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Abstract

This paper analyzes the effect of educational mismatch on wages, using a rich panel dataset of workers in the major euro area countries from 2006 to 2009, drawn from the *European Union Statistics on Income and Living Conditions* (Eurostat). We use a consistent estimator to address the two econometric problems faced by the empirical literature: the omitted variable bias and measurement error. In principle, our fixed effect estimates confirm that overeducated workers suffer a wage penalty of similar magnitude to the return on each year of schooling attained. Interestingly, when we split the sample by age, we find that the wages of people aged under 35 basically depend on the level of education attained, while those of workers aged over 35 depend on job educational requirements. These results are interpreted taking into account the impact of the depreciation of skills on human capital. The main policy implication of the paper is that overeducation constitutes a waste of resources. Therefore public authorities should seek to reduce the negative impact of overeducation on the labor market.

JEL classification: I21 J24 J31
Keywords: overeducation, educational mismatch, wages, ability bias, measurement error, panel data

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1.- Introduction

The analysis of educational mismatch is a matter of public policy interest insofar as it may indicate an inefficient allocation of the resources invested in education. It should be noted that public expenditure on education accounted for 5.1% of the European Union's (EU) total GDP[1] in 2008, at the same time as public spending on tertiary education amounted to 1.1% of EU GDP. The EU countries, therefore, have invested heavily in education, as can be seen, amongst other indicators, in the significant rise in the number of students in tertiary education, which almost tripled between 1975 and 2009[2]. However, in 2010 one out of every five graduates of tertiary education in Europe worked in a low-skilled job[3].

The aim of this paper is to analyze the effect of educational mismatch on wages. In the literature, two alternative theoretical hypotheses have been put forward to explain this problem: a) the human capital theory (Becker, 1964), which states, in a nutshell, that wages depend on the human capital of the worker and b) the job-competition theory (Thurow, 1975) which proposes that wages are dependent on the educational requirements of jobs. In the event of the supply of skilled labor growing faster than demand, the human capital theory foresees a temporary reduction in skilled workers' relative wages. The job-competition theory, in contrast, predicts a permanent reduction in the wages of overeducated workers, the under-utilization of their skills, and ultimately a waste of the resources invested in education.

This theoretical debate has given rise to an extensive literature which attempts to test both hypotheses empirically. However, many of the papers that estimate the effect of educational mismatch on wages have been heavily criticized for not taking two important

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[1] Private funding represents 13.8% of total expenditure on education in the EU. See Eurydice (2012), pp. 88 and 93.

[2] The number of students in tertiary education (ISCED 5 and 6) in the EU increased by 122% between 1975/76 and 1999/2000 (Eurydice, 2002). During the following decade (2000-2009) the student population across the EU-27 increased by an average of 22% (Eurydice, 2012). The annual growth rate for each period is 3.4% and 2.7% respectively.

[3] Ibidem, Figure G7, pp. 181-182.

econometric problems into account: the omitted variable bias and measurement error of educational mismatch. For some authors the "*omitted variable bias is substantial and possibly explains the entire difference between returns on required schooling and overschooling and underschooling*" (Leuven and Oosterbeek, 2011). However, few empirical studies have considered these two problems and the results of those that have are mixed[4].

The main contribution of our work can be summed up as follows: 1) the use of a consistent estimator to address the problems of omitted variable bias and measurement error found in the literature, 2) the use of a new database, the European Union Statistics on Income and Living Conditions[5] (EU-SILC, Eurostat) covering a wide range of countries belonging to the Eurozone, and 3) the development of an interpretation that reconciles the claims of the job-competition theory and the human capital theory regarding the effect of educational mismatch on wages.

The main conclusions of our paper are as follows. First, after controlling for omitted variable bias and measurement error, the return on an additional year of schooling above the job educational requirements is very small. Workers experience some wage penalty for each year of schooling deficit, which is relatively larger for men than women. Second, the wages of workers aged under 35 basically depend on the level of schooling attained (human capital theory), while those of people aged over 35 are determined by job educational requirements (job-competition theory).

[4] Bauer (2002), Frenette (2004) and Tsai (2011) found that wages differentials between adequately and inadequately educated workers disappear after controlling for omitted variable bias. In contrast, Dolton and Silles (2008), Korpi and Tahlin (2009) and Verhaest and Omey (2012) conclude that the effect of educational mismatch on wages does not change after controlling for ability or family background. See the Literature Review in Section 2.

[5] The statistical information used in this article is a sample of full-time workers from 2006 to 2009 of countries belonging to the Eurozone in 2006 [excluding Germany, which is not included in the EU-SILC longitudinal database], that is, Austria, Belgium, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Portugal and The Netherlands.

Our interpretation of this second finding is that as we move away from the moment of transition from school to the labor market, the level of education attained is not a good proxy for workers' current skills and productivity. If the human capital of overeducated workers has depreciated because of technical obsolesce of skills or by atrophy (De Grip and Van Loo, 2002), and the human capital of the undereducated has appreciated through learning by doing, the wages of the over 35s really depends on their present productivity and skills, and not on those they may have had when they left the education system.

The main theoretical implication of our paper is that, if we take the depreciation (and appreciation) of human capital into account, we can reconcile the claims of the job-competition and human capital theories respectively. At a practical level, the economic policy implication of our paper is that overeducation implies a waste of the public and private resources invested in education, and for that reason, both researchers and public authorities should focus on investigating the problem, in a bid to better understand its causes and to design and implement measures that might reduce its impact on society.

This article is structured as follows. First, we provide a brief review of the literature on overeducation, focusing in particular on those studies that analyze the problem from a longitudinal perspective. Second, we describe our data, drawn from the EU-SILC (Eurostat), and explain the method used to measure educational mismatch. The next section introduces the econometric framework used in our research. Here we specify the income functions and estimation methods used in a bid to deal with the problems of omission of ability and measurement error in educational mismatch. We then go on to present the empirical results, before outlining our main conclusions in the final section of the paper.

2.- Literature Review

The publication of *The Overeducated American* (Freeman, 1976) spawned a considerable body of literature on "the economics of overeducation". Most of the studies in this field have focused on three main research areas: a) the analysis of the effect of educational mismatch on wages; b) the study of the measurement, incidence and either temporal or permanent character of educational mismatch; and c) the study of the determinants of overeducation. Here we briefly examine this literature in order to put own research into context, whilst those interested in further reviews are recommended to see Green et al. (1999), Hartog (2000), McGuinness (2006), Quintini (2011) and Leuven and Oosterbeek (2011).

The literature on overeducation is grounded in a theoretical debate on how the labor market operates. The human capital theory (Becker, 1964) maintains that wages depend on workers' investment in education. If the supply of a type of workers increases more than the demand, the outcome is a decrease in earnings. The mismatch between supply and demand does not lead to the underutilization of skills, but rather a temporary reduction in relative wages (Green et al., 1999). In the long-term firms adapt their production technologies to changes in the price of the factors, a process which at the same time stimulates the growth in demand. An alternative approach is offered by the *job-competition theory* (Thurow, 1975). According to this, marginal product and wages are properties of the job, not in the individual. Accordingly, since most people acquire their skills through informal on-the-job training, the labor market is a market for allocating training slots. Individuals do not compete on wages but for job opportunities, based on the relative costs of training them. In order to minimize training costs, employers rank potential workers on the basis of certain background characteristics, such as education or age. Workers are distributed across job (training) opportunities in accordance with their relative position in the labor queue. The most preferable workers get the best jobs. Therefore, if the supply of college workers outstrips the high-earning job opportunities, some of them will be forced to accept jobs for high-school graduates

and receive the wages paid that correspond to these occupations. Finally, at an intermediate point between the two theoretical frameworks, the assignment model (Sattinger, 1993) proposes that wages depend on both the worker's human capital and the nature of the job performed (McGuinness, 2006).

A large body of empirical research has been carried out in a bid to shed light on this debate about the influence of the individual ("who you are") and the job ("what you do") on the determination of wages. The starting point for these studies is the seminal work of Duncan and Hoffman (1981) who estimated the returns on the years of education required for jobs, and on the years of over- or under-education (the "ORU" earnings equation)[6]. In other studies, notably Verdugo and Verdugo (1989), the specification of the model combines years of schooling attained with two dummy variables representing overeducation and undereducation. However, as Hartog (2000) argues, it is preferable to transform the dummy variables into years of under- and over-schooling.

Most empirical studies use cross-sectional data to conclude that the returns on years of overeducation are positive but significantly lower than the returns on years of appropriate education. Moreover, the returns on years of undereducation are negative and smaller in magnitude than the returns on matched education (Leuven and Oosterbeek, 2011). In this sense, educational mismatch supposes a cost to both individuals and the economy as a whole, in that it implies the inefficient allocation of resources.

Nevertheless, if educational mismatch is temporary and the differences in the returns on schooling between adequately and overeducated workers disappear over time, we are dealing with a smaller problem. Some authors argue that overeducation may be product of the existence of imperfect information (Hartog, 2000) or of a strategy of maximizing income over the course of the working life, so that overqualified individuals are more likely to be promoted to a better occupation (Sicherman and Galor, 1990). The

[6]"ORU" stands for Overeducation, Required education, and Undereducation.

empirical evidence provided by career models confirm that the overeducated workers enjoy greater upward mobility (Sicherman, 1991). Furthermore, the incidence of overeducation tends to decrease with age and mobility (Alba-Ramírez, 1993).

However, other authors believe that overeducation is a more permanent problem (García-Serrano and Malo, 2003). As university tracer studies highlight, a large proportion of overeducated graduates in their first job do not find a job matching their educational level in the first six years after graduation (Dolton and Vignoles, 2000). Battu et al. (1999) reached a similar conclusion after finding that 30% of graduates never hold a job requiring a university degree.

The two most important econometric issues in the estimation of the effects of educational mismatch on wages are the omission of ability and measurement error (Leuven and Oosterbeek, 2011). The omission of relevant variables can lead to biases and inconsistencies in the estimates. If there is a correlation between ability (unobservable) and educational mismatch, the coefficients of the parameters obtained by ordinary least squares will be biased (Chevalier, 2003). Moreover, measurement error may generate attenuation bias in the estimation of returns on education, a problem that tends to be exacerbated when the variables are measured in differences.

In a bid to address the problem posed by the omission of relevant variables, some studies have included ability controls. This is the case of Green et al. (1999), who found that people who did better on a math test taken at the age of 16 are less likely to be overeducated later in life, although the results of the reading test suggested the opposite effect. Another solution to this heterogeneity problem is to analyze educational mismatch from a longitudinal perspective, for example by using panel data techniques. The estimation of wage equations in first differences corrects the bias resulting from the omission of innate ability, which it is assumed not to vary over time. On the other hand, the usual procedure for dealing with the problem of measurement error in the independent variables is to estimate by instrumental variables.

