# Overeducation and workers' heterogeneity: is overeducation a real phenomenon in the Spanish labor market? 

Lucia Mateos Romero (luciamr@unex.es)<br>Universidad de Extremadura<br>Francisco Pedraja Chaparro (pedraja@unex.es)<br>Universidad de Extremadura<br>$\mathrm{M}^{\text {a }}$ Mar Salinas Jiménez (msalinas@unex.es)<br>Universidad de Extremadura


#### Abstract

This paper analyzes the economic effects of overeducation in the Spanish labor market by relaxing the assumption of homogeneous workers within the same educational level. Only workers with a higher education level are considered, differentiating between properly educated and overeducated workers. Moreover, a distinction is made between real and apparent overeducation. The PIAAC database is used and different methods are employed to measure educational mismatch and to differentiate between real and apparent overeducation. Among the obtained results it is found that most of the workers with a higher education level who appear to be overeducated in the Spanish labor market could in fact be considered as only apparently overeducated, being the wage penalty associated to this educational mismatch lower than the wage penalty suffered by real overeducated workers. Different returns to educational mismatch found for each group of overeducated individuals point hence to the need of taking account of worker's heterogeneity within educational levels when analyzing the returns to education and to educational mismatch.


Key words: educational mismatch; workers’ heterogeneity; real and apparent overeducation.

## 1. Introduction

Overeducation is a widely studied phenomenon in most developed countries. Freeman (1976) was one of the first authors attracting the attention to overeducation when returns to education started to decline in the United States. Since then, lot of work on the effects of educational mismatch has been carried out given the extent of the phenomenon and its negative consequences on wages. In this sense, when analyzing the returns to education it is usually found that, within a job, overeducated workers receive a wage premium compared to properly educated workers, although the returns to years of overeducation are lower than those of the education which is actually required for doing that job. When the comparison is made not within the job but with other individuals with a similar level of education, the results suggest that overeducated workers suffer a wage penalty as compared to workers who, with the same educational level, are properly educated for the job they do ${ }^{1}$.

Traditional theories and measures of educational mismatch implicitly assume homogeneity of workers within a similar educational level. Hence, when human capital is proxied by attained levels of education or by years of schooling, it is assumed that individuals within an educational level achieve similar levels of skills. However, there is a growing dissatisfaction with the use of such as measures to proxy for the human capital which is really acquired through education and a new trend of the literature is claiming to take account of skills' heterogeneity among workers who show similar levels of education.

This work aims to contribute to this literature, analyzing the economic effects of overeducation in the Spanish labor market by relaxing the assumption of homogeneous workers within the same educational level. The existence of heterogeneity among Spanish individuals with a higher education level is tested following a definition of overeducation similar to that proposed by Chevalier (2003), which distinguishes between workers who are really overeducated and those who are only formal or apparently overeducated by taking account of workers' satisfaction about the adjustment degree between their levels of education and the requirements of the job they hold. We use the PIAAC database and consider only the sample of workers holding a higher

[^0]degree, so workers in our sample would be either adequately educated for the job they do or overeducated. Among overeducated workers, we then distinguish between real and apparently overeducated and analyze the wage penalties associated to each group in order to test whether heterogeneity among workers within a similar level of education translate into different returns to education.

The rest of the paper is structured as follows. First, a review of the literature on workers heterogeneity within similar educational levels is offered. In section 3, the PIAAC database and the methodology and variables used in this study are presented. Section 4 offers the results of the empirical analysis. Finally, the paper closes with a section where the main conclusions of the study are discussed.

## 2. Literature review

It is usually considered that overeducation exists when an individual has a higher educational level than that which is required to perform her job. Three methods have traditionally been used to estimate educational mismatch: the objective or job analysis method, the subjective (direct or indirect) method and the statistical one ${ }^{2}$. In any case, when looking at educational mismatch, the educational level of the individual is compared to the requirements of the job, thus assuming that education reflects the skills needed to perform a job. However, there is an increasing dissatisfaction with this hypothesis since workers with similar levels of education may show very different skills.

The idea of skills' heterogeneity among workers within a similar level of education has recently lead to different lines of research which aim to address this hypothesis. In particular, three lines of research stand out: the first one differentiates between educational and skill mismatches, showing that educational mismatch weakly correlates with skill mismatch; the second one uses panel data techniques to control for unobserved heterogeneity; and the last one aims to redefine overeducation taking account of other variables which allow to distinguish between real (or genuine) and formal (or apparent) overeducation.

[^1]Among the first group of works, Allen and van der Velden (2001) were pioneers in approaching the idea of skills heterogeneity. Using a sample of Dutch individuals, they aimed to test whether educational mismatch involves a mismatch in skills. For the measurement of both educational and skills mismatches they use the indirect subjective method and find a weak correlation between overeducation and a surplus of skills, although a large proportion of the overeducated individuals declared that they were not underutilizing those skills. Additionally, when educational and skills mismatches are introduced into a wage regression, educational mismatch shows a greater impact on wages than skills mismatch does.

A similar work is carried out by Di Pietro and Urwin (2006) with Italian individuals to prove to what extent overeducation reflects an underutilization of skills. Their sample is limited to workers with a University degree who are asked whether they use the skills they acquired during their studies at the University in their current job. They found a strong correlation between overeducation and skills underutilization. However, when variables of educational and skills mismatch are jointly introduced in a wage regression, the penalty to overeducation is not reduced by the underutilization of skills.

