the under-utilization of the individuals skills in the workplace.

In fact, Allen and Van der Velden (2001), using data for the Netherlands, checks whether the educational mismatch also implies a skill mismatch in terms of its wage effects. Di Pietro and Urwin (2006) do the same for Italy and Green and McIntosh (2007) for the United Kingdom. These studies results tend to question the assignment theory, in that the wage penalty of educated workers does not seem to be due to an underuse of their skills, but rather that both types of mismatches are weakly related, and hence, suggest that educational and skills mismatches are two different phenomena.

These results have two important implications. First, it paves the way to talk about heterogeneous competences, assuming that there is no straightforward correspondence between education attained and the skills acquired, suggesting that the education mismatch shown by some workers may be apparent or real. Individuals with a higher educational level than that required for their job, but who possess the right skills for the job, will have only formal or apparent overeducation. In contrast, if jointly showing high educational level and higher skills, they will be workers with genuine or real over-education (Green et al, 2002; Chevalier, 2003). Some authors have suggested alternative definitions to measure educational mismatch with the idea to distinguishing between apparent and real over-education, considering the skills individuals actually have (Chevalier, 2003; Green and Zhu, 2010; Mateos-Romero and Salinas Jiménez, 2017; Chevalier and Lindley, 2009; Mavromaras et

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al, 2013). These results show that the (wage) penalties of educational mismatch differ according to the level of skills reached by individuals, supporting the hypothesis of skill heterogeneity and highlighting the need to consider the differences in skills reached when studying the mismatch effects.

The second implication suggests that, when considering education and skills as different and independent phenomena, their economic effects may impact differently. Literature indicates that overeducation shows a greater effect on wages than skill mismatch (Hartog, 2000; McGuinnnes, 2006). Focusing exclusively on subjective measures of skill mismatch (see McGuinness and Sloane, 2011; Badillo-Amador and Vila, 2013), studies find that workers who do not use their skills suffer a wage penalty compared to those who fully use their skills on the job. Likewise, if considering both educational and skills mismatch, the wage penalty associated with over-education is reduced, although the salary effects of the educational mismatch remain statistically significant (Pecoraro, 2014). Studies using objective measures of skills mismatch based on the frequency of use of skills at their job are also consistent with these results (Green et al., 2002; Allen et al., 2013; Desjardins, 2014), supporting the idea that educational mismatch is a better predictor of the effects on wages than the relative use of skills in the workplace.

Hence, it seems that the educational and skill mismatch operate through different mechanisms, else, both mismatches should be able to explain the wage differential (Badillo-Amador and Vila, 2013). To overcome this debate, research is moving towards both different forms of skill-tasks mismatch (van der Velden, R. and Bijlsma, 2019) and the measurement challenges (Kracke and Rodrigues, 2020).

Mismatch in industry-working environments

Recent studies (CEDEFOP, 2015) have pointed out that the educational and skill level required to get a job is different from that necessary to develop it (CEDEFOP; 2015; Pineda i Herrero et al, 2016). This fact suggests that in some cases employers vary the recruitment/selection criteria to filter the best candidates (Spence, 1973), save on training costs (Thurow, 1975); protect their companies against uncertainty (Bulmahn and Krakel, 2002), encourage innovation or even pursue a successful

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adaptation when new technology is adopted (Nelson and Phelps, 1966; Autor et al, 1998). Further, this study recognizes that the requirements for education and skills also depend on the occupation and the industry in which individuals work or expect to work.

These findings open a space to suggest that education (and skill) mismatches may depend on the specific working environment of companies (DiPietro, 2002; Mahy et al, 2015) or sectoral/industrial environments (i.e. depressed markets or with lack of job opportunities) (Tarvid, 2015; Croce and Ghignoni, 2012), which together with the preferences of the workers (CEDEFOP, 2015), can lead individuals to accept jobs in which their educational levels or skills do not match with those required in the workplace.

