The pay-off to human capital competences for recent college Catalan graduates

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ABSTRACT:

In this paper the impact of different types of competences in the labor market for college graduates is investigated. We use a new data set comprised of Catalan college graduates interviewed three years after graduation. We use wages equation to calculate the payoff to management, communication, specific and instrumental competences. By far, management competences are those who command a higher pay-off. The mastering of foreign languages is also rewarded by employers. We show that most of the individual endowment in management competences is developed in the workplace. However, a strong background of theoretical knowledge (developed in the class room) helps a great deal to accumulate working related competences and, hence, has a large indirect pay-off.

1. Introduction

It is quite obvious that over the last years our economies have been experiencing a great deal of structural changes. A very fast pace of technological change and an unstoppable process of globalisation are creating a very competitive environment where firms must come up with new products and produce them efficiently. It has been argued that these changes are decisively affecting the kind of skills the workforce must bring to the labour market. Basically, most research studies come to the conclusion that workers have to upgrade their qualifications. In our future knowledge societies, those who lack the correct set of skills will fall behind and will face problems assuring a minimum level of income.

Alternatively, some research is pointing to potential problems of overeducation (Mane and Miravet, 2007). The argument is that the supply of highly skilled workers is outpacing their demand. The consequence is that we find workers in jobs where a lower level of education or experience would be just enough. In fact, it is too often taken for granted that a vast majority of firms are engaged in producing high-tech products using a very complex production process.

In recent years, there has been an intense academic debate in which researchers have been trying to discern which competences and skills are most appreciated by employers, and as a result, more profitable for the individual in terms of earnings. This article represents a new attempt of identifying the competences needed in the modern workplace. The process of Bologna, which aims to introduce deep changes in college education, stresses the importance of promoting the acquisition of competences and skills among university students, being an outcome of this intense debate. Thus, it is essential, in terms of both economics and education policy, to come across those competences that acquirement of which must be promoted in higher education.

The paper is organized as follows: in section 2 we overview the relevant literature that addresses the causal effect of competencies on earnings. Section 3 describes the data, whereas section 4 describes how factor analysis has been applied. Section 5 contains the empirical analysis. Section 6 covers how competencies are developed in the labor market and section 7 concludes.

2. Review of literature

There is not an agreement on the type of skills and competences that are necessary in the new scenario. Some researchers have underlined the importance of academic knowledge, such as mathematics, (Murnane *et al.*, 1995; Murnane and Levy, 1996; Tyler et al, 1999). Similarly, Hanusek and Kim (1995) conclude that academic competences are an important determinant of the workers' productivity. On the other hand, the evidence in Bishop (1995), Mañé (1999) and Bishop and Mañé (2004) favor the view that supports the significance of technical and professional competences. As opposed to the former evidence, Shapiro and Goertz (1998) show that employers make their decisions of selection of employees basing not on academic knowledge, but on soft skills (motivation, attitude…). More recently, some researchers have highlighted the value of the more generic competences (communication, problem-solving, working in a team, creativity…) in the new jobs (Appelbaum *et al.*, 2001; Gould, 2005). For Garcia-Aracil et al. (2004) and Heijke et al. (2003) specific knowledge appears to have no impact on earnings in opposition to other more generic competences. However, in the latter it becomes apparent that the level of specific knowledge plays a key role in allowing graduates the access to a job belonging to their domain of study.

The issue of the specific returns to computer skills has drawn by itself the attention of the literature, although the remaining degree of cleavage among researchers is even greater. On the one hand, there is a certain group of authors that advocate that these skills are essential to raise productivity and thus, to obtain higher earnings (Krueger, 1993; Bell, 1996). On the other hand, some researchers have cast some doubts on this point (Borghans and Weel, 2006). These authors are reluctant to side for a direct causality between earnings and the computer content of the job, and in their opinions, computer usage is correlated with abilities and skills that effectively increase earnings. More recently, Dickerson and Green (2004) find that computer usage alongside high-level communication skills generate a positive wage premium, in hedonic wage equation in which the covariates of interest were the job content in terms of generic skills. Silles (2005) presents relatively similar conclusions to computer usage as those obtained by Krueger. However, by means of a value added model she shows that the premium derives from unobserved ability.

3. Data

Data used originates from a poll conducted by the Catalan Agency for University Quality named as the *School to work transition of the Catalan Graduates*. The aim of this survey was to provide information about the quality of the school to work transition of the Catalan graduates 3 years after having obtained their degrees. Therefore, a wide number of variables describing jobs are included, in addition to the variables that provide the characteristics of each individual.

This survey took place during the first semester of 2005, and a total of 10,501 graduates could be interviewed out of an initial potential sample consisting of 21.018 records. The interviews were made by means of telephone calls. A 1.8% did not accept to be interviewed, a 37.1% could not be contacted, either because it was checked that the telephone number was mistaken, or because they had moved, or simply because nobody picked up the phone after several attempts. A 1.3% of the interviews could not be completed due to a variety of inconveniences (e.g. cut off). Another 9.1% was not interviewed because the accorded number of interviews had already been reached. The percentage of the initial sample that could not be contacted is not negligible at any rate. Dolton and Vignoles (2000) warned about the bias arising from non-respondents in the case they had fled without leaving any forwarding addresses According to them, if this mobility is non-random, it increases the chances of biasing the estimation. A 41% of the phone calls in our survey were made to mobile phones, technology which logically decreases the probability of not contacting a mover. Alternatively, with mobile phones it is more likely than the individual switches his telephone number. Although the no inclusion of the movers in the sample could result in the bias which Dolton and Vignoles (2000) put forward, it is plausible that the exclusion of people that have changed their mobile phone numbers in the sample responds to a random process and is not likely to affect our results. To sum up, although bias could exist, the irruption of mobile telephones can have softened it.

From the original sample composed of 10.501 individuals, those who had never been occupied had been dropped out of the sample due to obvious reasons. Likewise, those records of individuals who were not working at the moment of the interview were not included, taking into account that the moment when they worked is unknown, and therefore the real value of income is also unknown. Those who were receiving a scolarship were also deleted from the sample. Finally, the fact that 2 universities had conducted the poll in some degrees prior to the whole sample of the Catalan universities survey has yielded some differences in the questionnaire. Those differences are basically the exclusion of some of the variables of interest. This has made advisable to drop these individuals from the sample as well[1]. The final sample is composed by 8933

[1] Those graduates who had studied Arts at University of Barcelona, and the degrees of Cultural and Social Anthropology, History of Music and Science, Theory of Literature and Comparative Literature, Administrative and Political Science, Catalan Philology, Publicity and Public Relation, Social Education, Chemistry, Biochemistry, Geology, Physics, Mathematics, Food Science and Technology, Veterinary, Chemistry Engineering and Informatics Engineering.

individuals. Table 1 shows the basic descriptive statistics of the those variables related to the job, those related to the characteristics of the individual, and the wages, the variables concerning skills and qualifications, and our dependent variable, earnings .

[Table 1]

Descriptive statistics in table 1 reveal some interesting facts, such as the predominance of Social Sciences over the other branches of knowledge. Data also show that a percentage superior to 60% were working at some stage when they were studying, primarily in part-time jobs. This should be the reason that lies behind the low percentage of long-term unemployed, more if we consider that some of these individuals could be non-active while they were continuing their studies. The relative slender proportion of people having been involved in mobility experiences is at least remarkable. More than a 30% of people are working as civil servants, figure that surely influence the percentage of individuals with a stable occupation. It must be underlined that approximately one third of the sample lacks stability in their jobs. Logically, Barcelona is the province where more than 2/3 of the complete sample work. As we have introduced in the previous section, the dependent variable of our model is divided in 6 different intervals, so that we cannot know for certain the exact amount of money earned by each individual. Nonetheless, it can be noticed that almost a 1/3 of the whole sample is banded between the 12001 and 18000€, and little above another 1/3 earns between 18001 and 3000€. Another interesting fact is that the proportion of individuals below these two bands is higher than the proportion of the better-offs.

4. Factor analysis

Articles intending to measure the impact of skills on earnings have used techniques to reduce the number of competences included in the analysis by creating a lesser number of new variables that reproduce the generic content of the initial set of variables. The application of methodologies aiming this object offer the advantage of diminishing potential problems of colliniarity, as wells as helping to construct a more comprehensible framework of analysis. For instance, Heijke *et al.* (2003) use a hierarchical clustering method which groups their initial set of 36 competences in simply 3, used later on in the regressions: general academic competences, discipline-specific competences and management competences. One of the most popular techniques is factor analysis, in whichever of its variants. Factor analysis departs from the variances of the initial set of variables, which are decomposed in 2 parts: the first is the common part which is explained by the new variables (factors) created, whereas there is part which is specific of each initial variable and it is not possible to explain it by means of the factors. Therefore each of the variables can be rewritten as follows:

$$X_i = a_{i1}F_1 + a_{i2}F_2 + ... + a_{im}F_m + e_i \quad (4)$$

In the previous general factor analysis model, X_i represents the original variables which can be explained by each of the factors created (F_j). There is a total number of m factor, and each one of them is multiplied by a loading a_{ij}. This loading states the level of influence of the factor on the original variable. The factors are in fact indexes with mean equal to 0 and variance equal to 1[2]. This means that the factors can be used to measure both an individual endowment of a certain factor (the endowment of a combination of competences), and the endowment of a certain group of individuals. For instance, if a selected individual has a mean below zero, it can be derived that this individual is below the mean of the distribution of this variable.

There are infinite solutions for the factor analysis model. The first solution is not likely to be the most suitable one, since most of the variables will tend to be highly correlated with the same factor, or on the other hand, it is possible that one or more original variables can be correlated with more of one factor. Therefore, the next step is reaching a solution easier to be interpreted applying

[2] It is very difficult that the factor variances are equal to 1, since it would mean that the factors are perfect linear combination of the variables. It is almost impossible that the variances of the original variables are completely explained by the factors.

a rotation. The most popular techniques of rotation are Promax and Varimax. The factors obtained by the former are allowed to be correlated between them (i.e. this is also known as oblique rotation); whereas the latter yields factors that are uncorrelated between them (i.e. this is also known as orthogonal rotation).

This technique is not exempt from criticism, especially if we consider the certain level of subjectivity involved. First of all, there is not consensus in the number of factors that should be used to explain the common variance of the original variables. Later on, it will be detailed which criteria have led to the election in this article. Naming the factors is an exercise which implies an important level of intuition. Also the election of the rotation techniques or even the technique of factoring is subject to the choice of the researcher.

[Table 2]

The survey asked graduates to asses the education they had received in the university in terms of the levels of 14 competences in a scale ranging from 1 (very low) to 7 (very high). Afterwards, they were asked to range, according to the same scale, the extent to which these competences were required in their current jobs. Factor analysis and an orthogonal rotation was then applied to the requirements of the 14 competences (shown in table 2) included in the survey. Although oblique rotation allowing correlations between the factors tends to be more recommended because it provides more realistic solutions (the no correlation assumption could seem a quite an unrealistic constraint) as well as being more advisable in order to obtain a simpler distribution of loadings which make them easier to be interpreted; in our case the structure of the data prompted us to choose the varimax rotation[3]. The main reason lying behind this choice were the consequences emerging from having a sample in which all the individuals are graduates. The relative homogeneity of the sample is the source

[3] The groups obtained by applying an oblique rotation are quite similar to those obtained with the orthogonal rotation. The most important differences reside in the fact that the oblique rotation offers a more clear separation of the variables.

of the high levels of correlation between the oblique rotated factors[4]. Undoubtedly, the inclusion of these variables in the econometric specifications could result in problems of multicollinearity.

After rotation, next step is to decide how many factors should be retained. The question about how many factors should be retained is not clear to the extent that the factor analyst has to choose the model that according to him best suits to the data. Notwithstanding the existence of some criteria, the nature of the data and common sense are often the best tools of judgment. A preliminary principal component analysis was carried out in order to examine the eigenvalues. In only two cases the eigenvalue exceeded 1, and if we should consider the traditional rule of thump that suggests the rejection of any factor with an eigenvalue lower than the unity, we should only take into account those 2 factors[5]. However, with only two factors the model can explain only a 53% of the whole variance accounted for by the extracted factors. Moreover, in 11 out of the 14 initial competences', less than half of their variances are accounted for these 2 factors. As well as the statistical determinants, we found that the resultant factor structure did not meet our goals, since a structure with only two factors (one related to specific knowledge and the other related to all the practical competences was excessively simplistic and scantily informative). A third factor permitted the introduction of the expression skills in the scheme. Finally, we decided to retain 4 factors. The reasoning of this decision is based on the fact that the eigenvalue of the fourth factor extracted by principal components increased the proportion of variance accounted for to 2/3 of the total amount of variance accounted for by the factors. This proportion, although arbitrary, should be, according to our point of view, acceptable. As a second point, the structure with 4 factors is closer to satisfy the condition proposed by Thurstone (1947), who advocated for a straightforward factor analysis structure in which each original variable highly contributed to at most one factor[6].