Green and McIntosh (2007) continue this line of research working with a sample of British individuals. In their study, educational mismatch weakly correlates with skills mismatch since some overeducated individuals seem to show an excess of skills which are consequently been underutilized. However, a large part of the overeducated workers declare to hold a job which match their skills. As it was the case in previous studies, these authors do not find any decrease in the wage penalty to overeducation when skill mismatch is introduced in a wage regression.

Contrary to the assumptions of the assignment theory, all these works conclude that educational mismatch and skills mismatch are two different phenomena, what implies that individuals with the same level of education can show very different levels of skills, so that being overeducated does not necessarily lead to an underutilization of the skills.

A second group of works makes use of longitudinal or panel data to control for unobserved heterogeneity among workers. Bauer (2002) uses panel data from a sample of German individuals to check if the traditional effects of overeducation on wages remain once unobserved heterogeneity is controlled for. To this end, several specifications are estimated following Duncan and Hoffman (1981) and Verdugo and

Verdugo (1989). The results obtained with pooled OLS estimates are in line with the previous literature: the wage premium for years of overeducation is positive but lower than that estimated for years of required education ( $9 \%$ vs. $10.7 \%$ ). Moreover, when the comparison is done among individuals with a similar level of education, a $10.6 \%$ wage penalty is found for overeducated workers as compared to individuals who, with a similar education level, hold a job which match their qualifications. When these specifications are estimated by random and fixed effects the results change significantly. In the case of the ORU specification, the wage premium estimated for years of overeducation and for years of required education is very similar ( $6.2 \%$ vs. $6.9 \%$ ); and when the Verdugo and Verdugo's specification is estimated, the wage penalty for overeducated individuals is clearly reduced (4.2\% when random effects are used and $2.8 \%$ in the case of the fixed effect estimator).

Using longitudinal data for Canadian individuals, Frenette (2004) obtains similar results. When wage equations are estimated by OLS, the results are in accordance to previous literature on educational mismatch, but when a fixed effects estimator is used to control for unobserved heterogeneity, the wage penalty for overeducated workers decrease from $11.1 \%$ to $6 \%$. This estimates show that the economic effects of the overeducation may be overestimated if workers' heterogeneity is not taken into account.

In a similar vein, Lindley and McIntosh (2009) use panel data from Britain individuals and estimate the returns to education through an ORU specification by OLS and by fixed effects, finding that the differences between the returns to years of required education and to years of overeducation are reduced when account is taken of unobserved heterogeneity.

In sum, research with longitudinal or panel databases, using the appropriate econometric methods, provide evidence of the existence of unobserved heterogeneity among workers. However, unobserved heterogeneity explains only part of the wage differences which are due to educational mismatch, but they do not completely disappear when unobserved heterogeneity is considered.

The third line of research within the new literature on heterogeneous skills bases on alternative definitions for educational mismatch in order to reflect this heterogeneity in skills. The idea is that, within the group of workers classified as overeducated, it is necessary to distinguish between those workers who truly underutilize their skills
(individuals with real or genuine overeducation) and those who in fact do not hold the skills which one could expect according to their educational level (formally or apparently overeducated workers).

Chevalier (2003) was pioneer in proposing an alternative definition that considers the heterogeneity of workers within a same educational level. Using a sample of workers with a University education level from the United Kingdom, individuals are classified either as being adequately educated if they are employed in a qualified job or as overeducated otherwise. Next, he relies on a variable of satisfaction as regards the adjustment between the level of education and the job hold by the individuals, so that overeducated workers who declare to be satisfied with the match between their education and the job they hold would be considered as only apparently overeducated. On the contrary, overeducated workers who declare to be dissatisfied with the adjustment between their education and the job they do would be considered as genuinely overeducated. Once this distinction is made, the results of a wage regression show that the pay penalty is higher for the genuinely overeducated workers than for the apparently overeducated ( $23.2 \%$ vs. $5.1 \%$ ). These results hence support the hypothesis of workers heterogeneity within the same educational level by estimating different wage penalties for individuals with real and apparent overeducation.

Chevalier and Lindley (2009) extend that analysis and, in addition to differentiating between genuine and apparently overeducated workers, they consider whether the individuals have an excess or a deficit of skills. They also take account of unobservable skills given the longitudinal character of their database. Once again, and controlling for both observed and unobserved skills, they find significant wage penalties for overeducation, being this pay penalty greater in the case of genuine overeducated workers (20.8\% vs. 5.6\%).

More recently, Pecoraro (2014) combines the above approaches by taking account of both educational and skill mismatches and considering that overeducation is real when the individuals also declare to have a mismatch in skills. This study also controls for unobserved heterogeneity by means of fixed and random effects estimators. When the estimations are run by OLS, a pay penalty of $15.8 \%$ is estimated for workers with real overeducation, whereas a penalty of $8.3 \%$ is found for apparently overeducated workers. These pay penalties diminish, although they do not disappear, when the estimations are run by fixed and random effects models.

In short, the empirical evidence tend to support the hypothesis of heterogeneous skills among workers within a similar level of education, suggesting that education mismatch is only weakly correlated to skills mismatch and pointing to different economic effects of educational mismatch when a distinction is made between genuine and apparent overeducation.

## 3. Data and methodology

### 3.1. Database

The data used in this study come from the Programme for the International Assessment of Adult Competencies (PIAAC), a new survey developed by the OECD which provides information about adults aged 16 to 65. Two modules provide information on cognitive skills (i.e. literacy and numeracy) and skills' use at the workplace, whereas a background questionnaire offers information about the demographic characteristics, education and training, social background, income or employment status of the individuals.

