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The impact of overeducation on wages of recent economic sciences graduates An application to the case of the Universidad Nacional de Córdoba[#]

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Under the human capital theory, wages are determined by the worker productivity, which in its crudest form implies the return to education is not contingent on how the workers' skills are utilized in the labor market (Sloane, 2002). However, and after controlling for other differences, the empirical evidence has shown that workers with the same education can be paid differently. The literature has found young people are more likely to experience a mismatch between their formal education and the one required by the job. While there is not a consensus about the reasons for the mismatch, there is one about the consequences in terms of wages, overeducation means a penalty in terms of income.
Our evidence shows that overeducated graduates of the FCE-UNC suffer a wage penalty when compared to those working in a job requiring a university degree. The results are robust to different specifications and to the use of alternative estimators. While the difference is not statistically significant, the penalty for those severely overeducated is larger than for those with a mild level of overeducation. To have working experience while studing at the university helps to reduce the cost of overeducation. The overall impact found for the whole sample appears to be driven by the impact of overeducation on female graduates. While for the case of overeducation we find statistically significant effects, the same is not the case for the level of horizontal match, either in terms of skills and knowledge.

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1. Introduction

Traditionally, the standard characterization of the demand side of the labor market does not consider specific qualitative aspects of the job. However, jobs are quite different in many characteristics that impact on labor productivity. In this context, job requirements attract attention because comprising not only a level of schooling but also other dimensions of skills, abilities, and attitudes (Hartog, 2000). Empirical studies have found that a substantial proportion of young people experience a mismatch between their educational background and the requirements of the job. This mismatch can be vertical, meaning that the level of education of the worker differs to that required by the job, or horizontal in the sense that there is a difference between the field of study of the worker and the one required by the job. One of the most relevant consequences of overeducation is related to the wage penalty when compared to workers that can be considered to be well matched. This problem is more relevant for university graduates, since, among other reasons, investment in superior education is typically the highest per capita amongst all education categories and is often publicly funded, with overeducation representing a poor return on this investment for both the graduate and the society (Carroll and Tani, 2013).

In the specific case of recent university graduates, the analysis of the mismatch -overeducation and field mismatch- is particularly interesting since it could be a temporary phenomenon related to imperfect information about the labor market. But overeducation may also result from a deliberate choice because the low-level job is a good investment opportunity (Rubb, 2006).

As it is well known and remarked by the literature, young professionals are one of the groups that are more likely to be affected by the job mismatch phenomenon, since they are relatively new participants in the labor market and without work experience. For instance, Dekker *et al.* (2002) find using Dutch data that the percentage of overeducated individuals decreases as the range of age increases. If the mismatch phenomenon takes place mostly during a transitional period in which recent graduates exchange knowledge for other sorts of human capital, it could be that the transitional period was not so long. Sicherman and Galor (1990) remark that individuals may accept jobs with low returns to education if the odds of being upgraded is high. However, if genuinely mismatch is permanent, the effects of such a phenomenon are multidimensional and in this respect, the empirical literature vast.

This paper aims to provide evidence if the overeducation phenomenon is present for the recent graduates of economic sciences, which obtained their bachelor degree from the Facultad de Ciencias Económicas of the Universidad Nacional de Córdoba (FCE-UNC). Particularly, the study inquires on the relationship between wages and overeducation as well other key explanatory variables usually used in the wage equation literature.

Using a dataset specially designed for this study, we look at the penalty associated with the status of overeducation for the graduates of the FCE-UNC during the first year after finishing their studies. With this aim, we estimate different pooled and panel data models in which the level of income for salaried employees is explained by personal characteristics, and variables aimed at identifying the status of overeducation as well as the degree of horizontal match in terms of the knowledge and skills acquired in the university and those required by the job.

In the framework of the Verdugo-Verdugo model (Verdugo and Verdugo, 1989), overeducation means a penalty in income when compared with workers with a similar level of formal education but which are well matched. According to our empirical results, overeducated graduates of the FCE-UNC suffer a wage penalty when compared to those working in a job requiring a university degree. This result is robust to different specifications and to the use of alternative estimators. Also, while the difference is not statistically significant, the penalty for those severely overeducated is larger than for those with a mild level of overeducation. Also, having working experience while at the university helps to reduce the cost of overeducation. The overall impact found for the whole sample appears to be driven by the impact of overeducation on female graduates, with the effect on male being not significant. Finally, while for the case of overeducation we find statistically significant effects, the same is not the case for the level of horizontal match, either in terms of skills and knowledge. In both cases, the relationships with income show apparently an inverted u-shape form.

The rest of the paper is structured as follow. Section 2 briefly reviews the related literature. Section 3 presents and describes the data, while in section 4 we estimate and discuss the results of different econometrics models. Finally, section 5 is of summary and conclusions.

2. The related literature

An overeducated individual can be defined as an employee with more schooling than required by the worker's occupation, while an undereducated individual has less schooling than required (Rubb, 2006). In both cases, there is a mismatch between the required education level of the job and the worker's education. One topic, among others, that have attracted the attention of the mismatch literature is the impact that such mismatch has on pay according to the traditional approach of the salary equation. The literature about overeducation traditionally considers a standard earning function explained by Over-Required (O), Required (R) and Under-Required (U) education, widely known as the ORU model. Following Hartog (2000), the econometric specification can be written as follows:

$$\ln w_{it} = \beta_0 + \beta_1 E_{it}^r + \beta_2 E_{it}^o + \beta_3 E_{it}^u + \mathbf{X}_{it}\Gamma + \varepsilon_{it} \qquad (1)$$

where w_{it} is the individual's wage in the job, E_{it}^r are the years of school required for the job, E_{it}^o and E_{it}^u are the number of years of over or under schooling, and $\mathbf{X}_{it}$ includes other explanatory variables affecting the wage rate, and ε_{it} is a random error term. This function differs from the typical Mincerian equation because introduces characteristics of the demand side of the labor market. While in the former an education mismatch would not have an impact on earnings, in the ORU model these are also determined by the job characteristics.

In general, the empirical evidence suggests that overeducation (undereducation) impacts negatively (positively) on wages, being the effect of undereducation stronger (Allen and van der Velden, 2001). In this regard, using data from various annual demographic supplements of the Current Population Surveys for 1994–2000, Rubb (2006) finds that overeducated individuals earn less than similarly educated individuals who are at a job match but more than their just-educated co-workers, while those that are undereducated earn more than others with their level of schooling but less than their just-educated co-workers. This author also concludes that overeducated workers have higher probabilities of upward occupational mobility.

Badillo-Amador and Vila (2013) analyze the consequences of both skill and education mismatches on job satisfaction and wages using Spanish data from the European Community Household Panel (ECHP) survey for the year 2001. Their statistical analysis shows that educational and skill mismatches are weakly related in the Spanish labor market, and conclude that skill mismatches appear as key determinants of workers' job satisfaction, while educational mismatches have much weaker impacts, if any, on workers' job satisfaction; however, both skill and education mismatches have negative impacts on wages.

Some studies, instead, have focused on the consequences of educational mismatch in the specific case of university graduates. Allen and van der Velden (2001) analyze the relationship between skill mismatch and educational mismatch and their effects on wages from the perspective of assignment theory. In order to test the effect of mismatch on wages and job satisfaction, the authors use a sample of Dutch individuals who graduated from tertiary education seven years prior to the survey and were in paid employment for at least 12 hours per week. Their results confirm the negative effect of overeducation on wages is stronger than the premium of being undereducated and do not support the assignment theory, since skill mismatches account for only a small proportion of the wage effects of educational mismatches. Mavromaras *et al.* (2013) estimate the effects of being overeducated, overskilled or both on wages, job mobility and job satisfaction, with a panel data from the HILDA Survey, which began in 2010. It comprises all working-age male paid employees holding a university degree or equivalent qualification in full-time employment. The authors find that overeducation and overskilling are distinct phenomena and they have a different effect on different labor market outcomes such as pay and job satisfaction. The negative effect of being simultaneously overeducated and overskilled is larger than when the person experiences just one of those states. They remark that their econometric outcomes are more reliable since they use a panel data allowing to control for unobserved heterogeneity. Carroll and Tani (2013) analyze the evolution of overeducation and their impact on pay with data from Australian graduates with bachelor degrees who left college in 2007 and were followed up in 2008, 2009 and 2010. These authors show the rate of overeducation fell notably by 2010, especially for young graduates who were more likely to be overeducated initially and that the penalty of overeducation on young graduates' pay is not significant in comparison with their well-matched peers.