There are relatively few longitudinal studies analyzing the impact of educational mismatch on wages, and their results are mixed. Bauer (2002) estimates the earnings equations proposed by Verdugo and Verdugo (1989) and Duncan and Hoffman (1981) using a panel of German data covering the period 1984-1998. Bauer estimates the pooled OLS model obtaining the usual results in the literature on overeducation. However, when he estimated the fixed-effects model, wage differentials between adequately and inadequately educated workers shrank or disappeared completely. The same conclusions were reached by Marc Frenette (2004) in his analysis of educational mismatch of university graduates in Canada. When heterogeneity is controlled for using a fixed-effects model, the impact of overeducation on wages decreases considerably. Finally, Tsai (2011) obtains similar results and concludes that the lack of productivity controls in the standard OLS model is the main reason for the wage differentials attributable to educational mismatch.

Chevalier (2003) criticizes the scant attention paid in the literature on overeducation to heterogeneity, which leads to biases in the estimation of the effects of educational mismatch on wages. He analyses overeducation among university graduates in the United Kingdom (UK), taking into account the heterogeneity of both jobs and individuals with the same level of education. He finds that the wage penalty suffered by apparently overeducated graduates is between 5% and 11%, while in the case of the genuinely overeducated, who have lower skill endowment, this rises to 22%-26% of earnings.

However, not all studies using panel data techniques question the results obtained from cross section data. Dolton and Silles (2008), for instance, study the determinants and effects of overeducation in a sample of college graduates in the UK. The empirical evidence they provide suggests that the upward bias that causes the omission of ability is offset by a downward bias of similar magnitude caused by measurement error. Korpi and Tahlin (2009) study the Swedish case using a longitudinal database covering the period 1974-2000, concluding that the effect of educational mismatch on wages does

not change substantially when differences in ability are controlled for, and that the wage penalty does not disappear over time. On the other hand, Verhaest and Omey (2012) analyze the biases caused by the omission of ability and measurement error using a longitudinal database of young Flemish workers who were interviewed when 23 and 26 years old. Once both problems are taken into account, they find that standard random-effects models by GLS underestimate the effects of educational mismatch on earnings, a result that is explained because the negative bias resulting from the measurement error more than compensates for the upward bias resulting from unobserved worker heterogeneity.

Finally, we should emphasize that Robst (1994) constitutes one of the first papers to attempt to correct the bias caused by measurement error. Using instrumental variables techniques he finds that years of over-schooling do not have a significant effect on earnings, leading him to conclude that wages are determined by the requirements of the job rather than by workers' educational attainment.

3.- The data and mismatch measurement

Eurostat's EU-SILC[7] is an annual survey which provides harmonized information on the income, employment situation and living conditions of the EU population. In this paper we analyze the longitudinal database from 2006 and 2009. In order to use homogeneous data, we selected a sample of full-time employees from the Eurozone countries covered by the longitudinal file, namely Austria, Belgium, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Portugal and The Netherlands. The information includes 143,652 observations for 66,538 individuals. For the estimates of wage equations we have used the following variables (see Table 1): education, gender, work experience, experience squared, marital status and disability.

[Table 1, around here]

[7] Disclaimer: Eurostat has no responsibility for the results and conclusions presented in this paper, which are those of the authors alone.

Overeducation (undereducation) is defined as the excess (lack) of education of a worker in relation to the qualification required to perform his/her job. Three different procedures are used in the literature to measure educational mismatch: a) subjective indicators, that is, asking workers directly about the degree of use of their qualifications or about the level of education required for a job similar to theirs; b) external evaluation, whereby experts assess the educational requirements of jobs, such as the US Dictionary of Occupational Titles (DOT); and c) the statistical method, which compares individual educational levels with the mode or with the mean level of studies of the people in the same occupational category.

A number of studies have analyzed the advantages and disadvantages of these different methods for measuring educational mismatch (Green, McIntosh and Vignoles, 1999; Hartog, 2000 and, more recently, Leuven and Oosterbeek, 2011). Subjective measures have the virtue of providing accurate information, insofar as the information is provided by workers themselves, that is, the people who have the best knowledge of the characteristics of the positions they occupy. However, given the subjective nature of such assessments, we may find that two people in the same job have quite different opinions about the level of education necessary to perform their work. The fundamental problem of external evaluation methods, in contrast, is that the great expense of studies such as the DOT means that they are rarely updated.

In this paper we will use the statistical method to construct two indicators of educational mismatch by calculating the mean and mode of education in each occupation. This procedure has often been used in the literature, although it is not free of problems such as the failure to take into account heterogeneity in the educational requirements of jobs grouped in a single occupational category.

Following the method proposed by Verdugo and Verdugo (1989), we define the level of education required for a job as the range of a standard deviation of the mean distance of the years of schooling of workers in the same occupation, country and year,

using the International Classification of Occupations ISCO-88 to two digits. If an indivual's level of education is above this range, s/he is overeducated; if below it, s/he is undereducated. Additionally, we have used the procedure proposed by Kiker et al. (1997) to elaborate a second indicator of educational mismatch from the mode of years of schooling in each occupation, country and year. Unlike in the previous case, educational requirements are not defined according to the range of standard deviation, but are rather based on the point estimate of the statistic. However, given that the overall pattern of results is very similar for both indicators, to avoid duplication of the number of tables, we show only the estimates obtained with the mean index.

The mean indicator tends to provide estimates of educational mismatch of smaller magnitude than those obtained from the mode. While, following the mean, 10.46% of the observations are classified as overeducated, the figure rises to 16.81% if we take into account the mode. Meanwhile, 12.72% of the panel observations fall into the category of undereducated, according to the mean, well below the figure of 24.18% that is recorded from the mode. Finally, the proportion of observations that fall into the category of adequately educated is 76.83% based on the mean, but just 59.01% according to the mode. All-in-all, when comparing the classification results obtained from the mean and the mode we find that 79.79% of the observations of the panel fit into the same category (see Table 2).

[Table 2, around here]

Figure 1 shows the incidence of educational mismatch by age and educational level. The first conclusion to be drawn is that, when using the mean indicator, educational mismatch is polarized in the two extreme educational levels, ie in lower secondary (undereducation) and tertiary education (overeducation). Moreover, the incidence of undereducation increases with workers' age, as opposed to the incidence of overeducation which falls as age increases.

[Figure 1, around here]

Figure 2 shows the relationship between educational mismatch and wages. To the extent that individuals in our sample have different levels of education, we do not plot wages directly, but rather show the residuals of a regression of log wages on years of schooling and other controls. The horizontal axis represents educational mismatch measured by calculating the difference between workers' educational attainment and the mean of schooling for the job. A positive (negative) number represents an excess (deficit) of schooling compared to the mean of the occupation. As shown by the linear and lowess fits, there is a negative relationship between schooling mismatch and wages.

[Figure 2, around here]

On the other hand, Figures 3 to 5 show the kernel density estimates of log real wages by education and mismatch. Figure 3 focuses on workers with tertiary education and shows that the distribution of wages of the overeducated is to the left of the adequately educated individuals. In the case of upper secondary education (Figure 4), it is noteworthy that the undereducated tend to earn more than the adequately educated, while the overeducated, tend to earn less. At the same time, the undereducated and adequately educated workers with primary education (Figure 5) show similar histograms, although the former are situated slightly to the right of the latter. In any case, the wage distribution of the overeducated lies clearly to the left of the other two categories. Therefore, this descriptive overview of the data broadly coincides what most of the empirical literature concludes with respect to effects of educational mismatch on wages.

[Figures 3, 4 and 5, around here]

4.- Econometric models

4.1. - The earnings functions

This paper starts out from the two classic specifications of wage equations used in the literature on educational mismatch: the models proposed by Duncan and Hoffman (1981) and Verdugo and Verdugo (1989). To do this, Duncan and Hoffman break down the years of schooling attained (S_a) into years of schooling required by the job (S_r), years of overeducation (S_o) and years of undereducation (S_u), using the following expression:

$$S_{ait} = S_{rit} + S_{oit} - S_{uit} \tag{1}$$

Where

$$S_{oit} = \begin{cases} S_{ait} - S_{rit} \; if \; S_{ait} > S_{rit} \\ 0, otherwise \end{cases}, \quad \text{and} \quad S_{uit} = \begin{cases} S_{rit} - S_{ait} \; if \; S_{ait} < S_{rit} \\ 0, otherwise \end{cases}, \tag{2}$$

Replacing this expression in the Mincer wage equation, we obtain Duncan and Hoffman's model (3):

$$w_{it} = \mu + \beta_r \, S_{rit} + \beta_o \, S_{oit} + \beta_u S_{uit} \; + \; X_{it} \, \gamma \; + \varepsilon_{it} \tag{3}$$

where w_{it} is the log real wage of individual i in year t, X_{it} is a vector containing other explanatory variables (sex, work experience, experience squared, marital status and disability) with the corresponding vector of coefficients γ, and, finally, v_{it} is an error term.

β_r is the return on required schooling. The coefficient β_o represents the rise ($\beta_o > 0$) in a worker's wage for each additional year of overeducation compared to an individual performing the same occupation and whose years of schooling match the job requirements. In the same way, β_u measures the fall in a worker's wages ($\beta_u < 0$) for each year of education deficit compared with another worker in the same position and whose years of schooling match the job requirements.

The Mincer equation is a restricted form of the Duncan and Hoffman's model which incorporates the constraint of equal coefficients ($\beta_r = \beta_o = - \beta_u$), indicating that individuals' wages depend on their education and other personal attributes which determine their productivity, rather than on the job characteristics. The alternative view

is set out in the model of job-competition developed by Thurow (1975), who proposes that wages do not depend on the individual but rather on the characteristics of the jobs they hold. In Thurow's model, overeducation and undereducation coefficients are equal to zero ($\beta_o = \beta_u = 0$) and wages depend only on the years of schooling required for the job (β_r).

Meanwhile Verdugo and Verdugo (1989) use a specification that incorporates the level of education attained by the individual (S_a) rather than the years of schooling required by the job (Sr). Although in Verdugo and Verdugo the variables related to the educational deficit and excess are coded as dummies, in our work they are measured in years, resulting in the following expression:

$$w_{it} = \mu + \beta_a S_{ait} + \beta_o S_{oit} + \beta_u S_{uit} + X_{it}\gamma + \xi_{it} \tag{4}$$

In Verdugo and Verdugo's model, β_o represents the wage penalty (β_o <0) experienced by a worker for each year of overeducation compared to another worker with the same level of education who is employed in a position according to his/her education. Meanwhile, β_u measures the increase in wages (β_u> 0) of a worker for each year of education deficit compared to another worker with the same level of education in a job that matches his/her education.