The sample selection, in the case of Spain, was conducted by the National Institute of Statistics. A multistage stratified cluster sampling design was used and 14400 individuals were selected in two stages. First, 1200 census tracts with a probability proportional to their size were chosen. In a second step, people with the same probability were selected by systematic sampling. The result is a sample with 6055 observations. Since the sample design does not respond to a simple random selection, it is necessary to use sampling weights in the estimations. These weights, provided within the PIAAC dataset, are defined as the inverse of the probability of selection of an individual and its use corrects possible sampling errors.

In this study, the sample is restricted to employees with a higher education level. In addition, workers for whom information is not available to define the educational mismatch variables are dropped from the analysis and the maximum wage has been limited to 200 euros per hour (including bonuses) to avoid outliers that could distort the estimates. As result, the final sample used in the estimations contains 999 observations.

### 3.2. Methodology and variables

According to previous literature, the effects of overeducation on individuals' wages are estimated by an equation of the following form:

$$
\begin{equation*}
\ln \left(w_{i}\right)=\alpha+\beta_{O} O_{i}+\beta_{S} S_{i}+\gamma_{l} E_{i}+\gamma_{2} E_{i}^{2}+\delta X+u_{i} \tag{1}
\end{equation*}
$$

where $\ln \left(w_{i}\right)$ is the natural logarithm of the hourly wage, $O$ is a dummy variable for overeducated individuals, $S$ is a variable measuring years schooling, $E$ refers to work experience and $X$ is a vector of control variables relating to personal characteristics and employment status.

Next, in order to test the hypothesis of heterogeneity among workers within the same educational level, the overeducation variable is broken down into two categories to distinguish between genuine and apparently overeducated workers. A second specification of the model is then estimated:

$$
\begin{equation*}
\ln \left(w_{i}\right)=\alpha+\beta_{G O} G O_{i}+\beta_{A O} A O_{i}+\beta_{S} S_{i}+\gamma_{1} E_{i}+\gamma_{2} E_{i}^{2}+\delta X+u_{i} \tag{2}
\end{equation*}
$$

where $G O$ is a dummy variable showing if an individual is genuinely overeducated and $A O$ is a dummy for apparently overeducated workers. When these variables are included in the specification, one would expect to find different pay penalties for genuine and apparently overeducated workers if the hypothesis of heterogeneity among workers within a similar level of education stands out.

All the estimated specifications take as dependent variable the natural logarithm of the hourly wage (including bonuses) as declared by workers in the background questionnaire. As independent variables, we introduce some variables related to human capital, such as years of attained education and years of work experience (and its square), as well as other personal characteristics variables, like gender and nationality, and some labor status related variables (e.g. firm size, supervisory tasks, ownership sector) .

Table 1 offers the descriptive statistics of these variables. The hourly wage ranges from 2.06 to 107.87 euros, being the average hourly wage 14.43. As only individuals with a higher education level are considered, the minimum years of attained education are 14 and the maximum rise to 21 . Average years of experience stand at 15.64 . Males represent $46 \%$ of the sample and $92 \%$ of the individuals were born in Spain. As regards
the labor status variables, $57 \%$ of the employees in the sample work in small firms (having less than 50 employees), $24 \%$ in medium firms (those employing between 51 and 250 employees) and $19 \%$ in large firms (with more than 251 employees), and $36 \%$ carry out supervisory tasks and $40 \%$ work in the public sector.

Table 1. Descriptive statistics

| VARIABLE | MEAN | S.D. | MIN | MAX |
| :--- | :---: | :---: | :---: | :---: |
| Hourly wage | 14.43 | 9.23 | 2.06 | 107.87 |
| Years of schooling | 15.64 | 1.53 | 14 | 21 |
| Experience (years) | 15.64 | 9.70 | 0 | 48 |
| Experience square | 338.43 | 373.55 | 0 | 2304 |
| Male | 0.46 | 0.50 | 0 | 1 |
| Female | 0.54 | 0.50 | 0 | 1 |
| Spanish | 0.92 | 0.27 | 0 | 1 |
| Immigrant | 0.08 | 0.27 | 0 | 1 |
| Small firm | 0.57 | 0.49 | 0 | 1 |
| Medium firm | 0.24 | 0.53 | 0 | 1 |
| Large firm | 0.19 | 0.39 | 0 | 1 |
| Supervisor | 0.36 | 0.48 | 0 | 1 |
| Public sector | 0.40 | 0.49 | 0 | 1 |

Source: own elaboration using PIAAC data. Descriptive statistics calculated for 999 observations and using sampling weights.

As only individuals with a higher education level are considered, educational mismatch in this study refers to overeducation, so workers in the sample will be either adequately educated or overeducated. In order to analyze educational mismatch, the three traditional methods proposed in the literature are used: the objective method, the subjective method, and the statistical one. To apply the objective method we look at the information provided by the International Labor Organization, which allows one to establish a match between educational levels and occupational groups, so individuals with higher education level would be expected to be in skilled occupations if they were adequately educated for their job (occupational groups 1,2 or 3 ), while individuals in other occupations could be considered as overeducated ${ }^{3}$. As regards the subjective method, we compare the years of attained education by an individual (yrsqual in the PIAAC database) with the years she declared as required to get her job (yrsget in the PIAAC database); if years of attained education are equal to years required to get the job individuals are considered as adequately educated, whereas they are considered as overeducated if years of schooling are greater than those required for their job. Finally,

[^2]the statistical method is used considering the average years of education for each occupational group as a measure of realized matched, so workers in the range within plus and minus one standard deviation from the mean are considered as adequately educated, whereas those with more years of education than one standard deviation above the mean for their specific occupation are defined as overeducated.