Sellami *et al.* (2017) analyze the effects of both vertical and horizontal mismatches on the pay of individuals with a higher education degree in Flanders. They use a panel data from SONAR with the cohort of those that were born in 1978, surveyed at the 23 years old for the first time and followed-up when they were 26 and 29 years old. These authors estimate a wage equation and control for the measurement error in educational mismatch and unobserved heterogeneity. Their results consistently show that overeducated individuals without field of study mismatch earn less than adequate educated workers with a similar educational background and that for those individuals who are working outside their field of study such a penalty is not always observed.

Alternatively, Zhu (2014) applies a nonparametric technique to account for the effect of each individual's major-job mismatch on wage for recent graduates in China. Interestingly, the author finds that though the mean impact is negative, there are more or less 32% of individuals that present a positive coefficient. This result is in line with Robst (2007), which argues that individuals with a major-occupation mismatch may earn more than those individuals which show a well major-occupation match due to the fact that mismatched individuals may accept such a situation for career opportunity reasons. The study also finds support for the assignment theory; the level of wages is explained by college education, job characteristics and the major-job matching.

The literature reviewed here find that different variables of control are significant. According to Rubb (2006), the experience of overeducated workers is rewarded at lower rates than the experience of undereducated workers and tends to increase wages of young overeducated workers without necessarily increasing occupational mobility. In contrast, experience tends to increase the occupational mobility of older workers without necessarily having a beneficial impact on their wages. For the mismatched groups, Zhu (2014) estimates that for one more month of experience in the current job, in average, the monthly income increases by almost 2%.

The age of individuals seems to be relevant in the analysis. As remarked above, the overeducation phenomenon seems to affect different vulnerable groups such as young persons. Dekker *et al.* (2002) find in the Dutch sample that the percentage of overeducated individuals decreases as the range of age increases, i.e. 41.7% for the 15-19 age interval, 27% for the 30-40 age interval and 18% for the 49-64 age range. The mismatch phenomenon may appear to be transitional, since recent graduates may exchange knowledge for other sorts of human capital during a transitional period. Sicherman and Galor (1990) note that individuals may accept jobs with low returns to education if the odds of being upgraded is high. In this line, Sicherman (1991) finds support to the hypothesis that overeducated individuals have a greater probability to obtain promotion than those of are well matched in United State. Carroll and Tani (2013) found the rate of overeducation fell notably three years after graduation, especially for young graduates. The majority of graduates who are overeducated shortly after course completion are no longer overeducated three years later, reflecting, in fact, that overeducation can be a stepping-stone into appropriate employment. With regard to the effect on earnings, after controlling for unobserved heterogeneity they found young overeducated graduates' pay does not differ significantly to those of their well-matched peers. On the contrary, overeducation penalizes older overeducated graduates. Zhu (2014) evidences that age has little effect on average incomes of the Chinese graduates, but it affects negatively wages for two subgroups of interest, i.e. for the 25th and 75th percentiles of the estimated distribution for mismatched persons.

An interesting inquest is whether gender may play an important role when one analyzes the job mismatch phenomenon. At least, three questions may arise: i) if there is one, which is the gender more vulnerable to be overeducated? ii) does the impact of the mismatch on wages differ between males and women? and iii) are the reasons for accepting to be mismatched different for men and women?. Groot and Massen van den Brink (2000) suggest that overeducation is more frequent among women than men. On the contrary, by defining job mismatch in relation with the field of study, Robst (2007) finds that men are more likely to be mismatched than women; such a difference is statistically significant but relatively small (2%). The study also examines whether mismatched workers earn more or less than well-matched workers; mismatched women earn 8.9% less than well-matched women, while mismatched males earn 10.2% less than well-matched males, with the difference being statistically significant at the 10% level. Moreover, there are significant gender differences across the reasons for accepting to be mismatched. The results suggest that women are more likely to report being mismatched because of amenity/constraint-related reasons (family-related reasons, job location, and working conditions), while men are more likely than women to report being mismatched due to career-oriented reasons (pay and promotion opportunities or a change in career interests). The reasons for accepting to be mismatched also affect differently on wages. For the amenities/constraints and demand-side reasons, the wage losses range between 18%-29% and 17%-21% for men and women respectively. In contrast, workers of both genders that accept to be mismatched due to pay or promotion opportunities earn more than correctly matched workers. While the results are qualitatively similar, some coefficients are different according to the gender. The results show that when men are mismatched, they suffer greater wage penalties, while woman workers gain more when they accept to be mismatched due to pay and promotion opportunities. Women also have wage gains when the mismatch is because of a change in career interests while men have wage losses. Zhu (2014) finds that male graduates have a lower proportion of mismatch than women, and the econometric results show that the variable gender, which identifies males, is statistically significant and positively associated with the average income, as well as for all percentiles of the estimated distribution for mismatched individuals. The nonparametric model indicates that on average, mismatched males earn 5.25% more than mismatched females. Hence, the evidence about how the gender plays a role presents mixed results.

Skill mismatch seems also to be relevant to explain salaries. Mavromaras *et al.* (2013) find that when controlling for unobserved heterogeneity, graduate men who change status from a well-matched job to an overeducated job or an overskilled job, do not suffer a wage penalty. It is only well-matched graduate men who change status to a job where they are both overeducated and overskilled that suffer an approximate 5.9% wage penalty.

As pointed out before, in addition to the vertical mismatch in terms of the level of required education and the one held by the worker, Sellami *et al.* (2017) include a measure of horizontal mismatch (defined in term of the match between field of study and competencies required for every occupation) and its interaction with overeducation. Interestingly, their results indicate that it is not associated with a wage penalty and, on the contrary, it even is associated with a wage bonus, in cases where these individuals are employed in labor market segments that face labor shortages, resulting in upward wage pressure.

Different arguments have been proposed to explain the phenomenon of educational mismatch. Following Rubb (2006), the existence of overeducation can be explained by the human capital theory, since overeducated workers may substitute weaknesses in other areas of human capital by having more schooling than required. Such weaknesses include lower quality schooling (Robst, 1995), less experience due to career interruptions (Mincer and Polachek, 1974; Albrecht et al., 1999), less on-the-job training (Sicherman, 1991), and a variety of other possibilities. Conversely, undereducated workers may substitute their lack of schooling with strengths in other areas of the human capital. Hartog (2000) suggests that from the human capital perspective, overeducation may result from a deliberate choice because the low-level job is a good investment opportunity; but, at the same time points out that a mismatch can be the result of job search in an imperfect information context, especially in the early career development, so it is likely to be a temporary status. The latter attracts more attention when overeducation is analyzed among recent graduates. In this regard, Carroll and Tani (2013) find the rate of overeducation fell notably after a few years of graduation, and the majority of graduates who were overeducated shortly after course completion are no longer overeducated three years later, reflecting that overeducation can be a stepping-stone into appropriate employment. This finding could suggest that the mismatch tends to decrease as workers gain experience in the labor market. In this regard, Hartog (2000) points out that the fact that overeducation is typically higher in the phase of the transition from school to work is often taken as evidence for this interpretation. However, others have argued, from the point of view of human capital theory, that the high incidence of overeducation among school-leavers reflects these workers' lack of work experience. Van der Velden (2001) and Hartog (2000) notice that the assignment theory, can be a good explanation. According to this theory, the allocation is optimal when workers are allocated top-down according to their skills, whereby the most competent worker is assigned to the most complex job and the least competent worker is assigned to the simplest job. The incidence of educational mismatches can thus be explained by differences in the shares of complex jobs and skilled workers.