Empirically, using data from 27 countries, Tarvid (2015) analysed the prevalence of overeducation in 12 industries. His findings suggest that overeducation is more prevalent in industries where individuals are concentrated in groups 4-9 of the ISCO classification (below tertiary occupations), being the administrative, accommodation, transport and public administration services the highest (shares above 15%), whereas professional-scientific or ICTs, the lowest (below 10%). Mahy's et al, (2015) study for Belgium, found that overeducated individuals exert positive and significative impacts on firm productivity when considering the different working environments. Specifically, overeducated showed higher returns in those firms (technologically intensive and facing uncertain economic environments) having a larger fraction of high-skilled jobs.

Methodology: General specification, data and variables used.

Working environments

To consider working environments individuals/jobs will be grouped by industries characterised by the innovative intensity and economic performance of firms.

Innovative intensity. Innovative working environments exist when firms highly engage in innovation activities. We measure these dynamics using the innovation intensity indicator defined as the ratio between the costs incurred in innovation activities and its turnover. The indicator used comes from the Technological Innovation Panel (PITEC) annual survey which collects information about innovation activities at firm level of a representative sample of Spanish firms, developed by the Spanish Statistical Institute (INE) and the Spanish Foundation for Science and Technology. Higher values of the index will represent a greater innovative effort and vice versa. Firms have been grouped according to their innovation intensity index by branches of economic activity (CNAE). Data refers to annual figures in 2014.

Uncertain economic environment. Uncertain economic environment occurs when economic conditions are permanently changing within a business environment. As a result, management has little influence over factors that are outside of the company's control. Hence, firms facing a high uncertain economic environment (rapid changes with low adaptation) will tend to perform worse. To measure this situation, we used the annual profits before taxes figures in 2013 and 2014[1] and defined the ratio profits 2014/ profits 2013. Values above/below 1 indicates an annual increase/ decrease of profits. Data was compiled from the Central Balance Sheet Data Office of the Bank of Spain, which collects accounting information of firms in an annual basis. Firms have been grouped according to the profit before taxes ratio by branch of economic activity (CNAE). Data refers to the period 2013-2014.

The 22 branches of the economic activities (CNAE) have been merged into 6 major industries: Knowledge Intensive Services (KIS), Manufacturing, Public Services, Construction, Tourism and Commercial activities. The criterion followed for grouping companies in these 6 industries where chosen because they have a sufficient number of observations to perform the analysis. Industry figures have been obtained by calculating the average values of firms belonging to the branches of activities that make up each industry.

Table I shows for each industry, the branches of economic activity that make up each of the industries represented by their CNAE codes, the values of the indexes of innovative intensity and economic uncertainty. Figures suggest that those industries that have invested the most in innovation have differentiate themselves and have been able to improve their competitiveness, reflected in an annual increase in their profits before taxes. The highest and lowest scoring industries on both indexes where: KIS (2.12 and 3.0 respectively) and commercial services (0.10 and 1.3).

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(1) Mahy et al (2015) uses the mean rate of bankruptcy indicators at a NACE3-digit level supplied by Statistics Belgium.

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TABLE I. Sector Intensity of Innovation (2014) and Profits before Taxes (2013/2014). Data for Spain, 2013 and 2014

Industry labels	Description	Innovation index (2014)	Profit Before taxes ratio (2014/2013)	Profit or loss 2013
KIS	Knowledge Intensive Service (J, K, M, N**)	2,12	3,0	1,0
Manuf	Manufacturing industry (C**)	1,98	2,7	1,0
PubServ	Public Services (O, P, Q**)	0,59	1,1	1,0
Rest_IND	Rest of industries (A, B, S, T**)	0,50	1,9	1,0
Construc	Construction industry (D, E, F, L**)	0,28	1,1	0,0
Tourism	Tourism industry (H, I, R**)	0,23	2,3	1,0
Commerc	Commercial Activities (G**)	0,10	1,3	1,0

Source: Own elaboration based on the Spanish Innovation Survey (INE) and the Central Balance Sheet (BdE)
(*) CNAE codes.