Once the variables of educational mismatch are defined, we follow Chevalier's (2003) idea to distinguish between genuine and apparently overeducated workers according to their satisfaction with the match between their level of education and their job, so overeducated workers who are satisfied with their match are considered as apparently overeducated whereas those who are dissatisfied are seen as genuinely overeducated. In particular, in the background questionnaire of the PIAAC database we find the next question: "Thinking about whether this qualification is necessary for doing your job satisfactorily, which of the following statements would be most true?". Possible answers are: (1) This level is necessary, (2) a lower level would be sufficient and (3) a higher level would be needed. In order to define the heterogeneity related variables, we consider those overeducated employees who think that their level of education is necessary to do their job satisfactorily as apparently overeducated workers. On the contrary, those who answer that a lower level of education would be sufficient (they are hence dissatisfied with the match between their level of education and their job) are considered as genuinely overeducated.

Table 2 offers the distribution of educational mismatch according to the objective, subjective and statistical methods and using the variable related to the individuals' satisfaction about the match between their level of education and the needs of their job to differentiate between genuine and apparently overeducated workers. As can be observed, most workers appear to be adequately educated (between $53 \%$ and $76 \%$ depending on the method used to measure educational mismatch), although the percentage of workers showing overeducation is relatively high (between $13 \%$ and $32 \%)$. It is also noteworthy that, regardless of the method used to measure educational mismatch, most of the overeducated workers declare to be satisfied with the match between their level of education and needs of their job, being hence classified as only apparently overeducated. In fact, apparently overeducated workers represent between four and five times more than the percentage of employees who are classified as genuinely overeducated.

Table 2. Educational match and genuine and apparently overeducation according to the satisfaction between levels of education and needs of job (percentage).

|  | Objective method | Subjective method | Statistical method |
| :---: | :---: | :---: | :---: |
| Adequately educated | 62,46 | 53,35 | 75,88 |
| Genuinely overeducated | 6,31 | 5,21 | 2,20 |
| Apparently overeducated | 25,63 | 26,63 | 11,11 |
| (Missing values) | $(5,61)$ | $(14,61)$ | $(10,81)$ |

Source: Own elaboration using PIAAC data.

PIAAC also provides information about overall satisfaction in the current job. In this case, the question asked is as follows: "All things considered, how satisfied are you with your current job?". We also use this variable as an alternative to classify overeducated workers as apparent or genuinely overeducated depending on whether they declare to be satisfied or dissatisfied, respectively, with their job. Table 3 shows the distribution of workers according to their educational match and distinguishing between real and apparent overeducation on the basis of this variable of overall satisfaction with the job. We find again that most of the overeducated workers can be classified as apparently overeducated, with the percentage of apparent overeducation being even greater than before (the percentage of apparently overeducated workers are now around ten times higher than that of genuinely overeducated employees).

Table 3. Educational match and genuine and apparently overeducation according to overall satisfaction with the job (percentage).

|  | Objective method | Subjective method | Statistical method |
| :---: | :---: | :---: | :---: |
| Adequately educated | 62,46 | 53,35 | 75,88 |
| Genuinely overeducated | 2,90 | 2,90 | 0,80 |
| Apparently overeducated | 28,73 | 32,03 | 12,11 |
| (Missing values) | $(5,91)$ | $(11,71)$ | $(11,21)$ |
| Source: Own elaboration using PIAAC data. |  |  |  |

## 4. Results

To study the hypothesis of workers' heterogeneity we estimate different specifications of equations (1) and (2) in order to check if different wage penalties appear depending on whether the individuals are genuine or apparently overeducated. In particular, these equations are estimated for each measure of educational mismatch and for the two definitions used to differentiate between real and apparent overeducation.

In all the estimates, the Heckman's methodology (Heckman, 1979) is used to control for possible sample selection bias that could appear as result of wages being observed only for employees. To this end, the probability of being employed is first analyzed by a probit model in which the explanatory variables are years of attained education, work experience and its squared, age, gender (male), nationality (immigrant), marital status, skilled and semi-skilled occupations and children at home. Then, the inverse Mills ratio is calculated and introduced as an explanatory variable in the wage regression so any possible sample selection bias would be corrected.

Table 4 offers the estimates of the earning equations with educational mismatch being measured by the objective, subjective and statistical methods. In all cases, the overeducation variable is first included without considering any heterogeneity among workers (first column in each case) and then distinguishing between genuine and apparent overeducation by means of the satisfaction declared by the individuals as regards the match between their educational level and the needs of their job (second column for each method of mismatch measurement).

Despite some differences depending on the method used to measure educational mismatch, the results obtained when the overeducation variable is introduced into the analysis, without taking account of workers heterogeneity, are consistent and in line with the existing literature on educational mismatch. As regards the educational variables, returns to years of schooling are estimated in the range of 5\% (with the objective method) to $9 \%$ (using the statistical method) whereas a pay penalty to overeducation is estimated between $17 \%$ (subjective and statistical methods) and $21 \%$ (objective method). The control variables also show the expected coefficients: a bonus of $2-3 \%$ is estimated for each year of work experience, males earn more than females (12-13\%) and immigrants earn less than Spanish workers (9-11\%); labor status variables show that employees in medium or large firms earn more than workers in small firms ( $13 \%$ and $17 \%$, respectively), and carrying out supervisory tasks and working in the public sector also show positive effects on wages. The inverse of the Mills' ratio is negative and significant, so if sample selection bias were not corrected the results would be underestimated.

