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The impact of overeducation on wages of recent economic sciences graduates[#]

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According to human capital theory, wages are determined by workers' productivity, which in its crudest form implies that return to education does not depend on how workers' skills are used in the labour market (Sloane, 2003). However, after controlling for other differences, the empirical evidence has shown that workers with the same education can be paid differently. The literature has found that young people are more likely to experience a mismatch between their formal education and that required for their jobs. While there is no consensus on the reasons for the mismatch, there is a consensus on the consequences in terms of wages; overeducation means a penalty in terms of income.

Our evidence shows that overeducated graduates of the *Facultad de Ciencias Económicas* of the *Universidad Nacional de Córdoba* (FCE-UNC) suffer a wage penalty compared to those working in a job that requires a university degree. The results are robust to different specifications and the use of alternative estimators. While the difference is not statistically significant, the penalty for people with a severe level of overeducation is higher than for those with a mild level of overeducation; having had work experience while studying at university helps to reduce the cost of overeducation; women exhibit a similar penalty to men. While on average overeducation means a wage penalty, there is great heterogeneity among overeducated graduates, with those at the top end of the wage distribution experiencing a much lower penalty, or even a premium in some cases. Finally, while in the case of overeducation we find statistically significant effects, the same is not true of the horizontal mismatch in terms of knowledge.

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1. Introduction

Traditionally, the standard characterisation of the demand side of the labour market does not consider specific qualitative aspects of the job. However, jobs are quite different in many characteristics that impact on labour 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 worker's level of formal education differs to that required by the job, or horizontal in the sense that there is a difference between the field of study (or the knowledge it provided) of the worker and the one needed for 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 matched correctly. 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 usually implies an important share of public funds, 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. For instance, it has been argued that over- and undereducation may help to explain wage dispersion among university graduates in OECD countries (Ordine and Rose, 2015). Also, there is the hypothesis that the mismatch could be a temporary phenomenon related to imperfect information about the labour market, but also it may be the result from a deliberate choice because a low-level job is a good investment opportunity (Rubb, 2006). In any case, with the empirical evidence suggesting that the first job can have significant long-term impacts in a person labour history, be overeducated can influence a person's future work opportunities. In this regards, Battu *et al.* (1999), who analyze the labour history of two cohorts of university graduates in the United Kingdom over a period of 11 years, find that overeducation was not a temporary phenomenon, however their results suggest a pattern from graduation into a job which requires a degree, and then into work where the degree's importance is denuded.

As it is well known, and the literature has remarked it, 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 labour market and without work experience. For instance, Dekker *et al.* (2002), using Dutch data, find 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 is 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. For instance, Dolton and Vignoles (2000) report that the wage penalty associated with overeducation falls during the first six years after graduation. However, if genuinely mismatch is permanent, the effects of such a phenomenon are multidimensional, and in this respect, the empirical literature is 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). In line with the argument made by Zhu (2014), who points out that for the case of developing countries there is some void in the literature regarding how the occupation-education mismatch affects college graduates' earnings, it is important to stress that to the best of our knowledge, this paper is the first attempt to dealt with this issue in the case of Argentina using a dataset specially designed through which we followed four cohorts of graduates during the first year after graduation.

Particularly, the study inquires on the relationship between wages and overeducation as well as other 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 personal characteristics explain the level of income for salaried employees and variables aimed at identifying the status of overeducation as well as the degree of horizontal match in terms of the knowledge acquired in the university and those required by the job.[1] Also, we estimate a nonparametric model to incorporate the heterogeneity that exists among overeducated graduates.

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 who 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 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. Interestingly, having working experience while at the university helps to reduce the cost of overeducation. In terms of gender, it appears there is not much difference between female and male overeducated graduates. When we move beyond the mean effects, independently of the categorisations we work with, in all cases is possible to observe some heterogeneity among overeducated graduates, with a not minor share of them experiencing a wage premium instead of a penalty, which is more likely as we move upward along the wage distribution. Finally, while for the case of overeducation we find statistically significant effects, the same is not the case for the level of horizontal mismatch in terms of knowledge.

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 laid out the empirical approach. Section 5 presents and discusses the results of different econometrics models. Finally, section 6 is of summary and conclusions.

[1] We also worked with an additional variable looking at the degree of match between the skills acquired in university and the required by the job, but it proved to be not significant in the econometric analysis.

2. 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 level of education needed for the job and the worker's education. One topic, among others, which 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 the standard earning function, in which, the wage rate is 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:

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

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, $\mathbf{X}_{it}$ 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 it introduces characteristics of the demand side of the labour 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) analyse the consequences of both education and skill mismatches on job satisfaction and wages using Spanish data from the European Community Household Panel (ECHP) survey for the year 2001. Authors capture the employees' status in terms of both matches by taking into account workers' answers whether the studies or the training provide them the skills needed at the present type of work, as well the workers' feeling about if the skill or personal capacities would allow them to do a more demanding job than the one that they have now. Their statistical analysis shows that educational and skill mismatches are weakly related in the Spanish labour 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, as ours, have focused on the consequences of educational mismatch in the specific case of university graduates. Allen and van der Velden (2001) analyse the relationship between skill mismatch and educational mismatch and their effects on wages from the perspective of the assignment theory. The authors, to test the effect of the mismatch on wages and job satisfaction, use a sample of Dutch individuals who graduated from tertiary education seven years before the survey and were in paid employment for at least 12 hours per week. They use a worker's self-rating of the level of education most suitable for the current job. Authors determine whether individuals are working below or above their onw level of study by comparing employees' highest attained degree with their self-response. Also, workers are asked to answer about the field of education that is most adecuate for their jobs by delimiting the responses to these categories: only the own field of education, the own or related field of education, a completely different job of education, for the job there is no specific field required, and for the job there is not exist a specific field yet. 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. To define whether workers are in a situation of job mismatch, authors take into account the mark that responders give to the sentence: I use many of my skills and abilities in my current job; for which a mark of one means a strong disagreement with the sentence, while a mark of seven denotes a strong agreement with it. The study finds that overeducation and overskilling are distinct phenomena and they have a different effect on different labour 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. Authors highlight they use panel data allowing to control for unobserved heterogeneity, being their econometric outcomes more reliable than those from cross sections. Carroll and Tani (2013) analyse 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. In oder to contruct the overeducation variable, authors implement the Job Analysis (JA) method, which measures overeducation on the basis of occupational definitions. Besides, the study uses the Worker Self-Assessment (WA) method in order to code manually the graduates' occupations in 2007 and 2010; in this case, individuals had to give responses about the full title of their ocupation and describe the main tasks and duties in their job. Authors follow this mix of methodological strategies to address one of the main critisims of JA method, which is related to the assumption that employees with the same ocupational title do tasks with the same difficult degree. The analysis shows a notably fall of the rate of overeducation 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) analyse the effects of both vertical and horizontal educational mismatches on the pay of individuals with a higher education degree in Flanders. In this study, vertical educational mismatch is measured by the gap between the years of education that the job requires and the ones a person coursed in its study program. 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 a 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. Like other studies, the major mismatch variable is constructed by using employes' self-assessment about their current job; they have to choose between two alternatives: i) I am now employed, and the job is related to my major and ii) I am now employed, but the job is unrelated to my major . The mismatch variable equals to 1 if the person answers alternative ii) and 0 otherwise. 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 because 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 finds 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 the 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, on 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 of obtaining promotion than those who are well matched in the United States. 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 that overeducation can be a stepping-stone into appropriate employment. About 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 penalises older overeducated graduates. Zhu (2014) evidences that age has little effect on average incomes of the Chinese graduates, but it affects wages negatively 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 analyses 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 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 gender plays a role presents mixed results.