Database and variables used

The dataset used was the Spanish sample of the Programme for the International Assessment of Adult Competencies (PIAAC) of the OECD. Data was collected between mid-2011 and mid-2012 and first released by the end of 2013. This survey assesses proficiency in key information-processing skills - literacy, numeracy and problem solving in technology-rich environments of adults aged 16-65. Additionally, PIAAC gathers information and data on how adults use their skills at home, at work and in the wider community. The competences analysed refer to numeracy skills[2], however, we repeat the entire analysis using literacy comprehension skills as a robustness test[3].

(2) In fact, some studies (See Flisi et al, 2017) have disregard problem solving as it is administered only to people who report having some computer experience, which is not a representative sample of the population.
(3) Results are available upon request.

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The overall Spanish sample has 6,055 observations. We restricted this sample to employees[4]. Likewise, we have excluded workers having an apprenticeship and training contract and those without a contract but working (students)[5]. We have also removed from the analysis those workers (observations) not having all the information needed to be considered in the analysis. The final sample has 2,221 observations.

Dependent variable. The dependent variable refers to the gross hourly wage, including bonuses in purchasing power parity and comes from the PIACC DB (earnhrbonusppp). For our purpose, we will use its natural logarithm. Table II shows the descriptive statistics of the variables used.

Independent variables. Educational mismatch and skills mismatch variables are measured as the difference between the level of education/skills achieved by the worker and the level of education/skills required to perform the job. Literature recognizes three ways[6] of measuring the educational and skill mismatch (see Hartog, 2000; Desjardins and Rubenson, 2011; Flisi et al, 2017, for a review).

TABLE II. Descriptive Statistics of the Variables Used

Variable	Variable Type	mean / freq	SD / freq %	Min	Max
Wages	Cont	15,9	11,8	1,7	188,0
Job satisfaction	dummy	1.930	0,8	0	1
Job in satisfaction	dummy	444	0,2	0	1
Overeducation	dummy	828	0,3	0	1
Undereducation	dummy	404	0,2	0	1
Overskilled	dummy	1.361	0,6	0	1
Underskilled	dummy	68	0,0	0	1
Wrong-skilled	dummy	835	0,4	0	1
Schooling (yrs.)	cont	12	3,5	6	21
Numeracy score (PVNUM)*	cont	258,8	47,1	63,8	397,4

(4) According to OECD approach (Flisi et al, 2017), self-employed individuals present very peculiar and diversified features, making them non-comparable within regions.

(5) Following Allen et al (2013) these group of individuals are often low-skilled temporary jobs or a combination of education and work.

(6) There is some consensus about the impossibility to affirm that one measure is strictly better than the others and, in practice, the choice of one measure often depends on the availability of data (Hartog, 2000; McGuinness 2006).

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Experience (yrs.)	cont	17	11	0	55
Male	dummy	1.263	0,5	0	1
Female	dummy	1.113	0,5	0	1
Immigrant (1G)	dummy	259	0,1	0	1
Native person	dummy	2.064	0,9	0	1
Excellent health	dummy	353	0,1	0	1
Very good health	dummy	693	0,3	0	1
Good health	dummy	972	0,4	0	1
Fair health	dummy	328	0,1	0	1
Poor health	dummy	29	0,0	0	1
Number living households	cont	3	1	1	16
Living w/spouse-partner	dummy	1.632	0,7	0	1
Having children	dummy	1.509	0,6	0	1
Number of children	cont	2	1	1	8
Increasing hiring	dummy	316	0,1	0	1
SME	dummy	2.037	0,9	0	1
Big firm	dummy	332	0,1	0	1
Private sector	dummy	1.755	0,7	0	1
Public sector	dummy	585	0,2	0	1
Third sector	dummy	35	0,0	0	1
Supervising employees	dummy	1.709	0,7	0	1
Full time	dummy	1.898	0,8	0	1
Part time	dummy	369	0,2	0	1
REQ_Well-qualified	dummy	763	0,3	0	1
REQ_Semi-qualif White collar	dummy	825	0,3	0	1
REQ_Semi-qualif Blue collar	dummy	438	0,2	0	1
REQ_Basic qualification	dummy	328	0,1	0	1
Involved_F & NF educ FJ	dummy	1.120	0,5	0	1
Not Involved_F & NF educ FJ	dummy	1.150	0,5	0	1

Source: Own elaboration using data from the Spanish PIAAC sample. (*) Populations means and standard deviations for each Plausible Value where computed using Balanced Repeated Replication (BRR) (OECD, 2009).