When the overeducation variable is decomposed into real and apparent overeducation, different pay penalties are estimated for each group of overeducated workers. Thus,
regardless of the method used to measure educational mismatch, a pay penalty between $21 \%$ and $23 \%$ is estimated for genuinely overeducated workers whereas the wage penalty estimated for apparently overeducated individuals reduces to $8-9 \%$. These results point to the existence of workers heterogeneity among individuals with the same level of education (in our case, with a level of higher education) and suggest that when homogeneous workers are considered the effects of overeducation would be overestimated. As regards the other explanatory variables, the estimated coefficients remain very close to those reported above, so we do not extend here on their comments.

Table 4. Effects of overeducation on wages. Genuine and apparent overeducation defined according to satisfaction between level of education and needs of the job.

|  | Objective method |  | Subjective method |  | Statistical method |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Overeducation | $\begin{gathered} -0.210^{* * *} \\ (0.0382) \end{gathered}$ |  | $\begin{gathered} -0.174^{* * *} \\ (0.0311) \end{gathered}$ |  | $\begin{gathered} -0.176^{* * *} \\ (0.0457) \end{gathered}$ |  |
| Genuinely overeducated |  | $\begin{gathered} -0.206 * * * \\ (0.0587) \end{gathered}$ |  | $\begin{gathered} -0.220^{* * *} \\ (0.0651) \end{gathered}$ |  | $\begin{gathered} -0.235 * * * \\ (0.0863) \end{gathered}$ |
| Apparently overeducated |  | $\begin{gathered} -0.0897 * * \\ (0.0384) \end{gathered}$ |  | $\begin{gathered} -0.0939 * * * \\ (0.0342) \end{gathered}$ |  | $\begin{aligned} & -0.0794 \\ & (0.0515) \end{aligned}$ |
| Years of schooling | $\begin{gathered} 0.0547 * * * \\ (0.0104) \end{gathered}$ | $\begin{gathered} 0.0594^{* * *} \\ (0.0104) \end{gathered}$ | $\begin{gathered} 0.0766^{* * *} \\ (0.0105) \end{gathered}$ | $\begin{gathered} 0.0705^{* * *} \\ (0.0105) \end{gathered}$ | $\begin{gathered} 0.0913^{* * *} \\ (0.0123) \end{gathered}$ | $\begin{gathered} 0.0772^{* * *} \\ (0.0122) \end{gathered}$ |
| Experience | $\begin{gathered} 0.0289 * * * \\ (0.00742) \end{gathered}$ | $\begin{aligned} & 0.0209 * * * \\ & (0.00706) \end{aligned}$ | $\begin{gathered} 0.0202^{* * *} \\ (0.00694) \end{gathered}$ | $\begin{aligned} & 0.0176^{* *} \\ & (0.00692) \end{aligned}$ | $\begin{aligned} & 0.0168^{* *} \\ & (0.00691) \end{aligned}$ | $\begin{aligned} & 0.0153^{* *} \\ & (0.00688) \end{aligned}$ |
| Experience ${ }^{2}$ | $\begin{gathered} -0.000453^{* *} \\ (0.000182) \end{gathered}$ | $\begin{gathered} -0.000261 \\ (0.000175) \end{gathered}$ | $\begin{aligned} & -0.000261 \\ & (0.000171) \end{aligned}$ | $\begin{gathered} -0.000193 \\ (0.000172) \end{gathered}$ | $\begin{aligned} & -0.000169 \\ & (0.000172) \end{aligned}$ | $\begin{aligned} & -0.000136 \\ & (0.000172) \end{aligned}$ |