Skill mismatch also seems 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 labour market segments that face labour 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. This issue attracts more attention when overeducation is analysed 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 mismatch tends to decrease as workers gain experience in the labour 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, and from the point of view of human capital theory, others have argued that the high incidence of overeducation among school-leavers reflects these workers' lack of work experience. Allen and 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 analysing 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 utilisation. Individuals respond about the suitability of the field of study for the first job, which gives an indication of the horizontal educational matching and the appropriate level of education required by the first job, which provides an indicator of the vertical educational matching. Also individuals answer about the usefulness of the knowledge they acquired during the university studies for the job, which hand an indication of the skill matching. 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. 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 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

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 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, also 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, it 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, in which capital city is located, but also the centre and the north-west of the country.[2]

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 half of that population for the years 2016 and 2017. More specifically, we include those who registered for the third and fourth graduation ceremonies in each of the two years. 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.

[2] 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 Brazil and Venezuela.

In our dataset, graduates were 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 information 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. Except for 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 goodwill 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. Just above half of the individuals completed the four follow-up surveys, with the percentage reaching 68.3% if we also include 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 the 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.

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.
- The age at which graduates finish their studies is well beyond the expected age of 22/24 years old.
- 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 five 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 behaviour 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 labour market. This pattern emerges more 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 2.6 years also reflects that a large proportion of students start working well before they finish their studies.
- At the moment of graduation those who declare having formal employment, which we approximate by employers complying with contributions to social security, represent about two-thirds of the sample, increasing to almost 72% in the follow-up surveys. These figures, especially for the follow-up surveys, mean a slight increase relative to the average of the Argentinean labour market, in which about 35% are informal workers.
- Most graduates, almost half, work in organisations 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 hrs., which represent almost 20%.

Before we take a look at the variables we are most interested in, it is important to state as clear as possible the definitions of the different mistmatches we use from here on in. Educational mismatch is understood to arise when the level of formal education of the person is not the same as the one required by the job he/she is in employed in. Since we work with university graduates, only overeducation can arise. In regards to what in the literature is referred as skill mismatch, we control for the degree of match between the knowledge acquired during the university studies and those required by the job. Because in the case of the overeducation we are working with formal levels of education that have a natural order, in the literature this mismatch is usually refered as vertical. Instead, in the case of the knowledge mismatch, our comparisson does not look at if the graduate has more or less knowledge than the required by the job, but instead to what extent he/she makes use in his/her job of the knowledge acquired in the university, thus this mismatch is refered hereafter as horizontal.[3]

[3] While the meaning of over/under-education is quite well established in the literature, with their measurement depending on the information available to the researcher, the mismatch in terms of skills is a more elusive concept. In the literature we can find, at least, two approaches. One that looks at the skills in terms of the formal knowledge the person acquired at the school, while the second approach tries to identify the role of innate or acquired abilities. Among the first approach we have the aforementioned works of Allen and van de Velden (2001), Deželan and

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, or the so-called "empirical or statistical 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.[4] Each of the three alternatives has its advantages and disadvantages.

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 26.3% in the fourth follow-up survey.[5] 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 behaviour. Interestingly, 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 held by the person and the one required by the job, the second mismatch we work with looks at comparing the knowledge acquired during the studies and those required by the job. This second mismatch we refer to it as a horizontal. Thus, to identify the existence of a horizontal mismatch, we make use of the following question, that like in the case of overeducation, correspond to a self-assessment each person makes of his/her situation. The question asks the graduates to rank, in a range from 1 (the worst match) to 10 (the best match), to what extent he/she uses in the job the knowledge learnt during their undergraduate studies at the FCE-UNC.

As reported in Graph 2, the knowledge match is quite stable over the first year after graduation, showing also a clear negative relationship with the status of overeducation, whit the proportion of those who declare themselves as overeducated decreasing as the level of horizontal match increases (see Graph 3).

Hafner (2014), Zhu (2014), and Sellami *et al.* (2017), all of whom look at the mismatch between the field of study or the knowledge acquired in school and that required by the job, Deželan and Hafner (2014) and Sellami *et al.* (2017) refer to this mismatch as horizontal. Examples of the second approach are Badillo-Amador and Vila (2013) and Mavromaras *et al.* (2013), both looking at to what extent a person uses in the job his/her personal capabilities and abilities, which are not necesarilly derived and/or related to the person's formal education.

[4] Examples of other studies using a self-declared status are Battu *et al.* (1999), Dolton and Vignoles (2000), and Ordeine and Rose (2015). Kler (2005) makes a comparison of the other two definitions using data of Australian university graduates.

[5] Even when it is not possible to make a direct comparison, these figures are within the range found in the literature on the topic.

4. Empirical approach

As pointed out before, this research aims 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 by the degree of correspondence between the knowledge acquired during the undergraduate studies at the FCE-UNC and the ones required by the job.

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 to respond: to declare a specific income or identify the range in which their income falls into. [6]

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 two options. Firstly, as in Preston (1997) and Kler (2005), for each individual we assigned him/her an income equal to the middle point of the interval he/she declared.[7] Secondly, instead of allocating a particular income, the interval declared by the respondent is used. Because 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. For the first option, we use both a pool and a random effect linear estimator, while for the second option we used an interval regression estimator in its pool and random effect versions. We estimate also some fixed effect models, as well as use a nonparametric estimator following Zhu (2014).

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:

[6] There were 24 possible intervals, the first one corresponded to those who declared an income of less than A$3000 a month, while the last one represented an income of A$25000 or more. The remaining intervals were defined using a A$1000 range.

[7] For the lowest interval we use the upper limit of it, while for the highest interval we use its lower limit.

$$E_{it} = E^r_{it} + E^o_{it} + E^u_{it}$$

$$E^o_{it} = \begin{cases} E_{it} - E^r_{it} \text{ if } E_{it} > E^r_{it} \\ 0, \text{ otherwise} \end{cases}$$

$$E^u_{it} = \begin{cases} E^r_{it} - E_{it} \text{ if } E_{it} < E^r_{it} \\ 0, \text{ otherwise} \end{cases}$$

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

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

with:

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

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

In equation (2) the coefficients β_2 and β_3 are interpreted relative to 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 (equation (3)), 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 $\beta_2 < 0$ (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).[8]

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[9]:

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

[8] 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.

[9] 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 very few cases people have declared to be in such situation, we choose to consider them as correctly matched.

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. Variable HMK_{it} is a proxy for the degree of horizontal match, measured in terms of 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 favour of δ_2 being negative or positive; moreover, as we show later when commenting on the results, the relationship between HMK_{it} and wages shows an inverted u-shape form.