Educational mismatch has been estimated by the indirect subjective method. Subjective or self-evaluation methods require that employee/ employer determine the type and level of formal education that is necessary to address the tasks associated with a given job. It should be recognized in these cases that the literature distinguishes between educational levels required to get a job and to do their job. In this study, the first option has been considered. This level is then compared to the level of education attained by the worker. To estimate the incidence of mismatch, 3 dichotomous variables have been constructed; the first two, overeducation/undereducation, where calculated if the educational level attained by the workers measured in years of education (variable yrsqual derived by PIAAC), is greater/lower than the years of education indicated as required by the worker to get the job (variable yrsget). The third variable, refers to the adequate education level, calculated if both variables (yrsqual and yrsget) coincide.

As for the skill mismatch variables, they have been constructed using two questions of the PIAAC questionnaire relating the worker's skills with respect to the tasks required in their jobs. These questions are the followings:

- Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job? (f_q07a from the PIAAC database)
- Do you feel that you need further training in order to cope well with your present duties? (f_q07b from the PIAAC database)

TABLE III. Distribution of labour mismatches (education and skills) in Spain (2014)

Pool	Skill match	Overskilled	Underskilled	Wrong skilled	Total
Education match	50,54%	45,63%	52,94%	51,26%	48,03%
Overeducation	22,58%	40,12%	25,00%	28,86%	35,00%
Undereducation	26,88%	14,25%	22,06%	19,88%	16,97%
Total	100,00%	100,00%	100,00%	100,00%	100,00%
Pool	**Skill match**	**Overskilled**	**Underskilled**	**Wrong skilled**	**Total**
Education match	4,15%	54,86%	3,18%	37,81%	100,00%
Overeducation	2,55%	66,18%	2,06%	29,21%	100,00%
Undereducation	6,25%	48,50%	3,75%	41,50%	100,00%
Total	3,95%	57,74%	2,89%	35,43%	100,00%

Source: Own elaboration from the Spanish PIAAC sample.

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While the first question provides insight about skills underutilization, the second question provides information on whether employees have the skills necessary to perform their job tasks. Based on these two questions, four dichotomous variables have been defined. Workers who answer both questions negatively have the right skills for their current job, those who answer both questions positively are workers who may have the skills to perform more demanding jobs, but do not have enough skills for their current position, so they are workers with misleading skills (wrong skills). Those workers who respond positively to the first question, but negatively to the second, would be overskilled workers, while those who respond negatively to the first question and positively to the second would be underskilled workers. Table III shows the distributions of the educational and skills mismatch.

Rest of independent variables. The rest of the independent variables considered refer to their individual and family characteristics (age, gender, immigrant-status, living-alone, having children), workers' human capital (years of schooling, PIAAC test-scores in numeracy-skills, experience) and the employment-status variables (SME; public sector, hiring-trend, employee-supervising, working-situation, training activities).

General specification and estimation techniques

To assess the wage impact of overeducation across different working environments (industries), a group of wage equations have been estimated at the individual level. For each of the estimates, human capital, individual characteristics, and employment status of worker's have been included as control variables.

More precisely, the specification of the wage equation (I) is as follows:

$$log(w_i) = \alpha + \beta_1 S_i + \delta X_i + u_i \quad (I)$$

where $ln(w_i)$ is the logarithm of the hourly wage of worker i; X_i is a vector of control variables related to personal, human capital and employment status characteristics. Further, $\beta_i S_i$ refers to education and skill mismatch variables. Several studies (Duncan and Hoffman, 1981; Verdugo and Verdugo, 1989), when analysing the educational mismatch, break this

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variable down into three: years of education required for the job, years of overeducation and years of undereducation; u_i is the error term having mean zero and a constant variance.