[4] The correlations between the obliquely rotated factors never falls below 0.8, while with the orthogonally rotated factors it is around 0.2 at the most. Anyway, the groups of variables appearing in table 3 could also be obtained with the oblique rotation.

[5] This rule is grounded in the fact that any factor with an eigenvalue below the unity should be rejected given that explains less variation than the original variables.

[6] Table 3 shows the loadings of the 4 retained factors after applying the varimax rotation. Figures in bold refer to the values of the variables which are relatively strongly related with the factors. As it can be

Notwithstanding the fact that this condition was not fully satisfied, basically due to the election of the orthogonal rotation method, the structure obtained was closer to meet this requirement in comparison to the 3 and 5 factor structures. A third element is that, despite the fact that both the third and the fourth factors' eigenvalues are less than 1, they do not drop below 0.8. It also supports our choice the fact that a fourth factor increases to 8 the number of original variables, the explained variance of which is above the 50%. The introduction of a fifth factor in the scheme would permit to introduce a new variable highly related to the creativity and critical thinking competences, as well as increase the variance explained up to the 70%. However, these competences are also highly related to the first factor, and thus, we made the decision of retaining just 4 factors.

[Table 3]

Table 3 shows how the original competences are distributed across the new generic competences after having applied factor analysis to the data and orthogonally rotated it. We have bolded the figures above 0.4 and put in italics those above 0.35[7]. At his stage, the judgment of the factor analyst plays its part again to determine the taxonomy of each new generic competence. In our case, the simplicity of the factor structure makes things much easier:

Management competences: Working in a team, Leadership, Problem-solving ability, Decision-making, Critical thinking, Creativity and Management

Expression skills: Written communication skills and Oral communication skills

Specific knowledge competences: Theoretical knowledge and Knowledge of methods

Instrumental competences: Documenting ideas and information, foreign languages and computer skills.

observed, only twice an original competence is strongly related with more of one factor. With 2 and 3 factors this condition was not satisfied in 2 and 3 occasions respectively, whereas with 5 factors orthogonally rotated the problem appears 3 times again.

[7] Dickerson and Green (2004) stick to a 0.4 criterion, although other researchers such as Garcia-Aracil et al. (2004) just select the highest loading.

Table 3 also reveals that computer skills and oral communication skills could also be included in the management skills variable following the 0.4 criterion. Working in a team, leadership and management are very close to reach the 0.4 in the second column. Despite being most related to management skills these loadings come as no surprise since it is common sense that an important factor of these variables has to do with expression skills.

Although there is no consensus when classifying competences across the literature, our taxonomy is relative consistent with other classifications obtained by in previous investigations. Heijke et al. (2003) gave rise to 3 categories by means of a hierarchical clustering method: general academic competences, management competences and discipline-specific competences. The methodological competences and the specialized competences in Garcia-Aracil et al. (2004) are akin to our instrumental competences and our Specific knowledge competences respectively. Dickerson and Green (2003) distinguish different levels of communication skills, and also identify a level of technical know-how which points towards specialized knowledge. Other classifications are not the outcome of a statistical technique, but either the result of a theoretical reflection or the result of a mere process of data simplification by means of a relatively subjective criterion. The former is the case of Bunk (1994), who puts forward a 4-competence-classification: specialized knowledge, methodological competence, social competence and participatory competence. Allen and Van de Weert (2005) select those competences that are attributed a higher level of importance by the graduates who were interviewed.

Finally, once the rotated factor loadings have been examined, the factors (with numerical values for each of the individuals) must be constructed. Two methodologies are available: the regression method and the Barlett method. We have sided for the former, which yields factors that have the smallest mean square error from the true factors but may be biased. On the other hand, the latter produces unbiased factors with the drawback that they are less accurate in comparison with those produced by the regression method.

The factor scores obtained are a very useful tool in order to elucidate the situation of skills among the Catalan graduates. The required level of generic competences has a mean equal to 0, and "theoretically", a standard deviation equal to 1. The survey also provides information about the level of the same competences that the individual attained at college. In order to obtain a comparable scale, we have to replicate the factors obtained with the requirements of competences. First, the levels of attained competences must be standardized, and afterwards, they are multiplied by the scoring coefficients emerging from the regression method applied to compute the scores of each of the generic required competences[8]. The estimation of these new scores will allow us to decompose the required levels of generic competences in 2 parts: attained level of generic competences and variation of the levels of generic competences during the 3 years after graduation.

[Table 4]

Table 4 shows the required level of generic competences, the attained level at college, and the difference in the whole sample separated by males and females. It comes apparent that the level of generic competences attained at college is clearly below the required level of competences, especially in the case of the management skills which are almost 2/3 out of a half deviation below the job requirements. In the case of instrumental competences, the level attained is almost 1/3 below their requirement and in the case of expression skills, the level attained is 1/4 below their requirement. On the other hand, the specific knowledge learnt at college is visibly above the job requirements. How should we interpret these results? The first temptation is to identify the former as underskilling and the latter as overskilling. Alternatively, it is assumed that the level of skills that the individual has at a certain point in time is equal to the level of required competences in his/her job, as Dickerson and Green (2004) had previously done. This assumption seems plausible if we consider that a person at the very start of his/her career will be easily and cheaply fired unless

[8] Since the correlations between the estimated factor scores of the generic required competences were very low because of the previously selected varimax rotation method, we had to make sure that the correlations between the factor scores of the generic attained levels of competences were still low. The correlation matrix gave similar values of correlation.

he/she meets the job requirements. Likewise, a person who promotes in a firm has to attain the new demands of the job. Indeed, the learning process is very active in the first steps given in the labor market. Thus, we do not associate a level of a required skill larger than the attained level of the same skill to underskilling because it does not make sense that a person who enters a highly skill-demanding job is unable to increase his/her skills in a period of 3 years. Conversely, a utilization of skills below the attained level must be considered an underutilization of skills by the firm, unless we presume that there has been an eroding process of these skills. Another interesting element of analysis is the standard deviation of both level of attained competences and job requirement of skills. The former are lower comparing with the latter in the 4 factor scores, which undoubtedly leads to think that some individuals have been able to develop a higher level of skills and competences than their peers in the labor market. Intuitively, this also could lead us to think about the existence of a residual inequality, which we intend to estimate in the next sections.

The factor scores become even more useful as indicators of the situation of certain groups within the sample. Since the job requirements of generic competences have mean equal to zero and standard deviation approximately equal to 1, we can benchmark the means and standards deviations of these groups against the whole sample standardized values. We proceed to undertake this exercise to compare men and women situation in Table 5. Apart from management skills, women access to jobs that demand for a higher level of any of the generic competences.

[Table 5]

5. Estimating the returns to competences

The traditional Mincer's human capital model has been repeatedly used to estimate the returns to education. There is a large array of articles that, by means of a typical log-linear earnings equation, have attempted to compute the result of an additional year of education. An example of the basic Mincer equation would be the following one:

$$\ln y = \alpha + \beta_1 S + \beta_2 X + e \quad (1)$$

Where y denotes earnings and S refers to the years of schooling. The vector X consists of a set of control variables which capture the effects of individual variables such as experience. According to this model, β_1 should be interpreted as the percentage variation of earnings resulting from a one year variation in years of education. However, this initial model neglects the impact of innate ability on earnings, part of which will presumably fall into the estimate of the rewards to the years of education given the correlation between years of education and innate ability.

The access to better sources of data has enabled researchers to refine the previous equation by including data referring to skills and in a very limited number of occasions, even IQ indicators. The inclusion of skills responds to the question of what really matters in the labor market. The conclusions in some recent articles (Green and McIntosh, forthcoming; Di Pietro and Urwin, 2006) defy the postulations stated by the assignment model which assume the correspondence between skills and education. Disentangling this issue requires thus, not only taking into consideration the years of education, but also having some sort of measure of the skills that an individual has.

Our data base is composed only by graduates three years after having left university. Thus, we are focusing on the characteristics of both individuals and jobs that will yield higher earnings: we specially aim to identify the impact of the generic skills we have created from the factor analysis in the previous section. We are also conscious that the access to better jobs will presumably be in part conditioned by the innate ability of the individuals to increase his/her level of skills with respect to their peers. Therefore, those graduates who prove the capacity of increasing their level skills should be likely to be better off in comparison with those graduates that have not. In conclusion, our model is an augmentation of the initial basic Mincer model (1) so that it overcomes some of the limitations commented:

$$\ln y_i = \alpha + \vec{\beta} SK + \vec{\delta} H + \vec{\varphi} X + \vec{\gamma} Z + e_i \quad (2)$$

This new model introduces a new variable H which denotes a vector of human capital variables, such as experience and its quadratic term[9], skill content of jobs and dummy variables which take a value equal to 1 if the individual has followed any the next means of continuing education: master, other degrees, specialized courses, Ph D and other. Other dummy variables indicate which the branch of knowledge studied and in which of the main Catalan universities has been graduated[10]. Vector X refers to other individual's information which is not included in the human capital matrix such as: if the individual had worked while studying, sex, mobility experiences and the means by which he/she obtained the first job. Vector Z captures information regarding the job: type of tasks carried out, economic sector, labor status, private/public firm, size and location[11]. This vector also controls for overeducation situations. However, our most important variables in this model are those referring to the skills. The skill contents of jobs (SK) are derived from the required generic competences obtained by means of the factor analysis of the data shown in the previous section. The inclusion of these variables in the model will allow the identification of the competences that receive a pay-off, and which do not. In research on overeducation, earnings have been often estimated based on the separation between required level of education, surplus education and education deficits[12]. We undertake a similar exercise, yet in the reverse direction. In our model we decompose the returns to the required level of generic competences in attained level of generic competences and variation during the 3 years after graduation. This will enable us to compute separately the returns to skills acquired at

[9] The survey does not provide exact information on the experience of the individual. Nonetheless, there is information on the year in which the individual entered his/her current job and how long it took him to find his/her first job after graduating. If the individual found a job after graduation we just subtracted to 3 (years after being graduated) the time it took him/her to find the first job. If the individual was working by the time of graduation the experience value becomes 3, and finally, if the individual has stayed in the same company longer than 3 years, we stick to the tenure value.

[10] These branches of knowledge are Humanities, Social Sciences, Experimental Sciences, Health and Technical Degrees.

[11] Although functions enter the equation as dummy variables, the fact that some individuals report that their jobs involve more than 1 function forces the inclusion of 8 different independent variables (each denoting one funcion) that take value 1 if the job involves the specific function, and value 0 otherwise.

[12] This refers to the so-called ORU specification.

college and skills acquired later on, as well as providing very useful information about the competences that should be promoted at higher education.

$$\ln y_i = \alpha + \vec{\beta}_1 SK^{attained} + \vec{\beta}_2 SK^{increase} + \vec{\beta}_3 SK^{surplus} + \vec{\delta} H + \vec{\varphi} X + \vec{\gamma} Z + e_i \quad (3)$$

The dependent variable is the logarithm of earnings, as traditionally used in this kind of models. However, the survey does not provide information on the exact amount of earnings the graduate is receiving since data is only observed to fall within continuous intervals. As a result the estimation strategy must be changed. Stewart (1983) shows that assigning mid-point values or other ad hoc procedures do not provide such as good estimators than those obtained by assigning each observation its conditional expectation by assuming a probabilistic distribution for the dependent variable. In this case log-normally distribution of earnings is supposed, which seems quite plausible, and the maximum likelihood estimator is computed.

[Table 6]

Table 6 shows the estimates of equations (2) and (3) and its variations without controlling for additional human capital and other individual or firm related variables. In the first column, the model only considers requirements of each competence as sole covariates, whereas in the other columns the requirements are broken into attained level, and the positive and negative variation in competences in the 3 subsequent years after graduation. A 1 standard deviation increase in the requirements in management skills appears to have a large impact, approaching 6.9% increase in earnings[13]. The same augment for instrumental competences has a positive impact around 1.7%. On the other hand, expression skills have a negative impact, although not significant, and a 1 standard deviation increase in the requirements of specific knowledge has a negative impact on earnings that is larger than 2.2%. Once the requirements of

[13] Notwithstanding its mean equal to 0, the standard deviation of the factor scores is not equal to 1 because of residuals. In the specific case of the management skills, the standard deviation is above 0.86, as a result, one standard deviation increase in these skills would bring about a 6.9% increase in earnings, instead of the 7.7% appeared in Table 6. It is calculated as exp (0.8642x0.0773)-1=0.0691.

competences are broken up, it is noticeable that only the management skills acquired during Higher Education are capable to yield higher earnings, whereas in contrast there is a persistent negative relation between income and expression skills and specific knowledge. Surprisingly, level attained of instrumental skills appears to induce no significant effect. There is a relatively large negative impact of the excess of management and instrumental competences which only smoothes moderately after introducing the positive variation in competences. According to this table, those individuals that have not been able to enter a job that requires at least the level of competences acquired at college will undergo a worrying income penalization. On the other hand, there is a premium for those who can attain a job which requires more management and expression competences in comparison with those learnt at college. As opposed to these competences it is remarkable the strong negative implication once again related to the specific knowledge. Before improvising justifications for the non significant impact of instrumental competences on earnings (neither in terms of attained level at college or subsequent increases in the 3-year-following period), we should wait for models adding controls for individual and firm characteristics.