5. Results and discussion

In Table 4 we report the results for the pooled sample for each of the two dependent variables. The main result that emerges quite clearly is 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 1%. Looking at the results, the status of overeducation means a penalty of about 8.7% to 10.5%.

With regards to the match in terms of knowledge, the results are statistically significant, with the relationship showing an inverted u-shape form.

For the remaining control variables[10], we obtain positive and significant coefficients for men, non-single status, working in the formal sector, working in larger firms, 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 also means 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 not significant.

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

[10] 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 find 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.

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%, 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 correlated negatively with the probability of being overeducated. The penalty associated with the status of overeducation now varies between 7.1-7.7% compared with the 8.7-10.5% range reported in Table 4.[11] 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).

The results for the horizontal match, are now not significant. This result could mean that the significant coefficients obtained with the pooled data was not real but simply resulted from unobserved characteristics.[12]

In Table 6 we run once again the random effect model, 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, 9.2/9.8% compared to 5.9/6%. However, as reported at the bottom of Table 6, we cannot reject the null hypothesis that the penalties are statistically the same. Once again, the coeficients for the horizontal match are not significant.

In Table 7 we allow for the effect of overeducation varying in terms of some personal characteristics: working experience during the time as student and gender. In all cases, the coefficients are statistically significant at 1%. The penalty for those with working experience is lower than for those without it, and also for men than form women. However, we cannot reject the null that the penalties are statisticaly the same. Only the the case of general working experience the impact of being overeducated appears to be statistically different, but only at the 10%.

A result that emerges from the panel data models is that when we control for the horizontal match, the magnitudes of the coefficients for the overeducation variable are quite similar to when that control is not included. Di Pietro and Urwin (2006) point out that a reduction in the penalty associated with overeducation would suggest that the assignment theory of overeducation would fit the data better than the alternatives. This appears not to be the case in our study.

[11] 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.
[12] Sellami *et al.* (2017) obtain a similar result.

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 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 35% 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 severe and mild.

Regarding the results, the Breusch-Pagan test favours 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 favoured over the random one. When looking at the magnitudes of the penalty associated with 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 results are qualitatively quite similar to the ones reported before. The wage penalty is larger for those who are severely overeducated, and lower for those who worked while studying at university. Instead, women exhibit now a larger penalty than men. However, if we consider the fixed-effect model as the most appropriate, the differences are not statistically significant.

Nonparametric estimates

All the models reported previously provided us with a single estimate of the wage penalty associated to overeducation for each of the different subgroups we considered, which, as pointed out by Zhu (2014), may conceal a heterogeneity in the results. As it is shown in Graphs 4 and 5, there is some degree of heterogeneity within those who are categorised as overeducated. For instance, in Graph 4 it is possible to observe that not a minor share of overeducated graduates have incomes well above those of their well-matched peers. While for men the income distribution of the non-overeducated graduates is slighted shifted to the right of their overeducated peers, for the case of female graduates the density functions are quite similar by most part. Graph 5 confirms the intuition that for many overeducated graduates there appears not to be a wage penalty.

To lift the constraint imposed by just estimating the mean effects, we follow Zhu (2014), who looks at the case of recent college graduates in the Shandong province in China and estimate a nonparametric model using the local linear kernel estimation developed by Li and Racine (2004).[13] Unlike with our previous estimates, now no functional form or distribution assumptions are imposed, allowing to obtain for each

[13] As pointed out by Zhu (2014), the method of Li and Racine is appropriate when most explanatory variables are discrete, as it is in our case.

overeducated graduate an individual wage effect, which can then be used to look at the heterogeneity across different groups.[14]

In Table 9 we present the results from the nonparametric model, which, on average, give us similar results as the one reported previously. The mean wage penalty associated with the status of overeducation is around 10.3%. As mentioned before, an advantage of the nonparametric estimation is that we obtain a single estimate of the wage penalty/premium for each overeducated graduate. Using this set of estimates, we can calculate the mean values for different groups of graduates. Working this way, we obtain that the average penalty for men is slightly larger than for women and that having working experience during the time as student, either related or not to the field of study, means a lower wage penalty. An interesting result is that the figures we obtain are similar to estimates obtained when using the parametric panel data models.

In Table 10 we further test alternative hypotheses regarding marginal effects on wages conditional on some graduate's characteristics. The results show that in despite that even when overeducated men and women earn on average less than non-overeducated graduates, the mean penalties for the two groups are not statistically different between them. The same result emerges when comparing those with and without working experiences. Instead, when the working experience is related to the field of study, the marginal effect of having such experience relative to not having it is positive and significant at 5%.

As mentioned in section 2, Robst (2007) argues that individuals with an occupation mismatch may earn more than those individuals that experience well occupation match because mismatched individuals may accept such a situation for career opportunity reasons. In this regards, we obtain that even when on average there still exists a penalty of being overeducated, this falls with the level of income. As reported in Table 9, while for the first quartile of the salary level the penalty averages around 16%, for the fourth quartile the figure falls just below 3%.[15] As we can appreciate from Graph 6, this result is robust to dividing the sample of overeducated graduates in terms of different dimensions. Overall, 13.1% of overeducated graduates does not suffer a wage penalty. In terms of women and men, the proportions are 12.5% and 14.3% respectively, with larger differences when we consider having or not working experience, 15.3-15.7% for those without and 10.6-12.6% for those with it. In all cases, when the average monthly wage is above $9.500, we have that some overeducated graduates exhibit a wage premium instead of a penalty.[16]

[14] An alternative approach, as in Ordine and Rose (2015), would be the estimation of a quintile regression model, which would also provide us with different estimates along the wage distribution.
[15] These figures are similar to the values found by Ordine and Rose (2015) for the case of young Italian university graduates. Using a quintile regression approach, the authors found the wage penalty diminishes from a 14.6% for the first quartile to a 6.6% for the fifth one.
[16] Among the overeducated graduates whose income put them at the fourth quartile, around one third enjoys a wage premium.

6. Conclusions

Under the human capital theory, wages are determined by worker productivity, which is among other things, influenced by the level of education. As put clearly by Sloane (2003), in its crudest form the return to education is not contingent on how the worker's skills are used in the labour market. However, jobs are quite different in many characteristics that impact on labour 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 labour market.

As summarised in section 2, alternative theoretical explanations have been proposed to explain the existence of over and undereducation in the labour 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. Interestingly, and in despite that no direct comparison is possible, our estimates are within the figures usually found in the literature, from 7.4% to 27% according to McGuinness, 2006. Not least important, our results are robust to different specifications and the use of alternative estimators. The robustness of our results are not only qualitative but also in terms of the magnitude of the (average) wage penalty associated with the status of overeducation. While the difference is not statistically significant, the penalty for those severely overeducated is larger than for those with a mild level of overeducation. Having had working experience while in the university helps reduce the cost of overeducation. The penalty for women appears to be similar to that for men. From the nonparametric models, we find evidence that even when in average the results are similar to the one reported previously, there appears to be heterogeneity among overeducated graduates, in particular in terms of their level of income, with about a 13% experiencing a wage premium. These graduates belong to the upper part of the wage distribution. Finally, while for the case of overeducation we find statistically significant effects, the same is not the case for the level of horizontal mismatch, measured in terms of the use in the job of the knowledge acquired in the university.