Regarding the estimation technique, wage equations has been estimated by three different methods: M1: Ordinary Least Squares (OLS) using robust SE estimators, a more specific approach to PIAAC-data suggested by Pokropek and Jakubowski (2013, hereafter M2: PJ), and a M3: Heckman two step technique (Heckman, 1979). OLS and PJ (PIAACREG) techniques estimates unbiased and efficient population estimators, these techniques use jackknife methods to derive robust SE, nevertheless, to prevent for possible problems of endogeneity[7] and sample selection biases, we use the Heckman two step[8] specification (Heckman, 1979) technique.

Results and discussion

Incidence of overeducation across working environments

Overeducation (and overskilling) incidence across industries in Spain are presented in Table IV. We observe, on the one hand, that both types of mismatch have a high and positive correlation (97%) and present a similar average value (14.3% vs. 14.2%). On the other hand, when comparing both types of mismatches, the incidence of overskilled presents a lower standard deviation (5.2%) with respect to the incidence of overeducated (6.1%), also reflected, from another point of view, in a lower range (16.4% and 19.1%, respectively).

(7) Unobserved part of the wage's determinants.
(8) The probit equation of the probability of being employed includes as explanatory variables gender, experience, experience squared, years of attained education, immigrant status, number of children, whether individual is living with spouse/partner or not, and regional dummies.

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TABLE IV. Overeducation and Overqualification incidence by Industry

Sector Environment	Overeducation (Sector %)	Overskilling (Sector %)	OvEd & OvSkill (Sector %)
PubServ	24,15%	23,44%	20,33%
Tourism	17,87%	15,94%	19,23%
Commerc	16,55%	14,84%	17,95%
KIS	14,01%	15,43%	14,10%
Manuf	12,20%	13,96%	13,19%
Rest_Sect	10,14%	9,33%	11,17%
Construc	5,07%	7,05%	4,03%
TOTAL	**100,00%**	**100,00%**	**100%**
Mean	14,3%	14,2%	14,3%
SD	6,1%	5,2%	5,6%
Range	19,1%	16,4%	16,3%
Correlation	0,97		

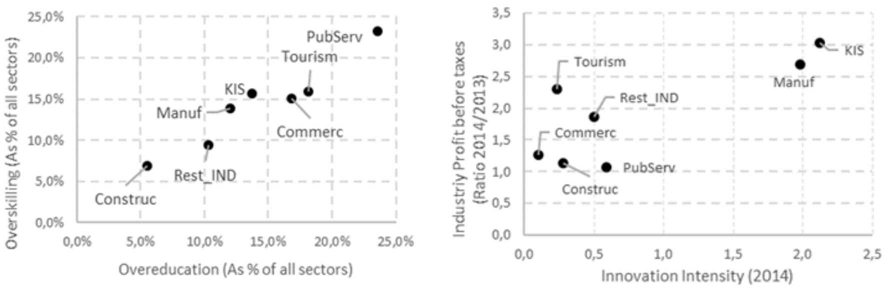
Source: Own elaboration using data from the Spanish PIAAC sample.

By industries, Public Services (24.15% and 23.44%), Tourism (17.87% and 15.94%) and the Commercial activities (16.55% and 14,84%) show the higher incidence both of over-education and over-qualification. In contrast, the Construction industry (5.07% and 7,05%), Manufacturing (10,14% and 9.33%) and Knowledge Intensive Services (12.2% and 13.96%), present the lower incidence.

These figures are in line with what the literature shows (Mahy et al, 2015; Tarvid, 2015; DiPiero, 2002), suggesting that industrial environments may exert some type of influence on the overeducation and overskilling incidence, regardless whether referring to overeducation or overqualification. Those industries that have a greater innovative intensity (Knowledge Intensive Services and Manufacturing), shows, on average, lower incidence of both overeducation and overskilling. Surprisingly, Public Services and Commercial activities, showing a lower innovative intensity and uncertain economic environment, present, on average, a higher level of overeducation (see Graph I).