Finally, Deželan and Hafner (2014) study the success of political science graduates during the transition from High School to the employment market in Slovenia. Though the authors do not inquire into the relationship between job matching and wages, they investigate the education-job matching of graduates in the first job by analyzing the educational and skill matches. Based on human capital, credentialist, assignment predictions as well contextual characteristics, disciplinary idiosyncrasies, and period effects, they regress binary logistic econometric specifications in which dependent variables are the appropriate level of education for the first job, overall educational matches (horizontal and vertical ones) and good skill utilization. Estimations corroborate many of the theoretical hypotheses from different backgrounds of the related literature. Particularly, job satisfaction increases the odds of being well educational matched; in fact, political science graduates that are fully satisfied with their first job increase the chances by 4.8 times in having an overall educational match in comparison to those graduates that indicate that were not satisfied with their first job. As expected, the sector in which graduates work is relevant in predicting a good match in education and skills; those individuals that work in the public sectors are more likely to have an adequate matching. Also, there is evidence for the credentialist premise which states that employers perceive the differences in the type of degrees as a signal trainability. Though gender and the human capital hypotheses are not corroborated in all estimations; the outcomes present a weak evidence for gender discrimination against women and for the fact that graduates with higher degrees increase the odds of being educational matched.

3. Data and descriptive statistics

In order to carry out the study here proposed we need information which for the case of Argentina is not available, at least from Official Statistical Offices. Thus, we generated our own dataset, which besides requiring a great deal of effort it also demands important financial resources. In light of these restrictions, we limited our analysis to the case of the FCE of the UNC. The UNC, in addition being the oldest university of Argentina, is the second largest after the Universidad de Buenos Aires, with around 115 thousand students. In the particular case of the FCE, is also among the largest in the country in terms of the number of students, with an area of influence that includes not only the Province of Córdoba, of which is its capital city, but also the center and the north-west of the country.[1]

The population subject of our study is the graduates of the three undergraduate degrees granted by the FCE of the UNC, these are Bachelor of Science in Economics, Bachelor of Arts in Administration and Public Accountant. Every year, the FCE celebrates four graduation ceremonies, in which approximately 700 students graduate. Our sample covers about half of that population for the year 2016 (those who registered for the third and fourth graduation ceremonies) and a quarter of 2017 (those who registered for the third graduation ceremony).[2] By large the main number of graduates corresponds to the degree of Accountancy, followed by Administration, and then a small number of BSc in Economics.

In our dataset, each individual was interviewed at the time of registering for the graduation and then four additional times, one every three months, on aspects related to their job performance, as well on some piece of informarion about personal characteristics. The main reason why we choose the beginning of the survey to be the moment graduates register for the ceremony was it allowed making the survey compulsory since it was included as a requisite by the FCE-UNC. However, for the follow-up surveys, we depended on the goodwill of the graduates to answer them. All surveys were carried out online using the tool LimeSurvey. With the exception of objective variables, such as age, gender, civil status, and other of a similar nature, answers given by the respondents are self-reported perceptions.

Even when for the follow-up questionnaires we depended on the good-will of the respondents, we managed to achieve very high rates of responses (see Table 1).

Another important challenge for this type of surveys is to keep as low as possible the attrition of the original sample. As reported in Table 2, we were quite successful in this regards. Half of the individuals completed the four follow-up surveys, with the percentage reaching 69.4% if we include also those who responded three out of the four surveys.

Table 3 shows some descriptive statistics about the variables we use in the econometric exercises, distinguishing between the base and follow-up surveys. The aim of Table 3 is twofold. Firstly, it gives a summary picture of the personal characteristics of the population under study. Secondly, it helps to gather an idea if the patterns of attrition reported in Table 2 may be of concern in terms of our results being biased by a problem of self-selection. Let take a look at this second issue first.

In Table 3, variables identified with a (*) refer to questions made only for the base survey. Thus, the figures reported for these variables in the columns corresponding to the follow-up surveys are for the answers given on occasion of the base survey but considering only those individuals that responded to the follow-up questionnaires. If the attrition of the original sample would mean a self-selection problem, we could expect that the summary of the figures reported for the base and follow-up surveys show important differences; however, this is not the case.

[1] The FCE is located at the capital of the Province of Córdoba; but an important number of students come from the provinces of Catamarca, La Rioja, Santiago del Estero, Tucumán, Salta and Jujuy. Historically, the UNC has been the destiny of students coming from neighboring countries, especially Bolivia, Paraguay and Peru. Recently there has been an important influx of students from Venezuela.

[2] By the time this draft is written we are finishing the last follow-up survey corresponding to the fourth graduation of 2017. We plan to incorporate the fourth sample in next versions of this research.

With regards to the characteristics of the individuals that constitute our sample, some interesting results are worth mentioning.

- Women constitute 60% of graduates.
- 83/87% declare their civil status to be single.
- The share whose parents have a university degree is around 30%, both for the case of the father or the mother.
- A well-known problem, closely related to the length of time to finish the studies, is the low average mark with which students graduate, just above 5 on a scale from 0 to 10.
- One of the main features of university students in Argentina is that a large percentage of them start working before they graduate. Among the reasons behind this behavior is the lack of enough funding to support their studies as well as a mean of gaining experience during the transitional period before they finish their studies when they will look to enter into the labor market. This pattern emerges clearly when looking at Table 3, with almost three out of four students having declared they had a working experience, excluding the job they may have at the moment of graduation.
- Of those who declared a working experience while studying, 75% declared their job was somehow related to their field of study.
- Considering that our period of study covers the first year after graduation, and related to the two previous points, the average tenure of around 2.5 years reflects also that a large proportion of students start working well before they finish their studies.
- At the moment of graduation those who declare having a formal employment, which we approximate by employers complying with contributions to social security, represent about two-thirds of the sample, increasing to almost 75% in the follow-up surveys. These figures, especially for the follow-up surveys, mean a slight increase relative to the average of the Argentinean labor market, in which about 35% are informal workers.
- Most graduates, almost half, work in organizations with at least 50 employees, followed by those with between 6 and 20.
- 60% of the people surveyed work more than 40 hrs/week, followed by those who work between 30 and 40 hs, which represent almost 20%.

Let now take a look at the variables we are most interested in. For the case of overeducation, we consider a person to fall into that category if he/she declares that his/her job requires a tertiary non-university degree or less; additionally we distinguish two categories among overeducated people: moderately overeducated are those whose job requires a tertiary non-university degree, while those in a job which does not require a tertiary/university degree are classified as severely overeducated. Thus, it is important to stress that the status assigned to each person is the results of his/her self-assessment, as opposed to the alternative of using a systematic evaluation of the characteristics of each job, usually referred as “objective measure” of overeducation, and the so-called “empirical method” in which a person is compared to a group of his/her peers using the mean or modal values of formal education, usually measured in years, as point of reference.

Graph 1 reports that at the moment of graduation around a one-third of those working as salaried employees defined themselves as overeducated; this proportion rises in the first follow-up survey, and then it falls continuously, reaching a 26.9% in the fourth follow-up survey. When distinguishing between severe and mild overeducation, the first category shows a time pattern similar to that of overall overeducation, while mild overeducation shows a more unstable behavior. In general, as time passes on, severely overeducated people explain a larger share of those classified as overeducated.

While overeducation is the reflection of a vertical mismatch, in the sense that there is a difference between the level of formal education holds by the person and the one required by the job, another mismatch looks at comparing the skills and knowledge acquired during the studies and those required by the job. This second approach is sometimes referred to as a horizontal mismatch. Thus, in the line of Allen and van der Velden (2000), in order to identify the existence of a horizontal mismatch, we make use of two questions, that like in the case of overeducation, correspond to a self-assessment each person makes of his/her situation. The first question asks the graduates to rank, in a range from 1 (the worst match) to 10 (the best match), the degree of correspondence between the skills acquired during their undergraduate studies at the FCE-UNC and the skills that are required by the job, while the second question asks the person to rank to what extent he/she uses in the job the knowledge learnt during their undergraduate studies at the FCE-UNC. The first case we refer to it as skills matching, while the second one we refer to it as knowledge matching.

As reported in Graph 2, the knowledge match is higher than the skills match, however, is the later the one showing a clear improvement as the time from graduation moves forward. In spite of these different temporal behaviors, both matchings can be considered to be somehow low.