Finally, our results have important implications from a policy point of view. While in most universities in Argentina, as is the case with the FCE-UNC, is not uncommon to assist students to obtain some training and internships during the time of studying, there are no similar efforts in helping to find jobs once the students graduate. In this regards, there is room for the design and implementation of programs aimed at facilitating a better match between the supply of the graduates and the demands of the labour market. This issue becomes even more important in the context of the FCE-UNC which, like all other schools belonging to public universities in Argentina, is fully funded with public resources, and so it becomes important that the investment made by the society as a whole translates into graduates having jobs for which they have prepared for, which in line with the literature on the topic would translate into higher productivity.

7. References

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Table 1. Sample sizes and rates of response

	Sample 1	Sample 2	Sample 3	Sample 4
Size	158	164	165	160
Rates of response (%)				
Base	100.0	100.0	100.0	100.0
Follow-up 1	90.5	88.4	93.9	93.1
Follow-up 2	69.6	69.5	70.9	73.1
Follow-up 3	67.1	65.2	70.9	65.6
Follow-up 4	69.0	69.5	64.8	66.3

Source: own.

Table 2. Patterns of attrition

Surveys with responses					N° Cases				
Base	**FU 1**	**FU 2**	**FP 3**	**FP 4**	**Sample 1**	**Sample 2**	**Sample 3**	**Sample 4**	**TOTAL**
X	X	X	X	X	78	82	84	86	51.0
X	X	X	X		8	5	12	12	
X	X	X		X	10	8	5	7	17.3
X	X		X	X	11	6	12	3	
X		X	X	X	4	7	1	1	
X	X	X			6	9	15	11	
X	X		X		1	5	6	2	
X	X			X	3	7	4	7	13.0
X		X	X		1	0	0		
X		X		X	1	2	0		
X			X	X	2	1	0	1	
X	X				26	23	17	21	
X		X			2	1	0		15.0
X			X		1	1	2		
X				X	0	1	1	1	
X					4	6	6	8	3.7

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	0.19	0.39
Moderately overeducated (proportion)	0.20	0.40	0.14	0.34
Horizontal match: use of knowledge (scale 1 -lowest- to 10 -highest)	6.46	2.46	6.46	2.22
Age	27.53	4.98	28.13	4.96
Male (proportion)	0.39	0.49	0.40	0.49
Non-single (proportion)	0.13	0.33	0.17	0.37
Previous working experience (proportion) (*)	0.76	0.43	0.75	0.43
Previous working experience in field of study (proportion) (*)	0.57	0.50	0.57	0.49
Formal employee (proportion)	0.64	0.48	0.72	0.45
Firm size (1: Up to 5; 2: 6 to 20; 3: 21 to 50; 4: More than 50)	2.84	1.16	2.95	1.14
Labor tenure in main current job (in years)	2.64	3.80	2.57	3.67
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)	3.77	1.34	4.35	1.05
Training activities (proportion)	0.39	0.49	0.44	0.50
Dependents (proportion)	0.10	0.31	0.12	0.33
Father: complete university education (proportion) (*)	0.31	0.46	0.33	0.47
Mother: complete university education (proportion) (*)	0.30	0.46	0.30	0.46
Average mark (*)	5.40	1.24	5.41	1.22

(*) Correspond to a question 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:	**Log of monthly income: point value**		**Log of monthly income: interval**	
	(1)	**(2)**	**(3)**	**(4)**
Overeducated: Yes	-0.0910***	-0.1034***	-0.0973***	-0.1107***
Knowledge-job match: use of learned knowledge: 1 to 10 (a)		0.0431**		0.0454**
(a)^2		-0.0043***		-0.0045***
Age	0.0016	0.0009	0.0020	0.0013
Gender: male	0.0391**	0.0383**	0.0485***	0.0477***
Civil status: non-single	0.0948***	0.1020***	0.1164***	0.1237***
Working experience: yes	0.0988***	0.0933***	0.0941***	0.0881***
Working experience in econ. sciences: yes	0.0372	0.0385*	0.0449*	0.0463*
Formal labor: yes	0.1034***	0.1058***	0.0983***	0.1008***
Firm size: 6 to 20	0.1946***	0.1897***	0.1941***	0.1889***
Firm size: 21 to 50	0.2486***	0.2431***	0.2609***	0.2553***
Firm size: more than 50	0.2978***	0.2900***	0.3145***	0.3061***
Tenure (years)	0.0275***	0.0276***	0.0305***	0.0307***
Working hours: 11 to 20	-0.3258***	-0.3149***	-0.3272***	-0.3156***
Working hours: 21 to 30	-0.0831*	-0.0791*	-0.0818*	-0.0777
Working hours: 31 to 40	0.2268***	0.2322***	0.2299***	0.2354***
Working hours: more than 40	0.2885***	0.2937***	0.3004***	0.3058***
Training activities: Yes	-0.0141	-0.0118	-0.0167	-0.0144
Survey: Follow-up 1	0.0191	0.0146	0.0188	0.0142
Survey: Follow-up 2	0.0473*	0.0434	0.0553**	0.0513*
Survey: Follow-up 3	0.0942***	0.0914***	0.1018***	0.0990***
Survey: Follow-up 4	0.0910***	0.0872***	0.1093***	0.1052***
Observations	1,712	1,712	1,712	1,712
R-squared	0.438	0.442		
ln(σ)			-1.0247***	-1.0290***
Left-censored observations			16	16
Right-censored observations			112	112
Interval observations			1584	1584

*** p<0.01, ** p<0.05, * p<0.1.

Table 5: random effect models

Dependent variable:	**Log of monthly income: point value**		**Log of monthly income: interval**	
	(1)	**(2)**	**(3)**	**(4)**
Overeducated: Yes	-0.0739***	-0.0767***	-0.0766***	-0.0799***
Knowledge-job match: use of learned knowledge: 1 to 10 (a)		0.0215		0.0250
(a)^2		-0.0021		-0.0024*
Age	0.0068*	0.0066*	0.0082**	0.0080**
Gender: male	0.0586**	0.0579**	0.0727**	0.0720**
Civil status: non-single	0.0471	0.0497*	0.0587*	0.0616*
Working experience: yes	0.0920**	0.0891**	0.0898**	0.0864*
Working experience in econ. sciences: yes	0.0399	0.0410	0.0477	0.0490
Formal labor: yes	0.1041***	0.1050***	0.1001***	0.1012***
Firm size: 6 to 20	0.1368***	0.1363***	0.1312***	0.1309***
Firm size: 21 to 50	0.2043***	0.2051***	0.2090***	0.2103***
Firm size: more than 50	0.2386***	0.2373***	0.2473***	0.2458***
Tenure (years)	0.0171***	0.0171***	0.0180***	0.0180***
Working hours: 11 to 20	-0.2343***	-0.2290***	-0.2413***	-0.2354***
Working hours: 21 to 30	-0.1233***	-0.1196***	-0.1301***	-0.1259***
Working hours: 31 to 40	0.1282***	0.1330***	0.1228***	0.1282***
Working hours: more than 40	0.1968***	0.2018***	0.1961***	0.2017***
Training activities: Yes	0.0048	0.0050	0.0054	0.0056
Survey: Follow-up 1	0.0416**	0.0389**	0.0448***	0.0418**
Survey: Follow-up 2	0.0674***	0.0647***	0.0808***	0.0778***
Survey: Follow-up 3	0.1204***	0.1183***	0.1319***	0.1297***
Survey: Follow-up 4	0.1265***	0.1243***	0.1531***	0.1507***
Observations	1,712	1,712	1,712	1,712
Number of individuals	545	545	545	545
σ_u			0.3042***	0.3028***
σ_e			0.2200***	0.2199***
Rho			0.657	0.655
Left-censored observations			16	16
Right-censored observations			112	112
Interval observations			1584	1584