4.2.- The Fixed-effects Estimator

Let us assume that wages are set according to Duncan and Hoffman's model and as expressed as follows:

$$\begin{gathered} w_{it} = \mu + \beta_r S_{rit} + \beta_o S_{oit} + \beta_u S_{uit} + X_{it}\gamma + (\alpha_i + \varepsilon_{it}) \\ \varepsilon_{it} \sim iid\ (0, \sigma_\varepsilon^2) \end{gathered} \tag{5}$$

in which the error has an idiosyncratic component ε_{it} and an individual component α_i, time invariant, which represents ability. In the event that there is correlation between the explanatory variables and ability, the estimation by OLS may be biased:

$$\hat{\beta}_{OLS} = \beta + \left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x})(x_{it} - \bar{x})'\right]^{-1}\left\{T\sum_{i=1}^{N}(x_{it} - \bar{x})(\alpha_i - \bar{\alpha})\right\} \quad (6)$$

The ordinary least squares estimator of β is inconsistent if the second component of expression (7) does not tend to zero (Hsiao, 2003). The bias depends on the correlation between x_{it} and α_i. For example, to the extent that the ability correlates positively with years of undereducation and negatively with years of overeducation, the bias will reduce the absolute value of the coefficients β_u and β_o in Duncan and Hoffman's model.

The use of panel data techniques allows us to control the influence of the omitted variables in the model, either by taking first differences or, as in this paper, by estimating the deviation from the mean of each individual. If you calculate the mean wage of each individual over time as

$$\bar{w}_i = \mu + \beta_r\,\bar{S}_{rit} + \beta_o\,\bar{S}_{oit} + \beta_u\,\bar{S}_{uit} + X_{it}\,\gamma + (\alpha_i + \bar{\varepsilon}_{it}) \quad (7)$$

the specification in differences from the mean of each individual can be obtained by subtracting (7) from (5). As can be seen, the constant μ and the individual component of the error representing ability α_i, disappear:

$$w_{it} - \bar{w}_i = \beta_r\,(S_{rit} - \bar{S}_{ri}) + \beta_o\,(S_{oit} - \bar{S}_{oi}) + \beta_u\,(S_{uit} - \bar{S}_{ui}) + (X_{it} - \bar{X}_i)\,\gamma + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (8)$$

It is important to remember that the fixed-effects estimator uses the "within" information and it does not enable us to estimate the effect of the characteristics that do not vary

within each individual, such as sex or country, which, moreover, disappear from the model in differences.

4.3. - Measurement Error in Educational Mismatch

One of the problems facing the literature on overeducation is the bias resulting from errors in measuring educational mismatch (Leuven and Oosterbeek, 2011). In this study we use two alternative indicators to measure educational mismatch, the mean and the mode. They classify 79.79% of the observations into the same categories (overeducated, properly-educated and undereducated). In turn, the correlation between the two measures of years of education required (S_r), years of overeducation (S_o) and years of undereducation (S_u) are, respectively, 0.9048, 0.8512 and 0.8497. The correlation is high but not perfect, suggesting the existence of some degree of measurement error in the regressors. As we know, fixed-effects estimation is more sensitive to measurement error when variables are expressed in deviations from the mean rather than in levels (Angrish and Pischke, 2008).

In this paper we will use instrumental variables estimation to correct the bias resulting from measurement error with respect to educational mismatch. Following a procedure similar to that used by Robst (1994), Dolton and Silles (2008) and Verhaest and Omey (2012), the S_r, S_o and S_u variables calculated with the mean will be instrumented with the respective variables obtained with the mode. Estimation by instrumental variables is the method commonly used to correct the biases of unknown size and unknown direction resulting from the estimation of models in which one or more of the independent variables are measured with error (Green, 2003). However, the results should be interpreted with caution, bearing in mind Leuven and Oosterbeek's (2011) criticism of the satisfaction of the assumptions of classical type measurement error in the ORU earning equations.

5. - Results

Table 3 shows the results of the estimation of the Mincer wage equation. The left panel shows the OLS estimates for each year's sample. The return on an additional year of attained schooling increases moderately during the period, so we can state that the demand for skilled labor must have grown in the Eurozone, in a context of the expansion of tertiary education, a fact that is consistent with the hypothesis of skilled-biased technological change. Moreover, the coefficients are similar to those obtained in the literature (see Card, 1999; Murillo et al., 2011). Women earn a lower salary than men, and wages rise with experience at a decreasing rate. On the other hand, people whose activity is severely limited by health problems (the *disabled*) suffer a wage penalty, while married people show higher earnings than other individuals. The parameter estimates are stable over time and are consistent with the results found in the literature.

[Table 3, around here]

The right panel of Table 3 compares the estimates of the pooled model by OLS with those obtained using panel data techniques, estimating by GLS (random effects) and by covariance (fixed effects). Given the nature of the data, where individuals in the sample constitute a larger population, we consider a random-effects model (Hsiao, 2003). However we cannot estimate by generalized least squares because of the correlation between the individual effects and the regressors. The estimation by GLS is inconsistent since the Hausman test rejects the null hypothesis. The fixed-effects estimation uses the covariance estimator, which is less efficient but consistent, and only uses the within-group variability. Regressions with different constants for each individual allow us to control for the effect of omitted variables, such as ability or family background, which do not vary over time and may be correlated with education.

The results of estimating the pooled OLS model are very similar to those of the OLS estimates for each year discussed immediately above. However, the F-test indicates that there is heterogeneity in the individual constants. The hypothesis that the individual

constants (α_i) are homogeneous is rejected, so the estimation of the pooled OLS model, which considers that the constants do not vary across individuals, is inconsistent.

The estimation of the Mincer equation by GLS shows similar results to those obtained in the pooled model. The return on each additional year of schooling falls slightly, while significant changes are not observed in the other parameters, except in the case of the *disabled* variable, the effect of which is reduced by half. However, the decrease in the size of the coefficients is very important in the estimation of fixed effects in this case, especially in the case of the return on attained education, which falls to less than one tenth of that obtained in the pooled model. The coefficients of disabled and married also show a fall. It should be noted, finally, that the serial correlation of the errors within the same individual is corrected by estimating cluster-robust standard errors.

We have calculated the transition matrices between the three categories of overeducated, adequately educated and undereducated in order to assess whether there is sufficient variability to estimate the effect of educational mismatch on wages. With the mean indicator, 8.3% of individuals changed category from one period to the next, while with the mode indicator the proportion rises to 9.7%. As a point of reference, Bauer (2002) found transitions of 5.3% with the mean and 16.2% with mode.

Table 4 shows the results of the estimations of Verdugo and Verdugo's (1989) model with the mean index measure of job educational requirements. As with the Mincer equation, we estimate the pooled OLS model and the random-effects and fixed-effects models, as shown in the first three columns. The inclusion of the years of overeducation and undereducation, increases the return on schooling from 8.0% to 12.0% in the pooled model. Workers suffer a 7.7% penalty for each year of overeducation, and a return of 9.3% per year of undereducation. The pattern of these results is similar to those given by Tsai (2009), who obtained a return of 11.4% on attained schooling, a 3.8% penalty for each year of overeducation, and a return of 5.7% for each year of undereducation. The generalized least squares estimates (random-effects) barely

change compared to those obtained in the pooled model. In contrast, the fixed-effects estimation shows a considerable drop in the size of the coefficients to 1.7% of return for each year of schooling, -1.5% for each year of overeducation and 1.0% for each year of undereducation.

[Table 4, around here]

A reduction in the absolute value of the coefficients in the fixed-effects estimation is also observed by Tsai (2009) and Korpi and Tahlin (2009), but not by Bauer (2002). As explained by Korpi and Tahlin (2009), the fall in the coefficients in the within-group estimation may be explained by: a) the failure to measure the influence of other regressors that do not vary over time and disappear from the fixed-effects estimation, b) the time period covered by the panel, that may not be long enough to collect the total effect of changes in the educational mismatch; and c) the attenuation bias that the measurement error can generate, which tends to be exacerbated when the variables are measured in differences. As noted in a previous section, this paper corrects the measurement error through estimation by instrumental variables.

As for interpretation, it should be noted that in the fixed-effects model we measure the effect on the wages of those individuals who change their educational level (S_a) or their occupation (S_r, S_o or S_u). For example, if the level of a worker's education increases, his/her wage may rise if s/he finds a new job with higher educational requirements, so that S_o and S_u do not change. If the worker does not change jobs, S_o will increase, or if s/he is undereducated, S_u will fall. In the event of the individual's educational level not changing, wages vary with changes in employment between jobs with different educational requirements, which in turn will cause changes in the years of over- and underschooling.

The last column of Table 4 shows the estimates of the fixed-effects instrumental variable model, where years of overeducation and undereducation calculated using the mean are instrumented with the corresponding variables calculated using the mode. Overeducated workers suffer a wage penalty of similar size to the return on attained

education, while the return on underschooling is of similar magnitude to the return on attained schooling. Moreover, the estimation by instrumental variables increases the size of the coefficients, suggesting that the measurement error produces attenuation bias. The return on attained schooling rises from 1.7% to 3.0%; that of underschooling from 1.0% to 2.9%, and the penalty for overschooling increases from -1.5% to -2.5%. This result coincides with that obtained by Robst (1994), Dolton and Silles (2008) and Verhaest and Omey (2012).

The human capital theory tests, in which the years of overeducation and undereducation do not have a significant effect on wages ($\beta_o = \beta_u = 0$), are rejected in all the specifications. In parallel, the test of the job-competition model ($\beta_a = -\beta_o = \beta_u$) is rejected in the pooled model and in the random-effects model. However, it cannot be rejected at a level of significance of 1% in the fixed-effects model and at 10% in the fixed-effects instrumental variable model. As a result, we can provisionally conclude that once the omitted variable bias is controlled, wages depend on the job educational requirements rather than exclusively on the level of attained schooling.

Table 5 shows the estimates of the ORU equation (Duncan and Hoffman, 1981), using the mean index. The results of the pooled model and of the random-effects model are very similar. If we focus on the latter, wages rise 12.9% for each year of required education and 3.8% for each year of overeducation, and decrease by 2.7% for each year of undereducation. Moreover, the size of the effects falls in the fixed-effects estimation to a return of 2.7% on required education, and a penalty of 0.5% per year of undereducation, while the overeducation coefficient is not statistically different from zero. Finally, the last column shows the estimates of the fixed-effects instrumental variables model, where we instrument the mean indexes of S_r, S_o and S_u with the mode counterparts. As in the previous case, the absolute size of the coefficients increases in the model estimated by IV, suggesting the existence of attenuation bias. The return on overschooling is significant at 10%, although its magnitude (0.6%) falls substantially to less than 20% of the coefficient estimated for required schooling (3.5%). In addition,

undereducated workers experience a penalty in their remuneration of similar size (-0.8%). Therefore, wages depend basically on the educational requirements of jobs. As in Verdugo and Verdugo's model, the test of human capital theory ($\beta_r = -\beta_o = \beta_u$) is rejected in all the specifications and the test of job-competition theory ($\beta_o = \beta_u = 0$) is rejected in all cases except in the fixed-effects model, that cannot be rejected at a 1% level of significance.

[Table 5, around here]

One condition of the method of instrumental variables is that the instruments have to be partially correlated with the endogenous explanatory variables once the other exogenous variables have been netted out (Wooldridge, 2010). In order to assess the relevance of the instrumental variables, Table 6 shows the reduced form equations for the variables measured with error. The first three columns of the table exhibit the linear projections of S_r, S_o and S_u calculated using the mean on the counterpart variables calculated using the mode. The next three columns show the same linear projections including all the exogenous variables. The reduced form results indicate that there is a strong and positive relationship between the two alternative measures of educational mismatch. In the case of the Verdugo and Verdugo model (see panel A) the coefficients for the instruments of overeducation and undereducation are 0.592 and 0.398 respectively. In the case of the Duncan and Hoffman model (see panel B) the coefficients for the instruments of required education, overeducation and undereducation are 0.388, 0.705 and 0.755. Moreover, the estimation of the reduced form for the logarithm of wages on the instruments and the other exogenous variables show the same pattern of results obtained in tables 4 and 5.