When we compare the status of overeducation with the level of horizontal match, there is a clear negative relationship with the two variables, whit the proportion of those who declare themselves as overeducated decreasing as the level of horizontal match increases (see Graph 3).

4. Empirical approach and results

As pointed out before, the aim of this research is to look at the effects on salaried income of the vertical and horizontal mismatches between formal education and the requirements of the job. The vertical mismatch is approximated by the relationship between the person's level of formal education, undergraduate studies in the case of our sample, and the level of education required by the job. In the case of the horizontal mismatch we measure it alternatively in two ways: the degree of correspondence between the skills acquired during the undergraduate studies at the FCE-UNC and the ones required by the job, and the extent the person uses in his/her job the knowledge learned during their undergraduate studies at the FCE-UNC. As referred above, the first case we refer to it as skills matching, while the second one we refer to it as knowledge matching.

Before going on to comment on the results arising from the different specifications we estimate, it is necessary to make some observations on our dependent variable. At the time of carrying out the different surveys, those who declared to be employed were asked to declare the level of income earned in their main occupation, having two options of responces: to declare their specific income or identify the range in which they income fall into.

Because the majority of respondents chose the second alternative, we need to define a criterion to assign a certain income level to each individual. In particular, we work with three options. Firstly, the dependent variable is defined in an ordinal manner in the range of 1 to 24, with each value corresponding to a given income range.[3] Secondly, for each individual, we assign him/her an income equal to the middle point of the interval he/she declared.[4] Thirdly, instead of allocating a particular income, the interval declared by the respondent is used. For the second and third options, and because of the important increase in prices that occurred during the collection of the data, nominal values were deflated using the consumer price index, which as a side result means an increase in the possible values taken by our dependent variable, rendering it almost continuous.[5] For the first and second options, we use

[3] The value 1 corresponds to those who declared an income of less than $3000 a month, while the value 24 represents an income of $25000 or more. The remaining values are defined using a $1000 interval.
[4] For the lowest interval we use the upper limit of it, while for the highest interval we use its lower limit.
[5] This is not the case for the first option.

both a pool and a random effect linear estimator, while for the third option we used an interval regression estimator in its pool and random effect versions.

There are two main empirical specifications when looking at the effects of overeducation on wages, the so-called ORU model based on Duncan and Hoffman (1981), that decomposes actual years of schooling $\left(E_{it}\right)$ into required years of schooling $\left(E_{it}^{r}\right)$, years of overschooling $\left(E_{it}^{o}\right)$, and years of underschooling $\left(E_{it}^{u}\right)$, which can be estimated using the following equation:

$$\ln w_{it} = \beta_0 + \beta_1 E_{it}^{r} + \beta_2 E_{it}^{o} + \beta_3 E_{it}^{u} + \mathbf{X}_{it}\Gamma + \varepsilon_{it} \tag{2}$$

with:

$$E_{it} = E_{it}^{r} + E_{it}^{o} + E_{it}^{u}$$

$$E_{it}^{o} = \begin{cases} E_{it} - E_{it}^{r} \text{ if } E_{it} > E_{it}^{r} \\ 0\text{, otherwise} \end{cases}$$

$$E_{it}^{u} = \begin{cases} E_{it}^{r} - E_{it} \text{ if } E_{it} < E_{it}^{r} \\ 0\text{, otherwise} \end{cases}$$

and the model of Verdugo and Verdugo (1989), which is estimated using the following equation:

$$\ln w_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 OV_{it} + \beta_3 UN_{it} + \mathbf{X}_{it}\Gamma + \varepsilon_{it} \tag{3}$$

with:

$$OV_{it} = \begin{cases} 1 \text{ if } E_{it} > E_{it}^{r} \\ 0\text{, otherwise} \end{cases}$$

$$UN_{it} = \begin{cases} 1 \text{ if } E_{it} < E_{it}^{r} \\ 0\text{, otherwise} \end{cases}$$

In equation (2) the coefficients β_2 and β_3 are interpreted relative a workers in the same occupation (requiring the same years of schooling) which are correctly matched, with the following relationships between the coefficients $\beta_1 > \beta_2 > 0$ (the return to each year of schooling beyond those required is positive but lower than for the required ones), and $\beta_3 < 0$ and $\beta_1 > -\beta_3$ (the return to each year of underschooling is negative, but the absolute value of the penalty is lower than the return to each year of required schooling). The above means that overeducated (undereducated) workers earn more (less) than correctly matched workers in the same kind of jobs.

Instead, under the dummy variable approach proposed by Verdugo and Verdugo (1989), the comparison is between workers with the same level of education (equal E_{it}) but with one of them being overeducated (OV_{it}=1) or undereducated (UN_{it}=1). Under this approach, we expect β_2<0 (overeducated workers earn less than others with the same level of education that are correctly matched) and $\beta_3>0$ (undereducated workers earn more than others with the same level of education that are correctly matched).[6]

In our case, and because the population under study has all the same level of actual education, we cannot estimate the ORU model, so we are left with a variation of equation (3), in particular, we estimate the following specification[7]:

$$\ln w_{it} = \delta_0 + \delta_1 OV_{it} + \delta_2 HMS_{it} + \delta_2 HMK_{it} + \mathbf{X}_{it}\Gamma + \varepsilon_{it} \quad (4)$$

where OV_{it} is defined as in (3). As explained before, a person is defined as overeducated if he/she declares that his/her job requires a tertiary non-university degree or less. Variables HMS_{it} and HMK_{it} are proxies for the degree of horizontal match, measured in terms of skills (*HMS*) or knowledge (*HMK*) acquired in the university and effectively used in the job. While under the usual hypothesis that an overeducated worker would earn less than another worker with the same level of education but correctly matched, we expect coefficient δ_1 to be negative. With regards to the influence of the degree of horizontal match, arguments can be made in favor of δ_2 being negative or positive; moreover, as we show later when commenting on the results, the relationship between HM_{it} and wages shows an inverted u-shape form.

Results

In Table 4 we report the results for the pooled sample for each of the three dependent variables. The main results that emerge quite clearly are the significant and negative effect associated with the overeducation dummy. This outcome means that for any two graduates with the same characteristics than their overeducation status, the one for whom there is not a match between his/her level of education and the required by the job earns a lower income. This effect is in all cases significant at the 1%. Looking at the results from columns (3) to (6), the status of overeducation means a penalty of about 6.4 to 8.3 percentage.

With regards to the match in terms of skills and knowledge, the results are not statistically significant. However, in both cases, the relationship between the level of income is non-linear, with an inverted u-shape form. Also, the effect is always larger for the match in terms of skills than in terms of knowledge.

For the remaining control variables[8], we obtain positive and significant coefficients for non-single status, working in the formal sector, working in larger firms, longer tenure, as well as the time from graduation passes on. An interesting result is the positive and statistically significant relationship with having working experience during the time in university, but when this working experience was in jobs related to the area of study the coefficient means also a positive effect on wages but the estimates are less robust, mostly with a level of significance of 10%. Finally, an odd result is the negative coefficient associated with having performed training activities, but the coefficients are in most cases not significant.

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[6] If wages were paid according to the human capital theory we should have $\beta_1=\beta_2=-\beta_3$ for the ORU model, and $\beta_2=\beta_3=0$ for the Verdugo-Verdugo model.

[7] Since we are dealing with university graduates, undereducation is not a possible status unless a person declares his/her job requires postgraduate studies. Even when in a few cases people have declared to be in such situation, we choose to consider them as correctly matched.

[8] We also run our different models including other control variables, such as knowledge of foreign language and of software packages, sector of activity, having people economically dependent, average grade at university, and the degree obtained. In all cases we did not fin significant estimates, and since its exclusion did not affect the results for the remaining variables here reported, we choose to exclude them with the aim of simplicity and easy of presentation. These results are available upon request.