*** p<0.01, ** p<0.05, * p<0.1.

Table 6: random effect models

Dependent variable:	Log of monthly income: point value		Log of monthly income: interval	
	(1)	(2)	(3)	(4)
Severely Overeducated: Yes	-0.0922***	-0.0962***	-0.0981***	-0.1029***
Mildly overeducated: Yes	-0.0567***	-0.0612***	-0.0570***	-0.0622***
Knowledge-job match: use of learned knowledge: 1 to 10 (a)		0.0173		0.0202
(a)^2		-0.0018		-0.0021
Age	0.0068*	0.0065*	0.0082**	0.0079**
Gender: male	0.0592**	0.0586**	0.0735**	0.0728**
Civil status: non-single	0.0479	0.0506*	0.0595*	0.0626**
Working experience: yes	0.0935**	0.0900**	0.0916**	0.0875*
Working experience in econ. sciences: yes	0.0389	0.0401	0.0464	0.0479
Formal labor: yes	0.1036***	0.1046***	0.0996***	0.1007***
Firm size: 6 to 20	0.1371***	0.1366***	0.1316***	0.1312***
Firm size: 21 to 50	0.2053***	0.2058***	0.2102***	0.2111***
Firm size: more than 50	0.2388***	0.2372***	0.2474***	0.2458***
Tenure (years)	0.0172***	0.0172***	0.0182***	0.0182***
Working hours: 11 to 20	-0.2344***	-0.2297***	-0.2415***	-0.2362***
Working hours: 21 to 30	-0.1224***	-0.1199***	-0.1293***	-0.1264***
Working hours: 31 to 40	0.1279***	0.1323***	0.1224***	0.1274***
Working hours: more than 40	0.1960***	0.2007***	0.1951***	0.2004***
Training activities: Yes	0.0052	0.0054	0.0059	0.0062
Survey: Follow-up 1	0.0441***	0.0417**	0.0477***	0.0451***
Survey: Follow-up 2	0.0689***	0.0663***	0.0827***	0.0798***
Survey: Follow-up 3	0.1230***	0.1211***	0.1348***	0.1328***
Survey: Follow-up 4	0.1294***	0.1272***	0.1564***	0.1540***
Observations	1,712	1,712	1,712	1,712
Number of individuals	545	545	545	545
σ_u			0.3044***	0.3031***
σ_e			0.2197***	0.2197***
Rho			0.658	0.656
Left-censored observations			16	16
Right-censored observations			112	112
Interval observations			1584	1584
Severely Overeducated=Mildly overeducated (p-value)	0.158	0.174	0.118	0.131

*** p<0.01, ** p<0.05, * p<0.1.

Table 7: random effect models

Dependent variable:	Log of monthly income: point value					
	(1)	(2)	(3)	(4)	(5)	(6)
Overeducated without working experience	-0.1216***	-0.1246***				
Overeducated with working experience	-0.0568***	-0.0592***				
Overeducated without working experience in econ. Sciences			-0.0883***	-0.0914***		
Overeducated with working experience in econ. Sciences			-0.0622***	-0.0648***		
Overeducated (Female)					-0.0702***	-0.0745***
Overeducated (Male)					-0.0793***	-0.0802***
Knowledge-job match: use of learned knowledge: 1 to 10 (a)		0.0222		0.0215		0.0214
(a)^2		-0.0021		-0.0021		-0.0021
Age	0.0064*	0.0062*	0.0066*	0.0064*	0.0067*	0.0065*
Gender: male	0.0572**	0.0566**	0.0579**	0.0573**	0.0613**	0.0596**
Civil status: non-single	0.0483	0.0508*	0.0473	0.0499*	0.0473	0.0500*
Working experience: yes	0.0700	0.0670	0.0955**	0.0927**	0.0921**	0.0892**
Working experience in econ. sciences: yes	0.0435	0.0446	0.0291	0.0301	0.0402	0.0412
Formal labor: yes	0.1040***	0.1050***	0.1045***	0.1055***	0.1039***	0.1050***
Firm size: 6 to 20	0.1355***	0.1350***	0.1361***	0.1357***	0.1374***	0.1368***
Firm size: 21 to 50	0.2024***	0.2033***	0.2038***	0.2046***	0.2049***	0.2056***
Firm size: more than 50	0.2380***	0.2367***	0.2382***	0.2368***	0.2392***	0.2377***
Tenure (years)	0.0173***	0.0173***	0.0173***	0.0173***	0.0171***	0.0171***
Working hours: 11 to 20	-0.2403***	-0.2351***	-0.2361***	-0.2309***	-0.2342***	-0.2292***
Working hours: 21 to 30	-0.1247***	-0.1209***	-0.1241***	-0.1204***	-0.1232***	-0.1196***
Working hours: 31 to 40	0.1278***	0.1327***	0.1275***	0.1323***	0.1289***	0.1335***
Working hours: more than 40	0.1960***	0.2009***	0.1962***	0.2012***	0.1975***	0.2023***
Training activities: Yes	0.0062	0.0064	0.0052	0.0054	0.0047	0.0049
Survey: Follow-up 1	0.0417**	0.0390**	0.0415**	0.0388**	0.0415**	0.0388**
Survey: Follow-up 2	0.0668***	0.0642***	0.0670***	0.0643***	0.0673***	0.0647***
Survey: Follow-up 3	0.1207***	0.1186***	0.1203***	0.1183***	0.1203***	0.1183***
Survey: Follow-up 4	0.1260***	0.1239***	0.1263***	0.1241***	0.1263***	0.1242***
Observations	1,712	1,712	1,712	1,712	1,712	1,712
Number of individuals	545	545	545	545	545	545
Without working exp. = With working exp. (p. value)	0.096	0.094				
Without working exp. in econ. sciences = With working exp. in econ. Sciences (p. value)			0.448	0.439		
Female = Male (p. value)					0.791	0.869