These group of results suggest that, as overeducation has been calculated using indirect subjective measures, an adequate classification of the type of existing environment (in our case by innovative intensity and economic environment) could influence the perception that workers have on the levels of qualification with respect to those required in their jobs.

GRAPH I. Incidence of mismatch and dimensions of the working environments (innovative intensity / uncertainty of the environment)



Source: Own elaboration in Spanish sample database PIAAC, INE and BdE.

Wage effects of overeducation (and overskilling) across working environments

Wage effects of overeducation are presented in Tables V and VI. The first table shows the wage effects of overeducation for all industries (pool). In this case, we include 6 industry dummy variables as fixed effects, referring to the industries under study (Manufacturing, KIS, Construction, Tourism and Commerce). The second table refers to the wage effects of overeducation, but in this case (given space constraints), estimates presented have been made for two industries, those opposed in terms of their innovative intensity and the uncertainty of the environment, which are analysed on a case-by-case basis. For purely expository purposes, only a summary is presented with estimates of mismatch and human capital variables.

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TABLE V. Effects of job mismatch (education and skills) on wages

Dep variables: ln (wages)	M1: OLS		M2: PIAACREG		M3: Heckman (2Stps)	
Overeducation	-0,1154	***	-0,1152	***	-0,1289	***
Undereducation	0,0676	**	0,0672	**	0,0807	***
Overskilled	-0,0038		-0,0037		-0,0059	
Underskilled	-0,0421		-0,0434		-0,0736	
Schooling (yrs)	0,0447	***	0,0441	***	0,0495	***
Numeracy score*	0,0009	***	0,0006		0,0007	***
Experience (yrs)	0,0121	***	0,0120	***	0,0113	***
Experience^2 (yrs)	-0,0001		-0,0001	*	-0,0001	
Female	-0,1004	***	-0,0986	***	-0,1367	***
Immigrant (1G)	-0,0192		-0,0167		-0,0700	**
Excellent & Very good health	0,0070		0,0061		0,0172	
Living w/spouse-partner	0,0383		0,0375	*	0,0344	
Having children	0,0540	*	0,0536	**	0,0667	**
SME	-0,1603	***	-0,1606	***	-0,1565	***
Private Sector	0,0744		0,0781	*	0,1049	
Public Sector	0,2236	***	0,2264	***	0,2760	***
Supervising employees	0,1274	***	0,1271	***	0,1373	***
Full time	-0,0500	*	-0,0497	*	-0,0608	**
REQ_Well-qualified	0,1578	***	0,1571	***	0,1632	***
REQ_Basic qualification	-0,0499	*	-0,0502	**	-0,0214	
Involved_F & NF educ FJ	0,0785	***	0,0791	***	0,0744	***
Manufacturing	0,1926	***	0,1917	***	0,1694	***
Construction	0,1674	***	0,1676	***	0,1562	***
Commercial	0,1335	***	0,1328	***	0,1462	***
Tourism	0,1620	***	0,1617	***	0,1370	***
KIS	0,1657	***	0,1655	***	0,1468	***
Public Services	0,1416	***	0,1424	***	0,1105	***
_constant	1,4769	***	1,4560	***	1,4616	***

R-squared	0,4219		0,4225			
F	54,62	***				
Wald chi2					1507,07	***
Observations	2216		2216		2221	
rho					0,9667	
sigma					0,4423	
lambda / mills					0,4276	**
*** p < 0,01, ** p< 0,05, * p<0,1 NOTE: M1: OLS & M2: PIAACREG use Jackknife methods. M3: Heckman 2Stps						

Regarding the pool model (Table V), educational mismatch suggests that those workers who are overeducated suffer a penalty on their wages, compared to colleagues who have the same educational level, 11.5% (M1 and M2) and 12.9% (M3). Regarding workers with undereducation, we observe the opposite effect, that is, they benefit from a premium, compared to their peers with the same educational level. In this case, the premium has been 6,8% (M1 and M2) and 8.1% (M3). Over and under skilling variables are not conclusive, as estimates do not turn out to be statistically different from zero. Both groups of results are consistent with what is indicated in the literature (Hartog, 2000; McGuiness, 2006), regarding educational level. It should be recognized that, in this case, the skill mismatch does not influence wages.