The use of cross-section data, or as in the previous results a pooled one, raises the possibility that the results are biased due to unobserved heterogeneity. As pointed out by Bauer (2002), controlling for unobserved heterogeneity might be important if individuals with lower innate ability need more education to attain a job for which they are formally overeducated. If this argument is true, we could expect that the coefficient for the overeducation status be lower in absolute value (since the unobserved ability and the probability of being overeducated are negatively correlated). In the extreme case, overeducation is only a problem of measurement error, with apparently overeducated workers being, in reality, less able than others on other dimensions. Thus, when all relevant differences in abilities are taken into account, the returns to education should become independent of the skill requirements of the job (Korpi and Tahlin, 2009). In light of these arguments, in Table 5 we report the results of estimating different random effect models.

As we can see from the reading of Table 5, the results of making use of the panel structure of our data are qualitatively similar to the ones reported in Table 4. However, some differences are worth pointing out. As in Table 4 the coefficients for the variable measuring the status of overeducation are in all cases negative and statistically significant at the 1 or 5%, however the (absolute) values of the estimates are in all cases lower than the obtained for the pooled regressions, meaning that as expected unobserved ability is negatively correlated with the probability of being overeducated. Looking at columns (3) to (6), the penalty associated with the status of overeducation now varies between 5 and 5.6% compared with the 6.4-8.3% range reported in Table 4.[9] This reduction in the wage penalty associated with overeducation is in line with the finding in the literature as reported for example in Chevallier (2000), Allen and van der Velden (2001), and Korpi and Tahlin (2009).

As before, the variables that approximate by the horizontal matches in skills and knowledge are not statistically significant.

In Table 6 we run once again the random effect model for the interval regression estimator, but now we allow for the wage penalty to be different between those who are severely overeducated and those who are mildly overeducated. As we could have expected, the wage penalty associated with severe overeducation is larger than for mild overeducation, 5.3-6.2% compared to 4.9-5%. However, as reported at the bottom of Table 6, we cannot reject the null hypothesis that the penalties are statistically the same.

In Table 7 we run once again the interval regression model with random effects, but now allowing for the effect of overeducation varying in terms of some personal characteristics: working experience during the time as student and gender. The main results point out that the penalty associated to overeducation depends on having or not working experience, with the coefficients being significant only for those without it, and also that the average penalties reported before would be explained by the impact overeducation has on female graduates, while for the male graduates the estimates are not statistically significant.

Another result that emerges from the panel data models is that when we control for the horizontal matches, the magnitudes of the coefficients for the overeducation variable are now slightly smaller. As pointed out by Di Pietro and Urwin (2006), this result would suggest that the assignment theory of overeducation would fit our data better than the alternatives. However, this interpretation should be taken with great caution since, as just noted, the reductions in the magnitude of the estimates are rather small.

All previous panel data models assumed that the individual effects are random instead of fixed. In Table 8 we compare the results of the pooled OLS estimator with the random and fixed effects alternatives. Before looking at the results two points need to be made. Firstly, we need to exclude three variables from the analysis since they show no variability across time for each individual and so become perfectly collinear with the fixed effects: gender, and

[9] These values are close to the ones found by Di Pietro and Urwin (2006), who apply the Verdugo-Verdugo model to Italian university graduates three years after their graduation.

working experience while studying, either in jobs related or not to the field of study. Secondly and more important is the issue pointed out by Bauer (2002) regarding if the status of overeducation has enough variation within each individual to identify the effects of an educational mismatch on wages, luckily this is the case in our dataset. For whom we have more than one observation, around 36% experienced at least one change in their status when we distinguish between overeducated and not overeducated, and the percentage rises to 42% when overeducation is further divided into sever and mild.

Regarding the results, the Breusch-Pagan test favors in all cases the random effect model over the pooled OLS, while the Hausman test points out that the orthogonality assumption between the individual effects and the explanatory variables is rejected, so the fixed effect estimator is favored over the random one. When looking at the magnitudes of the penalty associated to overeducation a clear pattern emerges. The penalty is lower for the random effect models than for the pooled OLS, and it is further reduced when using the fixed effect estimator. Thus, as expected, when we account for the unobserved heterogeneity the effect of overeducation changes in the right direction. Still, the qualitatively the results are similar to the ones reported before. The wage penalty is lower for those who worked while studying at university and is larger for women than for men. The difference between severe and mild overeducation is still not statistically significant.

5. Summary and conclusions

Under the human capita theory, wages are determined by the worker productivity, which is among other things, influenced by the level of education. As put clearly by Sloane (2002), in its crudes form the return to education is not contingent on how the workers skills are utilized in the labor market. However, jobs are quite different in many characteristics that impact on labor productivity, and so in pay. In this context, job requirements attract attention because comprising not only a level of schooling but also other dimensions of skills, abilities, and attitudes (Hartog, 2000). In this regards, empirical studies have found that a substantial proportion of young people experience a mismatch between their educational background and the requirements of the job. As a response to this stylized finding, the literature has proposed different explanations, as well it has studied its effects over different outcomes of the labor market.

As summarized in section 2, alternative theoretical explanations have been proposed to explain the existence of over and undereducation in the labor market. While the empirical analysis has yet not so far reached a consensus over which of these different explanations is more likely to be behind the phenomenon, there is instead a clear message on the consequences of over and undereducation in terms of wages. In the framework of the Verdugo-Verdugo model, overeducation means a penalty in income when compared with workers with a similar level of formal education but which are well matched, while under the ORU model of Duncan and Hoffman (1981), the years of overeducation show a lower rate of return than the required years.

According to the empirical evidence presented in section 4, overeducated graduates of the FCE-UNC suffer a wage penalty when compared to those working in a job requiring a university degree. This result is robust to different specifications and to the use of alternative estimators. Also, while the difference is not statistically significant, the penalty for those severely overeducated is larger than for those with a mild level of overeducation. Also, having working experience while at the university helps to reduce the cost of overeducation. The overall impact found for the whole sample appears to be driven by the impact of overeducation on female graduates, with the effect on male being not significant. Finally, while for the case of overeducation we find statistically significant effects, the same is not the case for the level of horizontal match, either in terms of skills and knowledge. In both cases, the relationships with income show apparently an inverted u-shape form.

References

Albrecht, J., Edin, P-A., Sundström, M., and Vroman, S. (1999). Career interruptions and subsequent earnings: a reexamination using Swedish data. *Journal of Human Resources*, 34, 294-311.

Allen, J. and van der Velden, R. (2001). Educational Mismatches Versus Skill Mismatches: Effects on Wages, Job Satisfaction and On-the-Job Search. *Oxford Economic Papers*, 53, 434-452.

Badillo-Amador, L. and Vila, L. (2013). Education and skill mismatches: wage and job satisfaction consequences. *International Journal of Manpower*, 34, 416-428.

Bauer, T. (2002). Educational mismatch and wages: a panel analysis. *Economics of Education Review*, 21, 221-229.

Carroll, D. and Tani, M. 2013. Over-education of recent higher education graduates: New Australian panel evidence. *Economics of Education Review*, 32, 207-218.

Chevalier, A. (2000). Graduate Over-Education in the UK. Centre for the Economics of Education Discussion Paper, 07, November.

Dekker, R., de Grip, A. and Heijke, H. (2002). The effects of training and overeducation on career mobility in sequential labor market. *International Journal of Manpower*, 23, 106-136.

Deželan, T. and Hafner, F. (2014). First-job educational and skill match. An empirical investigation of political science graduates in Slovenia. *International Journal of Manpower*, 35, 553-575.

Di Pietro, G. and Urwin, P. (2006). Education and skills mismatch in the Italian graduate labour market. *Applied Economics*, 38, 79-93.

Duncan, J. and Hoffman, S. (1981). The incidence and wage effects of overeducation. *Economics of Education Review*, 1, 75-86.

Groot W., and Massen van den Brink, H. (2000). Overeducation in the labor market: A meta-analysis. *International Journal of Manpower*, 21, 584-595.

Hartog, J. (2000). Over-education and earnings: where are we, where should we go? *Economics of Education Review*, 19, 131-147.

Korpi, T. and Tahlin, M. (2009). Educational mismatch, wages, and wage growth: Overeducation in Swden, 1974-2000. *Labour Economics*, 16, 183-193.

Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P. and Wei, Z. (2013). Job Mismatches and Labour Market Outcomes: Panel Evidence on University Graduates. *Economic Record*, 89, 382–395.