The inclusion of the variables used to control for the increase in human capital do not produce significant variations concerning the results previously commented, as it is shown in table 7. According to our results, experience increases income almost 5% in the first year[14]. The successive years of experience also contribute to increase income, although the extent of the increase diminishes year after year[15]. It draws our attention the fact that having received continuous education in the form of specialized studies, another degree or other type of education are connected with a reduction in earnings not smaller than a 2%. On the other hand, having studied master increases income in all the cases.

Table 8 shows the results obtained with the full model specification, after introducing all the individual variables along with those capturing the

[14] Again we calculate impact as a percentage by computing exp(coefficient)-1.
[15] It would take longer than 44 years to completely offset the yearly effect of each year working.

characteristics of firms. It can be appreciated in the model which assesses the impact of the requirements of competences as a whole (model 1), that a one standard deviation increase in the management skills is translated into a 2.7% increase in income. In addition to the management skills, the larger the instrumental skills requirements, the larger the income received by the graduate, although the raise is much lower (inferior to 1%). Once the requirements are split as in the previous tables, and we control for individual and firm characteristics (model 1.4), the level attained in management skills is the only one that brings about an income raise, which, at any rate, is just above the 1.1% in case of a standard deviation increase. Actually, it is confirmed that the main responsible for increases in earnings are the increases in management skills – the individual that is capable to increase his/her management skills one standard deviation of the variation of management skills, will come across a 3,9% increase in income. Likewise, it is also noticeable, that expression skills are also likely to receive a payoff, although much lower, around 1% for a one-standard-deviation increase. Controlling for individual and firm characteristics has diminished the negative impact of the surplus of competences[16], nonetheless, all surpluses of the generic competences generate a drop in earnings, except excess specific knowledge. Excess of specific knowledge exerts no negative impact, because this impact is mainly captured by overeducation. Being overeducated lessens graduates' income around a 12.5%. Similarly, having studied a concrete specialization which is not really needed to work causes a 3.5% reduction in earnings. However, what is particularly remarkable in these results, is the large negative impact of the surplus instrumental competences on earnings, to the extent that the individual whose job is one standard deviation below what he/she learnt at college (in terms of instrumental competences) is punished with a 3.4% decrease in earnings. Negative impacts of a 1 standard deviation in surpluses of management and expression skills are around 3.2% and 2% respectively.

[16] Evidence reveals that overeducation has a diverse incidence in the Catalan labor market depending on the branch of study, as it has been recently shown in Mañe and Miravet (2007). In following sections of this paper, it will be also shown that this phenomenon also occurs in the case of skills. Thus, controlling for the branch of study and overeducation should have contributed to sweep out the negative impact of underskilling.

Experience in the labor market gets its impact on earnings halved once we control for individual and firm characteristics. Furthermore, only the master studies yield a significant positive impact on earnings of the 3%. Unfortunately, we do not have information about training provided within the firms. Despite the fact that control variables are not the main goal of this article, we will briefly review the most outstanding coefficients. A 4-year-degree is a 12.2% more profitable than a 3-year-degree. The field of study has a strong impact on earnings, it is especially notable that graduates on Health and Technical Sciences earn around a 25% and a 32% more than their counterparts in humanities. Women are penalized with a 13.5% reduction in earnings. The positive effect of having been previously working in a full time job, in particular if the field of study was related to the job (11% increase in earnings) as well as the positive implication of working mobility must be underscored. Some of the methods graduates use to access their jobs prove to either increase earnings (press, social servants' exams and university services) or depress them (public agencies). Reasons why this takes place lie behind the types of job give access to. The economic sector in which the firm operates exert a determinant impact in some cases: the most profitable sectors for workers are energy, chemistry and the building industry[17]. On the other hand, we have those workers in the public and social services which receive a noticeable punishment (11% and almost 14% respectively comparing with the manufactures) for being employed in those sectors. Graduates enrolled in the private sector receive a 9.5% less with respect to the civil servants; this coefficient serves to explain the apparent penalization received by the workers of the social and public services[18]. As expected, the omitted category – permanent workers – earn higher salary than their not so lucky peers. The situation for graduates without contract is especially precarious, given that their earnings are more than halved. As found in previous articles, size of the firm exerts a positive influence on earnings. Graduates working in Barcelona receive a pay-off, which is consistent with

[17] Although the first two results come as no surprise, the fact that the building industry offers 11% higher earnings in comparison with the manufacturer sector to the extent of being the most "generous" sector, are not predicted by previous articles. The justification might be in the housing-demand boom occurred in the Catalan and Spanish market, which has been conveyed to the demand of qualified workers.

[18] Public and social services labor force manly consists of civil servants employed in education, health, public administration and other publicly financed sectors. Since the positive impact of working as a civil servant is already captured (public exams giving access to jobs and jobs belonging to the public sector), it is not reflected in the coefficient of working in those specific sectors.

urbanization externalities (Henderson, 1997). This exclude neither those graduates who decided to work in other regions of Spain nor those who have moved to the rest of Europe obtain a premium around the 7% and 22% respectively. Finally and also logically, the kind of tasks assigned at work exerts an important influence on income, being management and commercial tasks the most gainful ones[19].

The results of our estimations signal management skills as the competences with a higher capacity of raising earnings. This is consistent with the evidence obtained in Heijke *et al.* (2003), and if we approximate our management skills to the participative competences in Garcia-Aracil *et al.* (2004), our results would also mirror theirs[20]. The lack of impact of specific knowledge is also consistent with both articles. In contrast, evidence in the latter article finds an important contribution of methodological competences to the increase of income, whereas our impact of requirements of instrumental competences was much smaller and was diluted once we decomposed the measure of requirements[21]. This apparent contradiction in the results along with the fact that the uniqueness of each of the 3 competences which had the strongest contribution to the instrumental competences were among the four highest ones, prompted us to estimate again the impact of the generic competences on earnings[22]. These were not the only arguments, since the literature has traditionally been very interested in assessing the impact of computer skills on earnings and the survey offered a splendid opportunity a shed some more light on the issue. Replicating exactly the same path followed in the factor analysis we obtained the new factor loadings which excluded computer skills, languages and documenting. The

[19] It is interesting to see that those graduates whose jobs involve commercial tasks receive a high premium, result which contrasts with the penalization that entails working in the sector of commerce. Undoubtedly, the productivity of the commercial sector is far below the productivity inherent in jobs in other sectors implying commercial tasks.

[20] In the latter, participative competences include planning, coordinating and organizing; negotiating; initiative; assertiveness, decisiveness, and persistence; leadership; taking responsibilities. It must be added that problem-solving ability, creativity and even oral communication skills, in spite of having been included in other categories, they still maintain a relatively high loading in relation to participative competences. The requirements of these participative competences are translated into a 5.8% raise in earnings.

[21] The requirements of the methodological competences consisting of, among other competences, foreign language proficiency, computer skills and documenting ideas and information, increased earnings around a 4.9%.

[22] Uniqueness denotes the percentage of variance explained by the retained factors.

latter competences are considered separately, and will be introduced in the regressions after being standardized[23]. As expected, if 3 generic competences were imposed, the factor loadings of the remaining 11 original competences considered in the factor analysis, notwithstanding some differences, originates the same groupings of requirements of the generic competences[24]. Computing the level attained at higher education of each of the 3 competences was once again the following step[25]. At this stage we could proceed to observe the situation on each of the 3 variables by simply calculating the differences in both sets of variables.

[Table 9]

Results shown in table 9 make apparent that individuals report that the levels attained in these competences are again clearly below the job requirements. The highest variation is found in computer skills, the usage of it is 3/4 of a standard deviation of the computer skills requirements. While graduates also have upgraded notably their situation with reference to expression skills, documenting has not manifested the same rate of growth. According to these figures in addition to our previous results, graduates manifest that their jobs oblige them to increase their instrumental skills without raising their incomes, yet a decrease should be expected unless their jobs are in the upper part of the distribution of the requirements of these competences. However, we have to be cautious, and therefore consider this interpretation just as a previous hypothesis that must tested by means of the reestimation of the model.

[Table 10]

[23] Because of this, these 3 variables will have mean equal to 0, and their standard deviation will be strictly equal to 1.

[24] Specific knowledge remains unaltered. The factor loading of oral expression related to management skills diminishes to the extent that can only be included in the expression skills (according to the 0.4 criterion). The opposed phenomenon occurs with leadership, and working in a team, which previously had a close to 0.4 loading associated with communication skills, and now their loadings exceed this bound. However, their higher loadings points towards management skills.

[25] Once again, it was necessary to obtain direct comparable measures with the job requirements. To meet this object, the level attained was standardized by using the mean and the standard deviation of the job requirements.

As the model remains unaltered, table 10 only presents the coefficients for the generic competences controlling for extra human acquired, individual and firm characteristics. There are no dramatic changes for the coefficients of the specific knowledge, management skills and expression skills either. Maybe, it could be underlined that coefficients of the management skills have been modestly reduced[26]. Yet, we are much more interested in the coefficients of the 3 new competences. The first interesting fact is the 1.9% increase in income derived from a standard deviation increase in the language content of the jobs. Not surprisingly, content in terms of documentation exerts no impact, and yet being more surprising, computer skills requirements appear as no significant at determining earnings. The level attained at college in terms of foreign languages raises income by 1.4% for a standard deviation increase. Once again, computer skills taught appear not to increase income at any rate. Documentation skills taught seem responsible for a drop in earnings; this could be explained by the type of job that the degrees in which these skills represent a key element give access to, discarding the idea that the more these skills are learnt, the lesser the income the graduate receives. If we analyze the impact of an augment of the competences, we can appreciate that the increase of foreign languages exerts a positive influence on earnings, whereas increases in the endowments of the other instrumental competences result in no significant effect. In fact, a 1 standard deviation augment in foreign languages is translated into an increment of 2% in income. Consistently with our previous results, underutilization of any of the three instrumental competences is translated into a drop of earnings, the highest of which corresponds to computer skills.

Grasping these results allow us to interpret some key elements. First of all, we have the correct choice in permitting to enter the three instrumental competences separately, because it is proved that they have distinct effects that otherwise are mingled. Second, evidence puts forward that foreign languages are a source of greater income for graduates; irrespective of they are learnt at higher education, or by other means. And third, it has favored the view that

[26] In the first factor analysis model, documenting and computer skills had loadings of 0.37 and 0.4 in that order in relation to the management skills. Thus, the inclusion of the instrumental competences separately was likely to modify to some extent the factor scores of the management skills.

computer skills are not a source of higher earnings, even though graduates boost computer usage while working. Yet it is a source of lower earnings unless graduates are able to enter a job that at least is commensurate with what they learnt at higher education. Explanation to the former phenomenon could reside in the extra profitability obtained by firms operating in the international market. In other words, those companies engaged in trade relations in the international markets are more profitable, and this profitability can be transmitted in terms of higher wages for those workers who have developed the needed abilities, in this specific case, foreign languages. The latter issue is more difficult to interpret; one could be tempted to identify it with an excess of computer skills in the labor market. This is immediately discarded once it is checked that this competence, being compared with the other 13, is the one that presents a higher growth in the 3 years posterior graduation. Another hypothesis that springs into mind is the possibility that this measure of computer skills usage is not distinguishing the level of complexity, and thus, a high level of computer skills requirements could be connected without distinction with intricate programming tasks or more basic office automation tasks. Dickerson and Green (2003) obtain that more complex and advanced computer usages received a higher pay-off in comparison with more straightforward usages. Nonetheless, our results in this case do not mirror that article, but are consistent with other articles that suggest computer skills can not increase earnings by themselves (Borghans and Weel, 2006; Silles, 2005). These articles put forward that computer skills are correlated with other unobserved individual characteristics that keep positive causality on earnings. Since we have controlled for a long set of skills, this reasoning becomes plausible at this stage.