[Table 6, around here]

In Table 7 we estimate the instrumental variables fixed-effects model by sex and age groups. We show the results of Verdugo and Verdugo's wage equation in the left panel and those obtained from Duncan and Hoffman's model in the panel on the right. Looking at the first two columns of each panel we find that the main conclusions drawn so far are upheld for both men and women. The main difference observed by sex is that women

show a higher return on attained and required schooling than men. Apart from that, the penalty for one year of overschooling is of the same magnitude as the return on one year of attained schooling in both samples. In other words, when we compare the wages of a person employed in a position commensurate with their level of education to other overeducated workers in the same job, the return on one year of overschooling is not statistically different to zero in the case of both men and women. As for undereducation, the variable is statistically significant in all four estimates, and we can see that, in Duncan and Hoffman's model, undereducated males tend to suffer a greater penalty in their wages than women, in comparison with the return on each year of required schooling. Finally, when we carry out the significance test for the coefficients, the human capital model is systematically rejected, but job-competition theory cannot be rejected at 5% level of significance in 3 of the 4 estimations by sex.

[Table 7, around here]

The last two columns of both panels of Table 7 show the estimates of the fixed-effects instrumental variable model by age groups. In this case the differences in the results are remarkable, pointing at a pattern whereby the wages of people aged under 35 are determined primarily by their level of attained schooling, while those of the over 35s are more subject to the educational requirements of the job. For example, in Verdugo and Verdugo's wage equation (left panel) the return on attained schooling is similar by age: 3.0% for the under 35s and 2.4% for the over 35s. In contrast, the penalty for each year of overeducation is very high for people aged over 35 (-3.1%) and low and statistically non-significant for people under 35 (-0.8%). On the other hand, the return on underschooling is smaller and less significant in the case of people aged under 35 than in the case of the over 35s.

Meanwhile, in the estimation obtained from Duncan and Hoffman's model, the return on required education is 3.2% for people under 35 and 2.9% for those over 35. In the case of the under 35s, overschooling shows a coefficient that is around two thirds of the

return on required education and underschooling a penalty of more than 50% of the return on required education. However, in the case of people aged over 35, overschooling does not show a positive but rather a negative coefficient, and the underschooling penalty is less than 15% of the return on required schooling. These conclusions are confirmed when comparing the significance tests for the coefficients by ages: while human capital theory is rejected in the two earnings equations for people aged over 35, it cannot be rejected in the two specifications for people under 35. However, job-competition theory cannot be rejected at 5% level of significance in either of the two estimates of people aged over 35 and it is rejected in the two wage equations of people under 35.

These results can be interpreted as follows. In the first stage of working life wages depend on education and experience[8] but as workers get older, their earnings come to depend on the educational requirements of jobs. It seems that when you are under 35 employers pay you based on *who you are* (human capital), while when you reach 35 and above, they pay you in accordance with *what you do* (job competition). In fact, this shift in the determinants of wages by age may reflect the fact that level of education is a valid indicator of worker productivity only in the early years of transition to the labor market. However, as age increases, the skills and productivity of individuals with the same level of educational attainment become far more heterogeneous[9]. Most workers maintain or increase their human capital stock by learning in the workplace (*learning-by-doing*); others, however, may suffer a depreciation of their human capital if they have never used their skills (overeducation) or if they experienced career interruptions[10].

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[8] Evaluated at the mean experience of each group, wages of people aged under 35 rise by 7.6% for each additional year of experience ($\hat{\beta}_{exp}$ = 0.174; $\hat{\beta}_{exp2}$ = -0.007), while those of the over 35s rise by just 1.0% ($\hat{\beta}_{exp}$ = 0.015; $\hat{\beta}_{exp2}$ = -0.0001).

[9] The same idea is defended by Green and McIntosh (2007) who claim that "it is necessary to remove the assumption that all individuals with the same qualifications are homogeneous". Similarly, OECD (2011) states that "*only a small fraction of educational mismatch actually reflects a mismatch in competencies and skills*".

[10] As pointed out by De Grip and Van Loo (2002), human capital can depreciate as a result of technical obsolescence of skills, either through wear (aging) or atrophy, i.e. the absence or limited use of skills due to career interruptions (e.g., unemployment or inactivity) and to overeducation. In a later work, De Grip et al. (2008) stress that "*workers who are employed in a job for which they are overeducated are more vulnerable to a decline in their productivity*".

The differences in the skills and productivity of workers with the same schooling, which sharpen with age, explain the apparent shift from a world governed by the human capital theory to a world governed by the job-competition theory. However, if our interpretation is correct, as we move away from the moment of transition from school to labor market, wages are actually set by the workers' skills and productivity. Therefore overeducation does not lead to an underutilization of skills, but it does reflect a certain waste of resources in relation to some of the human capital investments made in the past.

As mentioned above, career interruptions constitute one of the determinants of human capital depreciation. In order to shed some light on the effect of career interruptions on educational mismatch, we estimated a multinomial logit model with the sample of people aged 35 and over (see Table 8). Apart from the usual variables (sex, age or experience), we are interested in studying the influence on the likelihood of being overeducated and undereducated (the reference category is adequately educated) of: a) involuntary job changes from the previous year ("*end of temporary contracts, business closures, firing, child or dependent person care, or move due to partner's work*"), and b) changes in employment status from the previous year, from "unemployment to employment" and from "inactivity to employment". We assume that transitions from unemployment and inactivity to employment involve a loss of general and specific human capital, and involuntary job changes may imply a loss of specific human capital.

The left panel of Table 8 exhibits the coefficients with the robust standard errors, while the right panel presents the marginal effects evaluated at the mean of the two educational categories most affected by educational mismatch. In particular, we have chosen the category of tertiary education (16 years of attained schooling) to calculate the marginal effects of the independent variables on the probability of being overeducated, and primary education (10 years of attained schooling) to study the effects on the probability of being undereducated.

As expected, overeducation increases with years of attained schooling and decreases with work experience (the opposite is true of undereducation). However, women show a lesser likelihood of being overeducated and a greater likelihood of being undereducated, the contrary to what is suggested in the literature (see Frank, 1978). On the other hand, married people are less likely to be overeducated, while the disabled are more likely to be so. Instead, neither the marital status nor disability have a statistically significant effect on the probability of being undereducated.

As for the effect of changes of employment and transitions in activity status on the probability of being overeducated or undereducated, results are in all cases significant and show the expected sign. An involuntary job change increases the probability of being overeducated by 6.6 percentage points, while the transition from unemployment or inactivity to employment raises it by 16.9 and 9.4 percentage points, respectively. At the same time, an involuntary job change decreases the probability of being undereducated by 3.3 percentage points, while the transition from unemployment or inactivity to employment reduces it by 5.2 and 4.9 percentage points, respectively. It should be noted that the probability of being overeducated, calculated at the mean of the individuals with 16 years of attained schooling, is 22.8%, while that of being undereducated evaluated at the mean of people with 10 years of attained schooling is 18.1%.

[Table 8, around here]

6.- Discussion and Conclusions

Over the last three decades, the EU has invested heavily in education. At present, one third of the EU population aged 30-34 holds a tertiary education degree, and in 2009 the student population in higher education reached almost 19.5 million individuals (Eurydice, 2012). At the same time, the demand for skilled labor has increased, yet in

2010 21.2% of graduates worked in low skilled jobs, for which it was not necessary to hold a higher education degree[11].

In this paper we have sought to analyze the effect of educational mismatch on wages. The basic question we pose is whether wages depend on the educational attainment of the individual, regardless of the job performed, or rather are determined by the educational requirements of jobs. We have a twofold objective. First, to contrast two alternative theoretical approaches to the functioning of the labor market, namely, the human capital and the job-competition theories, with the empirical evidence for the EU. Second, to determine whether educational mismatch implies a waste of resources, and is therefore a problem which the public authorities need to address.

Most of the empirical studies that attempt to measure the impact of educational mismatch on wages have been criticized for not taking the omitted variable bias into account. If over- and under-education are correlated with ability or family background, the estimate of the effect of educational mismatch on wages will be biased. Moreover, error in the measurement of the variables may also generate a bias. This paper has employed a consistent estimator for the two econometric problems mentioned, using a rich database (EU-SILC, Eurostat) which gave us a sample of more than 66,000 full-time workers of 11 European countries.

The main conclusions of our paper are:

1) **During the period 2006-2009 the return on attained schooling did not fall, but remained stable or even showed a moderate rise**. From a basic supply and demand perspective, this means that the demand for skilled labor has grown, in parallel with the remarkable expansion of education in Europe, a result consistent with the **skill biased technological change** hypothesis.

[11] Eurydice (2012), information obtained from the European Labour Force Survey (Eurostat).

2) The instrumental variable fixed-effects estimation indicates that **overeducated workers suffer a wage penalty similar in magnitude to the return on attained schooling**. This result holds in the two alternative specifications of the wage equation, in samples of men, women and both sexes. In other words, **wages depend mainly on the educational requirements of jobs,** and the return of an additional year of schooling over the level of education required for the job is very small. Moreover, the **wages of undereducated people are slightly lower than those of workers in the same occupation but with the level of education required for the job**, with the wage penalty relatively higher in the case of men than women .

3) **The wages of people under 35 largely depend on the level of schooling attained (human capital theory),** regardless of the occupation held, **while those of people over 35 depend mainly on job educational requirements (job-competition theory).**

4) The pattern obtained, which varies in accordance with workers' age, is interpreted in terms of **the effect of skills depreciation (or appreciation) on human capital**. **As worker´s age increases, level of education attained becomes a less accurate measure of their human capital**, to the extent that skills appreciate (underschooling) or depreciate (overschooling) in function of their use. If this interpretation is correct, the wages of people over 35 are determined in accordance with their current productivity and skills (human capital theory), and not by the level of education attained at the moment of transition from school to the labor market (job-competition theory). Thus we believe that the distinction between education and skills may reconcile both theories and is the key to understanding the problem of educational mismatch.

5) **Transitions from inactivity and unemployment to employment, and involuntary job changes increase the likelihood of being overeducated and reduce the probability of being undereducated**. This result is consistent with the role that, in our opinion, the depreciation of skills plays in educational mismatch. Finally,

the probability of being overeducated (undereducated) increases (decreases) with attained schooling, and decreases (increases) with experience.