*** 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**	**Pool**	**FE**	**RE**	**Pool**	**FE**	**RE**
Overeducated: Yes	-0.0919***	-0.0657***	-0.0756***	-0.1100***	-0.0658***	-0.0798***						
Severely Overeducated: Yes							-0.0946***	-0.0864***	-0.0929***	-0.1117***	-0.0875***	-0.0989***
Mildly overeducated: Yes							-0.0888***	-0.0478**	-0.0591***	-0.1085***	-0.0492**	-0.0645***
Knowledge-job match: use of learned knowledge: 1 to 10 (a)				0.0410**	0.0149	0.0204				0.0406**	0.0110	0.0163
(a)^2				-0.0043***	-0.0014	-0.0021				-0.0043***	-0.0011	-0.0018
Observations	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712
Number of individuals		545	545		545	545		545	545		545	545
R^2	0.421	0.268		0.427	0.269		0.421	0.269		0.427	0.270	
R^2 (within)		0.268	0.248		0.269	0.248		0.269	0.249		0.270	0.249
R^2 (between)		0.242	0.435		0.245	0.439		0.247	0.434		0.250	0.439
Rho		0.757	0.638		0.756	0.635		0.756	0.639		0.755	0.636
Breusch-Pagan test (p. value)			0.000			0.000			0.000			0.000
Hausman test (p. value)			0.000			0.000			0.000			0.000
Severely Overeducated=Mildly overeducated (p-value)							0.846	0.153	0.179	0.918	0.165	0.182

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. 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**	**Pool**	**FE**	**RE**
Overeducated without working experience	-0.1996***	-0.1148***	-0.1533***	-0.2119***	-0.1146***	-0.1564***						
Overeducated with working experience	-0.0616***	-0.0478**	-0.0482**	-0.0768***	-0.0479**	-0.0518**						
Overeducated without working experience in econ. Sciences							-0.1386***	-0.0779***	-0.1068***	-0.1552***	-0.0780***	-0.1113***
Overeducated with working experience in econ. Sciences							-0.0470**	-0.0559**	-0.0485**	-0.0644**	-0.0561**	-0.0525**
Knowledge-job match: use of learned knowledge: 1 to 10 (a)				0.0455***	0.0150	0.0218				0.0424**	0.0148	0.0205
(a)^2				-0.0046***	-0.0014	-0.0022*				-0.0044***	-0.0014	-0.0021
Observations	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712
Number of individuals		545	545		545	545		545	545		545	545
R2	0.426	0.269		0.431	0.270		0.424	0.268		0.430	0.269	
R2 (within)		0.269	0.250		0.270	0.250		0.268	0.248		0.269	0.248
R2 (between)		0.261	0.439		0.264	0.443		0.245	0.435		0.248	0.440
Rho		0.754	0.638		0.753	0.635		0.756	0.638		0.755	0.635
Breusch-Pagan test (p. value)			0.000			0.000			0.000			0.000
Hausman test (p. value)			0.000			0.000			0.000			0.000
Without working exp. = With working exp. (p. value)	0.000	0.125	0.004	0.000	0.127	0.004						
Without working exp. in econ. sciences = With working exp. in econ. Sciences (p. value)							0.002	0.572	0.066	0.002	0.574	0.063

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. 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**
Overeducated (Female)	-0.0939***	-0.0752***	-0.0838***	-0.1128***	-0.0763***	-0.0893***
Overeducated (Male)	-0.0885***	-0.0533*	-0.0634**	-0.1050***	-0.0521*	-0.0658**
Knowledge-job match: use of learned knowledge: 1 to 10 (a)				0.0412**	0.0155	0.0209
(a)^2				-0.0043***	-0.0014	-0.0021
Observations	1,712	1,712	1,712	1,712	1,712	1,712
Number of individuals		545	545		545	545
R2	0.421	0.268		0.427	0.269	
R2 (within)		0.268	0.248		0.269	0.248
R2 (between)		0.244	0.434		0.248	0.439
Rho		0.756	0.638		0.755	0.635
Breusch-Pagan test (p. value)			0.000			0.000
Hausman test (p. value)			0.000			0.000
Female = Male (p. value)	0.863	0.572	0.528	0.803	0.532	0.468

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

Table 9: average wage penalty for overeducated graduates from the nonparametric model (#)

		Coefficient	
Overall		-0.1088	***
Women		-0.1077	***
Men		-0.1108	***
Working experience	No	-0.1145	***
	Yes	-0.1074	***
Working experience in econ. Science	No	-0.1168	***
	Yes	-0.1011	***
Quartile of ln(wage)	1	-0.1763	***
	2	-0.1188	***
	3	-0.0691	***
	4	-0.0281	***

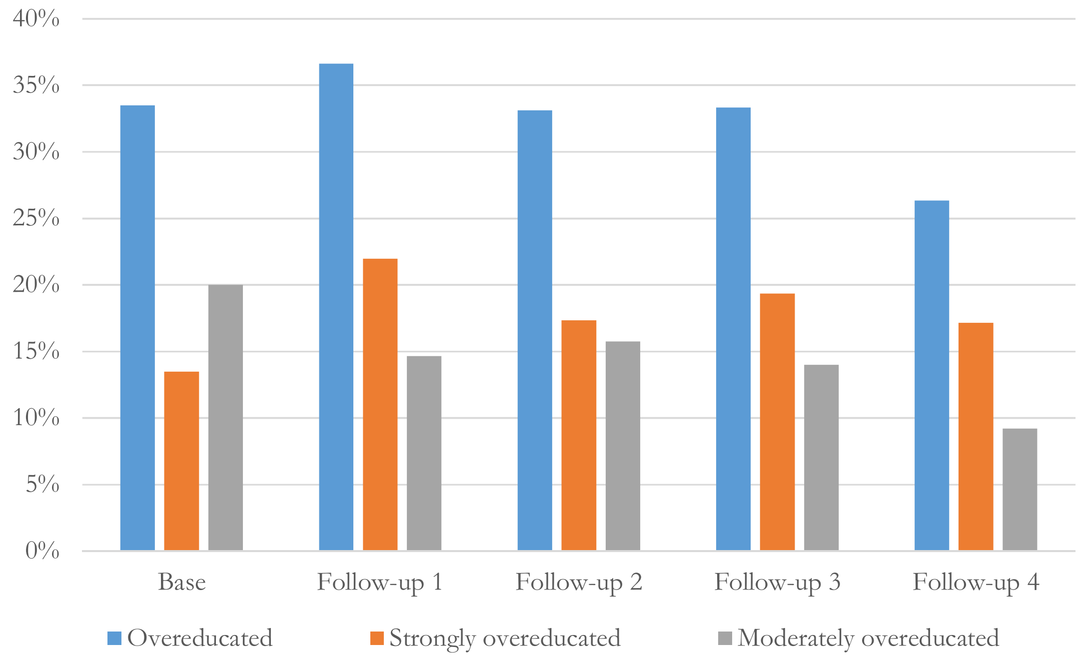
*** p<0.01, ** p<0.05, * p<0.1. (#) All figures correspond to the mean values for graduates categorised as overeducated.