| Male | $\begin{gathered} 0.129 * * * \\ (0.0289) \end{gathered}$ | $\begin{gathered} 0.118^{* * *} \\ (0.0291) \end{gathered}$ | $\begin{gathered} 0.127^{* * *} \\ (0.0286) \end{gathered}$ | $\begin{gathered} 0.121^{* * *} \\ (0.0289) \end{gathered}$ | $\begin{gathered} 0.116^{* * *} \\ (0.0291) \end{gathered}$ | $\begin{aligned} & 0.114^{* * *} \\ & (0.0292) \end{aligned}$ |
| Immigrant | $\begin{aligned} & -0.106^{*} \\ & (0.0638) \end{aligned}$ | $\begin{gathered} -0.107 \\ (0.0657) \end{gathered}$ | $\begin{aligned} & -0.0854 \\ & (0.0658) \end{aligned}$ | $\begin{aligned} & -0.0970 \\ & (0.0666) \end{aligned}$ | $\begin{gathered} -0.112^{*} \\ (0.0641) \end{gathered}$ | $\begin{gathered} -0.103 \\ (0.0648) \end{gathered}$ |
| Medium firm | $\begin{aligned} & 0.132 * * * \\ & (0.0311) \end{aligned}$ | $\begin{aligned} & 0.133 * * * \\ & (0.0317) \end{aligned}$ | $\begin{gathered} 0.126 * * * \\ (0.0318) \end{gathered}$ | $\begin{aligned} & 0.130^{* * *} \\ & (0.0320) \end{aligned}$ | $\begin{aligned} & 0.125 * * * \\ & (0.0316) \end{aligned}$ | $\begin{aligned} & 0.130 * * * \\ & (0.0320) \end{aligned}$ |
| Large firm | $\begin{aligned} & 0.171^{* * *} \\ & (0.0405) \end{aligned}$ | $\begin{aligned} & 0.165 * * * \\ & (0.0404) \end{aligned}$ | $\begin{gathered} 0.165 * * * \\ (0.0398) \end{gathered}$ | $\begin{gathered} 0.161^{* * *} \\ (0.0402) \end{gathered}$ | $\begin{gathered} 0.168^{* * *} \\ (0.0401) \end{gathered}$ | $\begin{aligned} & 0.165 * * * \\ & (0.0401) \end{aligned}$ |
| Supervisor | $\begin{gathered} 0.186^{* * *} \\ (0.0302) \end{gathered}$ | $\begin{aligned} & 0.191^{* * *} \\ & (0.0305) \end{aligned}$ | $\begin{aligned} & 0.169 * * * \\ & (0.0302) \end{aligned}$ | $\begin{aligned} & 0.182^{* * *} \\ & (0.0304) \end{aligned}$ | $\begin{gathered} 0.198^{* * *} \\ (0.0300) \end{gathered}$ | $\begin{aligned} & 0.202^{* * *} \\ & (0.0303) \end{aligned}$ |
| Public sector | $\begin{aligned} & 0.104 * * * \\ & (0.0318) \end{aligned}$ | $\begin{gathered} 0.116^{* * *} \\ (0.0317) \end{gathered}$ | $\begin{aligned} & 0.123^{* * *} \\ & (0.0312) \end{aligned}$ | $\begin{aligned} & 0.124^{* * *} \\ & (0.0314) \end{aligned}$ | $\begin{aligned} & 0.123^{* * *} \\ & (0.0317) \end{aligned}$ | $\begin{aligned} & 0.129 * * * \\ & (0.0317) \end{aligned}$ |
| lambda | $\begin{gathered} -0.270 \\ (0.165) \end{gathered}$ | $\begin{gathered} -0.527^{* * *} \\ (0.151) \end{gathered}$ | $\begin{gathered} -0.521^{* * *} \\ (0.141) \end{gathered}$ | $\begin{gathered} -0.614^{* * *} \\ (0.140) \end{gathered}$ | $\begin{gathered} -0.618^{* * *} \\ (0.140) \end{gathered}$ | $\begin{gathered} -0.662^{* * *} \\ (0.138) \end{gathered}$ |
| Constant | $\begin{gathered} 1.296 * * * \\ (0.202) \end{gathered}$ | $\begin{gathered} 1.318^{* * *} \\ (0.203) \end{gathered}$ | $\begin{gathered} 1.095 * * * \\ (0.208) \end{gathered}$ | $\begin{gathered} 1.202 * * * \\ (0.208) \end{gathered}$ | $\begin{gathered} 0.870^{* * *} \\ (0.232) \end{gathered}$ | $\begin{gathered} 1.100^{* * *} \\ (0.230) \end{gathered}$ |