6. Increasing competences after higher education

6.1 Analyzing factor analysis indexes

We now aim to assess which variables enable graduates to access those jobs which require a higher level of the competences that are translated into a better-off situation. Likewise, we will do the same exercise for the difference between competences acquired at college and competences required at work to appraise what makes individuals more likely to increase their most profitable competences. We have selected management and expression skills in addition to foreign languages, the competences the increase of which resulted in a wage premium. Before proceeding with the econometric analysis we will undertake a descriptive analysis using the factor scores. The aim of this exercise is to obtain raw measures that suggest which are the variables that will play a key role favoring the augment of graduates' competences. However, relations of causality cannot be inferred since many other variables exert an influence simultaneously. Nonetheless, it is a very useful exercise if it is considered that we are working with indexes that give realistic indications to the Higher Education system about the labor demand of qualified workers. Table 11 presents the mean of these indexes for some specific groups. We will pay special attention to the values of the management and expression skills, as well as foreign languages

[Table 11]

Men are in jobs that are more demanding in terms of management skills, whereas expression skills take a more remarkable role for women. Differences in foreign languages are almost negligible. In terms of growth, women undergo lower growths in the 3 competences. All the fields of study are below the mean of requirements of management competences except for technical degrees; analogously, the only field above the mean in expression skills is social sciences. Regarding foreign languages, humanities are well above the mean, as opposed to their well below the mean position in management skills and computer usage. This latter result is more outstanding if we take into account that humanities are the field of study that registers a higher growth in computer usage. The greater growth in the management and expression skills and languages are not surprisingly found to be in experimental sciences, health and technical degrees. It results more astonishing the fact that 4-year-graduates manifest being in jobs requiring clearly lower levels of management and expression skills, although more logically, the relation reverses for languages. On the other hand, 4-year-graduates experience higher rises in the 3 generic competences after graduation. As expected, overeducated workers are noticeably below the mean of requirements, although it must be stressed that these individuals are at the same time subject to rises in their levels of competences, save in the case of specific knowledge. In the case of experience, the lower levels in management and expression skills of those individuals being one standard deviation below the mean of experience come as no surprise. On the other hand, it is more striking the higher required level of languages in addition to the growth in this competence of those with shorter experience in the labor market. It could be inferred that these individuals have continued an educational path that could have allowed them to enhance their competence in foreign languages, and thus, gain access to highly demanding jobs in terms of foreign languages. With this explanation, we assume that foreign languages can be improved outside a job more easily rather than other skills and competences. Although it could be shocking at first sight, the lower levels of requirements of competences of the more experienced workers can easily be accounted for by the changes that have been taking place in the labor market in the recent decades. If we accept that jobs have deeply been transformed, it is understandable that older workers (our final sample includes people with up to 41 years of experience) will have more difficulties to update and readapt themselves to the new working environments. Those graduates who decide not to continue education are more likely to enter a less demanding job, whilst those graduates who join a master access to more demanding jobs. The more international working environment inherent to research justifies the importance of languages in PhD. It should be noticed, that individuals who study a PhD register the highest rises in all the competences, although they have not reported the highest requirements. Students from masters are just behind.

Continuing with the table, not surprisingly jobs involving non-qualified functions are below the mean of all the generic competences, even though, these graduates also present augments in all their generic competences with the exceptions of documentation and specific knowledge. Although broadly speaking well positioned, management functions show neither the highest levels of requirements of generic competences, nor the highest growths. Beside, it must be underlined the relative low requirements of their jobs in terms of foreign languages. Both design and I+D functions require the higher levels of management skills, whereas they are well below the mean in terms of expression skills. Moreover, the latter is highly demanding in terms of foreign languages. Expression skills appear as the most important competence for those jobs entailing education functions. It must be added that I+D functions register the highest growth in competences. By sectors, great disparities become apparent. On the one hand, sectors such as commerce and hostel present the lowest requirements and the lowest growths. On the other hand, the highly remarkable levels of requirements and growths which are constant across all the generic competences of the agriculture sector should be underlined. The other sectors present a more irregular behavior where some competences are essential, and others lack of relative importance. For instance, the metallurgic sector shows the higher requirement and growth of the management skills and foreign languages, whereas the expression skills seem relatively unimportant. In financial services, both management and expression skills are necessary competences to develop, while foreign languages seem more accessorial.

Broadly speaking, growths in competences and their relative situation tend to coincide across the groups chosen. However, some comments should be added. The first comment is that despite the fact that computer usage appears not to occasion any positive influence on earnings, the tables make apparent that computer usage is the competence that most strongly increases in the subsequent years after graduation, even for students from humanities. The second comment is that the more related a job with science, the higher growth in competences it shows. Whereas, the requirements, notwithstanding being high, they do not appear as the highest ones. According with these data thus, we could logically deduce that those individuals involved in scientific tasks acquire a lower level of competences during their higher education, view that seems utterly unfeasible. Some source of bias turns up in the analysis, in the sense that individuals with lower levels of requirements will tend to unconsciously inflate the demands of their jobs as they underestimate the competences they do not need to acquire.

6.2 Modeling growth in competences

The previous exercise has given us some hints indicating the variables that should be taking a part when explaining what makes some individuals more likely to increase their level of management and expression skills as well as enhancing their fluency in foreign languages. At this stage, our evidence points out that graduates will earn more money depending on their capacity of increasing their level of the 3 already identified generic competences once arrived into the labor market. Yet, the question we aim to answer now is whether the level of competences acquired at higher education, in spite of exerting little impact on earnings, enables graduates to access jobs where their levels of competences can be promoted and obtain higher levels of income. Thus, the equation we will estimate by OLS will have the following form:

$$\Delta comp_i = \alpha + \vec{\beta} SK^{attained} + \vec{\delta} H + \vec{\varphi} X + \vec{\gamma} Z + \upsilon_{i_i}$$

The dependent variable denotes the variation in each of the 3 competences of interest: management skills, expression skills and foreign languages (thus, we will estimate 3 different equations). We have considered both those individuals that access a job above their level of competences attained at college together with those that suffer from underutilization of competences. As explanatory variables we will focus on the levels of competences attained at higher education, and we will control for the same set of individual and firm characteristics as we did for the earnings equation.

Table 12 presents the results for the estimation of this equation for each of the 3 dependent variables. Obviously, the level of the competence attained during higher education exerts a strong negative influence; the more you have learnt, the less you have to learn later on. We have also estimated the same equations taking as dependent variables the final levels of each generic competence in order to examine the impact of the initial level of competences on them[27]. In the 3 cases, the initial level exerts a very strong influence on the final level of the

[27] These estimations have not been included because the coefficients are almost identical. The unique and remarkable difference appears in the mentioned attained level of the same competence.

same competence. Thus, the more you have learnt of a competence at college, the higher the requirement of the job you will be working at 3 years later. As a conclusion, it must me emphasized that an optimal acquirement of a specific competence during higher education enables the graduate to access a more complex job, and beside, the effort the graduate needs to make so as to enlarge that specific competence diminishes.

Model 1 shows the coefficients of the covariates regressed against the management skills. It must be highlighted the strong impact of the attained level of specific knowledge, which is the only attained level of competences that gives rise to posterior increments of the management skills. As expected, overeducation precludes the growth of management skills. In terms of extensions of human capital, on the other hand, continuing education (except for "other forms") enhances the management skills, especially if the graduate has followed a PhD. On the other hand, experience has no significant effect. The source of this non-significant effect is associated with the evolution in the labor market in the recent years, with deep transformations in some qualified jobs. More experienced workers might have had difficulties to adapt themselves to the new working environment and might have stagnated in terms of job complexity.

The second column estimates the variation in expression skills, where again attained specific knowledge play a determinant role. We cannot set aside the relatively high impact of the attained level of expression skills. Experience exerts no significant impact. According to our results, it is important to continue studying to promote these expression skills, although neither in terms of a PhD nor another degree.

Finally, the third column presents the results for the variation in the levels of foreign languages. As it had happened previously, the specific knowledge acquired at college strongly favors the development of the posterior learning of foreign languages. Furthermore, the fact that the attained level of expression skills also contributes to enhance posterior learning of foreign languages comes as no surprise. On the contrary, the initial level in documenting is related to an underutilization of the languages learnt. This could be explained by the specialization of the jobs demanding graduates coming from degrees where documentation is an important competence. In those jobs foreign languages end up as accessorial.

With respect to the control variables, 4-year-degrees, mobility experiences and having worked during the degree in a job connected with the field of study, strength the posterior growth of the 3 generic competences, especially in the case of the foreign languages[28]. On the other hand, the institution where graduates have studied does not make a difference in any of the competences[29]. Being a man has negative implications in relation to the development of expression skills and foreign languages, while having no effect on the development of management skills. Those methods of finding a job associated with a lack of working stability have a negative influence on the development of competences.

The economic sector is important in some cases. For instance, working in the commerce sector strongly diminishes the level of the managerial skills in addition to the learning of foreign languages. Working either in the agriculture, finance or public sector promotes expression skills in comparison with the manufacture sector. However, the development of languages is the competence most influenced by the economic sector, as the internationalization of companies varies across them. The only sector, in which graduates can develop better the acquirement of languages in comparison with the manufactures, is the metallurgical sector. On the other hand, the situation is especially negative for the energy sector, the building industry and the commerce sector.

Working in the private sector also enhances the learning of foreign languages. Being autonomous or having a non stable contract damages the growth of

[28] Learning of foreign languages is related with working during the course of studies, regardless whether the job was either related or not related to the field of study.

[29] However, there is one Catalan University specially striving towards the promotion of foreign languages among its students. This could be interpreted into either posterior improvements in foreign languages, or it could simply reflect that the students that attend this university are more motivated to learn foreign languages.

managerial and expression skills. The size and the location of the firm do not show a clear pattern of influence, although with relation to the latter, while working in other regions from Spain represents shrinking the growth of both managerial and expression skills, going to other countries from Europe is translated into logical increases of foreign language learning and diminutions in the expression skills. Finally, functions developed play an important part. All the qualified functions save design assistant functions and “other qualified functions”, increase the variation of managerial competences. The impact is notably higher for commercial and education functions. Technical, commercial and “other qualified functions” develops the level of expression skills, whereas assistant functions have the opposite effect. Finally, non-qualified hardly functions impinge on the learning of foreign languages in opposition with the important improvements derived from R+D functions.

In this section we have examined how the growth in competences is determined by the initial levels of competences attained at college, especially in terms of the specific knowledge, which did not impact directly on earnings. These results invite to reconsider the relative lack of importance of knowledge arising from the earnings equations, since it is essential that graduates have received the most suitable tools during the Higher Education stage so that they can develop appropriately the required competences during their initial steps in the labor market. However, we should be cautious at taking these results for granted, because despite having controlled for skills, it is difficult that we have got rid of the effect of individual ability on the data. Therefore, since specific knowledge might be correlated with individual capacity, we are likely to overestimate the coefficients of the effects of the specific knowledge acquired during the course of Higher Education.

7. Conclusions

The survey *School to work transition of the Catalan Graduates* offers wide information about job and individual characteristics. The most useful information for us is the valuation of skills, both at the time of graduation and its current importance at work. We have generated 4 generic competences by applying factor analysis on the job requirements of the original competences: managerial skills, expression skills, instrumental competences and specific knowledge. The factor scores obtained are very useful given that they become indexes against which the levels of competences can be benchmarked as well as being used in the earnings equations.

We have applied the scoring coefficients over the attained levels of the original competences. As a result, we have obtained measures of the attained level of the generic competences comparable with the required levels of generic competences. The main advantage of operating in this way is the possibility of assessing the evolution in time of the generic competences. Thus, we are able to identify a large positive variation of managerial skills during the 3 years after graduation, more modest positive variations of both instrumental and expression skills, and a negative variation of the specific knowledge. According to the previous literature we have to connect the positive differences with the access to jobs that enable the individual to boost his/her human capital, jobs that are challenging and motivating. On the other hand, those jobs that do not use at least the human capital that the individual has acquired during higher education are translated in the negative implications emerging from underutilization.

Our earnings equations serve to disentangle the consequences of the variation of skills. Increases of managerial skills are highly remunerated in the labor market. Rises in expressions skills are also translated in increases of income, although smaller. Growth of Specific knowledge has no effect, once we control for overeducation, neither does the growth of instrumental competences, contrasting with the fact that its requirements had a small but positive influence on earnings. As expected, underutilization of competences is penalized, specially the underutilization of instrumental competences. These results prompted us to estimate again the equation introducing instrumental competences separately (i.e. documenting, computer usage and foreign languages). Results signal that whereas the growth of foreign languages increases earnings, the enhancement of computer usage has no significant effect on earnings, despite the fact that this competence presents the highest positive variation after graduation.

Those results can be interpreted as the premium received by those graduates working in companies involved in operation in the international markets. On the other hand, the insignificance of the returns to computer usage is consistent with previous evidence that related it to unobservable ability that in fact was responsible for increments of income. However, according to our results individuals who are not capable to access a job where computers are important receive a large penalization.