Mincer, J. and Polachek, S. (1974). Family investments in human capital: earnings of women, *Journal of Political Economy*, 82, S76–S108.

Robst, J. (1995). College Quality and Overeducation. *Economics of Education Review*, 14, 221-228.

Robst, J. (2007). Education, college major, and job match: Gender differences in reasons for mismatch. *Economics of Education Review*, 26, 397-407.

Rubb, S. (2006). Educational Mismatches and Earnings: Extensions of occupational Mobility Theory and Evidence of Human Capital Depreciation. *Education Economics*, 14, 135-154.

Sellami, S., Verhaest, D., Nonneman, W. and Van Trier, W. (2017). The Impact of Educational Mismatches on Wages: The Influence of Measurement Error and Unobserved Heterogeneity. *The B.E. Journal of Economic Analysis*, 17, 1-21.

Sicherman, N and Galor, O. (1990). A theory of career mobility. *Journal of Political Economy*, 98, 169-192.

Sicherman, N. (1991). Overeducation in the labor market. *Journal of Labor Economics*, 9, 101-122.

Verdugo, R. and Verdugo, N. (1989). The impact of surplus schooling on earnings. *Journal of Human Resources*, 24, 629-643.

Zhu, R. (2014). The impact of major-job mismatch on college graduates' early career earnings: Evidence from China. *Education Economics*, 22, 511-528.

Table 1. Sample sizes and rates of response

	Sample 1	Sample 2	Sample 3
Size	158	164	165
Rates of response (%)			
Base	100.0	100.0	100.0
Follow-up 1	90.5	88.4	93.9
Follow-up 2	69.6	69.5	70.9
Follow-up 3	67.1	65.2	70.9
Follow-up 4	69.0	69.5	64.8

Source: own.

Table 2. Patterns of attrition

Surveys with responses					N° Cases			
Base	**Follow-up 1**	**Follow-up 2**	**Follow-up 3**	**Follow-up 4**	**Sample 1**	**Sample 2**	**Sample 3**	**TOTAL**
X	X	X	X	X	78	82	84	50.1
X	X	X	X		8	5	12	18.3
X	X	X		X	10	8	5	
X	X		X	X	11	6	12	
X		X	X	X	4	7	1	
X	X	X			6	9	15	12.9
X	X		X		1	5	6	
X	X			X	3	7	4	
X		X	X		1	0		
X		X		X	1	2		
X			X	X	2	1		
X	X				26	23	17	15.4
X		X			2	1		
X			X		1	1	2	
X				X	0	1	1	
X					4	6	6	3.3
					158	**164**	**165**	

Source: own.

Table 3. Descriptive statistics

Variable	Base survey		Follow-up surveys	
	Mean	SD	Mean	SD
Overeducated (proportion)	0.33	0.47	0.33	0.47
Strongly overeducated (proportion)	0.13	0.34	0.18	0.38
Moderately overeducated (proportion)	0.20	0.40	0.15	0.36
Horizontal match: skills (scale 1 -lowest- to 10 -highest)	5.33	2.41	5.81	2.27
Horizontal match: use of knowledge (scale 1 -lowest- to 10 -highest)	6.36	2.41	6.42	2.19
Male (proportion)	0.39	0.49	0.39	0.49
Non-single (proportion)	0.13	0.34	0.17	0.37
Previous working experience (proportion) (*)	0.75	0.43	0.75	0.43
Previous working experience in field of study (proportion) (*)	0.57	0.50	0.56	0.50
Formal employee (proportion)	0.67	0.47	0.74	0.44
Firm size (1: Up to 5; 2: 6 to 20; 3: 21 to 50; 4: More than 50)	2.86	1.15	2.97	1.14
Labor tenure in main current job (in years)	2.53	3.84	2.47	3.59
Working hours/week (1: Up to 10; 2: more than 10 to 20; 3: more than 20 to 30; 4: more than 30 to 40; 5: more than 40)	3.79	1.33	4.39	1.04
Training activities (proportion)	0.39	0.49	0.43	0.50
Dependents (proportion)	0.10	0.30	0.12	0.32
Father: complete university education (proportion) (*)	0.31	0.46	0.32	0.47
Mother: complete university education (proportion) (*)	0.31	0.46	0.32	0.46
Average mark (*)	5.47	1.24	5.46	1.21

(*) Correspond to a question was asked only in the Base survey, thus the figures for the Follow-up surveys correspond to the answers given in the base survey by those who also responded to the follow-up surveys. All figures correspond to salaried employees. Source: own.

Table 4: pooled models

Dependent variable:	Ordinal value: 1 to 24		Log of monthly income: point value		Log of monthly income: interval	
	(1)	(2)	(3)	(4)	(5)	(6)
Overeducated: Yes	-0.8098***	-1.1411***	-0.0658***	-0.0841***	-0.0674***	-0.0868***
Skill-job match: use of learned skills: 1 to 10 (a)		0.2970		0.0226		0.0219
(a)^2		-0.0249		-0.0019		-0.0018
Knowledge-job match: use of learned knowledge: 1 to 10 (b)		0.0963		0.0193		0.0186
(b)^2		-0.0237		-0.0026		-0.0026
Gender: male	0.3229	0.3236	0.0255	0.0256	0.0308	0.0310
Civil status: non-single	1.6822***	1.7687***	0.1079***	0.1152***	0.1313***	0.1383***
Working experience: yes	1.2722***	1.1540***	0.1219***	0.1139***	0.1176***	0.1094***
Working experience in econ. sciences: yes	0.5390	0.5914*	0.0413	0.0451*	0.0480*	0.0519*
Formal labor: yes	0.9250***	0.9672***	0.1072***	0.1101***	0.1013***	0.1043***
Firm size: 6 to 20	2.2875***	2.2444***	0.2118***	0.2093***	0.2137***	0.2112***
Firm size: 21 to 50	3.2086***	3.0870***	0.2685***	0.2618***	0.2790***	0.2721***
Firm size: more than 50	4.0002***	3.8812***	0.3245***	0.3167***	0.3431***	0.3349***
Tenure (years)	0.3880***	0.3824***	0.0290***	0.0284***	0.0329***	0.0323***
Working hours: 11 to 20	-2.6065***	-2.4884***	-0.2095***	-0.1991***	-0.2095***	-0.1986***
Working hours: 21 to 30	-1.8258***	-1.8767***	-0.0776	-0.0771	-0.0810	-0.0809
Working hours: 31 to 40	2.0669***	1.9912***	0.2534***	0.2502***	0.2549***	0.2514***
Working hours: more than 40	2.4721***	2.4777***	0.3011***	0.3027***	0.3152***	0.3166***
Training activities: Yes	-0.5009*	-0.4652*	-0.0031	-0.0011	-0.0083	-0.0060
Survey: Follow-up 1	1.0851***	1.0574***	0.0408	0.0375	0.0393	0.0362
Survey: Follow-up 2	2.2211***	2.1659***	0.0716**	0.0672**	0.0782**	0.0737**
Survey: Follow-up 3	3.8134***	3.8138***	0.1299***	0.1287***	0.1339***	0.1325***
Survey: Follow-up 4	4.7055***	4.6658***	0.1369***	0.1335***	0.1488***	0.1452***
Observations	1,282	1,282	1,282	1,282	1,282	1,282
R-squared	0.425	0.431	0.429	0.434		
$\ln(\sigma)$					-1.0537***	-1.0584***
Left-censored observations					12	12
Right-censored observations					71	71
Interval observations					1199	1199