| Obs. | 999 | 999 | 999 | 999 | 999 | 999 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| R-squared | 0.379 | 0.367 | 0.382 | 0.370 | 0.367 | 0.363 |

Standard errors in brackets. *** $\mathrm{p}<0.01$, ** $\mathrm{p}<0.05$, * $\mathrm{p}<0.1$
Source: PIAAC database. Equations have been estimated using sampling weights.

The above analysis is replicated by considering the overall satisfaction with the job as a means to differentiate between genuine and apparent overeducation. Table 5 offers the results when overall satisfaction is considered to take account of workers heterogeneity. Overall, the results are consistent with those presented in table 4 since different pay penalties are estimated for workers with real and apparent overeducation. The estimates for the real overeducation variables are however not statistically significant when educational mismatch is measured by the subjective or the statistical methods. In any case, when educational mismatch is measured by the objective method, both real and apparent overeducation remain significant and the pay penalty estimated for real overeducated workers doubles that estimated for apparent overeducated individuals ( $22,3 \%$ vs. $11,6 \%$ ), thus suggesting that the hypothesis of workers heterogeneity holds in the Spanish labor market for individuals with a higher education level.

Table 5. Effects of overeducation on wages. Genuine and apparent overeducation defined according to overall satisfaction in the current job.

|  | Objective method <br> (1) <br> (2) |  | Subjective method <br> (3) <br> (1) |  | Statistical method (2) <br> (3) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Overeducation | $\begin{gathered} -0.210^{* * *} \\ (0.0382) \end{gathered}$ |  | $\begin{gathered} -0.174^{* * *} \\ (0.0311) \end{gathered}$ |  | $\begin{gathered} -0.176 * * * \\ (0.0457) \end{gathered}$ |  |
| Genuinely overeducated |  | $\begin{gathered} -0.223^{*} \\ (0.116) \end{gathered}$ |  | $\begin{gathered} -0.173 \\ (0.116) \end{gathered}$ |  | $\begin{gathered} 0.224 \\ (0.328) \end{gathered}$ |
| Apparently overeducated |  | $\begin{gathered} -0.116^{* * *} \\ (0.0354) \end{gathered}$ |  | $\begin{gathered} -0.179 * * * \\ (0.0307) \end{gathered}$ |  | $\begin{gathered} -0.218^{* * *} \\ (0.0449) \end{gathered}$ |
| Years of schooling | $\begin{gathered} 0.0547 * * * \\ (0.0104) \end{gathered}$ | $\begin{gathered} 0.0600^{* * *} \\ (0.0104) \end{gathered}$ | $\begin{gathered} 0.0766 * * * \\ (0.0105) \end{gathered}$ | $\begin{gathered} 0.0761^{* * *} \\ (0.0106) \end{gathered}$ | $\begin{gathered} 0.0913^{* * *} \\ (0.0123) \end{gathered}$ | $\begin{gathered} 0.0891^{* * *} \\ (0.0123) \end{gathered}$ |
| Experience | $\begin{gathered} 0.0289 * * * \\ (0.00742) \end{gathered}$ | $\begin{gathered} 0.0216 * * * \\ (0.00715) \end{gathered}$ | $\begin{gathered} 0.0202 * * * \\ (0.00694) \end{gathered}$ | $\begin{gathered} 0.0200^{* * *} \\ (0.00694) \end{gathered}$ | $\begin{aligned} & 0.0168 * * \\ & (0.00691) \end{aligned}$ | $\begin{aligned} & 0.0162^{* *} \\ & (0.00689) \end{aligned}$ |
| Experience ${ }^{2}$ | $\begin{gathered} -0.000453^{* *} \\ (0.000182) \end{gathered}$ | $\begin{aligned} & -0.000285 \\ & (0.000177) \end{aligned}$ | $\begin{aligned} & -0.000261 \\ & (0.000171) \end{aligned}$ | $\begin{aligned} & -0.000258 \\ & (0.000173) \end{aligned}$ | $\begin{gathered} -0.000169 \\ (0.000172) \end{gathered}$ | $\begin{aligned} & -0.000155 \\ & (0.000171) \end{aligned}$ |
| Male | $\begin{gathered} 0.129 * * * \\ (0.0289) \end{gathered}$ | $\begin{gathered} 0.124^{* * *} \\ (0.0288) \end{gathered}$ | $\begin{gathered} 0.127 * * * \\ (0.0286) \end{gathered}$ | $\begin{gathered} 0.125^{* * *} \\ (0.0289) \end{gathered}$ | $\begin{gathered} 0.116 * * * \\ (0.0291) \end{gathered}$ | $\begin{gathered} 0.116 * * * \\ (0.0288) \end{gathered}$ |
| Immigrant | $\begin{aligned} & -0.106^{*} \\ & (0.0638) \end{aligned}$ | $\begin{aligned} & -0.0987 \\ & (0.0660) \end{aligned}$ | $\begin{aligned} & -0.0854 \\ & (0.0658) \end{aligned}$ | $\begin{aligned} & -0.0921 \\ & (0.0641) \end{aligned}$ | $\begin{aligned} & -0.112 * \\ & (0.0641) \end{aligned}$ | $\begin{aligned} & -0.114^{*} \\ & (0.0646) \end{aligned}$ |
| Medium firm | 0.132*** | 0.129*** | 0.126*** | 0.128*** | 0.125*** | 0.125*** |


|  | $(0.0311)$ | $(0.0316)$ | $(0.0318)$ | $(0.0315)$ | $(0.0316)$ | $(0.0317)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Large firm | $0.171^{* * *}$ | $0.168^{* * *}$ | $0.165^{* * *}$ | $0.170^{* * *}$ | $0.168^{* * *}$ | $0.163^{* * *}$ |
|  | $(0.0405)$ | $(0.0403)$ | $(0.0398)$ | $(0.0403)$ | $(0.0401)$ | $(0.0391)$ |
| Supervisor | $0.186^{* * *}$ | $0.191^{* * *}$ | $0.169^{* * *}$ | $0.173^{* * *}$ | $0.198^{* * *}$ | $0.197^{* * *}$ |
|  | $(0.0302)$ | $(0.0304)$ | $(0.0302)$ | $(0.0301)$ | $(0.0300)$ | $(0.0298)$ |
| Public sector | $0.104^{* * *}$ | $0.117^{* * *}$ | $0.123^{* * *}$ | $0.114^{* * *}$ | $0.123^{* * *}$ | $0.126^{* * *}$ |
|  | $(0.0318)$ | $(0.0316)$ | $(0.0312)$ | $(0.0317)$ | $(0.0317)$ | $(0.0315)$ |
| lambda | -0.270 | $-0.495^{* * *}$ | $-0.521^{* * *}$ | $-0.517^{* * *}$ | $-0.618^{* * *}$ | $-0.654^{* * *}$ |
|  | $(0.165)$ | $(0.150)$ | $(0.141)$ | $(0.140)$ | $(0.140)$ | $(0.136)$ |
| Constant | $1.296^{* * *}$ | $1.297^{* * *}$ | $1.095^{* * *}$ | $1.098^{* * *}$ | $0.870^{* * *}$ | $0.917^{* * *}$ |
|  | $(0.202)$ | $(0.203)$ | $(0.208)$ | $(0.210)$ | $(0.232)$ | $(0.232)$ |
|  |  |  |  |  |  |  |
| Obs. | 999 | 999 | 999 | 999 | 999 | 999 |
| R-squared | 0.379 | 0.367 | 0.382 | 0.382 | 0.367 | 0.373 |

Standard errors in brackets. *** $\mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05$, * $\mathrm{p}<0.1$
Source: PIAAC database. Equations have been estimated using sampling weights.

## 5. Conclusions

In this work, the assumption of homogeneous workers among individuals with the same level of education has been relaxed. Over the last decade, some researchers have suggested new ways to measure educational mismatch with the aim to consider the existence of heterogeneous workers, being the satisfaction self-declared by the individuals, as proposed by Chevalier (2003), one of the most commonly ways used to distinguish between genuine and apparently overeducated workers.