In terms of policy recommendations, we consider that:

- We should start out from the premise that **overeducated people aged over 35 suffer a wage penalty**, and for this reason we conclude that **overeducation implies a waste of resources**, both public and private. As noted in the introduction, public spending in tertiary education represents 1.1% of the EU GDP. According to the empirical results obtained in this paper, and correcting for the duration and the higher incidence of educational mismatch in the ISCED 5B programs, **the waste of resources is estimated at between 0.12 and 0.15 percentage points of EU GDP**, ie between 10.8% and 14.0% of public spending on tertiary education. It is this which makes the analysis of determinants of educational mismatch of particular interest. Hence, we must focus on the education system itself, and on the factors that cause the depreciation of skills.

- With respect to education, many authors point to the need to reform an education system that results in some graduates never obtaining a job matching their qualifications. As noted by Chevalier (2003), "*overeducation originates not from disequilibria in the market for graduates, but from the lack of skills acquired by graduates at university.*" In a similar vein, Green and McIntosh (2007) suggest that some workers "*have acquired a 'wrong' type of human capital, in the sense that these qualifications are less demanded on the labor market.*" Therefore, public authorities should **reform the education system to provide graduates with the skills the market demands**. **Better career guidance** may also play an important role in reducing educational mismatch, which varies considerably by field of study (Quintini, 2011).

- As for the depreciation of skills, the empirical evidence obtained in this study confirms that people who experience an involuntary job change and those who have had periods

of unemployment or inactivity are more likely to be overeducated. In a context of massive unemployment in some EU countries, **the public authorities should intensify their efforts to minimize the loss of human capital that unemployment and inactivity signify in the European labor force**. The basic instrument available to improve the unemployed's chances of finding work are demand-side stimulus policies. On the supply side, an attempt should be made to improve the information available on job vacancies in a bid to encourage national and international mobility and to promote lifelong learning.

Finally, one question that requires a further analysis is the treatment of the measurement error of educational mismatch[12]. Further research would also serve to cast greater light on the study of the determinants of educational mismatch, focusing on the education system itself and the analysis of the factors causing the depreciation of skills. Moreover, it would be interesting to investigate the effectiveness of lifelong learning in correcting the depreciation of human capital and, ultimately, in reducing the incidence of overeducation.

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7.- References

- Alba-Ramírez, A. (1993) Mismatch in the Spanish Labor Market. Overeducation?, *Journal of Human Resources*, 18 (2), 259-278.

[12] See Leuven and Oosterbeek (2011).

- Alba-Ramírez, A., and Blazquez, M. (2003) Types of Job Match, Overeducation and Labour Mobility in Spain. In Buchel, F., de Grip, A., and Mertens, A. (Eds.) *Overeducation in Europe: Current issues in theory and policy,* 65-90, Cheltenham, U.K. and Northampton, Mass.
- Angrish, J.D., and Pischke, J.S. (2008) *Mostly Harmless Econometrics: An Empiricist´s Companion*, Princeton University Press.
- Battu, H., Belfield, C.R., and Sloane, P.J. (1999) Overeducation among Graduates: a Cohort View, *Education Economics*, 7 (1), 21-38.
- Bauer, T.K. (2002) Educational Mismatch and Wages: A Panel Analysis. *Economics of Education Review*, 21(3), 221-229.
- Becker, G. (1964) *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. New York, National Bureau of Economic Research.
- Berman, E., Bound, J., and Machin, S. (1998) Implications of Skill-Biased Technological Change: International Evidence, *Quarterly Journal of Economics*, Vol. 113 (November), 1245-1279.
- Bishop, J.H. (1996) Is the Market for College Graduates Headed for a Bust? Demand and Supply Responses to Rising Wage Premiums, *New England Economic Review*, Special Issue on Earnings Inequality (May-June), 115-135.
- Borghans, L., and De Grip, A. (2000) : *The Overeducated Worker ? The Economics of Skill Utilization*, Edward Elgar, Cheltenham, UK.
- Büchel, F., and Van Ham, M. (2003) Overeducation, regional labor markets, and spatial flexibility, *Journal of Urban Economics*, 53, 482-493.
- Card, D. (1999) Education and earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*. North Holland.
- Chevalier, A. (2003) Measuring overeducation. *Economica*, 70, 503–531.
- Cohn, E. (1992) The Impact of Surplus Schooling on Earnings: Comment, *Journal of Human Resources*, 27 (4), 679-682.
- De Grip, A., and Van Loo, J. (2002) *The economics of skills obsolescence*, 21, 1-26.
- De Grip, A., Hosma, H., Willems, D., and van Boxtel, M. (2008) Job-worker mismatch and cognitive decline. *Oxford Economic Papers*, 60, 237–252.

- Dolado, J.J., Jansen, M., and Jimeno, J.F. (2009) On the job-search in a matching model with heterogeneous jobs and workers. *Economic Journal*, 119, 200–228.
- Dolton, P., and Silles, M. (2008) The effects of overeducation on earnings in the graduate labour market. *Economics of Education Review,* 27, 125–139.
- Dolton, P., and Vignoles, A. (2000) The incidence and effects of overeducation in the UK graduate labour market, *Economics of Education Review*, 19, 179-198.
- Duncan, G., and Hoffman, S. (1981) The incidence and wage effects of overeducation. *Economics of Education Review,* 1(1), 75–86.
- Frank, R. (1978) Why women earn less: the theory and estimation of differential overqualification, *American Economic Review*, 68(3), 360-373.
- Freeman, R.B. (1996) *The Overeducated American*, New York, Academic Press.
- Freeman, R.B., and Katz, L.F. (1995) *Differences and Changes in Wage Structures*, National Bureau of Economic Research Comparative Labor Markets Series.
- Frenette, M. (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.
- García-Serrano, C., and Malo, M.A. (2003) *Educational Mismatch and Expected Promotions*, mimeo.
- Gill, A.M., and Solberg, E.J. (1989) The Impact of Surplus Schooling on Earnings: A Critique, *Journal of Human Resources*, 27 (4), 683-689.
- Green, W.H. (2003) *Econometric Analysis*, 3rd Edition, Prentice Hall.
- Green, F., and McIntosh, S. (2007) Is there a genuine under-utilization of skills among the over-qualified? *Applied Economics*, 39, 427–439.
- Green, F., Mcintosh, S., and Vignoles, A. (1999) *Overeducation and Skills. Clarifying the Concepts*, Center for Economic Performance, Discussion paper n. 435, September.
- Groot, W. (1996) The incidence of, and returns to overeducation in the UK, *Applied Economics*, 28, 1345-1350.
- Hartog, J. (2000) Overeducation and earnings: where are we, where should we go?, *Economics of Education Review*, V. 19, 131-147.

- Hersch, J. (1991) Education Match and Job Match, *Review of Economics and Statistics*, 73 (1), 140-144.
- Johnson, G. E. (1970) The Demand for Labor by Educational Category, *Southern Economic Journal*, Vol. 37, 190-204.
- Hsiao, C. (2003) *Analysis of Panel Data*, Econometric Society Monographs, No. 34, Cambridge University Press.
- Kiker, B., Santos, M., and de Oliveira, M. (1997) Overeducation and undereducation: evidence for Portugal. *Economics of Education Review*, 16(2), 111–125.
- Korpi, T., and Tåhlin, M. (2009) Education mismatch, wages, and wage growth: overeducation in Sweden 1974–2000. *Labour Economics*, 16(2),183–193.
- Lassibille, G., Navarro, L., Aguilar, I., and Sánchez, C. (2001) Youth transition from school to work in Spain, *Economics of Education Review*, 20, 139-149.
- Leuven, E., and Oosterbeek, H. (2011) Overeducation and Mismatch in the Labor Market (283-326), Hanushek, E. A., Machin, S. and Woessmann, L., *Handbook of the economics of education*: Vol. 4, North-Holland, Amsterdam.
- Machin, S. (2001) The Changing Nature of Labour Demand in the New Economy and Skill-Biased Technology Change, *Oxford Bulletin Of Economics And Statistics*, Vol. 63, 753-776.
- Manacorda, M., and Petrongolo, B. (1999) Skill Mismatch and Unemployment in OECD Countries, *Economica*, 66, 181–207.
- McGuinness, S. (2006) Overeducation in the labour market. *Journal of Economic Surveys*, 20(3), 387–418.
- Murillo, I.P., Rahona, M., and Salinas, M.M. (2011) Effects of educational mismatch on private returns to education: An analysis of the Spanish case (1995-2006), *Journal of Policy Modeling*, http://dx.doi.org/10.1016/j.jpolmod.2011.07.012.
- Murphy, K. M., and Welch, F. (1993) Occupational Change and the Demand for Skill, 1940-1990, *American Economic Review*, Vol. 83, No. 2 (May), 122-126.
- Nickell, S., and Bell, B. (1995) The Collapse in Demand for the Unskilled and Unemployment across the OECD, *Oxford Review of Economic Policy*, Vol. 11, No. 1, Spring.

- OECD (2011) Right for the Job: Over-Qualified or Under-Skilled, *OECD Employment Outlook 2011*, OECD Publishing, Paris, 191-235.
- Quintini, G. (2011) "Over-Qualified or Under-Skilled: A Review of Existing Literature", OECD Social, Employment and Migration Working Paper, No. 121, OECD Publishing, Paris.
- Rumberger, R.W. (1987) The Impact of Surplus Schooling on Productivity and Earnings, *Journal of Human Resources*, 22(1), 24-50.
- Robst, J. (1994) Measurement error and the returns to excess schooling. *Applied Economic Letters*, 1, 142–144.
- Sattinger, M. (1993) Assignment Models of the Distribution of Earnings. *Journal of Economic Literature*, 31(2), 831-880.
- Sicherman, N. (1991) Overeducation in the Labor Market, *Journal of Labor Economics*, 9 (2), 101- 122.
- Sicherman, N., and Galor, O. (1990) A Theory of Career Mobility, *Journal of Political Economy*, 98 (1), 169-192.
- Sloan, P.J., Battu, H., and Seaman, P.T. (1996) Overeducation and the formal education / experience and training trade-off, *Applied Economic Letters*, 3, 511-515.
- Thurow, L.C. (1975) *Generating inequality: Mechanisms of distribution in the U.S. economy*. New York: Basic Books.
- Tsai, Y. (2010) Returns to overeducation: A longitudinal analysis of the U.S. labor market. *Economics of Education Review*, 29(4), 606-617.
- Verdugo, R.R., and Verdugo, N.T. (1989) The Impact of Surplus Schooling on Earnings: Some Additional Findings, *Journal of Human Resources*, 24 (4), 629-643.
- Verhaest, D., and Omey, E. (2012) Overeducation, Undereducation and Earnings: Further Evidence on the Importance of Ability and Measurement Error Bias, *Journal of Labor Research*, 33(1), 76-90.
- Wooldridge, J.M. (2010*): Econometric Analysis of Cross Section and Panel Data, Second Edition,* MIT Press.