Finally we have focused on the factors that raise competences. The most outstanding result is that specific knowledge acquired during the course of higher education is a decisive element contributing to the posterior growth of competences after graduation. This is a remarkable result, in line with Heijke *et al.* (2003), although in the latter the benefits from specific knowledge were translated into a payoff derived from entering a job commensurate with the field of studies. However, we must be cautious when considering the implications of this result, since the coefficients could be overestimated by the influence of individual ability. Any of the competences that are translated into later income inequalities should be promoted at higher education, since they permit the graduate to access a job with higher requirements, and at the same time the necessary effort of catching up with the job requirements is reduced. Finally, the working environment is also yields differences, especially in the case of the economic sector and the functions carried out.

References

Allen, J. and E. de Weert, E. "What Do Educational Mistmatches Tell us about Skill Mismatches?", *European Journal of Education*, 42 (1), 2007, pp.59-73.

Appelbaum, E., T. Bailey, and A. Kalleberg. *Manufacturing Advantage: Why High-Performance Work Systems Pay Off*, Cornell University Press, Ithaca, 2000.

Bell, B. "The labour market consequences of technical and structural change", Discussion Papers Series, nº 8, Centre for Economic Performance, Oxford University, 1996.

Bishop, J. "Expertise and Excellence", Working Paper 95-13, Center for Advanced Human Resource Studies, ILR, Cornell University, 1995.

Bishop, J. and F. Mañé "The impacts of career-technical education on high school completion and labor market success", *Economics of Education Review*, 23 (3), 2004, pp. 381-402.

Borghans, L. and B. Weel "Do we need computer skills to use a computer? Evidence from Britain", *Review of Labour Economics and Industrial Relations*, 2006, 20(3), pp. 505-532.

Bunk, G.P. "Teaching Competences in Initial and Continuing Vocational Training in the Federal Republic of Germany", *Vocational Training European Journal*, 1994, 1, pp. 8 -14

Dickerson, A. and F. Green. "The Growth and Valuation of Computing and Other Generic Skills", *Oxford Economic Papers*, 2004, 56 (3), pp. 371-406.

Di Pietro, G. and P. Urwin. "Education and Skills Mismatch in the Italian Graduate Labour Market." *Applied Economics*, 2006, 38 (1), pp. 79-93.

Dolton, P. and Vignoles, A. "The Incidence and Effects of Overeducation in the U.K. Graduate Labour Market." *Economics of Education Review*, 2000, 19 (2), pp. 179-98.

García-Aracil, A., Mora, J., y Vila, L.E. "The Rewards of Human Capital Competences for Young European Higher Education Graduates", *Tertiary Education and Management*, 2004, 10, pp. 287–305.

Gould, E.D. "Inequality and Ability." *Labour Economics,* 2005, 12 (2), pp. 169-189.

Green, F., and S. McIntosh "Is There a Genuine Underutilization of Skills Amongst the Overqualified?" *Applied Economics*, (forthcoming)

Hanushek, E. and R. Kim "Schooling, labor force quality and economic growth", Working Paper 411, Rochester Centre for Economic Research, Rochester, 2005.

Heijke, H., C. Meng, and G. Ramaekers "An Investigation into the role of human capital competences and their pay-off", International Journal of Manpower, 2003, 24 (7), pp. 750-773.

Henderson, V. "Externalities and Industrial Development", *Journal of Urban Economics*, 1997, 42, pp. 449-470.

Krueger, A. "How computers have changed the wage structure: evidence from micro data 1984-1989", *Quarterly Journal of Economics*, 1993, vol. 108 (1), pp. 33-60.

Mañé, F. "Trends in the payoff to academic and occupation-specific skills", *Economics of Education Review*, 1999, vol. 18, pp. 417-37.

Mañé, F. and D. Miravet "Adequació de la Formació Universitària" in The School to Work Transition of the Catalan Graduates, Catalan Agency for the University Quality, Barcelona, forthcoming.

Mañé, F. and D. Miravet "La Sobreeducación: una Revisión Bibliográfica", mimeo, 2007.

Murnane, R. and F. Levy *Teaching the New Basic Skills: Principles for Educating Children to Thrive in a Changing Economy*, The Free Press, New York, 1996.

Murnane, R., J.B. Willet and F. Levy "The growing importance of cognitive skills in wage determination", *Review of Economics and Statistics*, 1995, 77, 251-66.

Shapiro, D. and M. Goertz "Connecting work and school", paper presented at the annual meeting of the American Educational Research Association, San Diego, 1998.

Silles, M. "Computer use and earnings", Working paper 2005-05, Centre for Applied Microeconometrics, University of Copenhagen, 2005.

Stewart, Mark B. "On Least Squares Estimation when the Dependent Variable is Grouped." *The Review of Economic Studies*, 1983, 50 (4), pp. 737-753.

Tyler, J.H., R. Murnane, and J.B. Willet "Do the cognitive skills of school dropouts matter in the labor market?", Working Paper 7101, NBER, Cambridge, 1999.

Thurstone, L.L. Multiple Factor Analysis, University of Chicago Press, Chicago, 1947.

Table 1. Descriptive Statistics

INDIVIDUAL CHARACTERISTICS

	Variable	Obs	Mean	Std. Dev.	Min	Max
University	A*	8933	0,27	0,44	0	1
	B	8933	0,17	0,37	0	1
	C	8933	0,20	0,40	0	1
	D	8933	0,08	0,27	0	1
	E	8933	0,11	0,31	0	1
	F	8933	0,09	0,29	0	1
	G	8933	0,09	0,29	0	1
Degree	Humanities*	8933	0,12	0,33	0	1
	Social Sciences	8933	0,45	0,50	0	1
	Experimental Sciences	8933	0,06	0,24	0	1
	Health	8933	0,09	0,29	0	1
	Technique	8933	0,27	0,44	0	1
Previous activity	No work *	8933	0,38	0,49	0	1
	Part-time related	8933	0,29	0,45	0	1
	Part-time non related	8933	0,16	0,37	0	1
	Full-time related	8933	0,12	0,32	0	1
	Full-time non related	8933	0,05	0,22	0	1
Time to enter first job	While studying	8933	0,44	0,50	0	1
	< 1 month	8933	0,17	0,38	0	1
	< 3 month	8933	0,17	0,38	0	1
	< 6 month	8933	0,09	0,28	0	1
	< 1 year	8933	0,07	0,25	0	1
	> 1 year	8933	0,06	0,24	0	1
Sex	Man	8933	0,41	0,49	0	1
Means of finding job	Contacts*	8933	0,34	0,47	0	1
	Press	8933	0,10	0,30	0	1
	Public exams	8933	0,04	0,19	0	1
	Public agencies	8933	0,02	0,13	0	1
	Self employed	8933	0,01	0,09	0	1
	Stage in companies	8933	0,10	0,30	0	1
	University occupation services	8933	0,11	0,31	0	1
	ETT	8933	0,04	0,20	0	1
	Outplacement	8933	0,01	0,12	0	1
	Internet	8933	0,05	0,22	0	1
	Other	8933	0,18	0,39	0	1
Type of degree	4-year-degree	8933	0,55	0,50	0	1
Mobility	No mobility*	8933	0,64	0,48	0	1
	When studying	8933	0,13	0,33	0	1
	When working	8933	0,16	0,36	0	1
	Both Studying Working	8933	0,07	0,26	0	1
Experience	Experience	8933	3,60	2,91	0	41
	Experience ^2	8933	22.45	68.18	0	1681
Continuing education	Not continuing education*	8933	0.27	0.44	0	1
	Specialization	8933	0.17	0.38	0	1
	Another degree	8933	0.16	0.37	0	1
	Master	8933	0.24	0.43	0	1
	PhD	8933	0.04	0.2	0	1
	Other cont.	8933	0.12	0.32	0	1

Table 1. Descriptive Statistics (continued)

JOB CHARACTERISTICS

	Variable	Obs.	Mean	Std, Dev.	Min	Max
Functions	Management	8933	0,10	0,30	0	1
	Social or Medical Assistant	8933	0,08	0,28	0	1
	Commercial	8933	0,05	0,22	0	1
	Education	8933	0,19	0,39	0	1
	Design	8933	0,02	0,15	0	1
	Technical support	8933	0,21	0,41	0	1
	I+D	8933	0,03	0,17	0	1
	Other qualified	8933	0,37	0,48	0	1
	Other non qualified	8933	0,05	0,21	0	1
Sector	Agriculture	8933	0,01	0,12	0	1
	Energy	8933	0,02	0,15	0	1
	Chemistry	8933	0,04	0,19	0	1
	Metallurgic	8933	0,05	0,23	0	1
	Manufactures*	8933	0,04	0,19	0	1
	Building industry	8933	0,06	0,23	0	1
	Commerce	8933	0,06	0,24	0	1
	hostel	8933	0,01	0,10	0	1
	Transport	8933	0,01	0,12	0	1
	Telecommunications	8933	0,08	0,27	0	1
	Financial Services	8933	0,08	0,28	0	1
	Company Services	8933	0,11	0,32	0	1
	Public services	8933	0,39	0,49	0	1
	Social Services	8933	0,02	0,13	0	1
Working status	Stable*	8933	0,57	0,49	0	1
	Autonomous	8933	0,09	0,29	0	1
	Temporal	8933	0,33	0,47	0	1
	Without contract	8933	0,01	0,09	0	1
Public/Private	Private	8933	0,72	0,45	0	1
Size of the company	< 10 workers	8933	0,21	0,41	0	1
	< 50 workers	8933	0,29	0,45	0	1
	< 100 workers	8933	0,10	0,30	0	1
	< 250 workers	8933	0,09	0,28	0	1
	< 500 workers	8933	0,06	0,25	0	1
	> 500 workers*	8933	0,25	0,43	0	1
Geographic situation	Barcelona*	8933	0,68	0,47	0	1
	Tarragona	8933	0,09	0,29	0	1
	Girona	8933	0,10	0,30	0	1
	Lleida	8933	0,07	0,25	0	1
	Other in Spain	8933	0,06	0,23	0	1
	Rest of Europe	8933	0,01	0,08	0	1
	Rest of the world	8933	0,00	0,04	0	1
Education match	Education match*	8933	0,77	0,42	0	1
	Non matched	8933	0,04	0,21	0	1
	Overeducated	8933	0,18	0,39	0	1

Table 1. Descriptive Statistics (continued)

DEPENDENT VARIABLES

		Obs	Mean	Std. Dev.	Min	Max
Earnings	< 9000€	8933	0,08	0,27	0	1
	< 12000€	8933	0,15	0,35	0	1
	< 18000€	8933	0,31	0,46	0	1
	< 30000€	8933	0,36	0,48	0	1
	< 40000€	8933	0,08	0,27	0	1
	> 40000€	8933	0,03	0,16	0	1

* This variable is used as the referential category in the regressions.