Using the PIAAC database, we have studied the hypothesis of heterogeneous workers in the Spanish labor market for individuals with a level of higher education. To obtain robust results, different educational mismatch measures have been considered. In addition, we considered two variables related to job satisfaction to differentiate between genuine and apparently overeducated workers. It is worthy to note that the measure of satisfaction about the match between the level of education and the needs of the job seems to be more appropriate to differentiate between real and apparent overeducation given that the measure of overall job satisfaction might lead to endogeneity problems (the overall job satisfaction might reflect individuals’ feelings about other aspects related with the job like working conditions, promotion opportunities, or wages). In any case, the obtained results are robusts to the use of one or another measure of educational mismatch and to the satisfaction variable considered to differentiate between real and apparent overeducation.

Analyzing the phenomenon of overeducation among individuals holding a higher education degree in the Spanish labor market, a first outstanding result is that most of the overeducated workers could in fact be classified as apparently overeducated given that a high percentage of the overeducated workers declare to be satisfied with the match between their level of education and needs of their job. Furthermore, when we distinguish between real and apparently overeducated workers in a wage regression, we observe that genuinely overeducated workers suffer a greater pay penalty than apparently overeducated workers do. This result points hence to the existence of heterogeneous workers and suggests that, if homogeneous workers were considered, the effects of overeducation on wages would be overestimated.

## References.

- Allen, J. \& Van der Velden, R. (2001): "Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on - the - job search", Oxford Economic Papers, 53(3), 434-452.
- Bauer, T. (2002): "Educational mismatch and wages: a panel analysis", Economic of Education Review, 21(3), 221-229
- Chevalier, A. (2003): "Measuring Over-Education", Economica, 70 (279), 509-531.
- Chevalier, A. \& Lindley, J. (2009): "Overeducation and the skills of UK graduates", Journal of the Royal Statistical Society: Series A (Statistics in Society), 172(2), 307-337.
- Cohn, E. \& Ng, Y.C. (2000): "Incidence and wage effects of overschooling and underschooling in Hong Kong", Economics of Education Review, 19(2), 159-168.
- Di Pietro, G. \& Urwin, P. (2006): "Education and Skills Mismatch in the Italian Graduate Labor Market", Applied Economics, 38, 79-93.
- Dolton, P. \& Vignoles, A. (2000): "The incidence and the effects of overeducation in the UK graduate labour market", Economics of Education Review, 19, 179-198.
- Duncan, G. \& Hoffman, S.D. (1981): "The Incidence and Wage Effects of Overeducation", Economics of Education Review, 1, 75-86.
- Green, F. \& McIntosh, S. (2007): "Is there a genuine under-utilization of skills amongst the over-qualified?", Applied Economics, 39(4), 427-439.
- Frenette (2004): "The overqualified Canadian graduate: the role of the academic program in the incidence, persistence, and economic returns to overqualification", Economics of Education Review, 23(1), 29-45.
- Freeman, R. (1976): The Overeducated American, American Press, New York.
- Hartog, J. (2000): "Over-education and Earnings: Where are We, Where Should We Go?", Economics of Education Review, 19, 131-147.
- Hartog, J. \& Oosterbeek, H. (1988): "Education, allocation and earnings in the Netherlands: Overschooling?", Economics of Education Review, 7(2), 185-194.
- Heckman, J.J. (1979): "Sample Selection Bias as a Specification Error", Econometrica, 47(1), 53-161.
- Lindley \& McIntosh (2009): "A panel data analysis of the incidence and impact of overeducation", Department of Economics, University of Sheffield, ISNN 17498368.
- Murillo, I.P., Rahona, M. \& Salinas, M.M. (2012): "Effects of educational mismatch on private returns to education: An analysis of the Spanish case (1995-2006)", Journal of Policy Modeling, 34(5), 646-659.
- Pecoraro, M. (2014): "Is there still a wage penalty for being overeducated but wellmatched in skills? A panel data analysis of a Swiss graduate cohort", Labour, 28(3), 309-337.
- Verdugo, R.R. \& Verdugo, N.T. (1989): "The impact of surplus schooling on earnings: Some additional findings", Journal of Human Resources, 24(4), 629-643.


## Annex.

Table A.1. Match between occupational group and level of education.

| Skilled occupations | Higher education |
| :---: | :---: |
| 1. Legislators, senior officials and managers <br> 2. Professionals <br> 3. Technicians and associate professionals | ISCED 5A ISCED 5B ISCED 6 |
| Semi-skilled occupations | Secondary education |
| 4. Clerks <br> 5. Service workers and shop and market sales workers <br> 6. Skilled agricultural and fishery workers <br> 7. Craft and related workers <br> 8. Plant and machine operators and assemblers | $\begin{aligned} & \text { ISCED2 } \\ & \text { ISCED3 } \\ & \text { ISCED4 } \end{aligned}$ |
| Elementary occupations | Primary education |
| 9. Elementary occupations | ISCED1 |


[^0]:    ${ }^{1}$ See Hartog and Oosterbeck (1988) for Holland; Verdugo and Verdugo (1989) for the United States; Dolton and Vignoles (2000) for the United Kingdom; Cohn and Ng (2000) for Hong Kong; or Murillo et al. (2012) for Spain. An extensive review on the effects of educational mismatch can be found in Hartog (2000).

[^1]:    ${ }^{2}$ A good description of each of these methods and a discussion of their advantages and disadvantages can be found in Hartog (2000).

[^2]:    ${ }^{3}$ A table showing the match between educational levels and occupational groups is provided in the Annex.