Table 1.- Summary statistics

	Mean	SD (overall)	SD	SD (within)	Min	Max	Observ.	Indiv.
Log wage	10.01	0.72	0.75	0.23	2.27	12.41	143,652	66,538
Edu attained (years)	12.25	3.28	3.27	0.55	0.00	16.00	143,652	66,538
Mean Index								
Required education (years)	12.22	2.18	2.14	0.37	3.67	16.00	143,652	66,538
Years of overeducation (for those overeducated)	3.84	1.12	1.11	0.26	0.83	10.20	15,019	8,348
Years of undereducation (for those undereducated)	4.39	2.31	2.35	0.48	1.33	15.74	18,267	10,353
Mode index								
Required education (years)	12.66	2.78	2.71	0.62	0.00	16.00	143,652	66,538
Years of overeducation (for those overeducated)	3.41	1.64	1.60	0.39	1.00	13.00	24,153	13,343
Years of undereducation (for those undereducated)	4.07	2.30	2.28	0.63	1.00	16.00	34,728	18,250
Female	0.38	0.49	0.49	0.00	0.00	1.00	143,652	66,538
Experience	18.70	11.37	11.62	1.47	0.00	65.00	130,283	60,229
Exper. Squared	479.08	485.15	491.88	69.73	0.00	4225.00	130,283	60,229
Disabled	0.02	0.14	0.11	0.09	0.00	1.00	143,652	66,538
Married	0.58	0.49	0.49	0.09	0.00	1.00	143,652	66,538

Note: For a more precise definition of the variables, note that ***wages*** are defined as the "natural logarithm of annual gross wages in real terms (base 2005)", ***years of education*** are derived from the variable "highest ISCED level attained", ***experience*** measures the "number of years spent in paid work" and ***disabled*** is defined as "strongly limited in activities because of health problems".
Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 2.- Educational mismatch according to the mean and the mode measures (cells in %)

[all observations pooled]		**Mode index**			
		Overeducated	Adequately educated	Undereducated	Row total
Mean index					
Overeducated		9.63	0.82	0.00	10.46
Adequately educated		7.18	57.82	11.83	76.83
Undereducated		0.00	0.37	12.34	12.72
Column total		16.81	59.01	24.18	100.00

Note: Table 2 shows the relative frequency of each cell in the two-way table. "Row total" displays the educational mismatch according to the mean index, while "Column total" exhibits the educational mismatch according to the mode index. The diagonal shows the proportion of observations that fall into the same categories according to the two measures (79.79% of total).
Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 3.- Mincer wage equation

OLS	2006 Cross section	2007 Cross section	2008 Cross section	2009 Cross section	POOLED OLS	RANDOM EFFECTS	FIXED EFFECTS
Ln real wage	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**	**Coef. (Rob. S. E.)**	**Coef. (Rob. S. E.)**	**Coef. (Rob. S. E.)**
S_a	0.078***	0.078***	0.079***	0.085***	0.080***	0.069***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Female	-0.200***	-0.207***	-0.219***	-0.211***	-0.211***	-0.217***	---
	(0.009)	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)	---
Exp	0.046***	0.050***	0.049***	0.050***	0.049***	0.053***	0.051***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Exp2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disabled	-0.104***	-0.088***	-0.144***	-0.116***	-0.119***	-0.060***	-0.023**
	(0.029)	(0.020)	(0.018)	(0.021)	(0.013)	(0.010)	(0.010)
Married	0.106***	0.085***	0.080***	0.077***	0.083***	0.081***	0.037***
	(0.010)	(0.007)	(0.006)	(0.006)	(0.004)	(0.004)	(0.010)
Constant	8.641***	8.519***	8.485***	8.389***	8.468***	8.542***	9.298***
	(0.032)	(0.016)	(0.013)	(0.015)	(0.012)	(0.013)	(0.034)
	R^2 = 0.3997	R^2 = 0.4163	R^2 = 0.4401	R^2 = 0.4434	R^2 = 0.4308	R^2 = 0.4276	R^2 = 0.1196

Notes: In parenthesis, cluster-robust standard errors to heteroskedasticity and serial correlation, calculated with Stata. All regressions include country dummies. Hausman specification test**:** chi2(5)= 1,979. Prob>chi2 = 0.0000. R^2 refers to overall R^2 for the random effects and fixed effects models. Pooled sample size: 130,283 observations of 60,229 individuals. Annual sample size: 14,939 observations in 2006; 33,311 observations in 2007; 45,030 observations in 2008, and 37,003 observations in 2009.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 4.- Verdugo and Verdugo model

MEAN INDEX	POOLED OLS	RANDOM-EFFECTS	FIXED-EFFECTS	IV FIXED-EFFECTS
Ln real wage	**Coef.** **(Rob. S. E.)**	**Coef.** **(Rob. S. E.)**	**Coef.** **(Rob. S. E.)**	**Coef.** **(S. E.)**
S_a	0.120*** (0.001)	0.106*** (0.001)	0.017*** (0.003)	0.030*** (0.004)
S_o	-0.077*** (0.002)	-0.059*** (0.002)	-0.015*** (0.003)	-0.025*** (0.004)
S_u	0.093*** (0.002)	0.075*** (0.002)	0.010*** (0.002)	0.029*** (0.005)
Female	-0.232*** (0.004)	-0.235*** (0.004)	--- ---	--- ---
Exp	0.050*** (0.001)	0.053*** (0.001)	0.050*** (0.002)	0.050*** (0.001)
Exp2	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Disabled	-0.115*** (0.012)	-0.060*** (0.009)	-0.023** (0.010)	-0.023** (0.010)
Married	0.074*** (0.004)	0.075*** (0.004)	0.037*** (0.010)	0.036*** (0.009)
Constant	8.002*** (0.013)	8.103*** (0.014)	9.187*** (0.039)	9.023*** (0.049)
Test H.C. model ($\beta_o = \beta_u = 0$)	F(2, 60228) = 2551 Prob> F = 0.0000	chi2(2) = 3207 Prob> chi2 = 0.0000	F(2, 60228) = 20.56 Prob> F = 0.0000	chi2(2) = 56.43 Prob> chi2 = 0.0000
Test job Compet. Model ($\beta_a = -\beta_o = \beta_u$)	F(2, 60228) = 673 Prob> F = 0.0000	chi2(2) = 1533 Prob> chi2 = 0.0000	F(2, 60228) = 4.39 Prob> F = 0.0124	chi2(2) = 4.35 Prob> chi2 = 0.1136
	R^2 = 0.4678	R^2 = 0.4649	R^2 = 0.1478	R^2 = 0.1846

Notes: In parenthesis, cluster-robust standard errors to heteroskedasticity and serial correlation, calculated with Stata. All regressions include country dummies. Hausman specification test**:** chi2(7)= 2364. Prob>chi2 = 0.0000. R^2 refers to overall R^2 for the random effects and fixed effects models. Sample size: 130,283 observations of 60,229 individuals.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 5.- Duncan and Hoffman model

MEAN INDEX	POOLED OLS	RANDOM EFFECTS	FIXED EFFECTS	IV FIXED EFFECTS
Ln real wage	**Coef.** **(Rob. S. E.)**	**Coef.** **(Rob. S. E.)**	**Coef.** **(Rob. S. E.)**	**Coef.** **(S. E.)**
S_r	0.143*** (0.001)	0.129*** (0.001)	0.027*** (0.003)	0.035*** (0.004)
S_o	0.042*** (0.002)	0.038*** (0.002)	0.001 (0.003)	0.006* (0.003)
S_u	-0.030*** (0.001)	-0.027*** (0.001)	-0.005*** (0.002)	-0.008*** (0.002)
Female	-0.254*** (0.004)	-0.257*** (0.004)	--- ---	--- ---
Exp	0.048*** (0.001)	0.052*** (0.001)	0.050*** (0.002)	0.049*** (0.001)
Exp2	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Disabled	-0.116*** (0.012)	-0.060*** (0.009)	-0.023** (0.010)	-0.023** (0.010)
Married	0.071*** (0.004)	0.072*** (0.004)	0.036*** (0.010)	0.036*** (0.009)
Constant	7.790*** (0.013)	7.881*** (0.015)	9.078*** (0.044)	8.983*** (0.054)
Test H.C. model ($\beta_r = \beta_o = -\beta_u$)	F(2, 60228) = 3534 Prob> F = 0.0000	chi2(2) = 4995 Prob> chi2 = 0.0000	F(2, 60228) = 31.81 Prob> F = 0.0000	chi2(2) = 59.86 Prob> chi2 = 0.0000
Test Job Comp. model ($\beta_o = \beta_u = 0$)	F(2, 60228) = 692 Prob> F = 0.0000	chi2(2) = 1160 Prob> chi2 = 0.0000	F(2, 60228) = 3.41 Prob> F = 0.0330	chi2(2) = 17.85 Prob> chi2 = 0.0001
	R^2 = 0.4766	R^2 = 0.4745	R^2 = 0.1698	R^2 = 0.1933

Notes: In parenthesis, cluster-robust standard errors to heteroskedasticity and serial correlation, calculated with Stata. All regressions include country dummies. Hausman specification test**:** chi2(7)= 1924. Prob>chi2 = 0.0000. R^2 refers to overall R^2 for the random effects and fixed effects models. Sample size: 130,283 observations of 60,229 individuals.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 6.- Reduced form equations

	FIXED EFFECTS						FIXED EFFECTS	IV FIXED-EFFECTS
Variables	$S_{r\,(mean)}$	$S_{o\,(mean)}$	$S_{u\,(mean)}$	$S_{r\,(mean)}$	$S_{o\,(mean)}$	$S_{u\,(mean)}$	**Ln real wage**	**Ln real wage**
Panel A.- Verdugo and Verdugo model								
S_a					0.113***	-0.358***	0.017***	0.030***
					(0.003)	(0.003)	(0.002)	(0.004)
$S_{o\,(mode)}$		0.618***			0.592***	0.118***	-0.011***	-0.025***
		(0.002)			(0.002)	(0.003)	(0.002)	(0.004)
$S_{u\,(mode)}$			0.592***		0.074***	0.398***	0.010***	0.029***
			(0.002)		(0.002)	(0.003)	(0.002)	(0.005)
Constant		0.046***	-0.025***		-1.298***	4.461***	9.182***	9.023***
		(0.002)	(0.002)		(0.037)	(0.044)	(0.030)	(0.049)
Individual dummies		Yes	Yes		Yes	Yes	Yes	Yes
Other controls		No	No		Yes	Yes	Yes	Yes
		R^2 = 0.7245	R^2 = 0.7219		R^2 = 0.7152	R^2 = 0.6156	R^2 = 0.1507	R^2 = 0.1846
Panel B.- Duncan and Hoffman model								
$S_{r\,(mode)}$	0.365***			0.388***	0.113***	-0.358***	0.017***	0.035***
	(0.002)			(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
$S_{o\,(mode)}$		0.618***		0.005	0.705***	-0.240***	0.006***	0.006*
		(0.002)		(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
$S_{u\,(mode)}$			0.592***	-0.033***	-0.039***	0.755***	-0.008***	-0.008***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	7.594***	0.046***	-0.025***	6.958***	-1.298***	4.461***	9.182***	8.983***
	(0.021)	(0.002)	(0.002)	(0.038)	(0.037)	(0.044)	(0.030)	(0.054)
Individual dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	No	No	Yes	Yes	Yes	Yes	Yes
	R^2 = 0.8187	R^2 = 0.7245	R^2 = 0.7219	R^2 = 0.8113	R^2 = 0.7152	R^2 = 0.6156	R^2 = 0.1507	R^2 = 0.1933