Table 10: marginal effects of the nonparametric model

Change in status (#)		Change in ln(wage)	
From	To		
Overeducated women	Overeducated men	0.0208	
Overeducated without working experience	Overeducated with working experience	0.0325	
Overeducated without working experience econ. sciences	Overeducated with working experience econ. sciences	0.0410	**

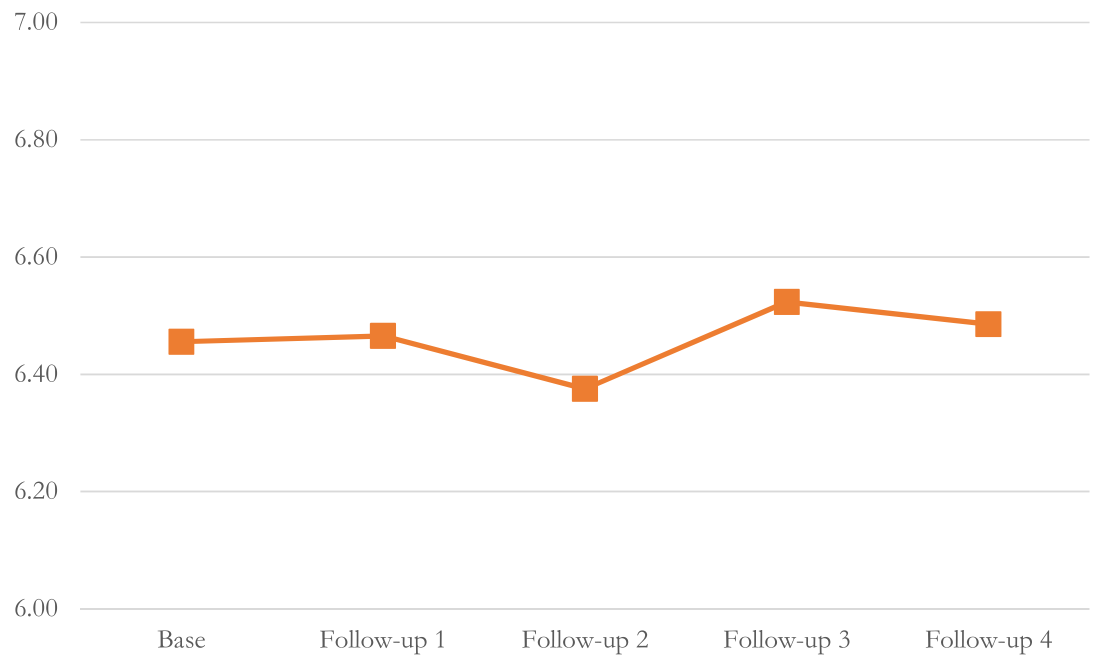
*** p<0.01, ** p<0.05, * p<0.1. (#) All other variables are kept at their sample averages.

Graph 1: incidence of overeducation (*)



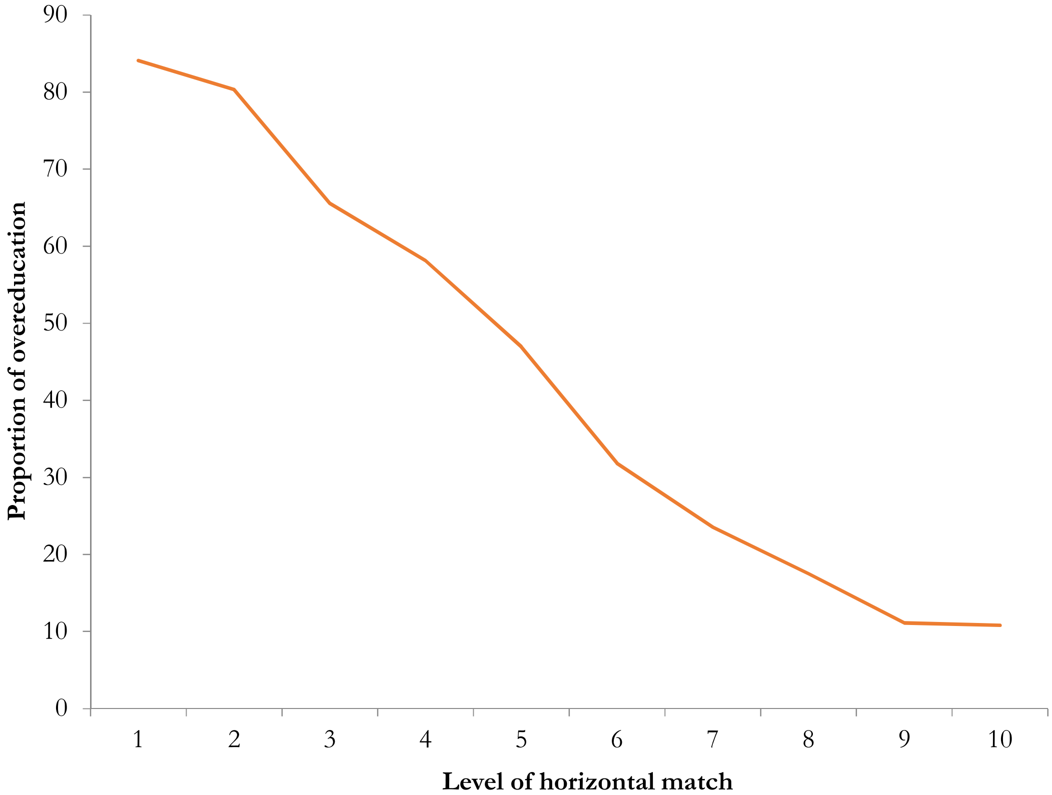
(*) All figures correspond to salaried employees. Source: own.

Graph 2: degree of horizontal matching (*)



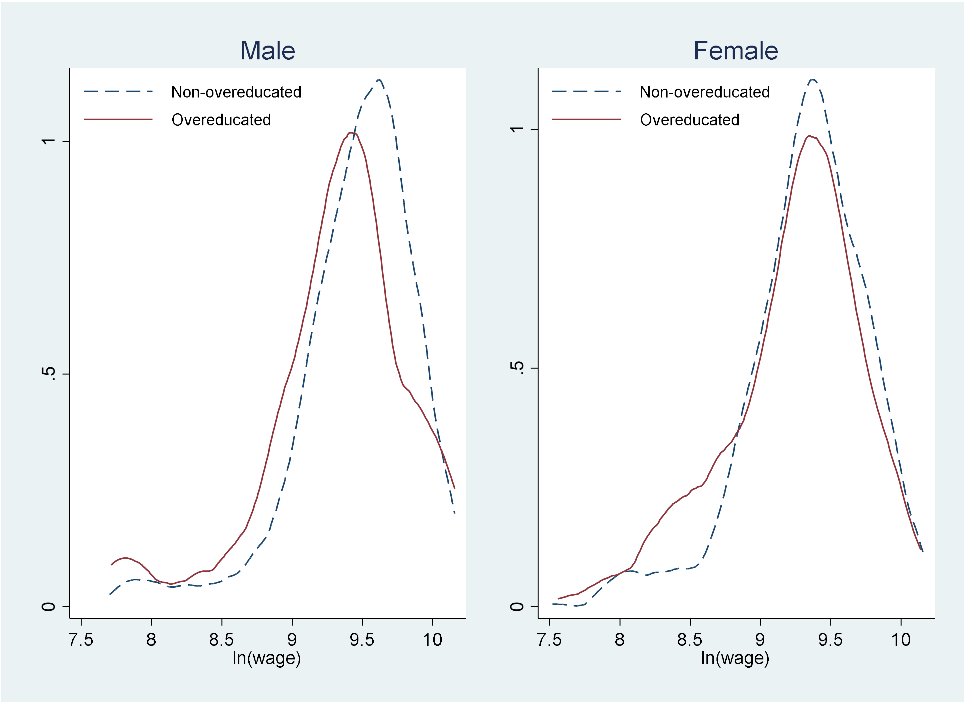
(*) All figures correspond to salaried employees. Source: own.