Table 2. List of Competences

Theoretical knowledge	Problem-solving ability
Knowledge of methods	Decision making
Oral communication skills	Creativity
Written communication skills	Critical thinking
Working in a team	Computer skills
Leadership	Languages
Management	Documenting ideas and information

Table 3: Factor loading coefficients of the competence requirement in graduates' jobs based on varimax rotation					
	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Uniqueness**
Theoretical knowledge	0.1887	0.1823	**0.583**	0.0796	0.5849
Knowledge of methods	0.261	0.2477	**0.557**	0.0755	0.5546
Written communication skills	0.3443	**0.533**	0.283	0.2291	0.4647
Oral communication skills	**0.4046**	**0.5452**	0.2725	0.1331	0.4472
Working in a team	**0.5285**	*0.3981*	0.2207	0.0512	0.5108
Leadership	**0.5897**	*0.3874*	0.1051	0.081	0.4846
Problem-solving ability	**0.7449**	0.1853	0.1692	0.1642	0.3552
Decision making	**0.7832**	0.1878	0.1881	0.1463	0.2945
Critical thinking	**0.5366**	0.1145	0.3547	0.2011	0.5327
Creativity	**0.5733**	0.1388	0.3277	0.2096	0.5008
Management	**0,6265**	*0.3983*	0.0791	0.1486	0.4205
Documenting ideas and information	*0.372*	0.2078	0.2998	**0.4026**	0.5664
Languages	0.2723	0.1943	0.1062	**0.4185**	0.7016
Computer skills	**0.4032**	0.2242	0.0687	**0.4309**	0.5968
Taxonomy of generic skills	**Management Skills**	**Communition skills**	**Specific knowledge**	**Instrumental skills**	
Standard Deviation	**.8641937**	**.6971132**	**.6003551**	**.7160977**	

Source: Graduates' School to Work Transition Survey
Factor loading coefficients greater than 0.4 in magnitude are shown in bold. Those greater than 0.35 but smaller than 0.35 are shown in Italics

Figure 1. Evolution of the learning process

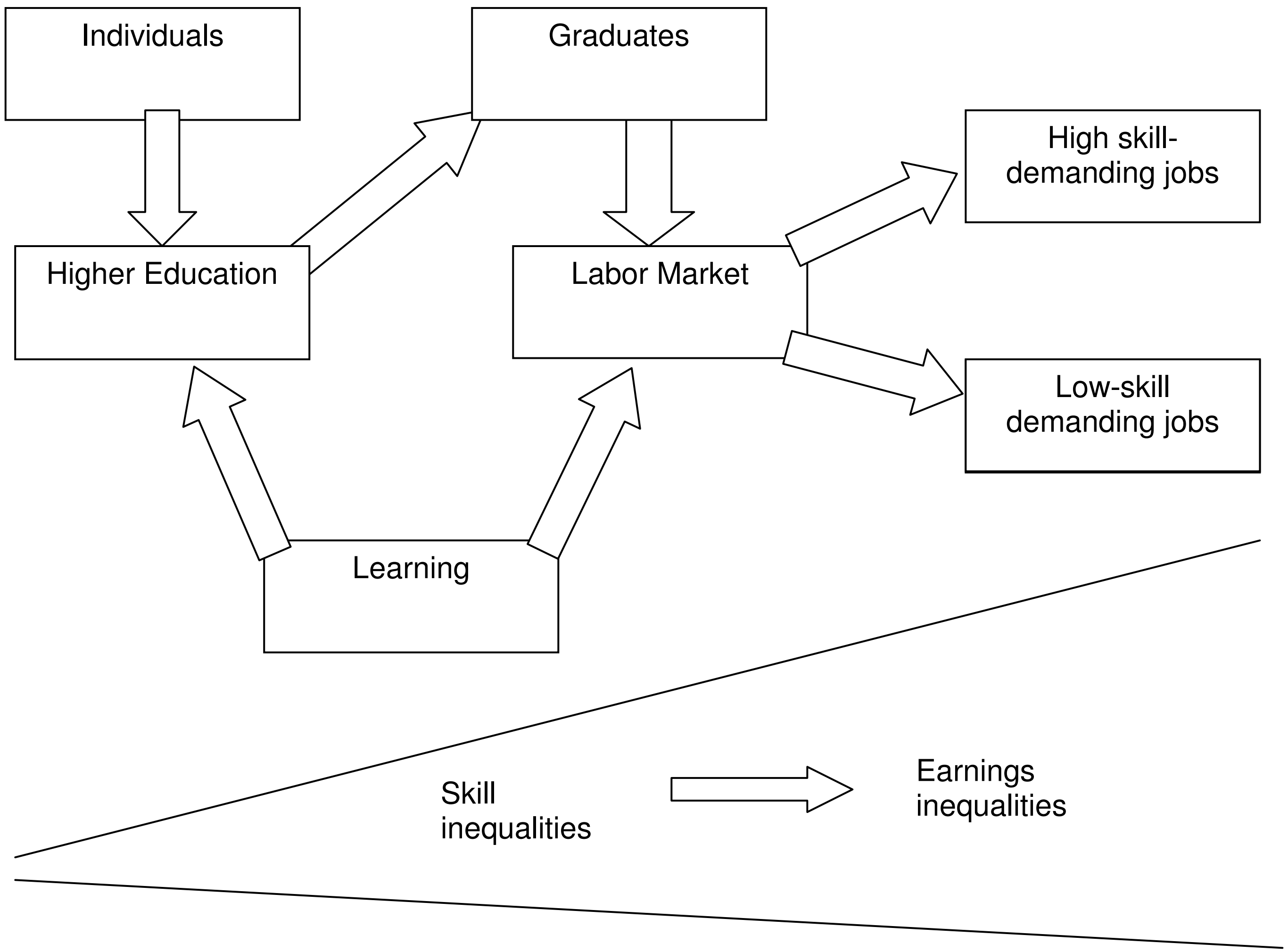

Table 4: Endowments of generic competences at the time of graduation, job requirements 3 years later and differences.

Total sample (n=8933)

	Attained level	Required level	Difference in level
Management skills	-0.6277	0	0.6277
Expression skills	-0.2509	0	0.2509
Instrumental skills	-0.2955	0	0.2955
Specific knowledge	0.3073	0	-0.3073

Table 5: Endowments of generic competences at the time of graduation, job requirements 3 years later and differences by sex.

Women (n=5267)			
	Attained level	**Required level**	**Difference in level**
Management skills	-0.6241	-0.0162	0.6079
Expression skills	-0.1613	0.0532	0.2145
Instrumental skills	-0.3165	0.0052	0.3217
Specific knowledge	0.3738	0.0694	-0.3044
Men (n=3666)			
	Attained level	**Required level**	**Difference in level**
Management skills	-0.6329	0.0232	0.6561
Expression skills	-0.3796	-0.0764	0.3031
Instrumental skills	-0.2653	-0.0075	-0.3113
Specific knowledge	0.2116	-0.0997	0.2578

Table 6: Returns to earnings	MODEL 1.1	MODEL 1.2	MODEL 1.3	MODEL 1.4
	Competence requirements	Attained level Increase in level	Attained level Underutilization	Full model
Req_manag	0,0773 (0,0063)***			
Req_expres	-0,0060 (0,0076)			
Req_instrum	0,0282 (0,009)***			
Req_knowled	-0,0319 (0,0072)***			
Att_ manag		0,0670 (0,0076)***	0,0290 (0,0067)***	0,0640 (0,0076)***
Att_expres		-0,0579 (0,0088)***	-0,0772 (0,0077)***	-0,0581 (0,0088)***
Att_instrum		-0,0007 (0,0108)	0,0081 (0,0101)	0,0074 (0,011)
Att_ know		-0,0801 (0,0099)	-0,0571 (0,0101)***	-0,0720 (0,0102)***
Inc_ manag		0,0784 (0,0078)***		0,0767 (0,008)***
Inc_expres		0,0530 (0,0108)***		0,0457 (0,0112)***
Inc_instrum		0,0209 (0,0116)*		0,0037 (0,0119)
Inc_ knowled		-0,1081 (0,0193)***		-0,1225 (0,02)***
Surp_ manag			-0,1638 (0,0216)***	-0,1048 (0,0218)***
Surp _expres			-0,0594 (0,0184)***	-0,0542 (0,0193)***
Surp_instrum			-0,1226 (0,0229)***	-0,1154 (0,0231)***
Surp _ know			0,0018 (0,0097)	-0,0259 (0,01)***
Constant	9,7481 (0,0049)***	9,7292 (0,0091)***	9,8003 (0,0087)***	9,7792 (0,0101)***

* Denotes significant at 10%; ** Denotes significant at 5%; *** Denotes significant at 1%

Table 7: Returns to skills				
	MODEL 1.1	MODEL 1.2	MODEL 1.3	MODEL 1.4
	Competence requirements	Attained level Increase in level	Attained level Underutilization	Full model
Req_manag	0,0762 (0,0061)***			
Req_expres	-0,0057 (0,0074)			
Req_instrum	0,0322 (0,0088)***			
Req_knowled	-0,0294 (0,0071)***			
Att_ manag		0,0662 (0,0075)***	0,0280 (0,0065)***	0,0630 (0,0074)***
Att_expres		-0,0545 (0,0085)***	-0,0726 (0,0076)***	-0,0549 (0,0085)***
Att_instrum		0,0043 (0,0106)	0,0124 (0,0099)	0,0129 (0,0108)
Att_ know		-0,0822 (0,0097)***	-0,0591 (0,001)***	-0,0734 (0,0101)***
Inc_ manag		0,0780 (0,0076)***		0,0766 (0,0078)***
Inc_expres		0,0495 (0,0106)***		0,0421 (0,011)***
Inc_instrum		0,0248 (0,0115)**		0,0069 (0,0118)
Inc_ knowled		-0,1004 (0,0192)***		-0,1160 (0,02)***
Surp_ manag			-0,1655 (0,0204)***	-0,1068 (0,0206)***
Surp _expres			-0,0581 (0,0184)***	-0,0551 (0,0194)***
Surp_instrum			-0,1303 (0,0224)***	-0,1219 (0,0226)***
Surp _ know			-0,0018 (0,0095)	-0,0286 (0,0097)***
Exper	0,0485 (0,004)***	0,0470 (0,0038)***	0,0488 (0,0037)***	0,0475 (0,0038)***
$Exper^2$	-0,0011 (0,0002)***	-0,0010 (0,0002)***	-0,0011 (0,0002)***	-0,0010 (0,0002)***
Specialization	-0,0177 (0,0148)	-0,0207 (0,0146)	-0,0213 (0,0147)	-0,0241 (0,0145)*
Other degree	-0,0698 (0,0148)***	-0,0727 (0,0146)***	-0,0704 (0,0147)***	-0,0745 (0,0145)***
Master	0,0401 (0,0135)***	0,0301 (0,0134)**	0,0337 (0,0134)**	0,0255 (0,0133)*
PhD	-0,0144 (0,0269)	-0,0277 (0,0267)	-0,0272 (0,0263)	-0,0317 (0,0265)
Other cont.	-0,0535 (0,0167)***	-0,0596 (0,0165)***	-0,0550 (0,0165)***	-0,0569 (0,0163)***
Constant	9,6090 (0,0142)***	9,6009 (0,0155)***	9,6684 (0,0156)***	9,6528 (0,0161)***

* Denotes significant at 10%; ** Denotes significant at 5%; *** Denotes significant at 1%

Table 8: Returns to skills (controlling for individual and firm characteristics)