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: random effect models

Dependent variable:	Ordinal value: 1 to 24		Log of monthly income: point value		Log of monthly income: interval	
	(1)	(2)	(3)	(4)	(5)	(6)
Overeducated: Yes	-0.6432***	-0.5294**	-0.0571***	-0.0513**	-0.0574***	-0.0519**
Skill-job match: use of learned skills: 1 to 10 (a)		0.1592		0.0174		0.0159
(a)^2		-0.0035		-0.0009		-0.0007
Knowledge-job match: use of learned knowledge: 1 to 10 (b)		0.2104		0.0118		0.0124
(b)^2		-0.0207		-0.0013		-0.0014
Gender: male	0.5859	0.6056	0.0371	0.0384	0.0452	0.0466
Civil status: non-single	1.0888***	1.1350***	0.0861***	0.0905***	0.1017***	0.1062***
Working experience: yes	1.2362*	1.2775*	0.1174**	0.1193**	0.1161**	0.1178**
Working experience in econ. sciences: yes	0.6209	0.6228	0.0428	0.0430	0.0505	0.0509
Formal labor: yes	0.9131***	0.9275***	0.0945***	0.0957***	0.0909***	0.0922***
Firm size: 6 to 20	1.0293**	1.0467**	0.1278***	0.1294***	0.1277***	0.1290***
Firm size: 21 to 50	2.2713***	2.2550***	0.2175***	0.2168***	0.2254***	0.2246***
Firm size: more than 50	2.6573***	2.6188***	0.2500***	0.2479***	0.2644***	0.2617***
Tenure (years)	0.2150***	0.2146***	0.0201***	0.0200***	0.0226***	0.0223***
Working hours: 11 to 20	-1.6311***	-1.5625***	-0.1612***	-0.1579***	-0.1764***	-0.1721***
Working hours: 21 to 30	-1.7359***	-1.6631***	-0.1265***	-0.1234***	-0.1373***	-0.1339***
Working hours: 31 to 40	0.8797**	0.8805**	0.1525***	0.1518***	0.1463***	0.1461***
Working hours: more than 40	1.2155***	1.2144***	0.1979***	0.1977***	0.1962***	0.1962***
Training activities: Yes	-0.0053	0.0047	0.0060	0.0067	0.0017	0.0025
Survey: Follow-up 1	1.3392***	1.2916***	0.0632***	0.0598***	0.0664***	0.0628***
Survey: Follow-up 2	2.5709***	2.5103***	0.0931***	0.0886***	0.1045***	0.0997***
Survey: Follow-up 3	4.1534***	4.0851***	0.1520***	0.1474***	0.1582***	0.1532***
Survey: Follow-up 4	5.1937***	5.1307***	0.1605***	0.1562***	0.1775***	0.1728***
Observations	1,282	1,282	1,282	1,282	1,282	1,282
Number of individuals	403	403	403	403	403	403
σ_u					0.2968***	0.2965***
σ_e					0.2112***	0.2106***
Rho					0.664	0.665
Left-censored observations					12	12
Right-censored observations					71	71
Interval observations					1199	1199

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: random effect models

Dependent variable:	Log of monthly income: interval	
	(1)	(2)
Severely Overeducated: Yes	-0.0639**	-0.0539*
Mildly overeducated: Yes	-0.0516**	-0.0506**
Skill-job match: use of learned skills: 1 to 10 (a)		0.0158
(a)^2		-0.0007
Knowledge-job match: use of learned knowledge: 1 to 10 (b)		0.0120
(b)^2		-0.0014
Gender: male	0.0453	0.0466
Civil status: non-single	0.1020***	0.1064***
Working experience: yes	0.1163**	0.1178**
Working experience in econ. sciences: yes	0.0503	0.0509
Formal labor: yes	0.0915***	0.0922***
Firm size: 6 to 20	0.1277***	0.1291***
Firm size: 21 to 50	0.2251***	0.2247***
Firm size: more than 50	0.2638***	0.2617***
Tenure (years)	0.0226***	0.0223***
Working hours: 11 to 20	-0.1762***	-0.1722***
Working hours: 21 to 30	-0.1368***	-0.1339***
Working hours: 31 to 40	0.1465***	0.1461***
Working hours: more than 40	0.1960***	0.1962***
Training activities: Yes	0.0017	0.0025
Survey: Follow-up 1	0.0670***	0.0630***
Survey: Follow-up 2	0.1047***	0.0998***
Survey: Follow-up 3	0.1590***	0.1534***
Survey: Follow-up 4	0.1813***	0.1730***
Observations	1,282	1,282
Number of individuals	403	403
σ_u	0.2968***	0.2965***
σ_e	0.2111***	0.2106***
Rho	0.664	0.665
Left-censored observations	12	12
Right-censored observations	71	71
Interval observations	1199	1199
Severely Overeducated=Mildly overeducated (p-value)	0.684	0.912

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: random effect models

Dependent variable:	Log of monthly income: interval		
	(1)	(2)	(3)
Overeducated without working experience	-0.1041***		
Overeducated with working experience	-0.0317		
Overeducated without working experience in econ. Sciences		-0.0611**	
Overeducated with working experience in econ. Sciences		-0.0434	
Overeducated (Female)			-0.0549**
Overeducated (Male)			-0.0477
Skill-job match: use of learned skills: 1 to 10 (a)	0.0168	0.0157	0.0160
(a)^2	-0.0008	-0.0007	-0.0007
Knowledge-job match: use of learned knowledge: 1 to 10 (b)	0.0125	0.0125	0.0125
(b)^2	-0.0014	-0.0014	-0.0014
Gender: male	0.0453	0.0461	0.0443
Civil status: non-single	0.1065***	0.1059***	0.1062***
Working experience: yes	0.0914*	0.1194**	0.1178**
Working experience in econ. sciences: yes	0.0549	0.0441	0.0507
Formal labor: yes	0.0923***	0.0926***	0.0922***
Firm size: 6 to 20	0.1272***	0.1283***	0.1288***
Firm size: 21 to 50	0.2232***	0.2239***	0.2244***
Firm size: more than 50	0.2617***	0.2611***	0.2615***
Tenure (years)	0.0221***	0.0224***	0.0223***
Working hours: 11 to 20	-0.1781***	-0.1728***	-0.1723***
Working hours: 21 to 30	-0.1337***	-0.1343***	-0.1339***
Working hours: 31 to 40	0.1466***	0.1456***	0.1458***
Working hours: more than 40	0.1956***	0.1957***	0.1959***
Training activities: Yes	0.0039	0.0027	0.0025
Survey: Follow-up 1	0.0634***	0.0629***	0.0629***
Survey: Follow-up 2	0.0993***	0.0994***	0.0996***
Survey: Follow-up 3	0.1537***	0.1532***	0.1532***
Survey: Follow-up 4	0.1725***	0.1727***	0.1728***
Observations	1,282	1,282	1,282
Number of individuals	403	403	403
σ_u	0.2972***	8.6362***	8.6333***
σ_e	0.2101***	0.2967***	0.2966***
Rho	0.667	0.665	0.665
Left-censored observations	12	12	12
Right-censored observations	71	71	71
Interval observations	1199	1199	1199

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: pooled OLS, random and fixed effect models

Dependent variable:	Log of monthly income: point value					
	Pool	**FE**	**RE**	**Pool**	**FE**	**RE**
Overeducated: Yes	-0.0914***	-0.0434**	-0.0545***			
Severely Overeducated: Yes				-0.0759**	-0.0434	-0.0564**
Mildly overeducated: Yes				-0.1035***	-0.0435*	-0.0531**
Skill-job match: use of learned skills: 1 to 10 (a)	0.0237	0.0174	0.0168	0.0240	0.0174	0.0167
(a)^2	-0.0021	-0.0007	-0.0009	-0.0021	-0.0007	-0.0009
Knowledge-job match: use of learned knowledge: 1 to 10 (b)	0.0199	0.0095	0.0122	0.0236	0.0095	0.0118
(b)^2	-0.0027	-0.0007	-0.0013	-0.0030	-0.0007	-0.0013
Observations	1,282	1,282	1,282	1,282	1,282	1,282
Number of individuals		403	403		403	403
R2	0.412			0.412		
R2 (within)		0.297	0.272		0.297	0.272
R2 (between)		0.185	0.414		0.185	0.414
Rho		0.773	0.666		0.773	0.666
Breusch-Pagan test (p. value)			0.000			0.000
Hausman test (p. value)			0.000			0.000