For human capital variables, we observe that schooling and numeracy skills (scores) are significant. An additional year of schooling leads to 4.5% (M1), 4.4% (M2) and 5.0% (M3) of additional salary. Regarding numerical skills (test scores), they show a lower effect than schooling. Average figures for the three models indicate that scoring an additional point wages increase in 0.1%. Regarding the skill occupational classification (being well qualified vs having a basic qualification), wages for those well qualified account for 16% on average (15,8%, 15,7% and 16,3%). In the case individuals are classified as to hold a basic qualification, their wage variation suffers a penalisation, of between 2,1% (M3) and 5% (M1 and M2). Experience is significant and positive (1.2% on average for the three models), suggesting that the skills acquired in the job (learning by doing) become relevant. Complementing experience, in the job training

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(variables “Involved in F and NF training for the job”), has an important effect, ranging from 7,4% (M3) to 7,9% (MI and M2).

Regarding the job characteristics, wages are lower (16% on average for the three model) if been employed in a SME. In contrast, working in the public sector, wages increase between 2,2% (M1 and M2) and 2,8% (M3). If individual have and supervise employees, wages increase, between 12,7% (M1 and M2) and 13,7% (M3). Last, regarding the current employment status, if working full time, wages decrease, by 5% (M1 and M2) and 6,1% (M3).

Focusing on industry variables (dummies), all variables are significant, have a positive effect but show varying effects (magnitude). The wages effects by industries range from: 13,3% (Commercial activities) to 19,2% (Manufacturing) in M1 and M2, and between 11% (Public Sector) to 17% (Manufacturing) in M3. Within industry ranges, in the former models (M1 and M2), those industries showing wage effects above its mean (16%) are Manufacturing (19,2%), Construction (16,8%), KIS (16,6%) and Tourism (16,2%). In the latter model (M3), Manufacturing (17%), Construction (15,6%), KIS (17,7%) and Commercial (146%), show wage effects above its average (14,4%). As for those showing the lowest industry wage effects, Commercial (13,4%) in M1 and M2, and Tourism (13,7%) in M3, but surprisingly, Public Services (14,2% in M1 and M2, and 11,1% in M3) shows the lowest industry wage effect in all models. This fact reinforces the idea that industrial environments influence individual productivity (approached by wages), but even more, it opens the debate to consider own industrial dynamics, such as intensity of innovation or economic uncertainty contexts, as determining factors of educational wage effects (or individual productivity).

Given space constraints, wage effects of overeducated across working environments (industries) are show for two industries: Knowledge Intensive Services and Commercial Services, which have been found to be in the opposite ends in terms of industry dynamics, this is, scoring the highest/lowest in both the innovative intensity and economic uncertainty indexes.

On the one hand, in both industries, a wage penalty of overeducated workers exists. In the case of KIS, figures refer to 11,5% in M1 and M2, and 12% in M3. As for commercial services, wage effects represent 18,2% (in M1 and M2) and 14,4% (in M3). Regarding undereducation, likewise, a salary premium is observed in both sectors, being 11,3% (M1 and M2) and 16% (M3) in the case of KIS, and 19,7% (in M1 and M2) and 30,1% (M3) in commercial services. In the case of skill mismatch, figures for underskilling in the KIS have shown to be negative (2,5% for M1 & M2) but statistically equal to zero according to M3.

These results, particularly those of over-education, although in line with the literature (McGuiness, 2006), allow us to reach an interesting conclusion. Specifically, it is observed that the magnitude of the penalties (both over-education and under-education) are lower in the knowledge-intensive services industry. This fact suggests that working environments that show higher innovative intensities and lower environmental uncertainties (perhaps via differentiation by innovation), reduce the salary impacts of over-education. Putting it differently, these group of results support the assumption that working environments clearly influence wage effects. KIS overeducated workers have a higher return (lower penalty) for overeducation when compared to the commercial overeducated workers (higher penalty).