	MODEL 1.1		MODEL 1.2		MODEL 1.3		MODEL 1.4	
	Competence requirements		Attained level Increase in level		Attained level Underutilization		Full model	
Req_manag	0,0305	(0,0051)***						
Req_expres	0,0071	(0,0061)						
Req_instrum	0,0122	(0,0073)*						
Req_knowled	-0,0059	(0,0063)						
Att_ manag			0,0153	(0,0063)**	-0,0054	(0,0054)	0,0146	(0,0063)**
Att_expres			-0,0071	(0,0073)	-0,0125	(0,0066)*	-0,0065	(0,0074)
Att_instrum			-0,0097	(0,0092)	-0,0056	(0,0085)	-0,0055	(0,0094)
Att_ know			-0,0064	(0,0084)	0,0008	(0,0087)	-0,0027	(0,009)
Inc_ manag			0,0409	(0,0063)***			0,0421	(0,0066)***
Inc_expres			0,0182	(0,0085)**			0,0145	(0,0088)*
Inc_instrum			0,0085	(0,0095)			0,0011	(0,0097)
Inc_ knowled			-0,0191	(0,0157)			-0,0208	(0,0161)
Surp_ manag					-0,0648	(0,0165)***	-0,0378	(0,0168)**
Surp _expres					-0,0265	(0,0148)*	-0,0297	(0,0156)*
Surp_instrum					-0,0574	(0,0174)***	-0,0576	(0,0177)***
Surp _ know					0,0005	(0,0086)	-0,0097	(0,0088)
Exper	0,0203	(0,0034)***	0,0201	(0,0034)***	0,0208	(0,0033)***	0,0204	(0,0034)***
Exper^2	-0,0003	(0,0002)**	-0,0003	(0,0002)**	-0,0003	(0,0001)**	-0,0003	(0,0002)**
Specialization	0,0029	(0,012)	0,0018	(0,0119)	0,0030	(0,012)	0,0009	(0,0119)
Other degree	0,0010	(0,0123)	-0,0023	(0,0123)	0,0006	(0,0123)	-0,0024	(0,0123)
Master	0,0339	(0,011)***	0,0306	(0,011)***	0,0336	(0,011)***	0,0298	(0,011)***
PhD	0,0125	(0,0227)	0,0053	(0,0228)	0,0103	(0,0226)	0,0050	(0,0227)
Other cont.	-0,0028	(0,0135)	-0,0053	(0,0135)	-0,0035	(0,0135)	-0,0055	(0,0135)
4-year-degree	0,1203	(0,0093)***	0,1150	(0,0094)***	0,1171	(0,0094)***	0,1155	(0,0094)***
B	-0,0221	(0,0129)*	-0,0165	(0,0129)	-0,0170	(0,0129)	-0,0161	(0,0129)
C	0,0899	(0,0175)***	0,0889	(0,0175)***	0,0895	(0,0176)***	0,0881	(0,0175)***
D	0,0370	(0,0161)**	0,0475	(0,0162)***	0,0440	(0,0163)***	0,0464	(0,0161)***
E	-0,0124	(0,0205)	-0,0074	(0,0205)	-0,0092	(0,0204)	-0,0079	(0,0205)
F	-0,0298	(0,0206)	-0,0284	(0,0205)	-0,0319	(0,0205)	-0,0301	(0,0205)
G	0,0038	(0,0197)	0,0064	(0,0197)	0,0075	(0,0199)	0,0084	(0,0197)
Social Sc.	0,1368	(0,0147)***	0,1317	(0,0151)***	0,1364	(0,0152)***	0,1305	(0,0151)***
Experimental	0,1185	(0,0198)***	0,1098	(0,02)***	0,1167	(0,0201)***	0,1116	(0,02)***
Health	0,2410	(0,0235)***	0,2288	(0,0237)***	0,2315	(0,0239)***	0,2255	(0,0238)***
Technique	0,2832	(0,0202)***	0,2788	(0,0205)***	0,2856	(0,0206)***	0,2783	(0,0205)***
Men	0,1293	(0,0092)***	0,1263	(0,0092)***	0,1260	(0,0093)***	0,1272	(0,0092)***
Part-time rel.	0,0367	(0,0097)***	0,0374	(0,0097)***	0,0386	(0,0098)***	0,0358	(0,0097)***
PT non rel.	0,0082	(0,0117)	0,0066	(0,0117)	0,0086	(0,0117)	0,0085	(0,0116)
Full-time rel.	0,1055	(0,0135)***	0,1038	(0,0134)***	0,1049	(0,0135)***	0,1016	(0,0134)***
FT non rel.	0,0641	(0,0196)***	0,0621	(0,0195)***	0,0667	(0,0196)***	0,0646	(0,0195)***
Mob_stud	0,0169	(0,0126)	0,0154	(0,0125)	0,0180	(0,0125)	0,0153	(0,0125)
Mob_working	0,0637	(0,0113)***	0,0611	(0,0113)***	0,0656	(0,0113)***	0,0605	(0,0113)***
Mob_both	0,0476	(0,0155)***	0,0441	(0,0154)***	0,0491	(0,0155)***	0,0448	(0,0154)***
Press	0,0289	(0,0135)**	0,0302	(0,0135)**	0,0292	(0,0136)**	0,0296	(0,0135)**
Public exams	0,1135	(0,0237)***	0,1136	(0,0237)***	0,1171	(0,0236)***	0,1144	(0,0238)***
Public ag.	-0,0645	(0,0284)**	-0,0635	(0,0285)**	-0,0669	(0,0285)**	-0,0663	(0,0283)**
Self empl.	0,0620	(0,0593)	0,0639	(0,0593)	0,0667	(0,0608)	0,0639	(0,0603)
Stage in firms	0,0035	(0,0136)	0,0040	(0,0135)	0,0044	(0,0136)	0,0038	(0,0135)
University oc.	0,0234	(0,0136)*	0,0265	(0,0136)*	0,0241	(0,0136)*	0,0255	(0,0136)*
ETT	-0,0103	(0,0179)	-0,0080	(0,0179)	-0,0117	(0,0179)	-0,0060	(0,0179)
Outplac.	0,0366	(0,0357)	0,0383	(0,0354)	0,0383	(0,035)	0,0408	(0,0351)
Internet	-0,0078	(0,0175)	-0,0045	(0,0175)	-0,0059	(0,0174)	-0,0040	(0,0174)
Other	0,0149	(0,0118)	0,0156	(0,0118)	0,0153	(0,0118)	0,0149	(0,0118)
More 1 job	0,0153	(0,0091)*	0,0135	(0,0091)	0,0141	(0,0091)	0,0131	(0,0091)

(Table 8 continued)								
Agriculture	-0,0842	(0,0362)**	-0,0886	(0,0363)**	-0,0876	(0,0366)**	-0,0908	(0,036)**
Energy	0,0701	(0,0295)**	0,0701	(0,0296)**	0,0710	(0,0296)**	0,0713	(0,0295)**
Chemistry	0,0842	(0,0275)***	0,0851	(0,0274)***	0,0847	(0,0275)***	0,0864	(0,0274)***
Metallurgic	0,0451	(0,0254)*	0,0447	(0,0254)*	0,0458	(0,0253)*	0,0437	(0,0253)*
Building ind.	0,1088	(0,0267)***	0,1050	(0,0266)***	0,1083	(0,0266)***	0,1072	(0,0266)***
Commerce	-0,0750	(0,0257)***	-0,0767	(0,0256)***	-0,0748	(0,0257)***	-0,0699	(0,0256)***
Hostel	-0,0234	(0,0405)	-0,0257	(0,0405)	-0,0194	(0,0413)	-0,0241	(0,0408)
Transport	0,0449	(0,0383)	0,0483	(0,0382)	0,0526	(0,0385)	0,0506	(0,0384)
Telecom.	-0,0371	(0,024)	-0,0356	(0,0239)	-0,0390	(0,024)	-0,0374	(0,0239)
Financial s.	0,0487	(0,0242)**	0,0488	(0,0241)**	0,0507	(0,0241)**	0,0482	(0,024)**
Company s.	-0,0120	(0,0233)	-0,0156	(0,0233)	-0,0156	(0,0233)	-0,0162	(0,0233)
Public serv.	-0,1136	(0,024)***	-0,1146	(0,0239)***	-0,1161	(0,0239)***	-0,1147	(0,0239)***
Social serv.	-0,1464	(0,0382)***	-0,1479	(0,0383)***	-0,1466	(0,0382)***	-0,1476	(0,0381)***
Priv	-0,1024	(0,0127)***	-0,1017	(0,0127)***	-0,0990	(0,0127)***	-0,1004	(0,0127)***
Autonom	-0,0736	(0,0187)***	-0,0774	(0,0187)***	-0,0825	(0,0188)***	-0,0792	(0,0187)***
Temporal	-0,1504	(0,0096)***	-0,1503	(0,0096)***	-0,1499	(0,0096)***	-0,1484	(0,0096)***
no_contract	-0,5490	(0,0614)***	-0,5522	(0,0617)***	-0,5555	(0,0611)***	-0,5530	(0,0614)***
< 10 workers	-0,1844	(0,0132)***	-0,1838	(0,0131)***	-0,1847	(0,0132)***	-0,1850	(0,0131)***
< 50 workers	-0,0998	(0,0111)***	-0,0976	(0,0111)***	-0,0988	(0,0112)***	-0,0993	(0,0111)***
< 100 work.	-0,0446	(0,0149)***	-0,0432	(0,0148)***	-0,0451	(0,0149)***	-0,0455	(0,0148)***
< 250 work.	-0,0285	(0,0151)*	-0,0263	(0,0151)*	-0,0264	(0,0151)*	-0,0285	(0,0151)*
< 500 work.	-0,0439	(0,0166)***	-0,0435	(0,0166)***	-0,0426	(0,0166)**	-0,0450	(0,0165)***
Tgna	-0,0393	(0,0184)**	-0,0379	(0,0184)**	-0,0380	(0,0185)**	-0,0381	(0,0184)**
Grna	-0,0347	(0,0196)*	-0,0353	(0,0196)*	-0,0335	(0,0196)*	-0,0350	(0,0196)*
Llda	-0,0162	(0,021)	-0,0127	(0,0209)	-0,0120	(0,021)	-0,0127	(0,0209)
Other Spain	0,0589	(0,0186)***	0,0643	(0,0186)***	0,0632	(0,0185)***	0,0659	(0,0186)***
Rest Europe	0,1954	(0,0621)***	0,2022	(0,0625)***	0,1895	(0,0626)***	0,1996	(0,0624)***
Rest world	0,1842	(0,1442)	0,1887	(0,1428)	0,1752	(0,1398)	0,1844	(0,1428)
Management	0,1057	(0,0178)***	0,1043	(0,0178)***	0,1095	(0,0179)***	0,1051	(0,0178)***
Assistant	0,0024	(0,0233)	0,0002	(0,0232)	0,0032	(0,0233)	0,0023	(0,0232)
Commercial	0,0849	(0,019)***	0,0866	(0,0189)***	0,0930	(0,019)***	0,0877	(0,019)***
Education	-0,0658	(0,0192)***	-0,0647	(0,0192)***	-0,0591	(0,0192)***	-0,0646	(0,0192)***
Design	-0,0385	(0,0265)	-0,0399	(0,0262)	-0,0383	(0,0263)	-0,0401	(0,0262)
Technical	0,0211	(0,0151)	0,0203	(0,015)	0,0242	(0,015)	0,0195	(0,015)
I+D	-0,0279	(0,025)	-0,0285	(0,0249)	-0,0291	(0,0252)	-0,0326	(0,0249)
Other qualif.	-0,0373	(0,0143)***	-0,0360	(0,0143)**	-0,0341	(0,0143)**	-0,0369	(0,0142)***
Non qualified	-0,1306	(0,0238)***	-0,1303	(0,0237)***	-0,1240	(0,0238)***	-0,1217	(0,0237)***
Over	-0,1446	(0,0121)***	-0,1482	(0,0116)***	-0,1404	(0,0122)***	-0,1338	-0,1446
Non_matched	-0,0360	(0,0185)*	-0,0408	(0,0184)**	-0,0380	(0,0186)**	-0,0353	-0,0360
Constant	9,6049	(0,0383)***	9,5855	(0,0392)***	9,6047	(0,0392)***	9,6039	(0,0394)***

* Denotes significant at 10%; ** Denotes significant at 5%; *** Denotes significant at 1%

Table 9. Endowments at the time of graduation, job requirements 3 years later and differences of the instrumental competences analyzed individually.

Total sample (n=8933)

	Attained level	Required level	Difference in level
Documenting	-0.1684	0	0.1684
Computing skills	-0.7523	0	0.7523
Languages	-0.5426	0	0.5426

TABLE 10: Returns to skills (decomposing instrumental competences)								
	MODEL 1.1		**MODEL 1.2**		**MODEL 1.3**		**MODEL 1.4**	
	Competence requirements		**Attained level Increase in level**		**Attained level Underutilization**		**Full model**	
Req_manag	0,0285	(0,0058)***						
Req_expres	0,0056	(0,0064)						
Req_knowled	-0,0058	(0,0065)						
Req_docum	-0,0033	(0,005)						
Req_comp	-0,0031	(0,005)						
Req_lang	0,0186	(0,0046)***						
Att_manag			0,0192	(0,0069)***	-0,0014	(0,0058)	0,0179	(0,0069)**
Att_expres			-0,0055	(0,0076)	-0,0140	(0,0068)**	-0,0064	(0,0077)
Att_knowled			-0,0007	(0,0089)	0,0034	(0,009)	0,0007	(0,0093)
Att_docum			-0,0140	(0,0059)**	-0,0044	(0,005)	-0,0107	(0,0061)*
Att_comp			-0,0104	(0,0061)*	-0,0053	(0,0053)	-0,0096	(0,0062)
Att_lang			0,0145	(0,0059)**	0,0086	(0,0061)	0,0158	(0,0063)**
Inc_manag			0,0384	(0,0071)***			0,0373	(0,0072)***
Inc_expres			0,0203	(0,0086)**			0,0185	(0,0088)**
Inc_knowled			-0,0140	(0,0149)			-0,0151	(0,0153)
Inc_docum			-0,0116	(0,0075)			-0,0115	(0,0075)
Inc_comp			-0,0044	(0,0058)			-0,0066	(0,0058)
Inc_lang			0,0208	(0,0056)***			0,0183	(0,0056)***
Surp_manag					-0,0516	(0,0172)***	-0,0325	(0,0174)*
Surp_expres					-0,0179	(0,0156)	-0,0170	(0,0162)
Surp_knowled					0,0054	(0,0091)	-0,0047	(0,0095)
Surp_docum					-0,0163	(0,0075)**	-0,0117	(0,0075)
Surp_comp					-0,0307	(0,0139)**	-0,0254	(0,014)*
Surp_lang					-0,0242	(0,0129)*	-0,0225	(0,013)*

* Denotes significant at 10%; ** Denotes significant at 5%; *** Denotes significant at 1%