Notes: In parenthesis, standard errors. Other controls: experience, experience squared, disabled, and married. R^2 refers to overall R^2 for the random effects and fixed effects models. Sample size: 130,283 observations of 60,229 individuals.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 7.- IV Fixed-Effects by sex and age groups

Ln real wage	Verdugo and Verdugo model (mean index)				Ln real wage	Duncan and Hoffman model (mean index)			
	MEN	WOMEN	AGE < 35	AGE >= 35		MEN	WOMEN	AGE < 35	AGE >= 35
	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)		Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)
S_a	0.025***	0.039***	0.030***	0.024***	S_r	0.029***	0.047***	0.032***	0.029***
	(0.004)	(0.007)	(0.009)	(0.004)		(0.005)	(0.009)	(0.009)	(0.005)
S_o	-0.020***	-0.030***	-0.008	-0.031***	S_o	0.006	0.006	0.020***	-0.005
	(0.005)	(0.006)	(0.007)	(0.004)		(0.004)	(0.006)	(0.007)	(0.004)
S_u	0.022***	0.042***	0.021*	0.025***	S_u	-0.008***	-0.009**	-0.018***	-0.004*
	(0.005)	(0.010)	(0.012)	(0.005)		(0.003)	(0.004)	(0.005)	(0.002)
Exp	0.050***	0.052***	0.174***	0.015***	Exp	0.049***	0.051***	0.173***	0.014***
	(0.002)	(0.002)	(0.005)	(0.002)		(0.002)	(0.002)	(0.005)	(0.002)
Exp2	-0.001***	-0.001***	-0.007***	-0.000***	Exp2	-0.001***	-0.001***	-0.007***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Disabled	-0.033***	-0.008	-0.020	-0.022**	Disabled	-0.033***	-0.007	-0.016	-0.022**
	(0.012)	(0.016)	(0.031)	(0.009)		(0.012)	(0.016)	(0.031)	(0.009)
Married	0.054***	0.012	0.044**	-0.013	Married	0.054***	0.011	0.043**	-0.013
	(0.012)	(0.015)	(0.018)	(0.012)		(0.012)	(0.015)	(0.018)	(0.012)
Constant	9.142***	8.798***	8.551***	9.543***	Constant	9.121***	8.724***	8.541***	9.498***
	(0.058)	(0.095)	(0.108)	(0.054)		(0.061)	(0.108)	(0.111)	(0.061)
Test H.C. model ($\beta_o = \beta_u = 0$)	chi2(2) = 23.46 Prob> chi2 = 0.0000	chi2(2) = 33.84 Prob> chi2 = 0.0000	chi2(2) = 3.05 Prob> chi2 = 0.2174	chi2(2) = 59.69 Prob> chi2 = 0.0000	Test H.C. model ($\beta_r = \beta_o = -\beta_u$)	chi2(2) = 24.10 Prob> chi2 = 0.0000	chi2(2) = 37.23 Prob> chi2 = 0.0000	chi2(2) = 2.77 Prob> chi2 = 0.2498	chi2(2) = 61.04 Prob> chi2 = 0.0000
Test J.C. Model ($\beta_a = -\beta_o = \beta_u$)	chi2(2) = 4.06 Prob> chi2 = 0.1311	chi2(2) = 1.91 Prob> chi2 = 0.3849	chi2(2) = 16.70 Prob> chi2 = 0.0002	chi2(2) = 3.10 Prob> chi2 = 0.2118	Test J.C. model ($\beta_o = \beta_u = 0$)	chi2(2) = 12.32 Prob> chi2 = 0.0021	chi2(2) = 5.61 Prob> chi2 = 0.0605	chi2(2) = 20.65 Prob> chi2 = 0.0000	chi2(2) = 5.51 Prob> chi2 = 0.0636
	R^2 = 0.1744	R^2 = 0.1946	R^2 = 0.1526	R^2 = 0.1492		R^2 = 0.1806	R^2 = 0.2108	R^2 = 0.1551	R^2 = 0.1710

Notes: Standard errors in parenthesis. All regressions include country dummies. R^2 refers to overall R^2. Male sample: 79,772 observations of 35,940 individuals. Female sample: 50,511 observations of 24,289 individuals. Age<35 sample: 40,504 observations of 21,648 individuals. Age>=35 sample: 89,779 observations of 40,611 individuals.

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Table 8.- Multinomial logits: determinants of educational mismatch (age >= 35). Mean index

Multinomial logistic regression			**Marginal effects at S_a=16 (dy/dx)**		
OVER	**Coef.**	**Robust S.E.**	**Pr(OVER)=0.2276**	**dy/dx**	**S.E.**
female	-0.300***	0.041	female†	-0.052***	0.007
exp	-0.015***	0.002	exp	-0.003***	0.000
Sa	0.650***	0.012	Sa	0.115***	0.003
married	-0.210***	0.042	married†	-0.038***	0.008
invjobcha	0.343***	0.091	invjobcha†	0.066***	0.019
unem_emp	0.805***	0.099	unem_emp†	0.169***	0.024
inac_emp	0.476***	0.137	inac_emp†	0.094***	0.030
disabled	0.321***	0.111	disabled†	0.061***	0.023
constant	-10.541***	0.182	-		
ADEQ = base outcome					
Multinomial logistic regression			**Marginal effects at S_a=10 (dy/dx)**		
UNDER	**Coef.**	**Robust S.E.**	**Pr(UNDER)=0.1815**	**dy/dx**	**S.E.**
female	0.195***	0.039	female†	0.030***	0.006
exp	0.027***	0.002	exp	0.004***	0.000
Sa	-0.766***	0.011	Sa	-0.114***	0.002
married	-0.043	0.040	married†	-0.006	0.006
invjobcha	-0.233***	0.082	invjobcha†	-0.033***	0.011
unem_emp	-0.386***	0.081	unem_emp†	-0.052***	0.009
inac_emp	-0.371***	0.133	inac_emp†	-0.049***	0.015
disabled	-0.024	0.081	disabled†	-0.004	0.012
constant	5.314***	0.132	-		
Pseudo R^2 = 0.3613					

Notes: In parenthesis, cluster-robust standard errors to heteroskedasticity and serial correlation, calculated with Stata. Regression includes country dummies. Sample size: 89,779 observations of 40,611 individuals.
(†) dy/dx is for discrete change of dummy variable from 0 to 1.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations.