Graph 3: overeducation and horizontal matching (*)



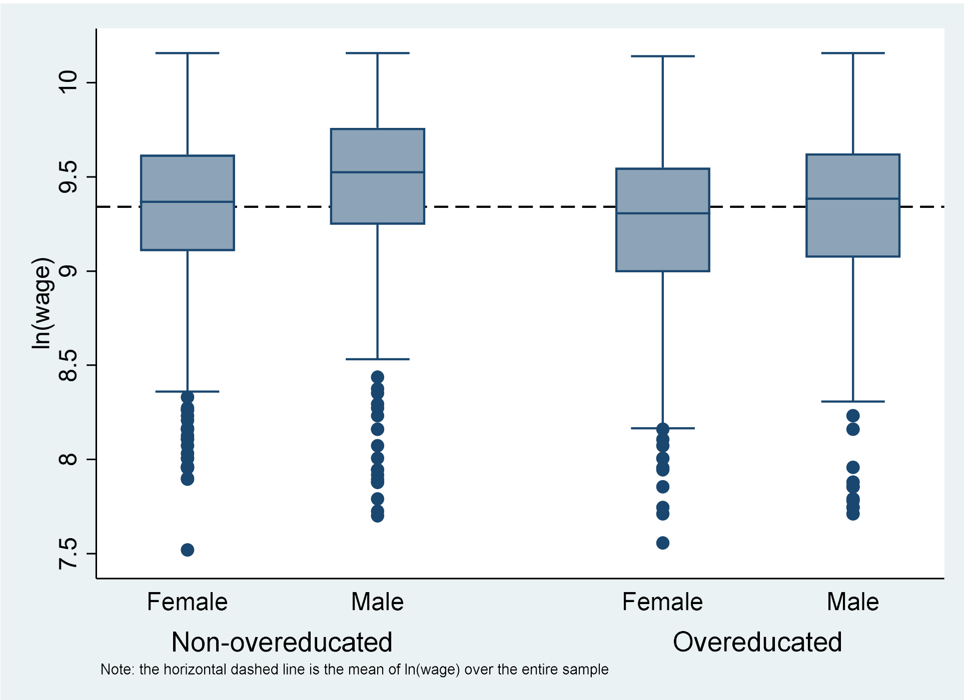
(*) All figures correspond to salaried employees. Source: own.

Graph 4: distribution of wages by gender and overeducation status (*)



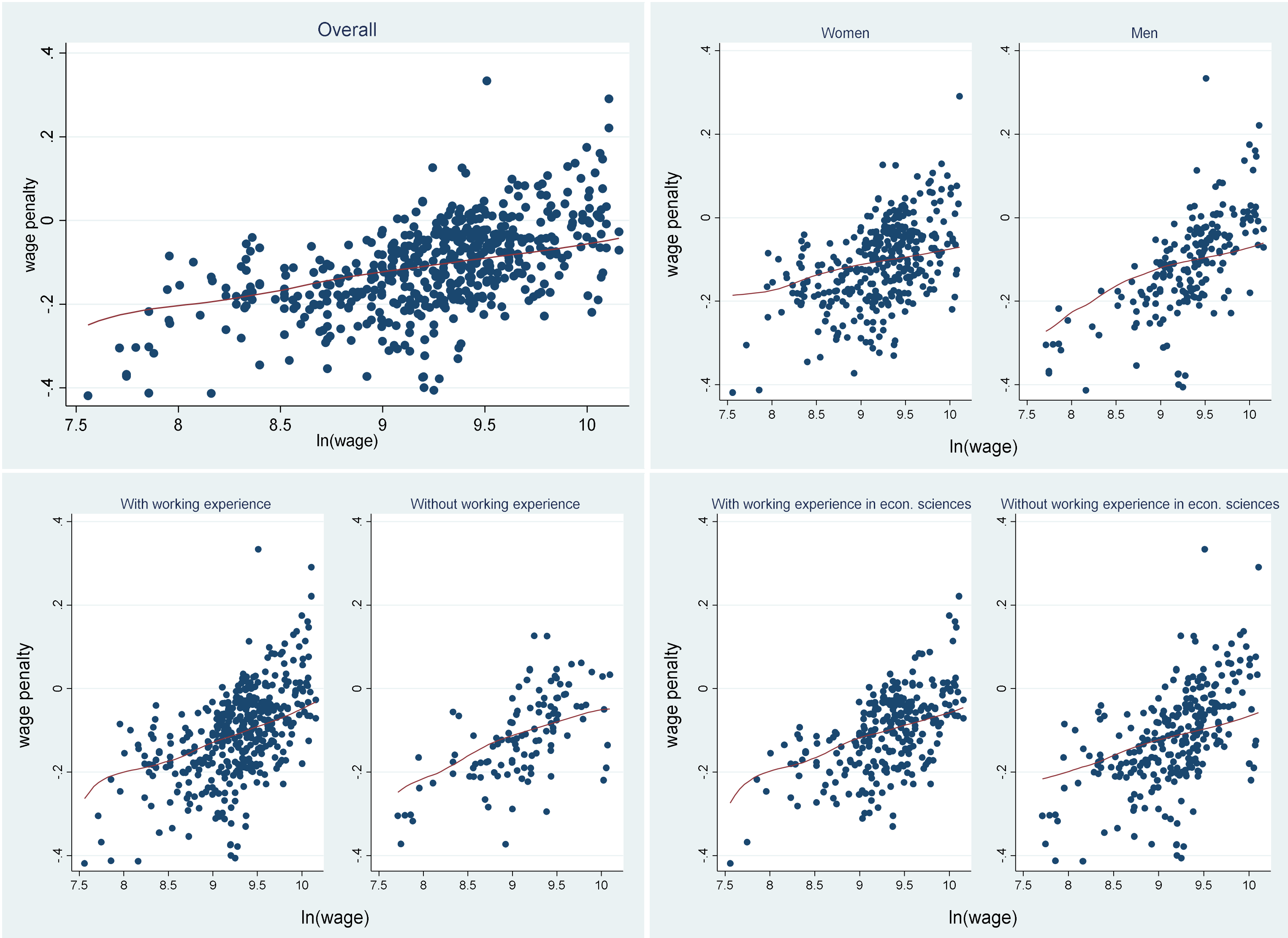
(*) All figures correspond to salaried employees. Source: own.

Graph 5: distribution of wages by gender and overeducation status (*)



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

Graph 6: overeducation wage penalty and wage levels (#)



(#) All graphs refer to graduates categorized as overeducated.