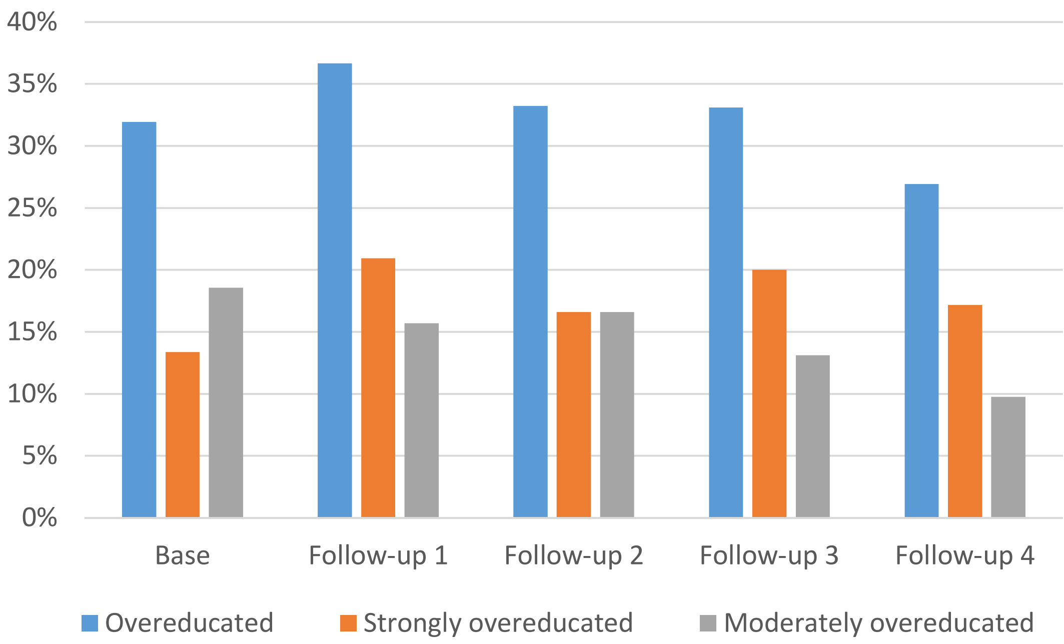
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Note: all regressions include other explanatory variables as in Tables 4 to 7, except gender, working experience, and working experience in econ. sciences.

Table 8 (*cont.*): pooled OLS, random and fixed effect models

Dependent variable:	Log of monthly income: point value								
	Pool	FE	RE	Pool	FE	RE	Pool	FE	RE
Overeducated without working experience	-0.2100***	-0.0982**	-0.1387***						
Overeducated with working experience	-0.0505*	-0.0215	-0.0212						
Overeducated without working experience in econ. Sciences				-0.1378***	-0.0525*	-0.0834***			
Overeducated with working experience in econ. Sciences				-0.0418	-0.0349	-0.0257			
Overeducated (Female)							-0.0976***	-0.0586**	-0.0671***
Overeducated (Male)							-0.0816**	-0.0232	-0.0361
Skill-job match: use of learned skills: 1 to 10 (a)	0.0254	0.0182	0.0185	0.0214	0.0171	0.0161	0.0241	0.0181	0.0175
(a)^2	-0.0022	-0.0008	-0.0010	-0.0020	-0.0007	-0.0009	-0.0021	-0.0008	-0.0010
Knowledge-job match: use of learned knowledge: 1 to 10 (b)	0.0223	0.0090	0.0121	0.0239	0.0094	0.0126	0.0197	0.0102	0.0125
(b)^2	-0.0028	-0.0006	-0.0013	-0.0030*	-0.0007	-0.0014	-0.0027	-0.0008	-0.0014
Observations	1,282	1,282	1,282	1,282	1,282	1,282	1,282	1,282	1,282
Number of individuals		403	403		403	403		403	403
R2	0.419			0.416			0.412		
R2 (within)		0.299	0.276		0.297	0.273		0.298	0.273
R2 (between)		0.202	0.417		0.190	0.412		0.186	0.412
Rho		0.770	0.665		0.772	0.666		0.773	0.666
Breusch-Pagan test (p. value)			0.000			0.000			0.000
Hausman test (p. value)			0.000			0.000			0.000

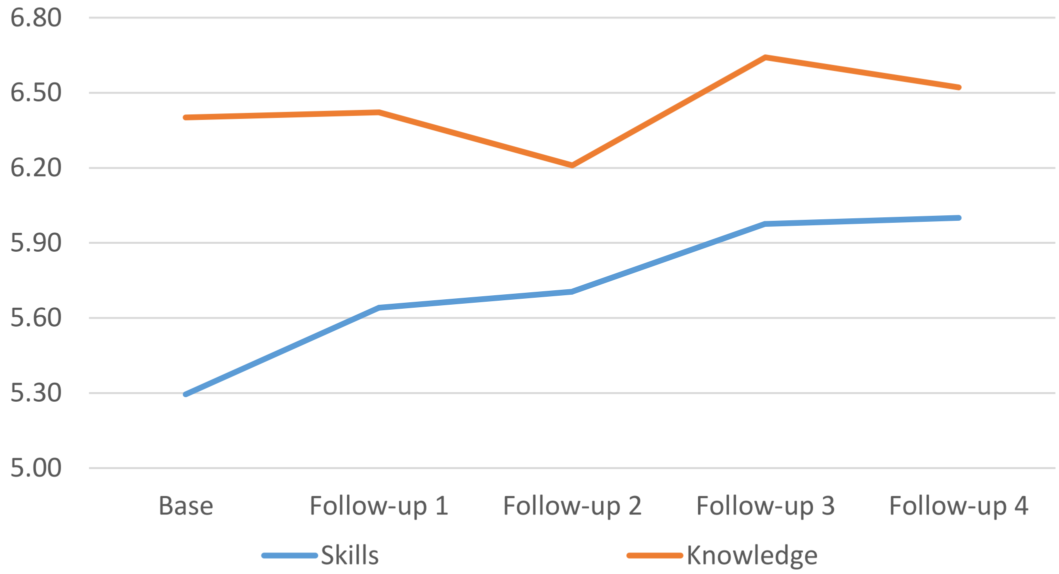
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Note: all regressions include other explanatory variables as in Tables 4 to 7, except gender, working experience, and working experience in econ. sciences.

Graph 1: incidence of overeducation (*)



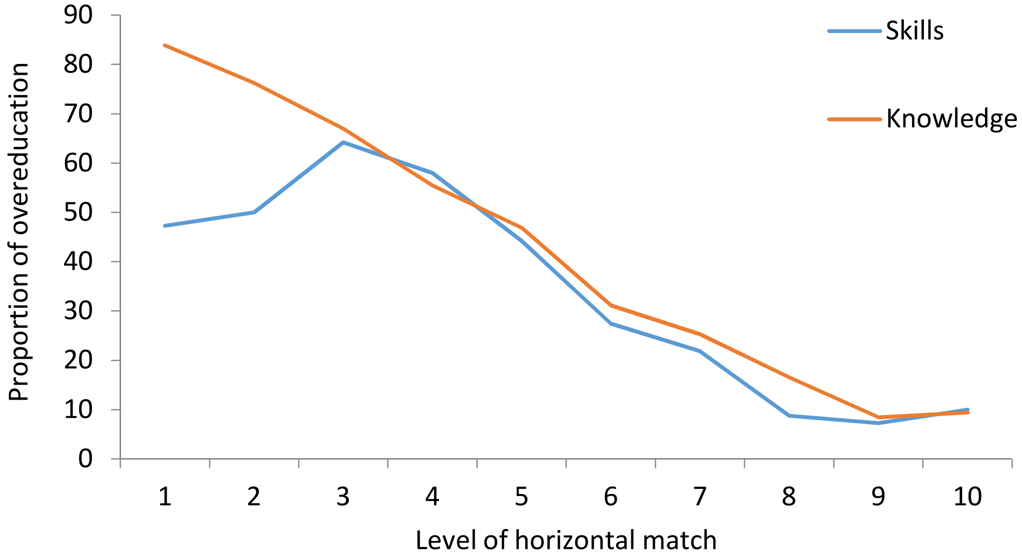
(*) All figures correspond to salaried employees. Source: own.

Graph 2: incidence of horizontal matching (*)



(*) All figures correspond to salaried employees. Source: own.

Graph 3: overeducation and horizontal matching (*)



(*) All figures correspond to salaried employees. Source: own.