TABLE VI. Effects of Mismatch (Education and Skills) on Wages (dichotomous variables) by industrya: KIS and Commercial activities

Dep Variable ln (wage)	KIS						Commercial					
	M1		M2		M3		M1		M2		M3	
Overeducation	-0,1154	*	-0,1151	**	-0,1191	**	-0,1821	**	-0,1823	***	-0,1446	*
Undereducation	0,1129		0,1112	**	0,1590	***	0,1974	*	0,1962	***	0,3007	***
Overskilled	-0,0195		-0,0198		-0,0121		0,0491		0,0471		0,0025	
Underskilled	-0,2532	*	-0,2520	***	-0,1871		-0,2325		-0,2312		-0,1015	
Schooling (yrs)	0,0635	***	0,0629	***	0,0657	***	0,0666	***	0,0655	**	0,0560	***
Numeracy score*	0,0021	***	0,0006		0,0016	***	-0,0004		0,0007	**	0,0003	
Experience (yrs)	0,0281	***	0,0283	***	0,0204	***	0,0055		0,0051	*	0,0038	
Experience^2 (yrs)	-0,0003		-0,0004	**	-0,0002		0,0001		0,0002		0,0001	
*** p < 0,01, ** p< 0,05, * p<0,1 NOTE: M1: OLS and M2: PIACCREG use Jackknife methods. M3: Heckman 2Stps												

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Conclusion and policy implications

The phenomenon of overeducation, in particular given the sustained growth in the level of human capital and the inadequate allocation in the labour market (Hartog, 2000; McGuinness, 2006), has been extensively analysed, focusing in the relation between education-employment (mismatch) and its economic (and psychological) effects (wages or productivity at organisational, regional or country level) (Verdugo and Verdugo, 1989; Battu et al., 2000; Sloane et al, 1999; and Dolton and Vignoles, 2000; Büchel, 2002; Hartog and Oosterbeek, 1988; Alba-Ramírez (1993) and Murillo et al, 2012; Mateos-Romero and Salinas-Jiménez, 2018).

Overeducation concerns in the recent years have challenge the productive value of education as wages (and their differences) seems to be determined by both job characteristics and the productive characteristics of the individuals (Sattinger, 1993). Jobs then limit and imposes a ceiling on the productivity of the individuals. This ceiling will not allow overeducated individuals develop all their skills, which will result in a lower wage than if they held a position according to their skill level. Conversely undereducated individuals have limited productivity due to their lower skills, although the higher requirements of their job will allow him to benefit from a higher salary than if his requirements match those of the job.

This investigation provided evidence about the role working environments play over the wage effects of overeducation. Results suggest that, under different environments, the wage effects of overeducation varies. Industries where the innovative intensity and the industrial performance are higher/lower, wage penalties show lower/higher values.

Regarding the concerns about the validity of the assignment theory, if considering working environments and its influence on education (and skill) mismatch, for the Spanish case, it seems that higher education policy should rethink education oriented towards high-skilled and innovative jobs, with a life-long and life-wide approach, encouraging a closer coordination and cooperation not only between the different educational levels (secondary, post-secondary and university), but also with the labour market.

Education systems should respond (if possible, anticipate) quickly to changing working environments. Together with improving acute measurement of the skills and tasks (required) in jobs (Van der Velden and Bijlsma, 2019; Kracke and Rodrigues, 2020), guidance systems for students/individuals (specially for younger people), better gearing the practical contents of training to working environments, promoting training experiences/work practices (dual training) (Albert et al, 2018), including under national/international mobility/exchange programs (Di Paolo and Ramos, 2018), and even promoting committees made up of professionals and academics, can become relevant. Further, in the job training programmes, specifically those aiming to "use the skills" must be enforced.

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Data Bases

- Panel de Innovación Tecnológica (PITEC), INE
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