Table 11: Variation in competences by groups							
	N	Managem.	Expression	Docum.	Computer	Languages	Specific knowledge
Whole sample	8933	0,6171	0,2785	0,1684	0,7523	0,5426	-0,2444
Men	3666	0,6418	0,3320	0,1837	0,6456	0,5873	-0,2591
Women	5267	0,5998	0,2414	0,1578	0,8266	0,5115	-0,2341
Humanities	1086	0,5871	0,1542	-0,1639	0,9264	0,3214	-0,4975
Social Sciences	4062	0,5826	0,2049	0,1625	0,7795	0,4468	-0,1856
Experimental Sc.	555	0,6396	0,4390	0,1988	0,5356	0,7055	-0,5106
Health	819	0,6772	0,2718	0,3483	0,9244	0,7136	-0,0711
Technique	2411	0,6630	0,4240	0,2599	0,6195	0,7080	-0,2269
4-year-degree	4934	0,6442	0,3215	0,1556	0,8425	0,6032	-0,3023
3-year-degree	3999	0,5836	0,2255	0,1843	0,6410	0,4678	-0,1729
Matched	6912	0,6755	0,3247	0,2888	0,7895	0,5909	-0,1255
Non-matched	398	0,6635	0,3075	0,0873	0,6507	0,5663	-0,4769
Overeducation	1623	0,3568	0,0747	-0,3241	0,6186	0,3310	-0,6934
Exper (< 1 St. dev.)	222	0,5588	0,3308	0,1703	0,7439	0,6302	-0,1756
Between stand. Dev	8031	0,6247	0,2791	0,1790	0,7563	0,5441	-0,2375
Exper (> 1 St. dev.)	680	0,5459	0,2553	0,0430	0,7078	0,4965	-0,3475
Not cont. education	2396	0,5268	0,2035	0,0829	0,6707	0,4341	-0,2752
Specialization	1525	0,6073	0,2880	0,1615	0,8052	0,5276	-0,2079
Another degree	1424	0,6459	0,2496	0,1708	0,6716	0,5305	-0,2237
Master	2173	0,7003	0,3363	0,2373	0,8160	0,6294	-0,2301
PhD	360	0,8162	0,4112	0,4962	0,9437	0,8529	-0,1659
Other cont.	1055	0,5579	0,3101	0,1156	0,7737	0,5427	-0,3110
Management	868	0,7067	0,3268	0,1861	0,7206	0,5859	-0,3050
Assistance	758	0,6487	0,2321	0,3161	0,7650	0,6022	-0,0335
Comerce	467	0,6284	0,2214	-0,1501	0,7174	0,6217	-0,4211
Education	1667	0,6534	0,2146	0,2578	0,6627	0,3171	-0,0660
Design	214	0,7048	0,3613	0,2279	0,9065	0,6873	-0,2436
Technology	1920	0,6814	0,3952	0,2794	0,8214	0,6755	-0,2454
I+D	254	0,8096	0,3594	0,4992	0,7864	1,0133	-0,1314
Other qualified	3334	0,5832	0,2929	0,1298	0,7938	0,5573	-0,2918
Other non qualified	431	0,2191	0,0328	-0,5247	0,4610	0,2426	-0,7547
Agriculture	123	0,7433	0,4133	0,3122	0,9505	0,7687	-0,1326
Energy	212	0,6032	0,2774	0,2358	0,6331	0,4302	-0,2577
Chemistry	318	0,6546	0,2832	0,1975	0,6990	0,8544	-0,2891
Metallurgic	488	0,7228	0,3590	0,1649	0,6704	0,9922	-0,2552
Manufactures	343	0,6848	0,2487	-0,0267	0,8178	0,7545	-0,3804
Building industry	521	0,6629	0,3977	0,2726	0,9932	0,4839	-0,1916
Commerce	553	0,3411	0,0747	-0,3980	0,5859	0,3471	-0,5505
hostel	84	0,5221	0,1206	-0,0653	0,6866	0,4605	-0,4085
Transport	130	0,4935	0,1933	-0,2204	0,7743	0,6722	-0,5985
Telecommunications	715	0,6059	0,2977	0,2694	0,6313	0,7226	-0,3365
Financial Services	748	0,6089	0,3028	0,0090	0,8320	0,4533	-0,3439
Company Services	1024	0,6872	0,3940	0,3036	0,8781	0,5596	-0,2447
Public services	3523	0,6148	0,2457	0,2457	0,7276	0,4439	-0,1321
Social Services	151	0,6416	0,2372	0,1211	0,6840	0,5566	-0,2307

Table 12: Estimates of the variation of skills						
	MODEL 1 Variation in Management skills		MODEL 2 Variation in Expression skills		MODEL 1 Variation in foreign languages	
Att_ manag	-0,5859	(0,0142)***	0,0495	(0,0102)***	0,0002	(0,0143)
Att_expres	0,0173	(0,0142)	-0,5344	(0,0135)***	0,0565	(0,0164)***
Att_knowled	0,0872	(0,0189)***	0,0811	(0,0151)***	0,0949	(0,0206)***
Att_doc	0,0113	(0,0108)	0,0066	(0,0089)	-0,0387	(0,0122)***
Att_inform	-0,0068	(0,0109)	-0,0053	(0,009)	0,0011	(0,0127)
Att_idiom	-0,0098	(0,0116)	0,0072	(0,0093)	-0,5346	(0,014)***
Exper	0,0045	(0,0076)	0,0069	(0,0055)	-0,0112	(0,0071)
Exper^2	-0,0005	(0,0004)	-0,0004	(0,0003)	0,0003	(0,0003)
Specialization	0,0568	(0,0249)**	0,0500	(0,0197)**	0,0630	(0,0282)**
Other degree	0,0870	(0,0259)***	0,0261	(0,021)	0,1279	(0,0298)***
Master	0,0882	(0,0235)***	0,0665	(0,0183)***	0,1153	(0,0265)***
PhD	0,1405	(0,05)***	0,0529	(0,0394)	0,3039	(0,057)***
Other cont.	0,0259	(0,0289)	0,0937	(0,0229)***	0,0836	(0,0332)**
4-year-degree	0,0367	(0,0196)*	0,0353	(0,0156)**	0,1518	(0,0227)***
B	-0,0178	(0,0265)	-0,0098	(0,0203)	0,0228	(0,0301)
C	0,0587	(0,0371)	0,0287	(0,0316)	0,0569	(0,0435)
D	-0,0175	(0,0344)	0,0035	(0,0263)	0,0660	(0,0397)*
E	-0,0125	(0,0431)	0,0404	(0,0339)	0,0056	(0,0491)
F	0,0058	(0,044)	0,0288	(0,0339)	-0,0274	(0,0493)
G	-0,0376	(0,043)	-0,0234	(0,0326)	0,0482	(0,0478)
Social Sc.	0,0927	(0,034)***	0,0406	(0,0258)	-0,1207	(0,0367)***
Experimental Sc.	0,0871	(0,0477)*	0,0349	(0,0392)	-0,0686	(0,0531)
Health	0,1063	(0,0528)**	0,0402	(0,0376)	0,1122	(0,0548)**
Technique	0,1413	(0,046)***	0,0381	(0,0371)	0,0000	(0,0524)
Men	-0,0170	(0,0194)	-0,0554	(0,0154)***	-0,0510	(0,0216)**
Part-time rel.	0,0668	(0,0204)***	0,0516	(0,0163)***	0,1480	(0,0239)***
Part-time non rel.	0,0074	(0,0259)	-0,0095	(0,0203)	0,0625	(0,0286)**
Full-time rel.	0,0802	(0,0288)***	0,0647	(0,0231)***	0,1121	(0,0326)***
Full-time non	0,0593	(0,0451)	-0,0180	(0,0353)	0,1181	(0,0489)**
Mob_stud	0,0760	(0,0258)***	0,0377	(0,0207)*	0,1257	(0,0303)***
Mob_working	0,1070	(0,0241)***	0,0749	(0,0191)***	0,1792	(0,028)***
Mob_both	0,0554	(0,0339)	0,1056	(0,0266)***	0,1569	(0,0401)***
Press	0,0181	(0,0296)	-0,0209	(0,024)	0,0332	(0,0338)
Public exams	0,0246	(0,05)	0,0609	(0,0369)*	0,0517	(0,0555)
Public ag.	-0,0083	(0,0605)	-0,0013	(0,052)	-0,0509	(0,0721)
Self employed	0,1127	(0,1072)	0,0361	(0,1026)	0,0394	(0,1133)
Stage in firms	-0,0068	(0,03)	0,0214	(0,0243)	0,0578	(0,0354)
University occ.	-0,0125	(0,028)	-0,0107	(0,0225)	0,0485	(0,0329)
ETT	-0,1404	(0,0443)***	-0,1151	(0,0343)***	0,0558	(0,051)
Outplacement	-0,0525	(0,071)	-0,0958	(0,0519)*	-0,0148	(0,0752)
Internet	-0,0400	(0,0376)	-0,0488	(0,0318)	0,0515	(0,0454)
Other	0,0132	(0,0248)	0,0155	(0,019)	0,0273	(0,0272)
More 1 job	0,0210	(0,019)	0,0364	(0,0149)**	-0,0224	(0,0217)

Table 12 (continued)						
Agriculture	-0,0069	(0,0805)	0,1326	(0,0674)**	-0,0897	(0,0974)
Energy	-0,0677	(0,0654)	-0,0031	(0,0558)	-0,3362	(0,0794)***
Chemistry	-0,0606	(0,0596)	0,0006	(0,0506)	0,0131	(0,0746)
Metallurgic	0,0372	(0,0523)	0,0597	(0,0467)	0,1882	(0,0668)***
Building industry	-0,0384	(0,0554)	0,0374	(0,0464)	-0,4618	(0,0651)***
Commerce	-0,2623	(0,0546)***	-0,0678	(0,0453)	-0,3007	(0,0644)***
Hostel	0,0329	(0,1021)	0,0106	(0,0802)	-0,1204	(0,1171)
Transport	-0,0418	(0,0851)	0,0888	(0,0682)	0,0705	(0,0957)
Telecom.	-0,0728	(0,0498)	0,0126	(0,0435)	-0,0910	(0,0613)
Financial Serv.	0,0027	(0,05)	0,1033	(0,0435)**	-0,2751	(0,0614)***
Company Ser.	-0,0488	(0,0484)	0,1194	(0,0421)***	-0,2244	(0,059)***
Public serv.	-0,0877	(0,0495)*	0,0450	(0,0419)	-0,2703	(0,0593)***
Social Serv.	0,0114	(0,0786)	0,0560	(0,0611)	-0,2340	(0,0888)***
Priv	0,0351	(0,0258)	-0,0172	(0,0194)	0,0550	(0,0286)*
Autonom	-0,0692	(0,0373)*	-0,0531	(0,0284)*	-0,0149	(0,0389)
Temporal	-0,0474	(0,0208)**	-0,0513	(0,0163)***	0,0033	(0,0238)
No_contract	-0,0341	(0,0938)	0,0168	(0,0717)	0,0037	(0,0977)
< 10 workers	0,0323	(0,028)	-0,0187	(0,0223)	-0,0920	(0,0316)***
< 50 workers	0,0432	(0,024)*	-0,0182	(0,0193)	-0,0340	(0,0278)
< 100 work.	0,0105	(0,0316)	0,0082	(0,0247)	-0,0429	(0,036)
< 250 work.	0,0884	(0,0317)***	0,0188	(0,0269)	0,0263	(0,0389)
< 500 work.	0,0527	(0,0364)	0,0069	(0,0289)	0,0220	(0,0423)
Tgna	0,0065	(0,0402)	-0,0220	(0,0305)	-0,0491	(0,0441)
Grna	0,0449	(0,0406)	-0,0424	(0,0327)	0,0043	(0,046)
Llda	0,0325	(0,0436)	-0,0357	(0,0337)	-0,0540	(0,0491)
Other Spain	-0,0628	(0,0369)*	-0,0885	(0,0288)***	-0,0521	(0,0426)
Rest Europe	-0,1734	(0,1124)	-0,2006	(0,0846)**	0,3500	(0,1387)**
Rest world	-0,1261	(0,1894)	-0,2108	(0,1379)	0,1872	(0,2101)
Management	0,0958	(0,0378)**	0,0203	(0,0307)	-0,0566	(0,0431)
Assistant	0,0436	(0,0501)	-0,0879	(0,0374)**	-0,1844	(0,0554)***
Commercial	0,1356	(0,0435)***	0,0547	(0,0352)	0,0697	(0,0509)
Education	0,1365	(0,0412)***	0,0231	(0,0322)	-0,0752	(0,0468)
Design	0,0631	(0,052)	-0,0744	(0,0493)	-0,0331	(0,066)
Technical	0,0826	(0,0315)***	0,0753	(0,0256)***	0,0310	(0,0372)
I+D	0,1222	(0,0519)**	-0,0407	(0,0455)	0,1647	(0,0681)**
Other qualif.	0,0481	(0,031)	0,0446	(0,0249)*	-0,0123	(0,0364)
Non qualified	-0,0992	(0,0526)*	-0,0438	(0,0394)	-0,1671	(0,0557)***
Over	-0,2354	(0,027)***	-0,1992	(0,0205)***	-0,2410	(0,0285)***
Non_matched	-0,0827	(0,0425)*	-0,0478	(0,0347)	-0,1225	(0,0466)***
Constant	-0,0185	(0,0817)	-0,0040	(0,0663)	0,3096	(0,0941)***

* Denotes significant at 10%; ** Denotes significant at 5%; *** Denotes significant at 1%