Figure 1

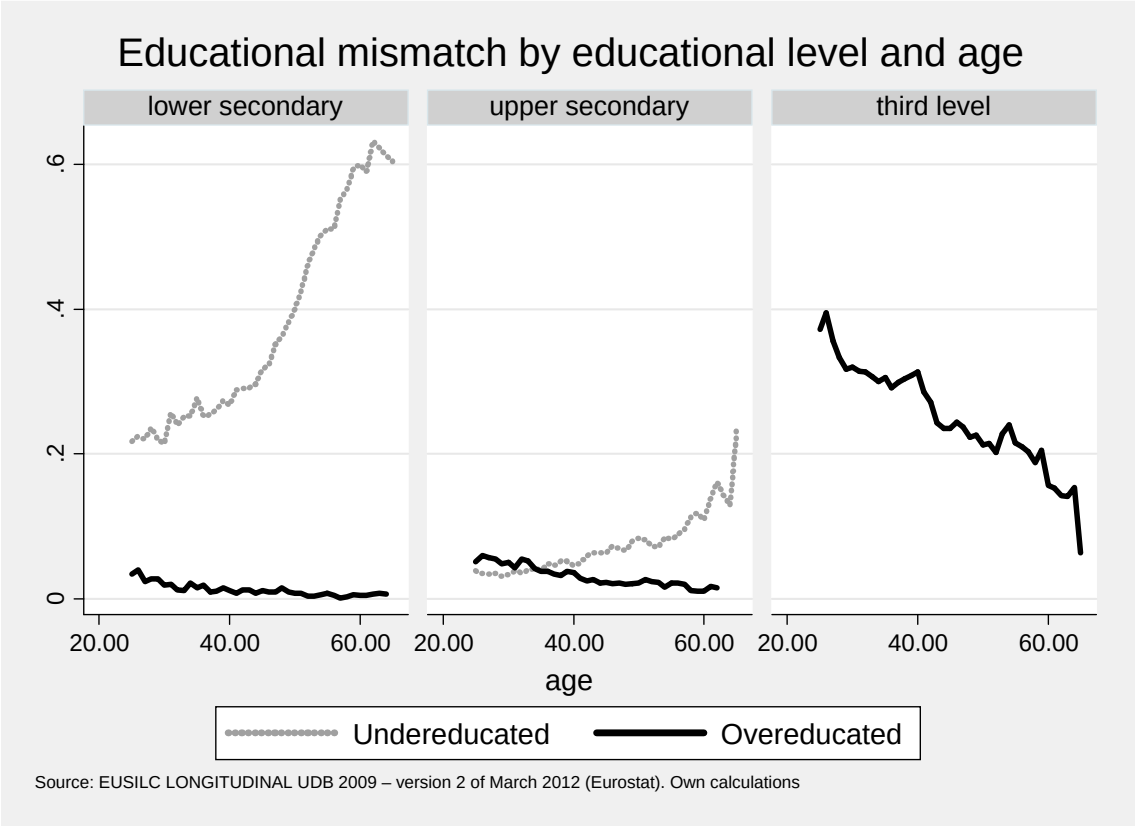


Figure 2

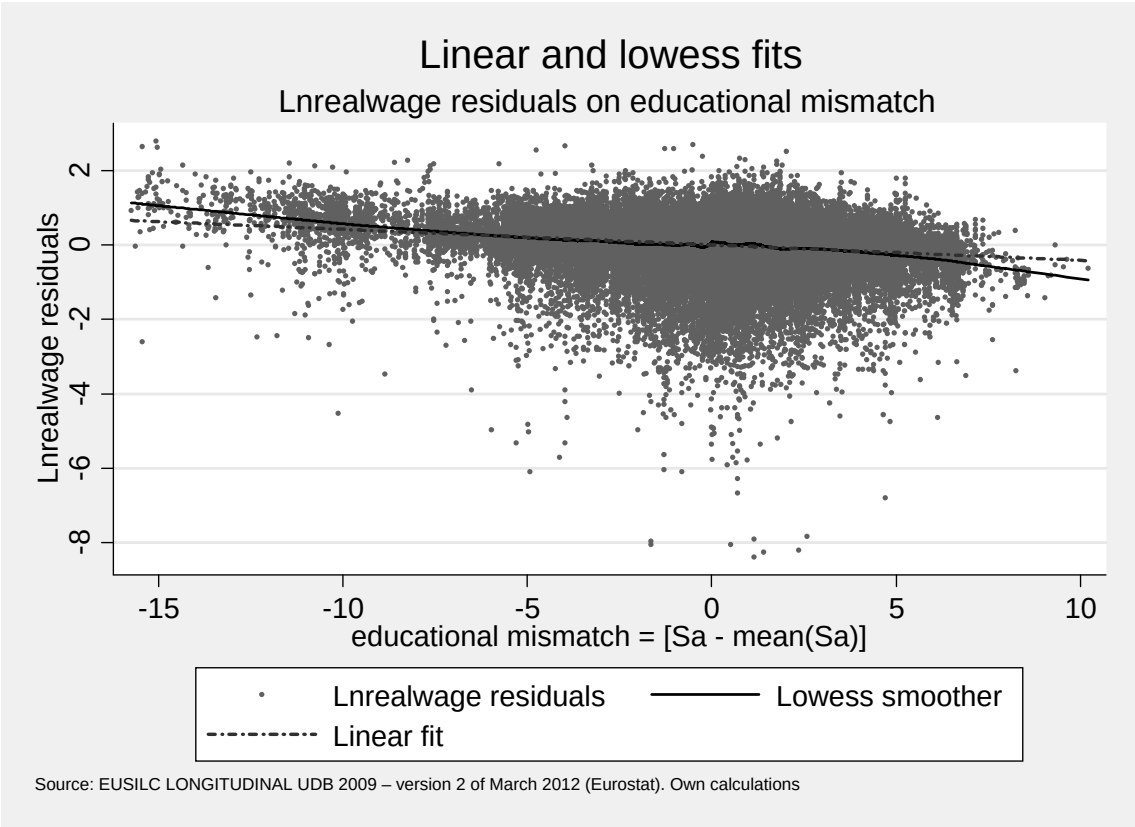


Figure 3

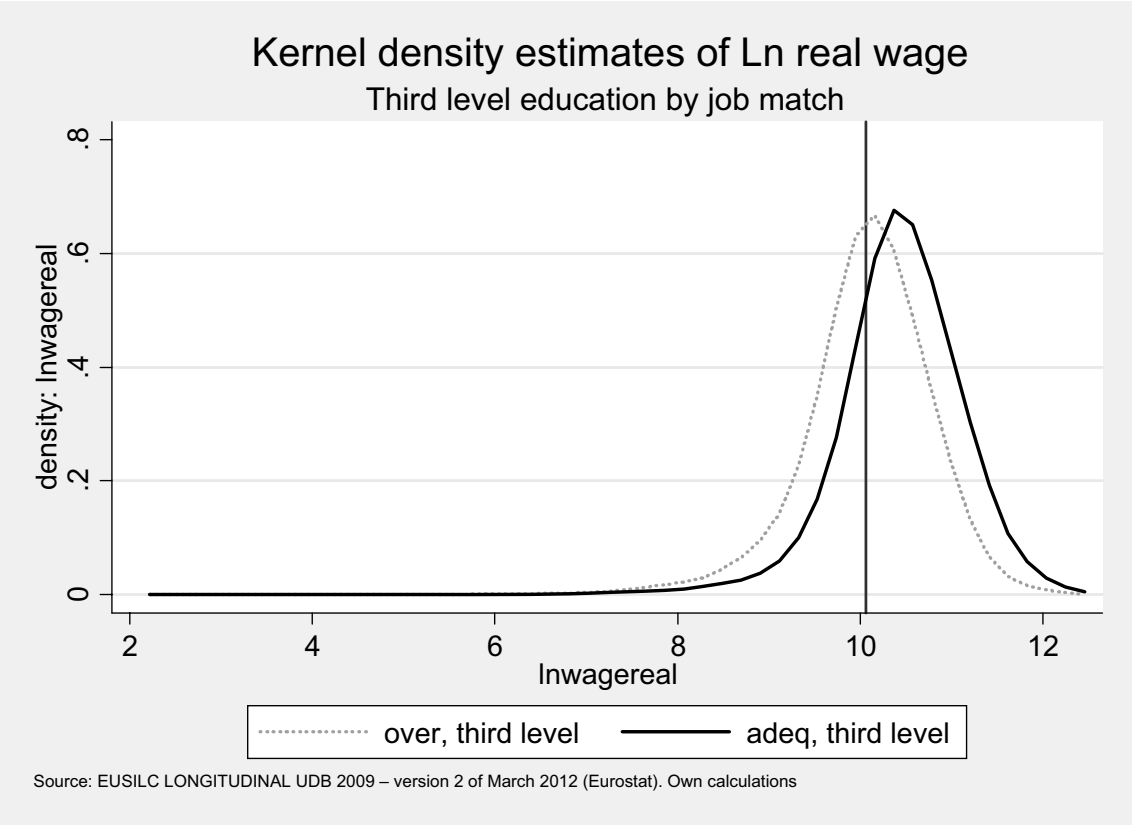


Figure 4

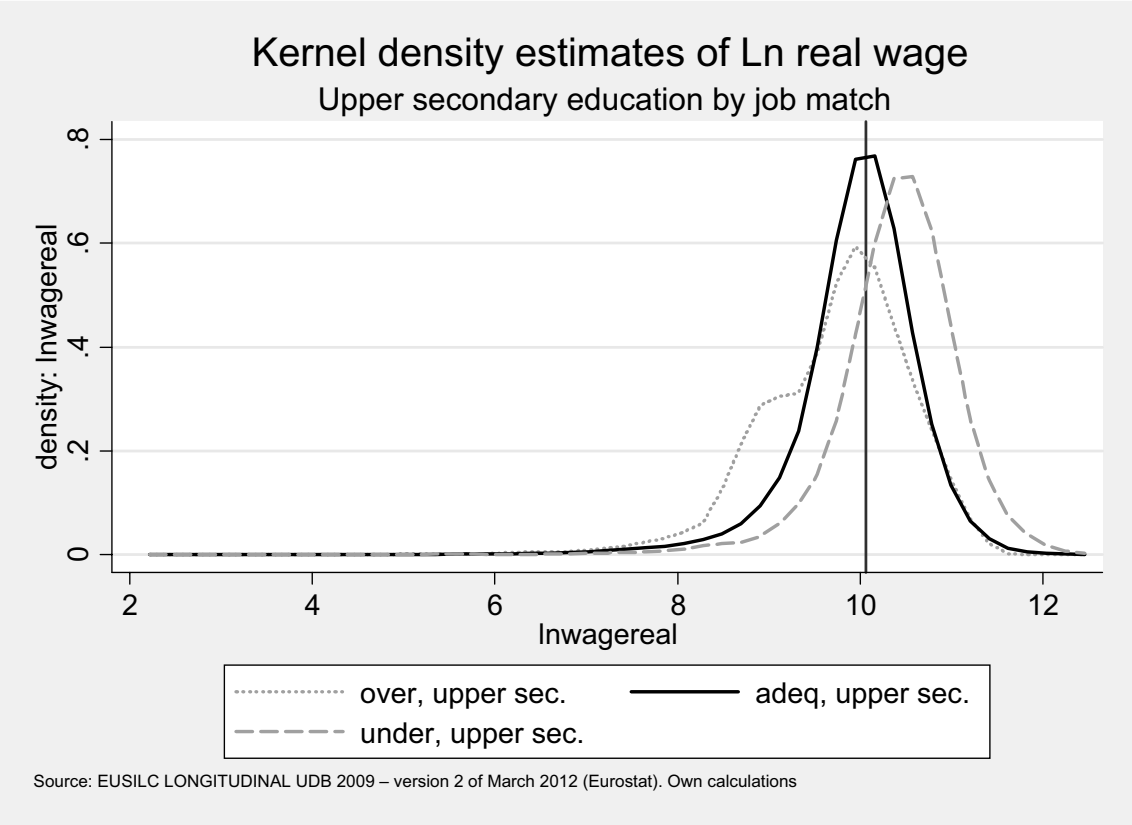
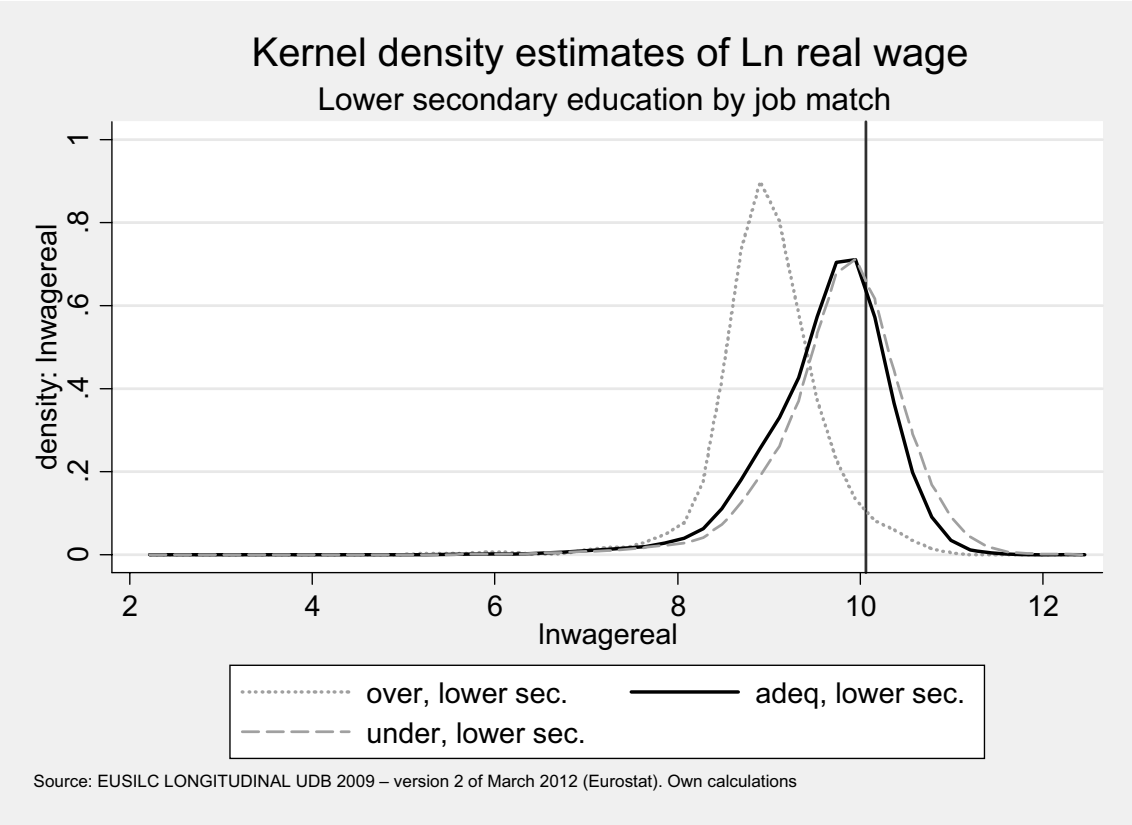


Figure 5


Kernel density estimates of Ln real wage
Lower secondary education by job match
density: lnwagereal
0
.2
.4
.6
.8
1
2
4
6
8
10
12
lnwagereal
over, lower sec.
adeq, lower sec.
under, lower sec.
Source: EUSILC LONGITUDINAL UDB 2009 – version 2 of March 2012 (Eurostat). Own calculations

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